Dynamic waste collection

Assessing the usage of dynamic routing methodologies

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Management summary

In this report, we evaluate how dynamic planning methods can best be applied for refuse collection, and then specifically for the refuse collection of underground containers at Twente Milieu. Twente Milieu is actively working on corporate social responsibility, and from that point of view, it tries to reduce its CO_2 emissions. The goal of this research is therefore to find out in what way dynamic planning methods can contribute to the reduction of CO_2 emission by reducing the number of kilometers driven by the refuse trucks. We will concentrate on creating more efficient emptying schedules, by emptying containers based on the actual level of refuse the containers, instead of using the same schedule every week.

We first evaluated the current planning and collection strategy used by Twente Milieu to evaluate at what points improvements might be possible and to find out which new strategies might work for Twente Milieu. Next, we combined this information with insights from our literature study to come up with suggestions for the use of dynamic planning methodologies.

Resulting from both the literature study and information on the current way of working at Twente Milieu, we found there are many different options for using a dynamic planning methodology. In our research, we distinguish four different possibilities to develop emptying schedules for emptying the underground containers. We compare the current planning methodology with three more dynamic variants and analyze which option leads to the best results for Twente Milieu. The four options we distinguish are:

1. Current planning methodology
2. Daily planning
3. Daily planning with rescheduling during the day
4. Continuous rescheduling

These four options vary between (almost) static and very dynamic and all have their own advantages and disadvantages.

1. The current methodology is simple, and all employees of Twente Milieu are familiar with it. However, it is a static method, which is not able to react to changes in the refuse volumes of the underground containers. While the schedule is the same for every week, there is some room for modifications on Friday, because then it is checked whether there are containers that need additional emptying before the weekend. This shows the current way of working is not completely static.
2. The daily planning option determines a new schedule at the start of each day. This schedule is based on the expected actual refuse volumes in the containers and expected handling times at the containers. A disadvantage of this option is that the planning for that day is fixed, while at the start of the day, it is still unknown what will exactly happen.
3. Daily planning with rescheduling is similar to the second option, but reschedules periodically. The advantage is that we will be better able to handle the uncertainties in handling times and refuse volumes. The planning might be updated when the actual refuse volumes do not match the expected amount of refuse. Rescheduling however, does require additional investments in board computers or requires another way to communicate between driver and planner.
4. The fourth option we distinguish, is continuous rescheduling. Every time a container is emptied, we reschedule to find the next container to empty. This option is the most flexible in handling uncertainties, but it is also very complex and computational intensive.

We decided to investigate options two and three further using a heuristic and a simulation model, and evaluate which option leads to the best results for Twente Milieu. The heuristic we developed consists of three elements, see Figure 1.

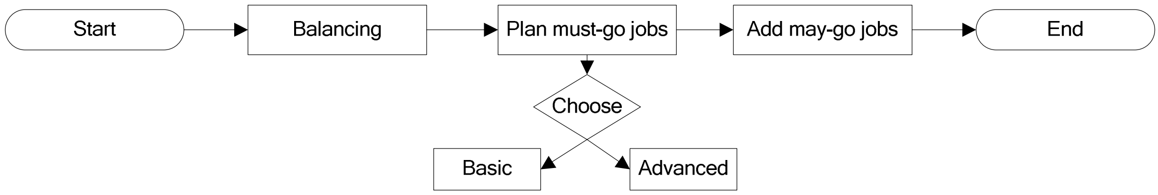


Figure 1 Steps in heuristic procedure

Our heuristic uses *must-go jobs* and *may-go jobs. Must-go jobs* are containers that need to be emptied on the current day, while *may-go jobs* are optional and are only included in schedules if there is space left in truck capacity and working hours. For planning the *must-go jobs*, we develope a basic and an advanced procedure. The basic method fills one truck at a time, while the advanced method assigns containers to all trucks simultaneously. 'Balancing' tries to balance the workload between days, using the expected *days left* of the containers. 'Add may-go jobs' attempts to increase the occupancy rate of the trucks by adding containers after all must-go jobs are completed. The 'Balancing' and the 'Add may-go jobs' elements are optional. In our simulation model, we evaluate whether these options lead to better results.

In the simulation model, we used, next to the elements in Figure 1, the number of containers, and the variance in the size of deposits to the underground containers as experimental factors. We used all these experimental factors to construct different scenarios which use different values of the experimental factors we stated. Next, we also varied between no rescheduling and rescheduling at mid-day. We did this to be able to analyze whether a more dynamic planning methodology leads to better results.

After simulating all scenarios, we concluded that the option to use a combination of balancing and the addition of may-go jobs leads to the best results. Although our simulations did not show an explicit difference between the basic and advanced heuristic, we do suggest to use the advanced heuristic. We think that the advanced heuristic is more flexible in its planning methodology. The use of rescheduling did not increase the results. A reason for this might be that the number and size of the deposits does not fluctuate much. Another reason might be the deterministic travel times we used. A suggestion for further research would be to investigate the influence of stochastic travel times. We assume that, in that case, using rescheduling will have more influence.

Managementsamenvatting

In dit verslag analyseren wij de bruikbaarheid van dynamische planningsmethoden bij afvalinzameling. Wij gaan specifiek in op de afvalinzameling uit de ondergrondse containers van Twente Milieu. Twente Milieu is momenteel actief bezig met duurzaamheid en in het kader hiervan probeert zij ook de CO_2 uitstoot te reduceren. Het doel van ons onderzoek is hierbij dan ook om inzicht te creëren in de manieren waarop dynamische planningsmethoden kunnen bijdragen in de reductie van CO_2 uitstoot door het aantal gereden kilometers te verminderen. Om dit te doen, kijken wij naar efficiëntere inzamelmethoden waarbij de containers geleegd worden op basis van de actuele vulgraden, in plaats van iedere week dezelfde planning te hanteren.

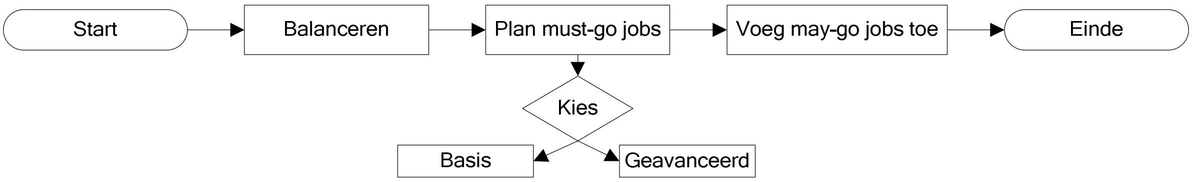
Wij zijn begonnen met een analyse van de huidige planning en inzamelstrategie die Twente Milieu gebruikt en hebben vervolgens gekeken op welke punten verbetering mogelijk is. Deze informatie hebben we gecombineerd met inzichten uit de literatuur, om zo te komen tot een aantal suggesties voor het gebruik van dynamische planningsmethoden. Als resultaat van zowel een literatuurstudie als informatie over de huidige manier van werken, blijkt dat er veel verschillende opties bestaan voor het toepassen van een dynamische planningsmethode. In ons onderzoek hebben wij ons gericht op vier verschillende methoden om schema's te ontwikkelen voor het legen van ondergrondse containers. We vergelijken de huidige methode met drie meer dynamische varianten en analyseren welke optie leidt tot de beste resultaten voor Twente Milieu. We onderscheiden de volgende vier methoden:

1. Huidige planningsmethode
2. Dagelijks plannen
3. Dagelijks plannen met bijsturing gedurende de dag
4. Continue bijsturing

Deze vier verschillende opties variëren van vrijwel statisch tot dynamisch en hebben allemaal hun eigen voor- en nadelen.

1. De huidige methode is simpel, en alle medewerkers van Twente Milieu zijn bekend met deze manier van werken. Echter, het is een statische methode, die niet in staat is om in te springen op veranderingen in afvalvolumes in de ondergrondse containers. Hoewel de schema's iedere week hetzelfde zijn, is er op vrijdag toch wat ruimte voor aanpassingen. Er wordt dan gekeken of er extra ledigingen nodig zijn voor het weekend.
2. De methode om dagelijks een planning op te stellen, doet dit aan het begin van een dag. Deze planning is gebaseerd op de verwachte werkelijke hoeveelheden afval in de containers en de verwachte tijd nodig om de containers te legen. Een nadeel van deze methode is dat de planning voor die dag vast staat, terwijl het nog niet bekend is wat er exact zal gebeuren op een dag.
3. Dagelijks plannen met bijsturen gedurende de dag, zorgt ervoor dat het makkelijker is om in te springen op onverwachte veranderingen. De optie met bijsturen is gelijk aan optie 2, maar stelt de planning gedurende de dag bij als de werkelijke hoeveelheden blijken af te wijken van de verwachte hoeveelheden. Hiervoor zijn wel extra investeringen nodig in boordcomputers of een andere manier van communicatie tussen chauffeur en planner.
4. De laatste optie die wij onderscheiden is continue bijsturing. Iedere keer als een container is geleegd, vernieuwen wij de planning om te bepalen welke container als volgende geleegd moet worden. Deze optie is het meest flexibel in het omgaan met onzekerheden, maar is ook erg complex en vergt veel rekentijd.

Wij hebben opties twee en drie verder geanalyseerd en een heuristiek ontwikkeld om te onderzoeken welke methode het best werkt. Hiervoor zullen we een simulatiemodel gebruiken. Onze heuristiek bestaat uit drie elementen, zie Figuur 2.



Figuur 2 Elementen van de heuristiek

Onze heuristiek werkt met *must-go* en *may-go* jobs. Een *must-go* job is het legen van een container die vandaag geleegd moet worden, terwijl *may-go* jobs optioneel zijn en alleen aan de planning toegevoegd worden als er nog ruimte over is in de truck en in werktijd. Voor het plannen van de *must-go* jobs, hebben we een basis en een geavanceerde procedure ontwikkeld. De basismethode voegt containers aan een truck toe, en gebruikt pas een nieuwe truck als de huidige vol is, terwijl de geavanceerde methode containers aan alle benodigde trucks tegelijkertijd toewijst. De optie 'Balanceren' probeert de werklast te spreiden over de verschillende dagen, door gebruik te maken van de verwachte tijd waarop containers vol zijn. 'Voeg *may-go* jobs toe' wordt gebruikt om de bezettingsgraad van de trucks te verhogen door extra containers toe te voegen nadat alle *must-go* jobs voltooid zijn. Zowel het 'Balanceren' als het 'Voeg *may-go* jobs toe' element zijn optioneel, we zullen deze opties analyseren in een simulatiemodel om te kijken of deze daadwerkelijk het gewenste effect geven.

We gebruiken in ons simulatiemodel, naast de drie eerder genoemde elementen, het aantal containers en de variantie in stortingsgrootte als experimentele factoren. Daarnaast hebben we ook gekeken naar het effect van bijsturing op de uitkomsten. Dit hebben we gedaan om te kunnen analyseren of een meer dynamische planningmethode betere resultaten geeft. Met deze experimentele factoren hebben we verschillende scenario's opgesteld om te kunnen beslissen welke combinatie van opties het beste resultaat geeft.

Nadat we alle mogelijk scenario's gesimuleerd hebben, concluderen wij dat de optie met zowel balanceren als het gebruik van *may-go* jobs tot de beste resultaten leidt. Hoewel onze simulaties geen duidelijk verschil tussen de basis- en de geavanceerde methode uitwijzen, stellen wij voor om de geavanceerde heuristiek te gebruiken. Wij denken dat de geavanceerde methode flexibeler is in het plannen van de containers. De optie om de gemaakte planning gedurende de dag bij te sturen, leidt in onze simulaties niet tot betere resultaten. Een reden hiervoor kan zijn dat het aantal en de grootte van de stortingen niet zoveel fluctueert. Daarnaast kan het ook het gevolg zijn van de deterministische reistijden die wij gebruikt hebben. Een suggestie voor verder onderzoek is dan ook om de invloed van stochastische reistijden te analyseren. Wij denken dat het bijsturen van de planning in dit geval ook meer invloed zal hebben.

Preface

Before you lies the report that ends my student life and my time at the University of Twente. On the one hand, this is a sad moment. I really enjoyed the last few years, I made new friends, learned many new things, and had a lot of fun. On the other hand, this is also the moment a new world opens up. A world full of new opportunities, possibilities and probably many new chances.

During my graduation period at Twente Milieu, I learned a lot, I knew only little about waste collection before I started. In general, I had a great time working there and getting to know all my colleagues. But, and I think as with every graduation project, I also had some periods I thought I would never be able to finish my project properly. However, in the end everything worked out, and this report enables you to read the result.

While working on my graduation assignment, I had help from a number of people. I would like to thank all of them for their time, trust, and patience with me. Especially, I would like to thank my supervisors for their advice and guidance. Martijn Mes, for his never ending patience when I, again and again, had trouble making a working simulation model. During the whole project, I learned a lot about the simulation program, and got more and more pleasure in puzzling to find solutions. Of course, I had most fun when the solutions resulted in a working model. Next, I would like to thank Marco Schutten for his critical evaluation of my report. I did not always like the additional work it cost me, but the comments and suggestions increased the quality of my report. Also, I would like to thank Gerbert Stegehuis, my supervisor at Twente Milieu. He showed me around in the world of waste collection and provided me with practical suggestions for finding the right information and solving problems. Finally, I would also like to thank my family for their support and trust in me. Their support really helped me to carry on and to keep faith in finishing this project properly.

Afke Stellingwerff

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Table of contents

1 Research design

In this chapter, we explain the outline of this graduation project at Twente Milieu. It starts with a short introduction to the company and the problem in Section 1.1. Next, Sections 1.2 to 1.4 indicate the research goal and the accompanying problem statement, and the description of the research questions, respectively. Section 1.5 describes the research methodology and the setup of the rest of this report.

1.1 Introduction

Nowadays, the environment gets a lot of attention because of the growing concerns about CO_2 emission, pollution, and the greenhouse effect. New environmental laws and larger awareness for climate change issues lead to a focus on refuse separation and recycling. Twente Milieu wishes to increase its corporate social responsibility within the company and her activities. This graduation project advances from these wishes. Twente Milieu is an important player in the field of refuse collection and the maintenance of public areas. Its main activity is the collection of household refuse by emptying containers and in this area Twente Milieu wants to improve the truck planning and container emptying as to save on fuel consumption and CO_2 emission.

Twente Milieu operates different types of containers, the most important types are mini containers, block containers, and underground containers. Mini containers are located at every house and for emptying, the residents have to put the containers along the side of the road. Block containers and underground containers are meant for a larger number of households and are most times located at apartment buildings. Underground containers can only be accessed with an access card, while block containers are freely accessible. The mini containers have to be emptied on pre specified days, because residents have to put the containers outside, whereas with the underground and block containers, this is not the case.

Emptying the containers results in large costs. These costs consist of transportation costs, maintenance costs of equipment, and personnel costs. At this moment, the process of emptying the containers is done by using a static planning, that is based on historic information on refuse volumes in containers. This planning states which containers should be emptied at what day and thereby providing a guideline to the driver which route to drive. For the mini containers, such a static planning is necessary, because citizens have to know when to place their containers near the road. However, for the underground containers, this approach is not necessary. The disadvantage of a static planning is the 'save' scheduling to prevent overloading. As a result, containers would most of the time not be full at emptying. Twente Milieu assumes that, on average, the underground containers are only for 40% filled at emptying, which means that these containers could be emptied less frequently. This could be done by introducing a more dynamic way of planning the emptying of underground containers. This means that a list of containers that should be emptied is composed based on *output ratios.* The *output ratio* gives the expected amount of refuse in the underground containers, expressed in a percentage. This list may differ between days or weeks. Of course, it has to be assured that the containers do not overflow, to ensure an optimal service level to the container users. For convenience, we assume a static planning is based on average historic data on refuse volumes rather than on the expected actual amounts of refuse in a container, while a dynamic planning is based on the expected amount of refuse in a container. Because the expected amount of refuse might fluctuated between days or weeks, a dynamic planning might be different for each day or week. These definitions will be used throughout this report. In Appendix A, we included a list of all definitions we will use in this report.

Another advantage of a dynamic planning is the possibility to adapt the schedule to situations such as the outside temperature. During the summer, some containers might cause odor nuisance and it is possible to select these containers for temporarily more frequently emptying. This applies for example for containers located in densely populated areas like city centers or containers used by restaurants.

This research will look at the different options to develop a methodology to use dynamic waste collection for the underground containers for household refuse. This should lead to an emptying schedule with less frequent emptying, which in turn results in an increased efficiency and savings on transportation costs and emission of CO_2. In turn, the containers should not overflow, to guarantee service to the users. This means that there has to be a balance between environment, costs, and service.

1.2 Research goal

The goal of this research is to evaluate the use of a dynamic trip planning for the collection of household refuse from the underground containers of Twente Milieu. The objective of this new way of planning is to decrease the logistical costs and at the same time also decrease the emission of CO_2, while keeping the same level of service.

1.3 Problem statement

Based on the research goal formulated in Section 1.2, we formulated the following problem statement which we will use throughout this research:

In what way could a dynamic planning methodology for emptying the underground refuse containers be used to lead to both company-economic benefits as well as to a reduction of CO_2 emission?

1.4 Research questions

We formulate the following five research questions that need to be answered before we can respond on our problem statement and conclude in what way a dynamic planning methodology would be beneficial to use:

1. How is the current refuse collection of the underground containers organized?
    - How is planning currently being done?
    - How often is this plan revised?
    - What are the good and bad aspects of the current system?
2. Which data are available about the underground containers, for example output ratios or emptying schedules?
    - Where to find this information?
    - How reliable are the data?
    - Could this information be used for developing a new planning methodology?
3. Which possibilities are known for making a dynamic planning?
    - Which possibilities are known in literature?
    - Are these approaches already used by similar companies?
4. How should a dynamic planning system for Twente Milieu be designed?
    - What are the requirements?
    - Which different options are possible?
5. What is the expected performance of this new planning methodology?
    - How does the performance compare to the current way of planning?

1.5 Research method

To be able answer the problem statement and so to achieve the goal of this research, we will have to find answers to the research questions formulated in Section 1.4. For this purpose we will use different research methods, as outlined in this section.

To gain insight in the current situation and to find an answer to research question 1, we interview involved employees. Beside this, it will also be useful to accompany a number drivers on their workday emptying the underground containers. This will give insight in the refuse collection processes and the current way of working, and it allows determining the good and bad aspects in the current planning processes of emptying the containers. This question is answered in Chapter 2 and includes sections about Twente Milieu, the emptying of underground containers and the planning procedure.

Research question 2 concerns the available data. For the construction of a dynamic planning methodology, a lot of data are needed and these data are collected from the databases of Twente Milieu. This includes information about the number of underground containers with locations and capacities; the number and capacity of trucks that can empty these containers; and information about the amount of refuse in the containers. Of course, the reliability of this information should be checked. Also, it is important to have an insight in the expectations for the future, for example in the increase of the amount of containers and the amount of refuse offered. Chapter 3 gives the results of the data analysis and answers research question 2.

To be able to explore the existing ways of dynamic planning as stated in research question 3, we will perform a literature study. Next to this, we will also verify whether there are other waste collection companies that already use a dynamic way of refuse collection and see how they have implemented this system. Chapter 4 presents the results of the literature study and also gives insight in the use of dynamic systems in the waste collection industry.

For answering research question 4, again employees of Twente Milieu are interviewed to find out about the ideas Twente Milieu has for implementing a dynamic planning. Next to this, the results from our literature study show whether there are options that will fit well with Twente Milieu and which options will not work for Twente Milieu. Chapter 5 and Chapter 6 answer research question 4. Chapter 5 discusses the possibilities to use dynamic refuse collection procedures at Twente Milieu and Chapter 6 outlines a planning model of the desired situation and explains the heuristic we developed.

To give an indication of the expected performance of the new planning methodology and so to answer research question 5, we will use a simulation model. According to Law (2007), simulation models are used to evaluate complex real-world systems which cannot be analyzed analytically. Another advantage of using a simulation model, is the possibility to test different scenarios without disrupting the actual system. In this report a simulation model will be used to compare the current way of planning with the new planning method and to test different scenarios. Chapter 7 answers this research question by presenting the simulation model, while the results of the simulation model are discussed in Chapter 8.

Finally, we will conclude this report with the conclusion and recommendations that followed from our research in Chapter 9.

2 Current situation

To be able to make a thorough suggestion about what a dynamic way of planning should look like, it is important to have a good understanding of the current way of working. This chapter describes the different aspects Twente Milieu deals with in relation with the process of emptying the underground containers. Section 2.1 introduces Twente Milieu as a company, followed by Sections 2.2, and 2.3, which describe the contracting process and information about the installed base. Sections 2.4 and 2.5 explain the actual planning and emptying process, and Section 2.6 outlines the data that can be retrieved from the underground containers. Section 2.7 illustrates the experiences of users with the underground containers and Section 2.8 concludes this chapter by giving an overview of the problems and other remarkable points in the current way of working.

2.1 Twente Milieu

Twente Milieu was founded in 1997 by means of a merger between the municipal cleansing departments of the municipalities Enschede, Hengelo, Almelo, and Oldenzaal. A few years later, also Hof van Twente (2001) and Losser (2006) joined. These six municipalities are the shareholders of Twente Milieu. The main activity of Twente Milieu is the collection and processing of refuse, but Twente Milieu also operates in the cleaning of streets and sewers, the mowing of verges, and the control of plague animals. Twente Milieu has its headquarters located in Enschede and has furthermore establishments in Hengelo and Almelo. All three locations have their own workshop. Table 1 displays some key figures of Twente Milieu about the size and realized results for 2008 and 2009. It shows a growth for 2009 in net results with regards to 2008 (Twente Milieu, 2009).

	2008	2009	
Net turnover	25.050.516	27.012.034	Euro
Net result	1.502.502	2.122.788	Euro
# Employees	202	219	
# Connected households	170.964	171.923	
# Vehicles	144	148	
Waste collected, total	221.537	214.800	x1000 kg
of which household garbage	99.733	97.043	x1000 kg

Table 1 Key figures Twente Milieu (Twente Milieu, 2009)

Currently, Twente Milieu belongs to one of the largest refuse collectors in the Netherlands when it comes to the number of households connected to its network. Looking only at companies that are government ventures, Twente Milieu is the third largest company of the country (Noordhoek, 2008).

2.2 Contracts with municipalities

There are six municipalities that ask Twente Milieu to install underground containers. Twente Milieu has two different options to do this: municipalities can either lease underground containers or buy them from Twente Milieu. Currently, the municipalities of Enschede, Hengelo, and Hof van Twente lease the underground containers from Twente Milieu. As part of the lease contract, Twente Milieu takes care of the purchase, the installation, the maintenance, and the lease contract includes emptying the underground containers once a week. Twente Milieu charges the municipalities one overall rate for this complete package.

The other option is used by the municipalities of Almelo, Oldenzaal, and Losser. These municipalities buy the underground containers from Twente Milieu. Twente Milieu has the possibility to purchase them low-priced, and for the municipalities, this is cheaper compared to the situation in which they have to buy them directly from the container manufacturer. The municipalities are responsible for the emptying and all other processes. However, often these processes are outsourced to Twente Milieu, but then under the authority of the municipalities. In this case, there is no investment made by Twente Milieu.

To Twente Milieu, the lease construction is most favorable, because of the stronger customer relations and the possibilities of additional sales. From the municipalities that lease the containers, Twente Milieu receives additional payments for each container emptying more frequent than once a week. The other municipalities pay for every emptying of a container. This is remarkable, because it means that it would be favorable for Twente Milieu to empty containers as often as possible and thus not to empty only full containers. Together with its efforts to use a dynamic planning methodology and reducing CO_2 emissions, Twente Milieu is also working on other contracts, based on the total refuse volume collected instead of the number of emptyings. This strategy works better when trying to reduce the number of emptyings of underground containers.

The necessity for new or additional underground containers is indicated by the municipalities together with the public utility housing enterprise. If they decide that a new container is necessary, the municipality orders Twente Milieu to install it.

2.3 Underground containers

At the end of March 2010, Twente Milieu operates 520 underground containers. These are both containers in ownership as well as containers of municipalities that outsource container operation to Twente Milieu. Table 2 shows the number of containers per municipality. Every week about twenty new containers are installed and at the end of 2010 the total number of underground containers is 745. Looking into the future, at most 1500 containers could be installed. This amount is based upon the fact that one container is used by, on average, 25 households and there will be a maximum of 35 to 40 thousands households that might be using an underground container in the future. Currently, there are still digital and non-digital underground containers. The digital containers have to be accessed with personal cards, and these containers register all deposits that are made by users. The intention is to replace all non-digital containers with digital ones, because of the introduction of '*diftar'.* This is a new way of charging citizens a different rate for different types and amounts of garbage. Therefore it is necessary to register all deposits made to the corresponding households and this is only possible if the underground containers operate with a digital access card.

	Digital	Non digital	**Total**	Still to install in 2010	**Grand Total (2010)**
Almelo	0	142	**142**	58	**200**
Enschede	169	0	**169**	131	**300**
Hengelo	39	151	**190**	10	**200**
Hof van Twente	12	2	**14**	6	**20**
Losser	0	1	**1**	14	**15**
Oldenzaal	4	0	**4**	6	**10**
Total	224	296	**520**	225	**745**

Table 2 Total amount of underground containers (March 2010)

The underground containers have a number of advantages over mini containers and block containers. Underground containers have a larger storage capacity, the underground containers used to put in household refuse have a capacity of $5m^3$. This is roughly five times as big as a normal block container. As a result of the digital underground containers only being accessible with an id-card, illegal waste deposit is hindered and the odor nuisance is less because of the solid locking of the containers. Another benefit is that only a small part of the container is visible, which makes the container suitable for use in public areas and contributes to an attractive environment.

Currently, only the digital underground containers have an electronic registration system. The non-digital containers are always emptied once a week because there is no information available about the output ratio. After three or four weeks, the truck driver has an indication whether emptying once a week is sufficient or if emptying should be done more frequently. All containers will be equipped with electronic measuring devices. Then it is possible to measure the number of deposits made for all underground containers. In Enschede and Hengelo, this happened during the summer of 2010; the other municipalities follow late 2010 or early 2011.

Normally, every household receives an access card to operate the underground container, this is paid afterwards with the municipal taxes. However, in some cases it is possible to use prepaid cards. Twente Milieu uses these cards for debtors; the cards give the right to make only a given number of deposits and after that number, a new card has to be bought. The advantage for Twente Milieu is that the use of the containers is paid in advance.

2.4 Route planning

A planning employee is responsible for determining which containers have to be emptied on a certain day. This employee decides which truck and which driver are assigned to a certain group of containers that need to be emptied. The planning is static and thus every week the same underground containers are emptied. The driver receives a list of containers that need to be emptied and with this list he has to make his own route. Although the planning is static, there are some differences between the even and odd weeks. This is because some containers are emptied every week while others are only emptied once every two weeks.

Changes in the emptying schedule are rarely made. The reason for this is that the underground containers are already in use for about seven or eight years and Twente Milieu has experience with the amount of refuse that is offered to the containers. For the plastic containers for example, a lot more adaptations are necessary, because Twente Milieu started collecting this only recently. Therefore not that much is known about the amounts offered. Any possible changes in the schedules have to be initiated by the municipalities. Twente Milieu does not make any changes on its own initiative.

Twente Milieu has five trucks available in 2010 for emptying the underground containers. There are a number of drivers capable of driving these trucks; this requires some experience with driving a large truck through the small streets of city centers, and it requires experience with the crane, that hoists the container out of the ground. In the near future, the number of underground containers will be doubled, which means that additional trucks might be needed to empty all the containers.

Every Friday morning, a list with actual output ratios is printed to see whether there are any additional containers that need to be emptied before the weekend or whether they can all wait until after the weekend. All containers are emptied by refuse trucks that depart from Hengelo, except for the underground containers located in the municipality of Almelo. These containers are emptied starting from the Twente Milieu location in Almelo. None of the containers in Almelo has a digital registration system, and therefore it is not possible to print a list with output ratios to see whether there are any containers that need emptying. This also means that there is no actual information available about the amount of refuse in the containers in Almelo. During 2011, these containers are replaced by containers that do have digital registration systems.

The performance of the planning and the routes is monitored by the use of database systems. The database contains information about the emptying frequency and the number of times a deposit to the container is made. This gives an indication whether the current emptying frequency is right. Section 2.6 discusses the database systems Twente Milieu uses in more detail. Of course, the use of databases is only possible for the digital underground containers. With all the new containers that are delivered, the planning has to be adjusted. The new containers are inserted in the current routes, but the maximum capacity of the routes and trucks will soon be reached. To overcome this problem, two new trucks are ordered, which arrive in October 2010.

2.5 Emptying the containers

The refuse truck driver starts his working day at 7.30 am when he receives his route with the containers for the day. He also receives a form on which the total weight of the deposed waste has to be noted. The planning of the day consists of a list of container locations. The exact order in which he empties these containers, is determined by the driver himself. In constructing a route along all containers, no planning tools or navigation devices are used. Because the routes are the same every week, the driver knows these routes by heart and does not need to look up the exact location or directions. During holidays, when other drivers take over the emptying of underground containers, it takes a lot of time to teach this new driver the route because the routes are not recorded. Before starting his route, the driver checks his truck on any failures or irregularities.

Figure 3 Emptying of an underground container

When the driver arrives at a container location, he empties it with the use of a remote controlled crane. To do this, he has a portable control panel, which is used to lead the crane, as can be seen in Figure 3. The driver of course has to be careful that the container does not hit any objects while pulling it up or down. Sometimes this is difficult, because the containers are located close to buildings, walls, lampposts, or parked cars. At the same time as the emptying of the containers, the driver checks whether the surrounding area needs cleaning. Any possible failures or other irregularities to the container are reported to the service department; the driver does not fix these problems himself. The driver also resets the counter of the underground container such that the number of deposits is zero again, this is of course only possible for the digital containers. Emptying one underground container takes around four minutes. When the refuse from the container is disposed into the truck, a press is activated to reduce the volume of the refuse with a factor five. This means that the refuse truck can contain five times as much refuse as a truck without this press and therefore visits to the dump site are necessary less frequently. On average, in the current situation, the refuse truck can empty thirty to thirty-five containers before its capacity is reached. The air content of a truck is 18.000 liter, combined with the press, this leads to maximum 90.000 liter of refuse in one refuse truck.

When the truck is full or when the driver has finished his complete route, the driver goes to Twence in Hengelo to dump the refuse. The truck is weighed at arrival and departure and the difference between these two is the total weight of refuse collected from the containers. After a tour through one municipality, first a trip to the dumping ground has to be made, before continuing to another city. This is because the different municipalities have to pay for the discarding of the refuse. Therefore the driver has a different card for each municipality; on this card the amount of dumped refuse is registered. However, in the near future all refuse trucks will be equipped with weighing tools, which makes these intermediate trips unnecessary. When leaving the dumping ground, the driver receives a note which states the weight of dumped waste. He registers this on the form he received in the morning. The note and form are stored for administration.

Normally, a workday has eight hours from half past seven until four o'clock, with a lunch break of half an hour at twelve o'clock. Of course, these times are a little variable with the different routes. With the current way of working, the driver has some freedom to make his own route. Because he does not have a board computer, the driver has to study the best route to drive himself.

Once a year, all containers get a thorough cleaning and service job. Every two or three months, the containers get a normal cleaning job; Twente Milieu has its own maintenance and service department that takes care of this. The most common repairs are on the bars of the containers, on the container floors, and on the cables. The underground containers have a lifetime of approximately fifteen years.

2.6 Data from the containers

Twente Milieu currently uses three registration systems to record data about the underground containers. All containers in Enschede use the Mic-o-data system, while the containers in Hengelo are registered in the Geometra database. As a third system, the AWRS system is used. This system contains information about containers in Oldenzaal, Almelo, Hof van Twente, and Losser. The AWRS system also contains information about the new containers in Hengelo and Enschede, and the intention is that the AWRS system will replace the older systems. These three registration systems record data on container locations, the number of times the lid of the container is opened and closed again, any possible errors, container configurations, and the historic emptyings.

The underground containers register the number of times a deposit is made. This gives an indication of the output ratio, because it registers the number of deposits, but not the size of the deposits. Every time the lid of the container is opened and closed again, the output ratio is raised by one percent. This means that a container is considered to be 'full' after 100 deposits and that it is also possible that some of the containers have a output ratio of over 100 percent. The AWRS system offers the possibility to tune the number of deposits before a container is marked as full.

For registering the number of deposits and sending this information to Twente Milieu, the container operates on a battery. This battery has an average lifespan of 2 years and when it is almost empty, it sends a signal to Twente Milieu. At this point in time, Twente Milieu has one month to replace the battery before it is really empty. Sending the information about the deposits is done using GPRS. Every morning at 7 am, the containers transfer this information. Any failures are reported immediately when they occur. For example, when a container is activated three times while the container lid is not opened, the container assumes a system failure and sends a message to Twente Milieu.

Some of the refuse trucks suitable for emptying the underground containers have the possibility to weigh the containers when they are emptied, but for the underground refuse containers this possibility is not yet used. As of 2011, the weighing of the containers will be utilized. Next to the data available from the containers, also the total amount of refuse dumped at Twence is registered. These data are recorded for each refuse truck that arrives at Twence, but of course this total amount is the sum of the refuse from all containers the driver emptied on his tour.

2.7 User experiences

In general, users do not have many problems or complaints about the use or the emptying of the underground containers. Especially when underground containers replace block containers, the transition is a large improvement. Sometimes people have some initial doubts about the system, but most times these doubts go away after they use the system for a while.

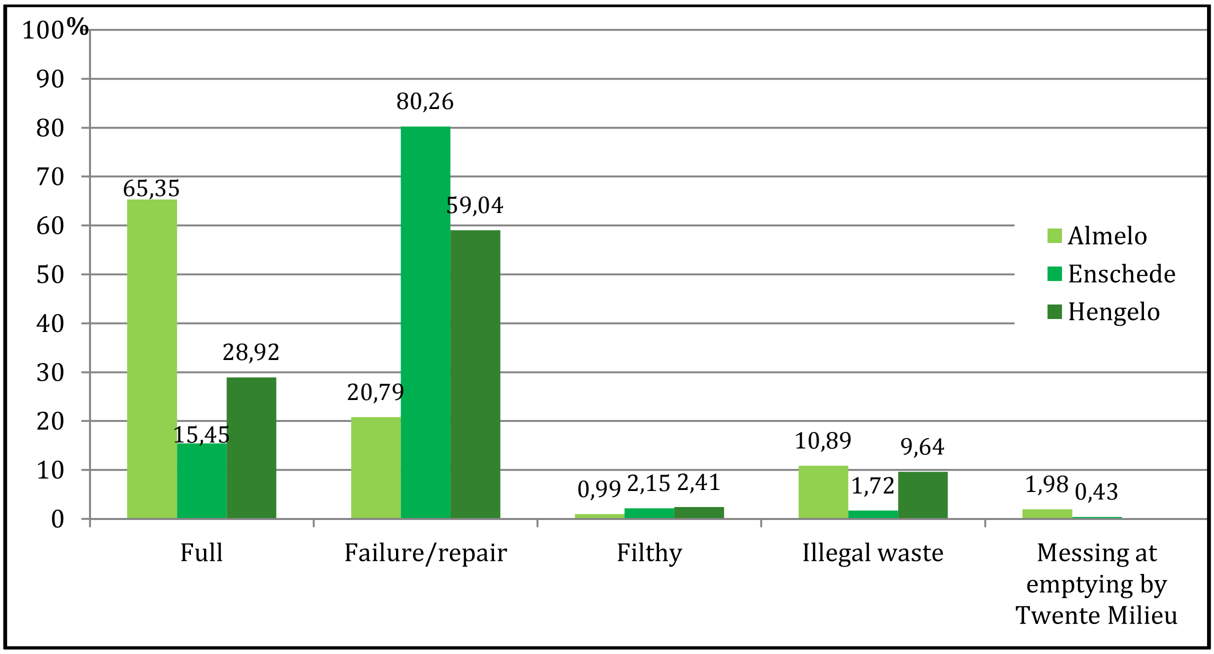


Figure 4 Reports or complaints about underground containers (2009)

Twente Milieu operates a front office to assist people when they have remarks or problems and this includes complaints and reports about underground containers. Figure 4 shows all complaints and reports on underground containers that are reported by users in 2009 for the municipalities of Almelo, Enschede, and Hengelo. In total, 417 reports were registered of which 233 came from Enschede. As can be seen, most comments are about full containers or failures on containers. One remarkable point is that in Almelo by far the most reports are about full containers, while in Enschede and Hengelo most reports are on failures. This distinction can be explained by the difference in containers between Almelo, and Hengelo and Enschede. The containers in Almelo do not have a digital registration system that gives an indication of the output ratio and therefore the emptying schedule is not based on actual deposits. This results in more complaints on containers being emptied too late. Another explanation can be found in the container locations. In Almelo, all underground containers are located in residential areas, while in Enschede and Hengelo a lot of containers are located in the city centers. The containers in the city centers suffer more from violation and therefore, the fraction of the complaints on full containers is relatively lower.

2.8 Conclusion

This chapter gave an overview of the current processes at Twente Milieu concerning the underground containers. This showed some remarkable points. The current way of working is very static and routes are driven intuitively by the truck drivers. The fact that there are no fixed routes gives problems when another driver has to take over the route. This happens for example during the holiday period.

It happens regularly that a driver diverges from his route and also empties some containers that are on the route for a different day, because they are nearby or that containers of this day are passed on to the next day. When using a dynamic route planning, these actions would undermine the savings that could be realized.

The charge per container emptying Twente Milieu uses when charging the municipalities is also notable. This way of charging does not stimulate less frequent emptying of the containers, but even seems to motivate for more frequent emptying, regardless of the amount of refuse in the containers. For a dynamic routing methodology to work well, this should be altered to a charge per refuse volume. This would also be more in line with the sustainability Twente Milieu strives for.

There is a important difference in the number of reports Twente Milieu receives on the underground containers. From Almelo, 65% of all reports are about full containers, while from Enschede and Hengelo this is only around 20%. This might indicate that the digital containers lead to a better insight in the amount of refuse deposited and therefore also a better emptying schedule.

3 Data analysis

This chapter discusses the data analysis performed to gain insight in the current processes, the usefulness of the data, and the accuracy of the available information and assumptions made by Twente Milieu. The results might be used as input for a simulation model that will be used in this research to test various planning methodologies. This chapter starts with briefly explaining how we gathered and cleaned the data in Section 3.1. Section 3.2 clarifies the outcomes and explains any irregularities that came out of the analysis.

3.1 Data collection and cleaning

As stated in Section 2.6, Twente Milieu has multiple databases with information about the underground containers, such as the output ratios and container failures. We performed a data analysis to check which data is available, whether it could be used in the rest of our research, and whether there is information lacking in the current databases.

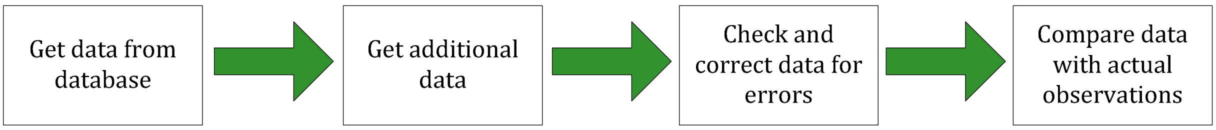


Figure 5 Structure of data analysis

Figure 5 shows the different steps of our data analysis. In this analysis, only data from the underground containers in Enschede is used. We decided to use only the underground containers in Enschede in our analysis, because in Enschede all containers are digital. Therefore, this data is the most up to date and complete, which ensures we get a good indication of the underground containers in the whole city of Enschede. Data from underground containers of the other municipalities is still not complete, because not all underground containers are digital. We started with collecting data from 2009 of all containers in Enschede, which we combined with records from Twence about the total weights the trucks dumped in 2009. Next to this, Twente Milieu recorded the actual weights of refuse in the containers in Enschede for a week. When combining all these data, we were able to detect any missing information or errors, for which we corrected our data file. With all this information it was possible to compare real data with the data from the database. Although we only analyze data from containers located in Enschede, we assume that these results will be representative for those in the other municipalities, because the containers in all municipalities are of the same type. Although Enschede differs from the other municipalities because it is larger, this does not influence the output ratios of a container because these are always used by around 25 households. For determining the number of containers to use in this data analysis and in the simulation model, we have taken the situation in the end of March 2010 as a reference value. At that moment, Twente Milieu operated in total 520 underground containers. Of those, 124 containers, all located in Enschede, are in the Mic-o-data database, and those are the containers included in the analysis.

While gathering the data, we ran into some errors and inconsistencies in the database and between data acquired from the databases and the data obtained from Twence.

- The output ratios in the database were sometimes only one or two percent. This occurred when a container was emptied twice within ten minutes. This is a result of the truck driver resetting the container multiple times. In some cases, there are refuse bags besides the container. When the container is emptied, the driver deposits these bags in the container and resets it again. Therefore the registered output ratios in the Mic-o-data database is only one or two percent.
- Containers were emptied on a certain day, while there was no trip made to Twence.

- On some days, there was a trip to Twence to dump refuse, while according to the database, no containers were emptied in Enschede.

During the data analysis, we used some assumptions to make calculations. These are assumptions Twente Milieu uses in its daily operation.

- One cubic meter of refuse weighs 110 kilos.
- The effective capacity of a container is 4800 liter
- All deposits made to the containers are of the same size.
  This assumption was made to calculate the average number of kilos of refuse in each container. Because the result is an average number of kilos, this assumption will not largely influence the outcomes. In our simulation model, we will vary the variance in the deposit sizes, to evaluate the impact when the real deposit sizes are smaller or larger than the averages we calculated.

Also, we tested some assumptions made by Twente Milieu to see whether they are right. These assumptions are:

- Average output ratio at emptying is 40%
- Average deposit size is 48 liter
- Increasing the output ratio with 1% after every deposit gives a good approximation of the real volume of waste in the container.

Appendix B explains all calculations made in this chapter.

3.2 Results

Based on the weights of the refuse dumped at Twence and the number of containers emptied on that same day, the average weight of refuse per container is 297 kilos. shows for each month the average weight per container. It shows some differences between the months, with the highest peak in March. However, these differences are not significant according to the statistical tests we performed.

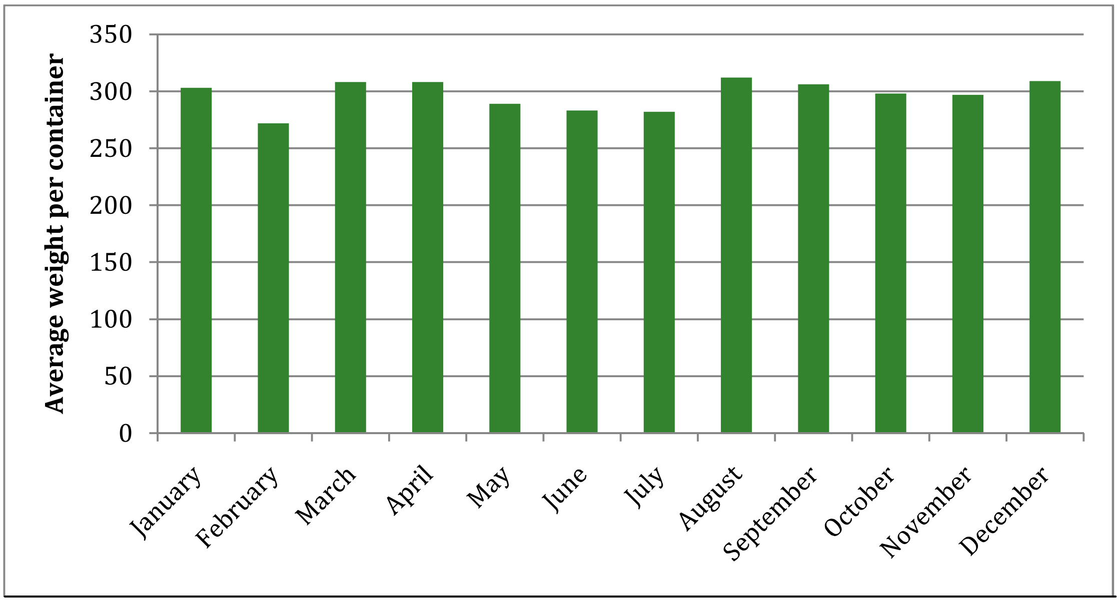


Figure 6 Average weight per container at emptying per month (2009)

The data analysis showed that there is a difference between the output ratios that are registered in the databases and the output ratios that are calculated with the weights of the refuse dumped at Twence. On average, the calculated output ratios at emptying are 18 percent lower than the registered output ratios at emptying. This result indicates that the actual deposits made to the containers are smaller than the 48 liters assumed by Twente Milieu, as stated in Section 3.1. For almost all underground containers, the calculated output ratio is lower than the registered output ratio. For only 15 of the 124 containers in Enschede, the calculated output ratio were higher. These 15 containers are almost all located near stores, so this indicates that stores deposit larger amounts of refuse than households. Table 3 summarizes briefly the outcomes of the data analysis. Next to the difference between the registered and calculated output ratios, it also shows a difference in average weight in the containers. In 2009, the average weight was 297 kilo. We tested whether these calculations were accurate by weighing the containers for one week, and we compared these results with the calculated weights from that same week from Twence. There is only a slight difference, but this is because of weighing inaccuracies. We can state, based on these results, that the calculations are accurate. This indicates that the calculated output ratios are correct.

	Average	**Standard deviation**
Registered output ratio	66,68%	27,46
Calculated output ratio	55,21%	21,38
Weight of refuse in the containers (based on data from Twence from 2009)	297,18	113,72
Weight of refuse in the containers (based on actual data from week 24, 2010)	254,99	113,27
Weight of refuse in the containers (based on data from Twence, week 24 2010)	258,03	145,14

Table 3 Summarized results data analysis Mic-o-data containers located in Enschede

Next to these general results, we also analyzed the data per container to see whether there are large differences between the different locations. The output ratios of the different underground containers differ between 19% and 173%, based on the registered number of deposits. The corresponding calculated output ratios differ between 15% and 134%. These figures both show that there are large differences between the containers and that the assumption of 1% for each deposit is not a good representation of the actual situation.

Twente Milieu assumed that most containers are only 40% full at emptying, but this is not true: the average calculated output ratio is 55%. Out of the 124 containers in Enschede, 19% have a output ratio below 40%. This number is based on the registered number of deposits, looking at calculated output ratios, 27% of all containers have a output ratio below 40% at emptying. When looking at containers that are only 50% filled at emptying, there are 34 containers, which is 27%, that have a registered output ratio of at most 50%. Looking at the calculated output ratios, there are 52 containers with an output ratio below 50% at emptying. This corresponds to 42%.

Table 4 shows some of the differences between containers that are emptied once a week and containers that are emptied twice a week. The underground containers are more full when they are emptied less frequently. This is evident by the fact that the containers that are emptied more than 90 times in 2009 have a lower registered output ratio than the containers that are emptied 45 to 56 times in 2009. The first group of containers has an average output ratio of 53 percent, while the other containers have a registered output ratio of 68 percent. The average registered output ratio for the containers that are emptied less than 45 times is 76 percent. In the calculated output ratios, which are based on the weight of waste rather than the number of deposits, there is not much difference between the groups. The calculated output ratios for these three groups are respectively 50, 51, and 54 percent. This indicates that the containers that are emptied twice a week contain more, but smaller deposits. The difference between the registered and calculated output ratios indicates that it might not be necessary to empty all containers that often. Table 4 also shows the deposit sizes for the different containers. The average deposit size is 41,30 liter with a standard deviation of 7,03. This is smaller than the 48 liter Twente Milieu assumes. In the future, Diftar will be implemented. These differentiated tariffs for different types of waste, will probably lead to larger deposit sizes and less variation, because then a household has to pay for every deposit made.

Street	No. of emptyings	Average output ratio (registered)	Standard deviation	Average output ratio (calculated)	Standard deviation	Weight (calculated)	Weight (actual)	Deposit size (liter)
Buitenweg	51	66,47	12,82	51,45	11,67	282,60	240	38,65
De Heurne 79	51	50,22	19,36	39,10	16,45	215,10	130	38,94
De Heurne 79	47	67,19	23,86	108,90	17,26	274,30	140	37,11
Dotterbloemstraat 10	52	29,04	11,23	22,41	9,79	123,25	100	38,59
Hofstraat 3	100	35,82	17,55	34,53	20,61	189,91	105	48,20
Hofstraat 3	103	39,27	17,81	38,83	20,76	213,54	175	49,43
Hofstraat 3	63	40,03	15,20	39,16	19,31	215,35	215	48,90
J.J. van Deinselaan	49	58,59	15,21	45,72	13,13	251,40	180	39,01
J.J. van Deinselaan	51	76,84	12,64	59,74	14,22	328,50	220	38,86
Marthalaan 8	52	67,50	14,72	52,25	13,86	287,26	160	38,69
Mooienhof 177	50	81,02	29,42	61,29	20,65	337,07	350	37,82
Mooienhof 177	50	73,86	35,16	56,80	26,04	312,41	240	38,45
Mooienhof 177	50	18,76	9,20	14,61	7,59	80,36	200	38,94

Table 4 Remarkable points resulting from the data analysis

The box plot given in Figure 7 also supports the statement that there are improvements possible in the emptying schedule. We would expect similar output ratios for the containers that are emptied equally often, but Figure 7 shows that this is not the case. Another strange remark is the scattering of the dots. Because of the static planning, we would expect straight lines at 26, 52 and 104 times of emptying. There are some clusters around these lines, but also more deviation than expected. This might be caused by errors in the registration of emptying, when drivers forget to reset the container or when they accidentally reset a container twice at the same time. Another explanation might be that Twente Milieu checks on Friday morning whether all containers will make it to Monday. If there are any containers that will be full during the weekend, these are emptied on Friday. This emptying is additional to the normal schedule and therefore might cause deviation from the line around 26, 52, or 104. When we develop a new dynamic planning method, we would expect to get a box plot with equally spread dots, fuller containers, and less deviation in the output ratios.

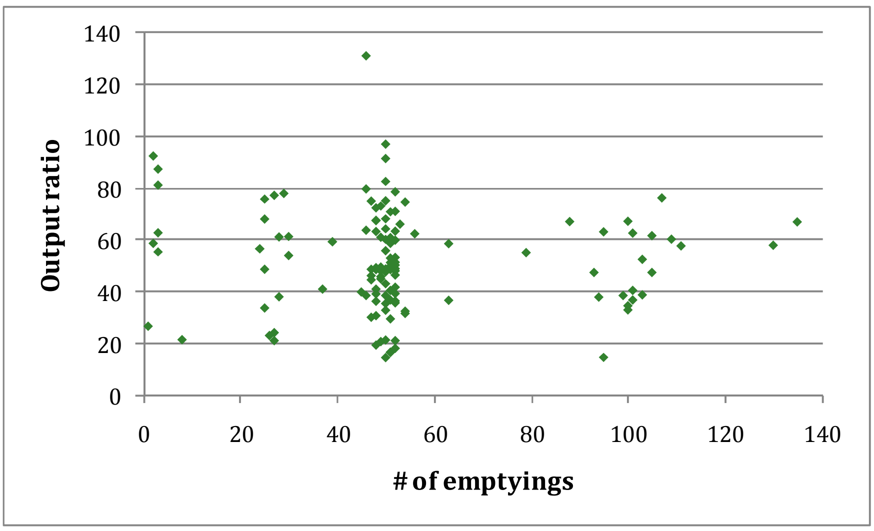


Figure 7 Box plot of the output ratio versus number of emptyings, containers Enschede 2009

As a final remark, Figure 7 also shows one containers with an average output ratio of 131%. This container is located at a retirement home, and therefore, the number of deposits is high, while the size of the deposits is small. This results in an output ratio of 131%, because normally, a container is considered full after 100 deposits. However, when the deposits are smaller, a container can handle more than 100 deposits.

As stated, there are some differences between the different container locations, but there are also differences in output ratio between containers that are at the same locations. The output ratios of the underground containers do not only differ between locations, but also when there are multiple container at the same location. As an example the location *'Mooienhof 177'* is shown in Table 4. This location has three containers, two with an average output ratio of around 75 percent, while the third container has a output ratio of only 18 percent. This indicates that the alignment of the containers influences the output ratios. Therefore, Twente Milieu tries to locate the containers at an apartment building in a triangular form, as can be seen in Figure 8. In this way, all containers are at an equal walking distance from the apartment building and the waste is better spread over the different containers.

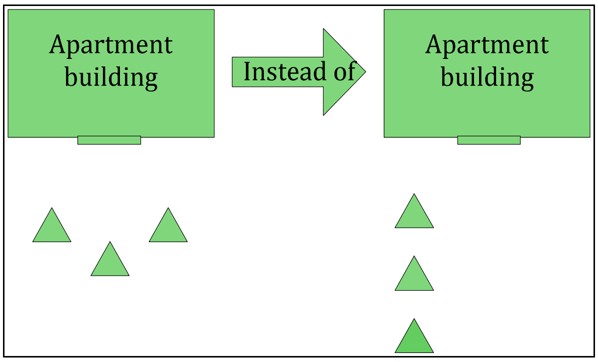


Figure 8 Optimal container location

3.3 Data overview

We added a table with all information gathered during the data analysis in Appendix C. This gives an overview of all data on the underground containers in Enschede. Per container we collected data on the number of times a container was emptied in 2009, the average registered and calculated output ratios, and the average deposit size and weight.

In Appendix D, we included a complete list of all 520 underground containers operated by Twente Milieu in of March 2010. Because not all containers are digital and the data in the databases is currently extended with new information, we do not have data of all containers. In case no information was available for a container, we took the average of all other containers as an approximation for the data of that container.

3.4 Conclusion

In this chapter we came across some remarkable points that in the data analysis. It illustrated that the underground containers are, on average, only for 50 to 60 percent full at emptying. This number is higher than the 40 percent as assumed by Twente Milieu, but it still indicates that there are possibilities to increase the efficiency in the emptying process with a dynamic collection methodology. The average deposit size is smaller than the 48 liter as assumed by Twente Milieu, according to our calculations it is only 41 liter. The third assumption we tested, about raising the output ratio with 1% for each deposit, is on average a reasonable approximation, but there are containers for which this is not accurate. It would be better to determine per container the deposit size, instead of using one general assumption for all containers.

As stated at the beginning of this chapter, the analysis was performed only on the underground containers in Enschede. However, the conclusions will also hold for the other municipalities, because all underground containers are equal in size and are used by the same amount of inhabitants.

The introduction of Diftar will lead to larger deposits and less variance in deposit sizes. This is beneficial for the use of a dynamic planning methodology, because it leads to more accurate estimates of the contents of a container and therefore also a better emptying schedule.

Another point of attention is the alignment of containers at apartment buildings, to ensure an equal distribution of refuse over the containers and at the same time ensure an efficient collection process. When there are multiple containers installed at one location, the container that is the furthest away from the apartment building has a lower output ratio than containers that are a few meters closer.

4 Literature review

This chapter gives an overview of the existing literature in the field of dynamic planning, collection strategies, and inventory routing. In Section 4.1, we provide some general insights on literature on dynamic routing strategies such as Vehicle Routing Problems (VRP), Pick–up and Delivery Problems (PDP), and Dial-and-ride Problems (DARP). Section 4.2 gives an overview specifically on Inventory Routing Problems (IRP), because this type of problems will be most relevant for our case. Section 4.3 discusses routing heuristics; these are important, because we do not only select which containers to empty, we also want to make a good tour to empty these containers. Section 4.4 then provides insight on waste collection, both from literature as well as from experiences at other companies or municipalities. Section 4.5 gives our contribution to the existing literature, and this chapter ends with Section 4.6, which gives the overall conclusions of this literature study.

4.1 Dynamic routing strategies

The literature on routing strategies is extensive. There are many different dynamic routing problems, of which the vehicle routing problem (VRP), pickup and delivery problem (PDP), and dial-and-ride problems (DARP) are the most important. Inventory routing problems (IRP) are also an important type of problems for our research, we will discuss the IRP in Section 4.2.

The general vehicle routing problem consists of one distribution point with multiple vehicles and a set of customers that have to be served. To serve all customers, multiple vehicles or multiple routes per vehicle are needed because of the size of the demands and capacity of the vehicles. Most times, the goal is to minimize the total travel costs of all vehicles and the number of vehicles. VRPs arise in areas such as grocery distribution, mail delivery, and refuse collection (Cordeau et al., 1997). VRPs are widely studied in literature. According to Cordeau et al. (1997), VRPs commonly satisfy five criteria:

- Each route starts and ends at a depot
- Each customers belongs to exactly one route
- The vehicle capacity is not exceeded by the total demand of the route
- The number of vehicles is minimized
- The objective is to minimize the total duration of all routes

The VRP is NP-hard; this means that the computation time grows exponentially with the number of customers that have to be served. Consequently, the VRP can only be solved to optimality for small instances, up to around fifty visiting points. Real life situations often require more visiting points and most VRPs are therefore solved using heuristics. Many different authors wrote about heuristics solving a VRP, using for example variations on the Clark &Wright algorithm and an improvement heuristic such as 2-opt. Cordeau et al. (1997) use a Tabu search heuristic to solve a periodic VRP. Contrary to many other Tabu search implementations described in literature, their Tabu search heuristic contains very few user-controlled parameters. The computational results for solving the periodic VRP using the algorithm of Cordeau et al. (1997) on instances taken from literature showed it outperformed other heurisitcs for solving this problem. Solomon (1987) tested the efficiency of different heuristics on solving VRPs with time windows. He evaluated a savings algorithm based on the Clark&Wright algorithm, a time-oriented nearest neighbor approach, an insertion heuristic, and a time-oriented sweep heuristic. Solomon (1987) concluded that the insertion heuristic that inserts customers based on the earliest deadline give the best results. He explains this because the sequencing aspect seems to drive routing problems with time windows, as opposed to the assignment component that is most importatn in normal routing problems.

Most of the studies on VRP are based on deterministic demand information. Bertsimas (1992) however, considers a probabilistic variation, with stochastic demands, of this classical VRP. This situation seems more realistic with the random demands of deliveries or collections a company has to make. Bertsimas (1992) assumes that demand follows some known probability distribution. One option to overcome the unknown demands is to change the routes whenever the demands are known, but this is not always possible because of additional costs and effort. Instead, two different strategies are proposed to update the routes. Figure 9 shows these strategies. Both start with the same a priori sequence. Under strategy A, the truck visits all customers in the same order as the a priori sequence, but only serving those with some demand. When the truck capacity is reached, the truck has to return to the depot. This strategy might be used when demands become known during the trip. Strategy B visits only the customers that have some demand, and does not visit customers with no demand. Again, when the truck capacity is reached, the truck returns to the depot. Skipping customers leads to savings on total travelling costs, but, instead of strategy A, this strategy requires demands to be known before the start of the trip. Because demand is known in advance, a re-optimization strategy is better to use, but a re-optimization strategy might also be time consuming. Bertsimas (1992) finds that working with an a priori sequence works quite well, especially when the demand distrubutions of the customers are the same.

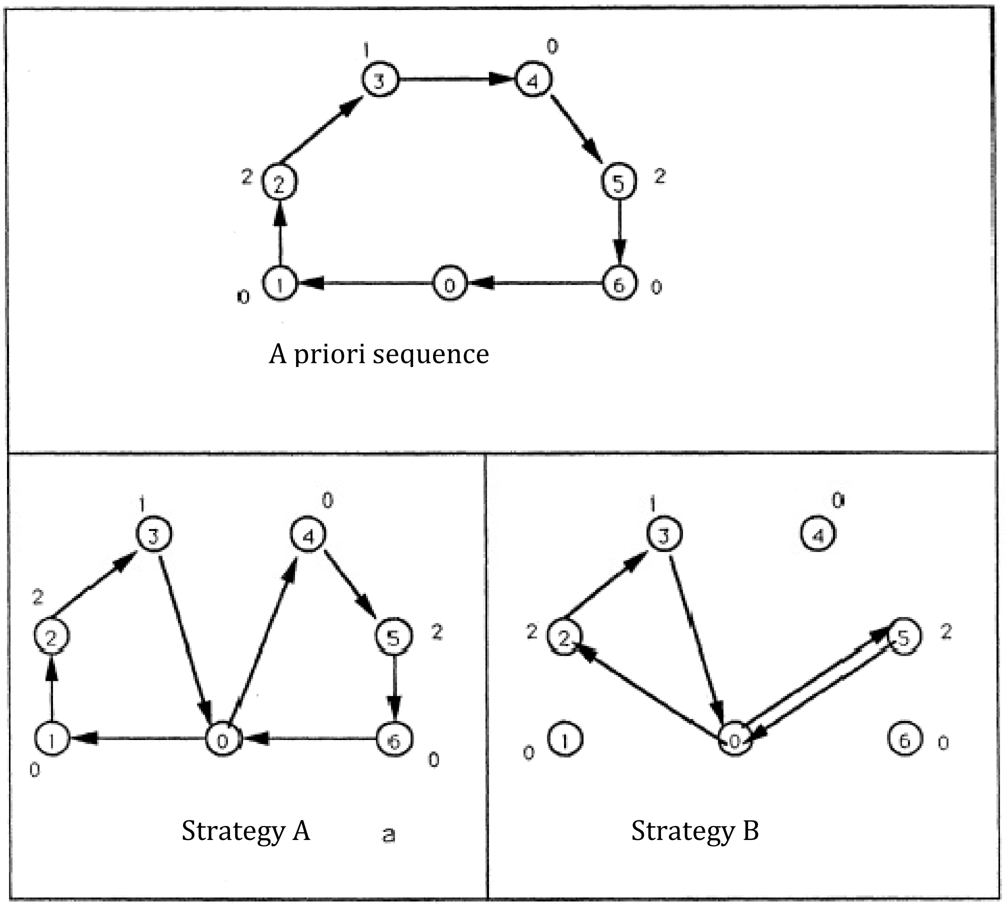


Figure 9 Updating strategies (Bertsimas, 1992)

Haugland et al. (2007) propose the use of delivery districts for VRPs. Each of these districts is served by one vehicle and the demand of a district is unknown at the time the districts are made. The idea of using districts lies in the need of the driver to get acquainted with his district. Designing the districts is a strategic or tactical decision, while routing decisions are made on an operational level. For determining the districts, Haugland et al. (2007) develop a tabu search algorithm and a multistart heuristic. It shows that the tabu search algorithm outperforms the multistart heuristic.

Savelsbergh (1985) develops a local search algorithm for routing problems with time windows. The routing problem with time windows is an extension of the normal VRPs. To solve the problem, Savelsbergh (1985) uses a k-interchange concept (see also Section 4.3.2) and develops a method to test feasibility of the results in $O(1)$ time. The problem of finding a feasible tour turns out to be NP-complete, this justifies the use of heuristics in the construction of a tour. Savelsbergh (1985) suggests an insertion heuristic for solving the routing problems with time windows.

Also, Laporte (1992) gives an overview of existing heuristics and exact algorithms to solve VRPs. Among others, they discuss dynamic programming, integer lineair programming, and direct tree search methods as exact algorithms and Clark & Wright, a sweep algorithm, and tabu search as heuristics. Laporte (1992) states that most heuristics used to solve VRPs, are derived from the travelling salesman problem (TSP). For that reason, it is import to check the feasibility of the created routes, because TSPs do not take into account vehicle capacity. The TSP is very similar to the VRP. The TSP describes for example a salesman who is currently in city A and has to travel to cities B, C, D, and E, and return to A again. The TSP finds the shortest tour from A and back, while visiting the four other cities as well (Smink, 2010). The TSP differs from the VRP because the vehicle routing problem considers the capacity of the vehicle and the travelling salesman problem does not. This difference might show in the solution of a VRP with multiple routes, while the TSP visits all locations in one route (Ho et al., 2007). In the case of Twente Milieu, the TSP will not be very useful, because capacity is an important issue. While TSP itself is not helpful, TSPs are often a basis for heuristics solving VRP s, while the VRP is an extension of the TSP.

In pickup and delivery problems (PDP), vehicles have to transport loads from origins to destinations without transshipment at intermediate locations (Savelsbergh and Sol, 1995). For the waste collection case of Twente Milieu, this could be seen as picking up refuse from the containers and delivering it to Twence. The PDP differs from the VRP, because the VRP has all origins located at the same depot. For the PDP, this does not have to be the case. Many real-life PDPs are demand responsive, which means that new request can become available at every time. At certain moments in time, the route has to be updated to deal with these new requests (Savelsbergh and Sol, 1995). Both the VRP and the PDP have dynamic variants, which are the DVRP and the DPDP, but the standard versions of these problems are static. Because of the long planning horizon used for PDPs, the concept of depots vanishes. This means that when new transportation request become available, the current routes are updated and the vehicles spread out over the planning area (Savelsbergh and Sol, 1995). With PDPs it is not the case, as it is with VRPs, that transportation requests with geographically close destinations are likely to be served by the same vehicle. The close destinations may have origins that are far apart and therefore it is not likely that the same vehicle serves these requests. Most PDPs are solved using dynamic programming when the number of request is relatively small. Savelsbergh and Sol (1995) state that although the single-vehicle PDP is NP-hard, it can be solved efficiently with dynamic programming when the number of requests is relatively low. For most practical PDPs this is the case, which leaves the main problem to be the assignment of transportation requests to vehicles.

Next to Savelsbergh and Sol, Yang et al. (2002) also study the pickup and delivery problem (PDP). They consider costs related to travelling distances, lateness, and rejection of jobs, which occur in almost all real life problems. For solving the PDP, Yang et al. (2002) propose an off-line mixed integer programming formulation that is combined with rolling horizon strategies to solve the real time problem. They found that a strategy that takes the expected future demand distributions into account, led to the best results, but also the optimization of the off-line problem showed competitive outcomes.

Another type of routing problem is the dial-a-ride problem (DARP). In the dial-a-ride problem, customers indicate the origin and destination of their requests to be served by vehicles (Attanasio et al., 2004). The DARP is comparable to the dynamic PDP, but with a focus on the service level. The objective of DARPs is to accept as many requests as possible without violating any constraints. The dial-a-ride problem can be either static, when requests are known one day ahead, or dynamic, when they arrive during the day and have to be inserted into existing routes. The DARP is a common application in, for example, door-to-door transportation services for elderly people (Attanasio et al., 2004) or in the shared taxi services (Charikar & Raghavachari, 1998). In literature, different models have been developped to solve DARPs. Most of these models are heuristics and literature shows that tabu search is the most powerful solving heuristic, because it is able to handle a large number of variants within one search framework. However, Attanasio et al. (2004) state that the running time of tabu search algorithms can be rather high. For static problems this long running time might not be a problem, but for dynamic problems it is. To solve this problem, Attanasio et al. (2004) came up with parallel computing and showed that this is benefical for solving real-time vehicle routing problems.

4.2 Inventory routing problems

Inventory routing is a widely studied research area. It combines inventory management with vehicle routing and the inventory routing problem (IRP) is therefore a very useful type of problem in the case of Twente Milieu. Among others, Kleywegt et al. (2004), Adelman (2004) and Chan et al. (2001) discuss the stochastic inventory routing problems. Abdelmaguid et al. (2009) study different heuristics to solve the inventory routing problems with backlogging. Webb & Larson (1995) developed a new approach to strategic inventory routing problem and achieved fleet reductions with their approach. The strategic inventory routing problem (SIRP) focuses on estimating the minimum fleet required, before the start of the actual delivery operations. The most important difference with normal, tactical IRPs is that all possible realizations of the tactical problem must be considered when solving the SIRP. To get an extensive overview of literature on inventory routing, we refer to Andersson et al. (2009). In the remaining part of this section, we will only discuss the papers on inventory routing that are most relevant for Twente Milieu.

The inventory routing problem (IRP) is concerned with the repeated distribution of a single product to multiple customers over a given planning horizon. All customers are served from one single location and the customers are assumed to consume the product at some given rate. Because the local inventory at the customer has a maximum capacity, the customers need restocks after a certain time (Campbell et al., 1998). To reach the objective of minimizing distribution costs, three decisions have to be made:

- When to serve a customer?
- How much to deliver to a customer when it is served?
- Which delivery routes to use?

The IRP differs from the VRP because it is based on the usage of customers rather than just the number of customer orders. This fact makes the IRP suitable for the case of Twente Milieu, because the volume of refuse in the containers is important. The containers, ideally, should be full at emptying, but at the same time should not overflow. This can be seen as an reversed IRP, were the customers do not receive products, but products are collected at the customers. The choice when to serve a customer is in this case the most important.

Solving an IRP is difficult. Most approaches that have been proposed solve only a short-time planning problem, while the IRP is actually a long-term planning problem which gets more complicated with the number of customers (Campbell et al., 1998). The short-term approach will postpone as many customers as possible to the next period, but this may lead to difficulties in this next period. Therefore Campbell et al. (1998) state that it is important to think of ways to model the long-term effect of the short-term decisions and which customers should be included in the short-term planning.

Campbell et al. (1998) also write about ratios to decide whether to include a job or not. They refer to, among others, Golden et al. (1984). To calculate which customers should be served first, Golden et al. (1984) use the ratio of tank inventory to tank size. When this ratio is smaller than some threshold, customers are excluded from service for that day. Campbell et al. (1998) also write about using a ratio of urgency to extra time required for the selection of customers.

Another aspect that might be of importance in our case of routing, is whether to use preemption or non-preemption. This comes forward when we decide to make adjustments during the day. We can then decide to stop all current operations and reschedule all jobs, which is called preemption, or use non-preemption, which implies all current jobs are finished and only the new jobs are rescheduled. Kubale (1996) states that using non-preemption might lead to better schedules and also Jeffay et al. (1991) note the benefits of using non-preemptive schedules for easier implementation and analysis of schedules.

To solve the IRP, integer programs are commonly used. Dror & Levy (1986) also apply node and arc exchanges to reduce costs and Jaillet et al. (1997) take a rolling horizon approach to tackle the differences between short-term and long-term solutions. They do this by determining a schedule for two weeks, but only implementing the first week. Campbell et al. (1998) use clusters of customers that can be served cost effectively. These clusters are not only based on the geographic locations, but also on whether the customers in the cluster have compatible inventory capacities and usage rates. Campbell & Savelsbergh (2004) also studied the optimization of delivery volumes for IRPs. They stress that it is necessary to be able to handle different usage rates at customers, because inventory rates might be used up faster at the beginning of the day and often production is shut down during the night. Campbell & Savelsbergh (2004) compare their method of delivery volume optimization with some other methods to schedule deliveries on a route. Delivery volume optimization turns out to give the best results. The 'Late Method', where every customers is served as late as possible, performs worse because too much time is spent waiting for the latetst time. Contrary, the 'Early Method', which delivers to customers as early as possible, performs bad because it makes deliveries when there is still a reasonable amount of inventory left and less space available for new products. Delivery volume optimization is a robust method that performs well in all tested scenarios and can result in significant cost savings compared to the other methods (Campbell & Savelsbergh, 2004).

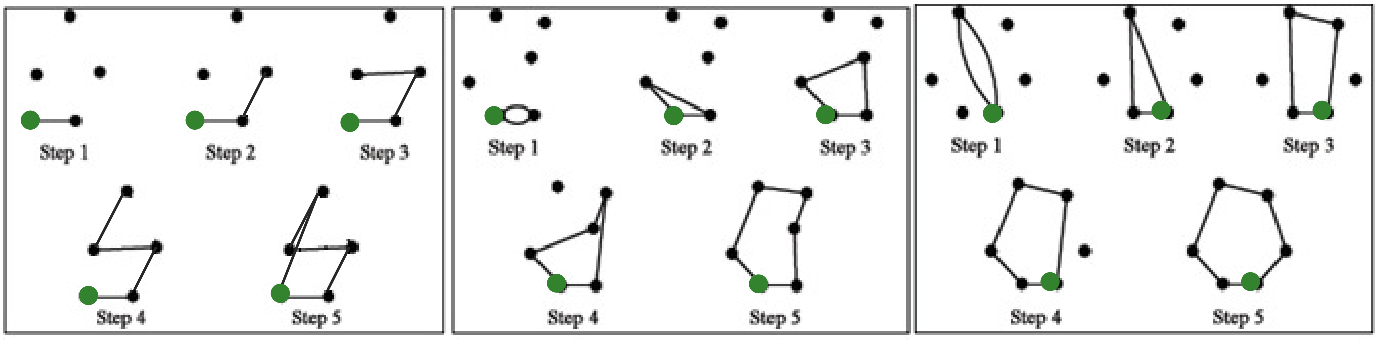
4.3 Routing heuristics

For implementing a new and dynamic planning methodology, it is important to choose the right heuristic. A heuristic determines the way a route is created and improved, and therefore the selected heuristic determines the quality of the solutions. We distinguish two different types of heuristics, construction heuristics and improvement heuristics. The first type starts with an empty route and adds locations until a tour originates. Of course, when choosing the next location, the best possible location should be chosen to be inserted in the right place. Examples of heuristics to construct a route are 'nearest neighbor', 'nearest insertion', and 'farthest insertion'. All these heuristics construct one long route and are used to solve TSPs. The VRPs are an extension of the TSPs, a VRP can be seen as a TSP with capacity restrictions. Therefore, the construction heuristics we discuss in Section 4.3.1, require some restrictions to deal with the capacity limitations on the vehicle before we can use them on the VRPs. The second type of heuristics, the improvement heuristics, tries to improve the current route. They start with a initial feasible route for each truck and try to improve upon this until no further improvements are possible. Some examples of existing improvement heuristics are for example 2-opt and *k*-opt (Smink, 2010).

4.3.1 Construction heuristics

The nearest neighbor heuristic is one of the simple construction heuristics. The route construction starts at the depot and the nearest point to the depot is chosen as next point on the route. Every time, the point closest to the last point inserted is chosen as next insertion. For the insertion, only the nodes that are not yet part of the route are examined. Figure 10A shows the buildup of this algorithm. The idea is that choosing each time the nearest location minimizes the distance between the points and also the distance of the total route. However, in reality the trip back from the last point to the depot is often a very long distance. (Meeran & Shafie, 1997).

The nearest insertion heuristic prevents the disadvantage of nearest neighbor, that the last point is far away from the depot, by always working with a complete route. This model starts with a route from the depot to the nearest location and back. The next insertion is the location closest to either one of the two points that are already in the route. This location is inserted at the most cost-effective location, it is calculated between which two points in the route it would fit best. This is continued until all locations are added to the route. This heuristic is shown in Figure 10B.



A B C

Figure 10 Construction heuristics

Farthest insertion is very similar to nearest insertion, only every time the farthest point is inserted. The idea behind starting with the farthest point is that in the end you do not get stuck with a far away location that is difficult to fit into the route. Figure 10C shows the graphical representation of this heuristic.

All three construction heuristics we described, are used to solve the TSP. The VRP might be seen as a combination of multiple TSPs. Solving the VRP requires some additional steps to cluster the jobs in multiple routes that fit the capacity restrictions of the vehicles used in the VRP. For solving a VRP, 'route first – cluster second', 'cluster first – route second', and 'assignment – sweep' are commonly used concepts. Route first – cluster second first creates a long tour to all locations which is then split up into smaller clusters. The long tour is created using for example one of the three heuristics discussed earlier. Based on the capacity restrictions of the truck, the route is then cut into clusters. Often it is possible to cluster in different ways, these solutions have been compared on total costs of the sub-routes (Beasley, 1983). Figure 11 shows an example of the method.

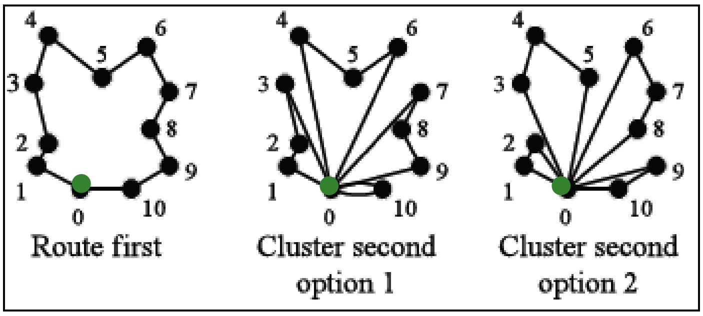


Figure 11 Route first, cluster second

Cluster first – route second starts with creating clusters and then creates routes. The size of the clusters depends on the capacity of the trucks. For clustering, a sweep algorithm may be used, this algorithm starts with looking at (for example) points north of the depot and makes a cluster of all northern points. Another option is to cluster clockwise or counterclockwise. Different clustering directions will lead to different clusters. Figure 12 shows this process of clustering. A disadvantage of this algorithm is that the chosen direction for clustering might not lead to the most optimal clusters.

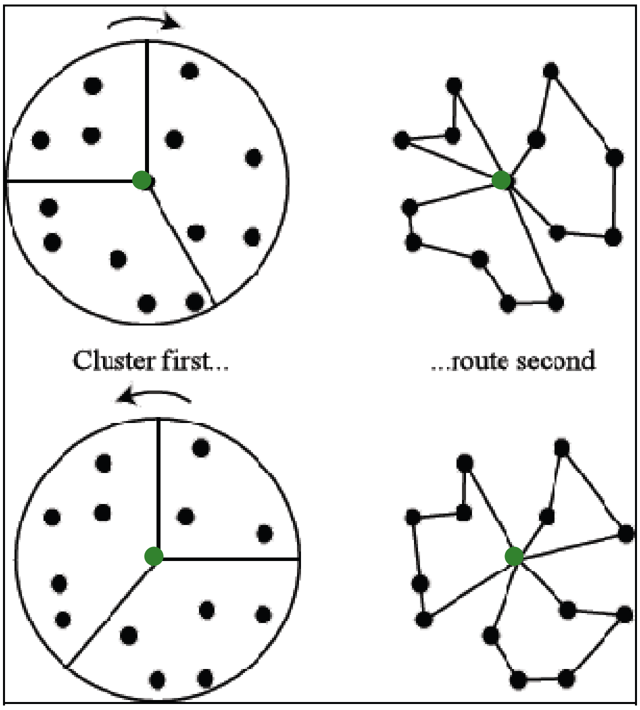


Figure 12 Cluster first, route second

In the case of multiple depots, a combination of the two above heuristics can be used. First, the locations are assigned to one of the depots. For the locations that are close to more than one depot, the relative distance should be calculated. If location C is close to depot A as well as depot B, the relative distance is equal to AC/BC. When the result of this calculation is close to one, both options should be considered in creating the routes, adding location C to depot A as well as to depot B. When all locations are assigned to depots, the route first, cluster second, or cluster first, route second method can be used to calculate the routes.

4.3.2 Improvement heuristics

After constructing a route, this route can be improved by using an improvement heuristic. Again, different types exist. The most important are 2-opt and *k*-opt. In fact, 2-opt is a specific version of *k*-opt. These heuristics improve a current route by switching connections between points. In case 2-opt is used, two connections are switched. These improvement heuristics are meant for the TSP, but might also be used for the VRP. Using improvement heuristic for the VRP tries to improve the different sub-routes of the different vehicles. Another option when improving a VRP, is to exchange customers from one sub-route with customers from another sub-route.

Figure 13 shows an example of 2-opt, the current connections between B and C, and between D and E are switched and replaced by the connections BD and CE. This is also possible with more connections, when switching *k* connections this is called *k*-opt, but then it requires more computation time.

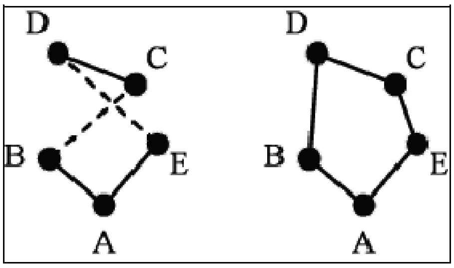


Figure 13 Improvement heuristic 2-opt

Savelsbergh (1992) state that the edge-exchange improvement methods are an efficient way of improving routes, but testing feasibility takes $O(n^3)$ time for a 2-opt. They propose the use of a specific search strategy in combination with a set of global variables to keep the time of testing for feasibility of an exchange takes no more than constant time. Their edge-exchange improvement methods turn about to be very efficient. This advantage increases with the number of locations, but even for a small number of locations, the edge-exchange leads to better performances than other methods.

4.4 Waste collection

This section gives insight in the current developments in the field of waste collection. The first part, Section 4.4.1, discusses the existing literature on this subject, while Section 4.4.2 sketches an overview of the current developments within companies operating in the waste collection branch.

4.4.1 Literature on waste collection

Next to the general literature discussed in the previous section, the last few years a growing amount studies were dedicated specific to waste collection. As McLeod and Cherrett (2008) state, efficient waste collection strategies are not only vital from economic perspective, but also from an environmental perspective with reductions in emission and traffic congestions. McLeod and Cherret (2008) describe the routing and scheduling problem as an capacitated VRP, which has constraints on vehicle capacity and working hours and they propose different ways to solve this waste collection problem. They tested tabu search, a genetic algorithm, and fuzzy logic methods. The genetic algorithm uses the 'survival of the fittest'-principle, giving the temporarily solutions with the best results the highest change of selection for the next steps. Fuzzy logic methods are generally more easy to understand by users. It is also well able to deal with unexact data. The genetic algorithm gave the best results, it was quick to run and very robust. However, when dealing with imprecise data, the fuzzy logic method turned out to be better.

Karadimas et al. (2007) also point out the importance of an efficient collection process, because 60 to 80% of the total costs are spent during the waste collection process. To solve the problem, they use an ant colony system algorithm, in which the optimal route is determined based on the behavior of ants and the pheromone trials they use. Most authors model the collections process as a VRP, for example Chang & Wei (2002), Kim et al. (2006), and Nuortio et al. (2006) use variants of the VRP. Nuortio et al. (2006) propose a stochastic variant, because the amounts of waste in the bins is highly variable. For solving the problem, they use a node routing approach. This approach makes it possible to consider each bin separately. Kim et al. (2006) describe a VRP that uses time windows. The time windows include stops for lunchbreaks and disposal operations. For solving the problem, they use a clustering based algorithm which also solves each cluster individually to increase compactness of the clusters.

Literature agrees on the complexity of the waste collection problem, and agrees that exact methods are not suitable in most situations. Instead, different heuristics are proposed and those are considered to give better and faster results in these situations. Most important is that the computation time of heuristics is a lot smaller than of the exact methods.

Chalkias & Lasaridi (2009) use a geographic information system (GIS) in their optimization of municipal solid waste collection. For the formulation of a model, they collected a lot of data about roads, environment, and bin locations, which was stored in a geodatabase using the GIS environment. They state that the success of decision making depends largely on the quality and quantity of the available data, in which the geodatabase can be very helpful. One remarkeble conclusion that Chalkias & Lasaridi (2009) make, is that fuel consumption relates more to time of operation and the number of stops than to distance travelled. This is assumed because most of the time is spent for bin loading and emptying.

As seen in the short summary of existing literature on waste collection, most articles are about routing problems, finding the optimal route along a set of containers. For Twente Milieu, this is important, but what is more important is the choice which containers are emptied. The current routes, based on experience, are probably quite good, because the drivers are familiar with the area they drive in. Because of the large number of containers and the short distance between the various locations, route optimization will probably not improve the routes very much. This means that existing literature in the area of waste collection is not very helpful for Twente Milieu.

4.4.2 Current developments

Looking at real-life cases in the Netherlands, more and more municipalities are changing to underground containers. According to Florizoone (2003), in the last few years a growing number of municipalities is using underground containers. The most important reasons for the use of underground containers are in his opion the reduction of trouble compared to the 'normal' containers and the introduction of diftar. The underground containers offer the possibility of digital registration and are therefore very well suited for this current evolvement. Another advantage Florizoone (2003) mentions is the favourable working conditions. Emptying an underground container can be done by only one operator and is not as heavy as emptying the old containers.

As the many different proposals from city councils show, underground containers and the refuse policies are important items on the agenda of municipalities. Among others, the municipalities of The Hague, Bunschoten, and Loon op Zand are implementing these containers in their cities. They mention the favours of the digital registration and the possibility to monitor the output ratio and empty the containers on time, but no one brings up possibilities for dynamic collection strategy (Ecoplanet BV, 2007) (Gemeente Bunschoten, 2006) (Gemeente Den Haag, 2009). This is remarkable, because the possibilities are present. Greengard (2010) reports about the options of RFID-tags in waste tracking. The possibilities of dynamic waste collection are exploited by companies offering software systems. Container management systems in combination with Google Maps, offering possibilities for maintenance, planning and service already exist (GRAM, 2009).

4.5 Contribution

As shown in the previous sections, there is a lot of research done in the area of routing and scheduling. This area is a known field, both in the static and dynamic variants, but also still relevant and developing. The waste collection area is not such an established field yet, but as of the nineties the number of publications in this area is growing. It would be interesting for the problem stated in this report, to combine the routing aspect with the selection of customers, which are in our case containers. Some literature exists that discusses this combination, but then it is mostly about the routing aspects and the order in which jobs should be served. Our research focuses mainly on the selection of containers to include in a route, and then to find the best route through this selection of containers. In existing literature, this is a rather unknown area and this report will try to make a start with filling this gap in the literature.

4.6 Conclusion

This chapter gave an overview of existing literature in the area of routing and scheduling, as well as waste collection. Because the problem discussed in this report focuses on the selection of the containers to empty, inventory routing would be the most relevant for solving the problem. Of course, inventory routing concerns delivering goods to customers, which means that we have to use a reverse inventory routing problem. The containers need to be emptied, not loaded. Looking at existing literature, there are no readymade solutions to our problem. Campbell & Savelsbergh (2004) presented some useful methods for solving this kind of problems, but their solutions also cannot be applied directly to our problem.

Next to the inventory routing, the pickup and delivery problem is relevant for determining routes once the containers are selected. While the focus is on container selection, the routing should be taken into account to ensure optimal results.

5 Dynamic planning at Twente Milieu

Chapter 4 showed different possibilities for solving routing problems. This chapter answers the question which option would fit best with Twente Milieu. Different alternatives all have their own advantages and disadvantages, and they differ from static to dynamic. In Section 5.1, we distinguish a number of different options that could be used as a planning methodology; Section 5.2 concludes this chapter with the selection of the best options.

5.1 Planning options

Currently, Twente Milieu uses a static planning methodology. We will examine a number of other options and check whether these alternatives could work well for Twente Milieu.

There are many different planning options which we could discuss, but we decided to distinguish four different possibilities for a new planning methodology. We distinguish these four, because they represent different levels between rather static and very dynamic and therefore we will be able to determine whether Twente Milieu will benefit from a very dynamic methodology or whether a somewhat less dynamic solution will give the best results. The four options we distinguish are:

1. Current planning methodology
   This option describes the current way of planning at Twente Milieu. We described this methodology in detail in Chapter 2. Currently, the same schedule is used for every week, and this schedule is rarely updated. The only dynamic aspect in this methodology is that on Fridays, the planner checks whether there are containers that need an additional emptying before the weekend to prevent overflowing of the containers. This schedule is based on experience rather than on output ratios. This option is the most static alternative, but also leaves some space for adjustment on Friday.

2. Daily planning
   This option daily determines a schedule for the coming day. Before the start of the day, a schedule with containers to visit is determined based on actual number of deposits, expected output ratios, and expected handling times at the containers and Twence. Making the planning for the coming day in the morning has the advantage that it is relatively easy to execute, because it only needs a list of containers to empty and an assignment of these containers to routes. The list of containers can be printed at the start of the day, to ensure actual information on refuse volumes in the containers. This option is more dynamic than the current methodology used by Twente Milieu. However, a disadvantage is that the planning is fixed during the day, whereas it is still unknown what precisely will happen during the day. This may lead to variances between the days, which are difficult to overcome with a limited number of available trucks and manpower.

3. Daily planning with periodic rescheduling
   This planning methodology is similar to the second option, except that this option allows periodic rescheduling during the day. We think this increases the accuracy and reduces the chance that containers are emptied too late. The schedules are based on historic information and averages, and therefore, there will always be some deviation when executing this schedule. For this reason, we think it is profitable to update the schedule during the day. With the periodic rescheduling, we will be better able to deal with uncertainties in for example the handling times and refuse volumes in the containers. For the periodic rescheduling option, we chose to review the schedule mid-day, but of course it is possible to do the rescheduling at other times or at multiple moments during the day. Our choice for mid-day rescheduling is chosen to see the effect compared to no rescheduling, but rescheduling could for example also be done after visiting Twence.

4. <u>Continuous rescheduling</u>
   The fourth option is uses continuous rescheduling. In the case of Twente Milieu, an initial schedule is necessary, also for continuous rescheduling, because the number of trucks to use has to be determined and some knowledge about containers to visit improves the routes. This means that every time a container is emptied, the schedule is updated to see whether any changes to the current schedule are necessary. Continuously rescheduling increases the ability to deal with deviations in handling times, travel times, and refuse amounts. This option is, on the other hand, also the most complicated variant. It requires all refuse trucks to be equipped with board computers and rescheduling after each emptying requires a lot more computational efforts compared to the other options.

As stated, the four options we distinguish vary between rather static and very dynamic. Figure 14 shows a graphical impression of these four options on the scale between static and dynamic. This is not an exact scale, but only meant to indicate the difference between the options.

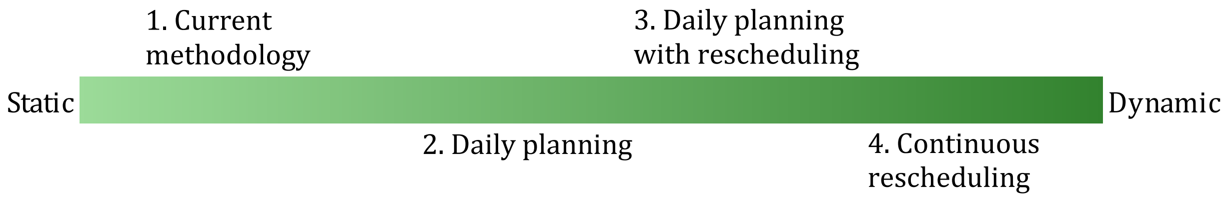


Figure 14 Level of dynamics for the different options

Table 5 summarizes the four options we discussed and gives the advantages and disadvantages. Based on the descriptions of the options we will determine the best option for Twente Milieu.

Option	Model	Description	Advantage	Disadvantage
1	Current methodology	Every week the same schedule is used. This schedule is based on experience rather than on output ratios.	- Drivers are familiar with this way of working - No need for board computers	- Rather static and therefore not able to deal with changes in demands - Planning is fixed
2	Daily planning	In the morning the schedule for the entire day is made. This is based on the actual output ratios of the containers.	- Most simple variant using expected output ratios - No need for board computers	- Planning for the day is fixed, while it is still unknown what will happen exactly that day
3	Daily planning with periodic scheduling	In the morning a schedule for the entire day is made. This schedule is updated at mid-day, to include any new containers that are almost full, and react on any unexpected deviations.	- Additional update during the day enables to react to unexpected changes that occur during the day - Uses expected output ratios	- There needs to be a contact moment between the driver and the planner. Either during lunch break, by phone, or with a board computer

4	Continuous rescheduling	This is the most dynamic variant. The emptying schedule is updated continuously with new containers that need to be included.	- Most flexible to handle uncertain events such as: more garbage than expected, extra or earlier trips to Twence etc. - Uses expected output ratios	- Most complex solution - Requires computers on board of the trucks - Computational intensive

Table 5 Different options for a dynamic planning methodology

Before choosing between the options, we again mention that currently it is necessary to make trips to Twence before serving containers in another municipality. This is necessary because the municipalities Twente Milieu works for, all request a specified invoice of the container emptyings. However, in the near future all refuse trucks will be equipped with weighing tools, which makes these intermediate trips unnecessary. Because these weighing tools will be in use soon, we will assume their presence in selecting the best planning methodology. This increases the possibilities of using a dynamic planning methodology.

What is also essential to keep in mind, is that the degree of improvement between the different options is not equal. Going from the current way of working to using option 2 might lead to larger benefits than going from option 3 to option 4. Implementing option 2 might lead to the largest improvement because it goes from an almost complete static planning to a more dynamic way of planning. Going from option 2 to option 3, or from option 3 to option 4 will likely increase the results, but the improvements might be smaller because of the different starting point. When choosing the best option for Twente Milieu, these different improvement levels will also play a role. Of course, the fourth option is the most dynamic variant, but the question is whether the additional costs and efforts are worth the benefits. The option of continuous rescheduling might even lead to a nervous system, because of the large uncertainty in containers to visit. In practice, an option between option 3 and 4 might also be beneficial. This alternative reschedules only when there are large deviations from the current schedule and after a visit to Twence. This option will not be further discussed in our research, but it is important to note that the four options we discuss in this chapter are only four options to indicate the possibilities of dynamic planning. In reality, there are a lot more options that might be used.

Another point of importance is the use of board computers. The first two options do not need board computers, while the fourth option of continuous updating does need a board computer in every truck. The third option, periodic rescheduling, needs a contact moment between the driver and the planner to present the rescheduled planning. This does not necessarily need to be a board computer, from example rescheduling might be done at the depot during lunch break. However, board computers are the most flexible way for updating the schedule during the day. The use of board computers requires additional investments by Twente Milieu and also additional training for the drivers.

The drivers' perception of the planning methodology is also important. When implementing the fourth option, the drivers have to adapt to the board computer and drive to the container displayed on the computer. This might be a large and unpleasant change for them. However, using board computers will be beneficial when other drivers need to take over the routes during the holiday periods, or due to illness of the driver. With the second option, the way of working will not change that much. The only difference is that they receive a different list each day with the sequence of the containers to visit, instead of making the same trips every week. Also, in the current situation it occasionally happens that drivers decide to include an additional container. This should be prevented when using a new dynamic planning methodology, because it undermines the improvements the new planning might achieve.

Working with a dynamic planning methodology will probably have more benefits with many containers. The larger the number of underground containers is, the more possibilities there are to reschedule and improve the current schedules. The data analysis in Chapter 3 already showed that a more dynamic planning methodology could lead to benefits. Because the number of underground containers operated by Twente Milieu will rise further to around 1500, we assume the third planning option will be best suited for Twente Milieu. It has a good balance between complexity and results, and with the rescheduling it will probably be possible to improve the performance of the current methodology. With a simulation model we will test the performance of the third planning option and compare it with the second option to evaluate whether the rescheduling indeed increases the results.

5.2 Conclusion

From the comparison of the different options, we expect the third option will be a good choice for Twente Milieu. This variant includes periodic rescheduling, and with the growing number of underground containers, this rescheduling will increase the results of the dynamic planning methodology. Moving from the current situation to using the second planning option will probable already give a large improvement in the schedules, with lesser kilometers to drive. The third option however, tackles the disadvantages of this second option by updating the schedule twice a day. By rescheduling, the third option is better able to deal with uncertainties and unexpected changes in for example handling times. Of course, updating the schedule twice a day is only an example of periodic rescheduling. This could be easily extended to more updating periods or updating at other points during the day.

In a simulation model we will test whether the third option really gives the best results. The second option is already a large improvement compared to the current situation. Therefore it is possible that the improvement in going from option two to option three might not be worth the additional efforts. The transition from the current system to the most dynamic variant is a large step, which might be too large to make in one time. The fourth option requires a lot of additional investments and might only increase the solution quality slightly compared to option three.

In the future, the refuse trucks will be equipped with weighing tools. When this equipment is in use, the need to make trips to Twence before moving to another municipality disappears. This will increase the possibilities to use a dynamic planning methodology and will also increase the results.

6 Planning model

This chapter discusses a model to develop a new planning methodology for emptying the underground containers. We start with giving some definitions in Section 6.1, to ensure understanding of the methodology. Section 6.2 gives the solution approach and indicates the options we thought of in developing a dynamic planning methodology. Section 6.3 specifies the corresponding parameters and variables for our problem. Section 6.4 outlines the assumptions and constraints we will use in our planning methodology and Section 6.5 gives an overview of the performance indicators used to compare the different options. Section 6.6 describes the heuristic we developed. Finally, Section 6.7 finishes this chapter with the conclusions.

6.1 Definitions

In this chapter we will use a number of concepts. To ensure good understanding, we will introduce them here. These definitions can also be found in the list of definitions in Appendix A.

Days left — The *days left* indicate after how many days a container is expected to be full and is calculated for each container. The *days left* might be different for each container, because it is based on the average number of deposits per day and the average deposit sizes for that specific container, combined with the time the container was last emptied, and the actual number of deposits made after the last emptying. This means the *days left* equals the container capacity minus the current inventory, divided by the number of requests per day times the request size.

Must-go day — The *must-go day* is a threshold that indicates which containers should at least be emptied on a certain day. For example, when the *must-go-day* equals 2, this means that all containers that have a *days left* of 2 or less, should be emptied on this day. The *must-go-day* might be adjusted depending on certain circumstances, for example to balance workload over the week.

Must-go job — The *must-go job* is the emptying of a container which has a *days left* that is equal to or less than the *must-go day.* The number of *must-go jobs* therefore might differ from day to day.

May-go job — The *may-go job* is the emptying of a container that is included in a route after all *must-go jobs* are planned. *May-go jobs* are used to increase the occupancy rate and are selected based on their ratio of additional travel time and additional amount of refuse. We only consider containers with a *Days left* that is maximum one day more than the *must-go-day* as possible *may-go jobs.*

6.2 Solution approach

The goal of our research is to develop a dynamic planning methodology for Twente Milieu. We will evaluate a number of different planning options, some more dynamic than others, see also Chapter 5, and see which of these options would fit best with Twente Milieu. Before introducing the planning heuristic we developed, we will shortly outline the problem and the difficulties our heuristic has to overcome.

Currently, Twente Milieu is responsible for emptying the underground containers in six municipalities. At this time, the underground containers are, on average, only for 50 to 60% full at emptying (see Chapter 3). Twente Milieu wants to increase this number, and at the same time reduce its CO_2 emission, by only emptying containers that are almost full. There are large differences between the containers in quantity and size of the refuse offered. Therefore, Twente Milieu assumes that changing to a more dynamic way of emptying the containers will lead to better results, both in a reduction in travelling distance and an increase of container output ratios.

For solving this problem, we need to think about different things. As stated in Chapter 5, implementing a very dynamic way of planning might not lead to the best results. We investigate whether a dynamic planning methodology actually leads to the desired results and which planning methodology leads to the best results. To evaluate different planning methodologies, we decided on using the following objective function as a primary performance indicator.

*Minimize K= α*Σ(travelling costs) + β*Σ(handling costs) + γ*Σ(penalty costs for emptying a container too late)*

With this primary performance indicator, we ensure efficient routes, because we minimize the travelling and handling costs, while at the same time ensuring the service level by penalizing when a container is emptied too late. The weights in the formula offer the possibility to make for example the penalty costs more important than the other two factors. The penalty costs are equal to the amount of refuse that exceeds the capacity of the container. This means that the more days a container is emptied to late, the more exceeding refuse there is, and the higher the penalty will be. With this rule, we ensure that the container with the most overflow, also gets the highest penalty. In calculating the travelling costs, we only take the variable costs into account. We decided on this, to be able to compare the efficiency of the routes created by different planning methodologies. A consequence is that some options might be more expensive than others, because they use more kilometers. This might indicate that the route is less efficient, but it can also be the result of a more efficient route, emptying more containers with the same amount of trucks and drivers. The objective function therefore gives an indication of the best option, but we still have to analyze the outcomes with respect to other performance indicators, which we will introduce in Section 6.5, and it might be the case that a more expensive option turns out to be the best option.

We develop a heuristic that selects the containers that need to be emptied on a certain day, and determines an efficient route along these containers. Because we only want to empty containers that contain a reasonable amount of refuse, we have to set a limit when we will start emptying a container. To do so, we will start with calculating the expected number of days before a certain container is full, this is called the *days left* of a container. Next, we have to select at which *days left* a container needs to be emptied. For example, it seems reasonable to empty all containers that have a *days left* smaller than two, because all these containers are expected to get full during the next day. In this case, we state that the *must-go day* is two. However, using a fixed *must-go day*, might lead to some problems, for example in the weekends. On Saturday and Sunday, no containers are emptied, but there are new deposits to the underground containers. This means that when on Friday, we only empty containers that are expected to be full on Saturday, this will lead to overflowing containers on Sunday and Monday. Therefore, we developed an option that uses some balancing during the week. This means when we expect the workload to be high for the next day(s), we will empty some additional containers on this day. To do this, we will vary our *must-go day* based on the expected workload. This means the *must-go day* is not a fixed number, but it might vary. The balancing option will be further explained in Section 6.6.1.

When selecting a *must-go day* in developing an emptying schedule for a certain day, we have a number of containers which have a *days left* smaller than the *must-go day*, these containers are the *must-go jobs.* However, it might be possible that after emptying all *must-go jobs,* there is still space left in time and capacity of the trucks to empty additional containers. Then, we might decide to add *may-go jobs* to our schedule, these jobs are selected based on their current fill level and the additional distance that needs to be travelled. In our simulation model, we will test whether the usage of *may-go jobs* leads to better schedules. We expect that it will increase truck utilization.

For solving this problem, there are different options. One of the options is to use a mathematical programming method. We refer the reader interested in using mathematical programming methods for solving IRP problems to Yang et al. (2004). Using a mathematical method has a number of disadvantages. The most important disadvantage is the large computation time it needs. The computation time grows exponentially with the number of input parameters, which in our case include for example 520 containers and the number of trucks in use. Instead, we will use a heuristic procedure, which we will explain in the rest of this chapter. We will implement our heuristic in a simulation model to find out the best planning options for Twente Milieu. The next sections will explain the heuristics we developed in more detail and give the corresponding variables, parameters, constraints, and performance indicators.

6.3 Specification of parameters and decision variables

In the solution approach as described in Section 6.2, a number of parameters and variables are important. Although we decided not to use a mathematical method, but a heuristic method, it is useful to have an understanding of all the parameters and variables that play a role in our attempt to develop a more dynamic way of planning. These parameters and variables will also be used as input for our simulation model. For the averages we use in the list of parameters and variables, and also in our simulation model, we use historic averages which are calculated based on data from 2009. This means time is fixed and the averages do not change.

6.3.1 Assumptions

Before we introduce all relevant parameters and decision variables, we have to state the assumptions we will use in the remainder of our report. We need these assumptions to avoid too complex situations when building a simulation model and to be able to simulate the container emptying process properly.

- All containers are identical in size.
- The handling times at a container are the same for all containers.
  Emptying a container requires the same steps at all containers, locating the truck, sliding out the crane, emptying the container, and sliding the crane back in. Because the steps are always the same, we assume the handling time will also be equal for all containers.
- The average deposit size per container is given and based on historic information.
- The size of the actual deposits made to a container is stochastic, and follows a Gamma distribution.
- The average number of deposits per day is given and based on historic information.
  We do not have information on the number of deposits for all containers. This information is not available. Therefore, we assume all containers are comparable to those of which we do have information on the number of deposits per day.
- The number of deposits made to a container follows a Poisson distribution.
- The deposits made to a container are equally spread over the day and the night.
  While in reality, during the night the number of deposits will be less than during the day, this assumption does not affect our results. We check in the morning the expected amount of waste in a container, and it does not matter whether the last deposits were made during the night or during the evening. The expected total amount of refuse in the morning will be the same.
- The travel times between the containers are deterministic.
  We made this assumption to avoid a too complex simulation model. Also, because the underground containers are located in city centers and residential areas, the trucks will encounter little traffic.

- There are no time windows for empting the containers, only a certain day and the work hours of the truck driver
  Using time windows for emptying the containers would needlessly increase the complexity of our schedules and it would also lead to a larger computation time. Using time windows would be necessary if inhabitants need to place their containers at the side of the road, which is not required for the underground containers.
- All trucks are the same
- The truck speed equals the speed of passenger cars
  In our simulation, we calculated the travel times between the container locations using Google Maps. Therefore, we assumed the truck speed is equal to the speed of passenger cars. Because the area in which Twente Milieu operates is rather small, the routes do not contain highways, and the speed of the trucks will equal the speed of passenger cars
- The trucks are refueled outside working hours
  In our model we do not take refueling the trucks into account.

6.3.2 Parameters

General parameters:

C	Set of containers $i = 1, \ldots, I$, with $i \in L$
D	Set of depots $i = 1, \ldots, I$, with $i \in L$
L	Set of locations, containing the location of containers from C and depots from D
N_l	Number of containers on location *l*, with $l \in L$
D_{ij}	Distance from location *i* to location *j*
TT_{ij}	Travel time from location *i* to location *j*
HTT	Average handling time at Twence
SD	Start time of the work day
ED	End time of the work day

Container parameters:

CAP	Capacity of a container
RPD	Average number of deposits per day for a container
RS_i	Average size of a deposit for container *i*
RSV_i	Variance of deposit size for container *i*
X_i	Number of deposits made since last emptying of container *i*
$E(G_i)$	Expected volume of refuse inside container *i*, estimated by (X_i * RS_i)
DL_i	Expected days left for container *i*, estimated by (CAP-E(G_i))/(RPD*RS_i)
HT	Average handling time at a container
W_i	Tardiness of container *i*, estimated by max(0; E(G_i) – CAP)

Truck parameters:

R	Set of trucks, $r = 1, \ldots, R$
SF	Shrink factor of the press in truck
AC	Volume of truck
CAPT	Refuse capacity of a truck, equal to (AC*SF)

6.3.3 Decision variables

We use four decision variables, these variables indicate which containers are emptied by which truck and which trucks are used.

MGD — Must-go-day, varies with the use of balancing. The *must-go day* determines which containers need to be emptied today, these are the *must-go jobs*. The *Must-go day* also determine the group of *may-go jobs*. The *must-go jobs* are a subset of C, consisting of all containers for which $DL_i \leq MGD$. The *may-go jobs* are the subset of C, for which holds that $MGD < DL_i < MGD + 1$. Section 6.6.1 gives the exact calculation of the MGD.

z_i Binary variable indicating whether we empty container *i* today

y_r Binary variable indicating whether truck *r* is used

$x_{i,j,r}$ Binary variable indicating whether arc *(i,j)*, which indicates location *j* is visited after location *i*, is part of the route of truck *r*

6.4 Constraints

Our model has to simulate the actual day-to-day operations at Twente Milieu to ensure the results represent the actual situation. However, we have to use some constraints to ensure the heuristic is solvable. We introduce the following constraints for our model:

- Each truck can only be assigned to one job at a time
- Each job, except the last job, is followed by only one other job
- Each job, except the first job, is preceded by only one other job
- Every job can be assigned to at most one truck
- A truck can only perform jobs as long as these jobs do not exceed the trucks' capacity, then it has to make a trip to Twence before continuing emptying containers
- The workday of a truck driver should not exceed eight hours
- All trucks start at the beginning of the day from the depot location in Hengelo
- At a single day, a truck is operated by only one truck driver
- A truck driver only operates one truck
- Containers are always entirely emptied, it is not possible to empty only half of the container

6.5 Performance indicators

For evaluating the planning methodology, and to make a comparison between the various simulation runs which configuration gives the best results, we specify a number of performance indicators. These are:

- Total costs = $K = \alpha \sum_{i=1}^{I} TT_{ij} + \beta \sum_{i=1}^{I} HT + \gamma \sum_{i=1}^{I} W_i$
- Service level = Percentage of containers that was emptied on time
- Fill level = Percentage of the total truck capacity filled with refuse when disposing refuse at Twence
- MaxTrucks = Maximum numbers of trucks in use
- Output ratio = Average output ratio of the containers at emptying

We decided on these indicators based on the requirements of Twente Milieu. They want to reduce the mileage to decrease fuel consumption and CO_2 emission, but at the same time emptying the containers has to remain profitable. This results in the first performance indicators. Next to the total costs that includes environmental aspects, the service to the users of the containers is also important. Therefore this is included as a performance indicator. The other indicators are included to be able to see the effect of the balancing option and extending the routes with may-go jobs.

Using the simulation runs, we are able to compare the configurations and the different planning heuristics based on their scores on these performance indicators. This will give an indication which of the tested options leads to the best results for Twente Milieu and will also provide insight into the future, when the number of containers will grow.

6.6 Dynamic planning heuristic

This section describes the heuristic we developed for the case of Twente Milieu. In Chapter 4, we mentioned several heuristic procedures for creating and improving routes. All these different procedures have some disadvantages when they would be used in the case of Twente Milieu. To overcome the problems with the existing procedures, we decided to combine those heuristics and develop a new heuristic that fits the situation at Twente Milieu. Figure 15 shows the three different components we include in our heuristic. These components are 'Balancing', 'Plan must-go jobs', and 'Add may-go jobs'. For planning the *must-go jobs*, we use the concept of *must-go days*, this idea is also used by Golden et al. (1984). We developed two different options to plan the *must-go jobs,* a basic heuristic and an advanced heuristic. In Sections 6.6.1, 6.6.2, 6.6.3, and 6.6.4, we describe the option 'Balancing', the basic heuristic, the advanced heuristic, and 'Add may-go jobs' in detail; the options 'Balancing' and 'Add may-go jobs' are optional, as is the choice for either 'Basic' or 'Advanced' as a planning method for the must-go jobs. Using simulation, we will examine the effect of all these different options.

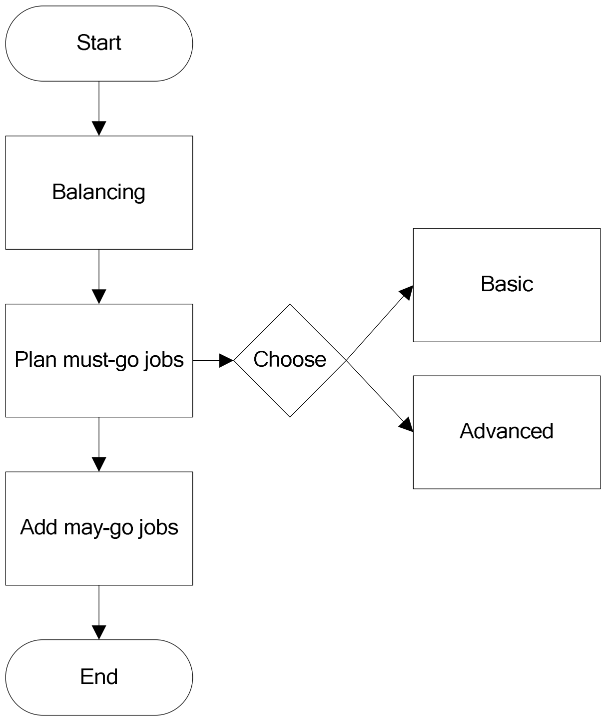


Figure 15 Components of the heuristic

For the creation of routes, we decided to use *cheapest insertion,* a procedure similar to the *nearest insertion* procedure (see Chapter 4). *Cheapest insertion* does not select the next container solely based on distance, as with *nearest insertion*, but, in our case, it selects the best container to insert based on the change in total costs. This means we look at distance, but also at additional handling and penalty costs before choosing which container to insert next. *Cheapest insertion* is a relatively easy and fast heuristic, and does not have the disadvantage that the distance from the final container location back to the depot is large, what would be more likely to occur when we would be using *nearest neighbor*.

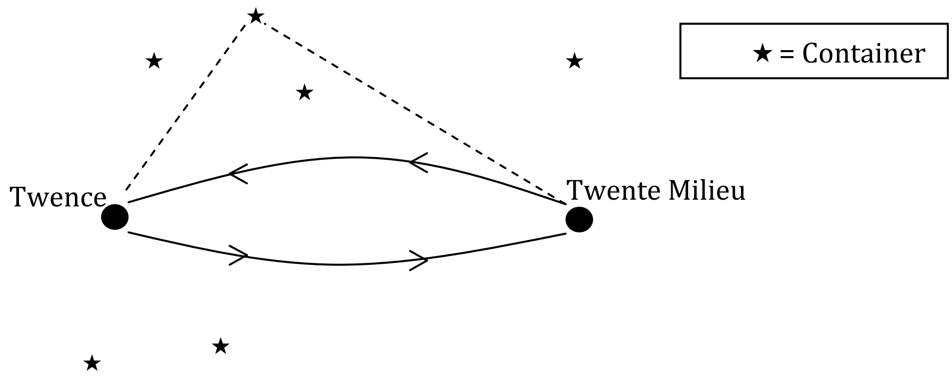


Figure 16 The basic operation of the route creation heuristic

Figure 16 shows the way we build up our schedules. We start with the trip from Twente Milieu to Twence and back, because this trip is always part of the schedule for a certain day. We extend the route by adding containers to it one by one, using *cheapest insertion*. At this point in time, only the containers on the *must-go* list are selected for insertion in the current route of the truck. *May-go jobs* might be inserted at a later stage. We will explain this in Section 6.6.4.

For the extension of the routes, we decided to look at the possibility to use *seed jobs.* A *seed job* is a job that is used as a starting point of a route. This route is then expanded with other jobs. The use of *seed jobs* might lead to more efficient routes, because it is an intelligent way of choosing a first container to use as a starting point for the creation of a route. For the selection of a *seed job,* there are a number of options. One option is to select the *seed job* based on distance, choosing the container that is the farthest away from the depot or Twence. We do this by calculating the distance from a container to both the depot and Twence for all *must-go jobs*, then we record the minimum of those two numbers and select the container with the highest number. Another option is to use a container that has the highest insertion costs as a *seed job* for a new route. The insertion costs are calculated using the additional time it takes when a container is inserted in a route. Again, the container with the highest insertion costs is selected as a *seed job.* The selection of *seed jobs* can be done for each truck, or for each route, which means we have four different options to select a seed:

- Seed on distance for each truck: this option spreads the trucks over the region only for the first sub-route of a truck
- Seed on distance for each route: this option spreads the trucks over the region for each sub-route of a truck
- Seed on insertion for each truck: this option spreads the trucks over the region, also taking into account the location of Twence, only for the first sub-route of a truck
- Seed on insertion for each route: this option spreads the trucks over the region, also taking into account the location of Twence, for each sub-route of a truck

The seed per route options can only be used in the advanced heuristic, because in the basic heuristic it is not known in advance how many routes will be used. This is explained further in Sections 6.6.2 and 6.6.3. When we start our simulations, we will perform some initial simulations to select the best seed selection rule.

6.6.1 Balancing

We decided to include balancing in our heuristic to level the workload between the days. The workload varies due to for example the holidays and weekends. On Saturday and Sunday, Twente Milieu does not empty containers, but there are deposits to the underground containers. Without balancing, this results in a high workload on Monday and also possibly overflowing containers.

Our heuristic uses the *days left* of a container together with the *must-go day* to select the set of must-go jobs. As a default setting, we start with a *must-go day* of 2, resulting in including all containers that are expected to be full tomorrow in our schedule of today. However, when we want to balance the workload, we need to vary the *must-go day*. Therefore, we use the formula given in Formula 1. This formula compares the workload for today with the expected workload for the coming days. When the next days are expected to be more busy than today, we will increase the number of containers we will empty on this current day. This does not work the other way around, when the next days are expected to be less busy, we will not empty less containers today. Emptying less containers requires to set the *must-go day* smaller than 2, which might lead to overflowing the next day.

$$NBN = \max\left(\#MGD, \frac{2}{3} * \frac{\#\,MGD + (\#MGD + 1)}{2} + \frac{1}{3} * \frac{\#\,MGD + (\#MGD + 1) + (\#MGD + 2)}{3}\right)$$

Formula 1 Calculating the new balanced number of containers

Formula 1 determines the new number of containers to empty, the *new balanced number* (NBN). To do this, we start with sorting all containers on their expected *days left.* We then determine the number of containers that has a *days left* smaller than the current *must-go day,* this is our value for #MGD. We also determine the number of containers with a *days left* between the current *must-go day* and the current *must-go day +1*, and the number of containers with a *days left* between the current *must-go day +1* and the current *must-go day +2*. With these numbers, we get an indication of the workload for the coming days. Formula 1 determines the maximum of the current number of containers and the weighted number of containers to empty based on the expected workload for the next days. We use a weighted calculation, because we think the workload for tomorrow and the day after tomorrow is more important than looking further ahead. The number and size of the deposits to the containers are uncertain, and the further we look into the future, the more the actual amount of refuse might deviate from the expected amount. We use the maximum of the weighted workload over the next days and the workload for today to ensure we will never empty less containers than indicated by the current *must-go day*.

When we calculated the new balanced number of containers to empty, we have to convert this number back to a *must-go day* for further use, for example in the addition of *may-go jobs*. We do this by sorting all containers on their *days left*, and choosing the *days left* of the container that is at the position in the row equal to the new balanced number we just calculated to be the new must-go day (NMGD).

6.6.2 Basic planning heuristic

The basic planning heuristic consists of several steps to select containers and create a route to empty these containers. Figure 17 shows a flowchart of these different steps we use to make a more dynamic planning methodology.

The basic planning heuristic starts with determining a list of *must-go jobs.* This list includes all containers that are almost full. This is determined by the use of the *must-go day*, which is a threshold to indicate which containers to empty. The default setting of the *must-go day* is 2, meaning that all containers that will be full tomorrow, with a *days left* of 2 or less, need to be emptied today. However, when we decide to use the 'Balancing' option, as described in Section 6.6.1, the *must-go day* changes based on the calculation of the NMGD.

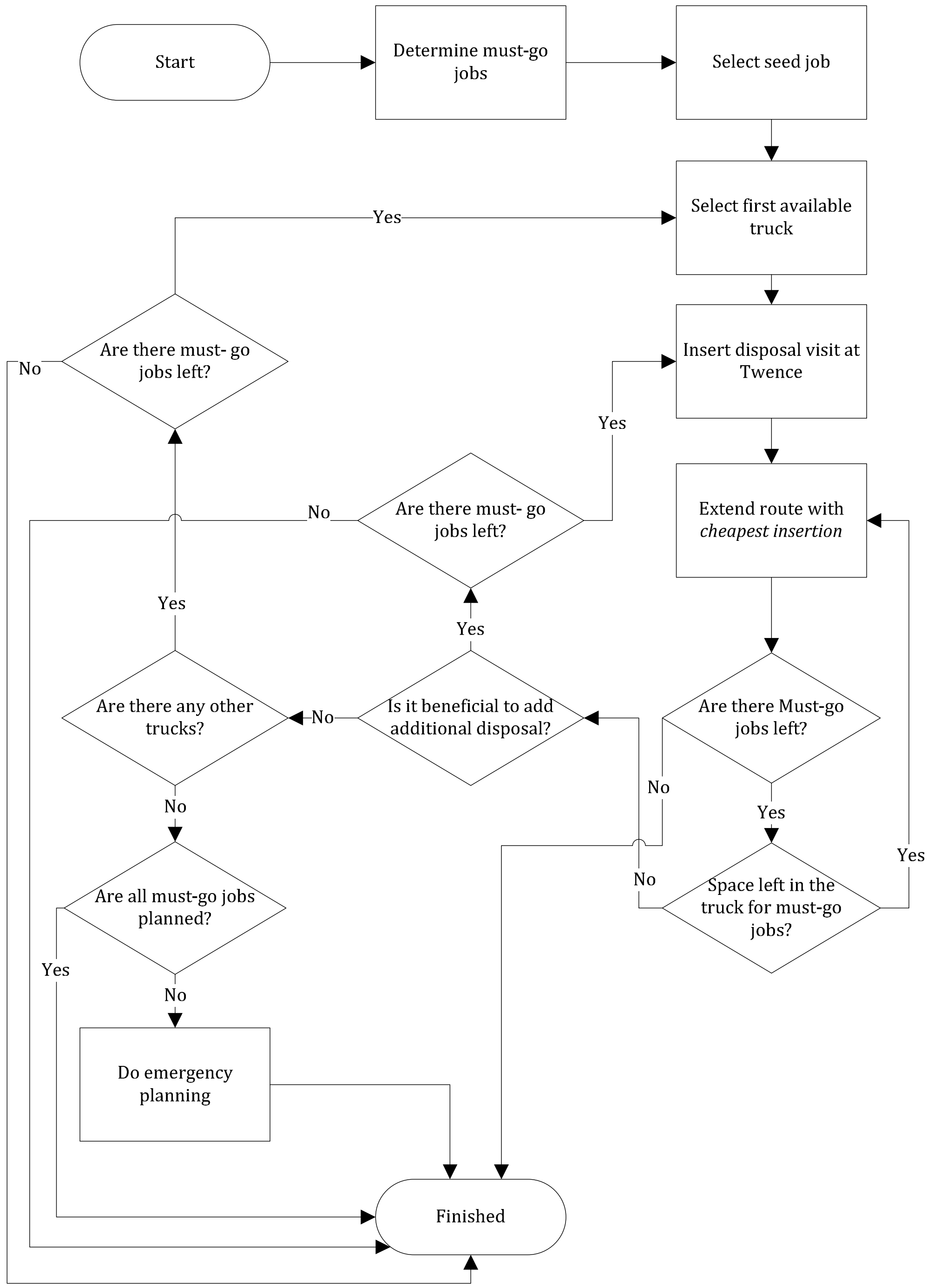


Figure 17 Basic planning heuristic

The next step in our heuristic is to select a seed job. The seed job is used to create an efficient route. Then we assign this seed job to the first available truck and assign other jobs from the *must-go* list to the route of this truck. This means we fill one truck before using another. By using only one truck at a time, we try to achieve a high fill rate of the truck. As indicated in Section 6.5, the fill rate is one of the performance indicators and a low fill rate, with a low number of jobs per truck, results in relatively high costs per kilo of collected refuse.

While extending the route, we have to check whether there is space left in the truck, both in truck capacity as well as in time. If there is space left, another *must-go* job can be assigned. When there is no space left in the truck, we have to make a decision whether to add an additional disposal trip. This depends on the time of the day. When the day is almost over, it might be a better decision to use a new truck. When we choose for an additional disposal visit, we can then again continue with creating a new sub-route for the truck. When deciding to use another truck, jobs are assigned to this new truck. In case all trucks have already been used, and there are still *must-go* jobs left, we have to do "emergency planning". Emergency planning is only necessary when the total number of *must-go* jobs does not fit into the maximum number of available trucks. When this happens, we delete all current schedules, sort the *must-go* jobs on ascending days left and assign as many jobs as possible to the available number of trucks, starting with the job that has the lowest days left. When the list of jobs is known, the problem becomes somewhat less complicated, because our IRP has one decision less to make.

6.6.3 Advanced planning heuristic

Next to the basic planning heuristic, we also developed a more advanced planning heuristic for assigning the *must-go* jobs to trucks. With our simulation model, we will find out whether this advanced method leads to better results. The main difference between the basic and the advanced heuristic is that the basic heuristic fills the trucks one truck at a time, while the advanced heuristic spreads the *must-go jobs* more evenly over all trucks. Of course, a requirement for this procedure is that the number of necessary trucks needs to be known. Figure 18 shows the steps of the advance heuristic.

As with the basic heuristic, we start with determining the *must-go jobs.* Again, this number might differ between days and is influenced by the use of Balancing. Next, we have to determine the minimum number of trucks required to empty all *must-go* containers. For determining this number of trucks, we use a procedure similar to the basic heuristic, which returns the number of trucks necessary to complete all *must-go* jobs. The next step in the advanced heuristic is to sort all *must-go* jobs on days left. By doing this, we make sure that the most urgent jobs are always scheduled first.

The fact that we know the number of trucks and routes to use, enables us to use *seed jobs* to send the trucks in different directions, either only for the first sub-route of a truck or for every sub-route a truck makes. In this way, we are able to avoid overlap between different routes.

After the selection of the *seed jobs*, we select other *must-go jobs* to add to the current trucks and routes. These jobs are spread among the different trucks, a difference with the basic heuristic is we do not fill trucks one by one, but we fill all trucks simultaneously. We check for each job on the *must-go* list, starting with the job with the lowest days left, in which truck it fits the best. This is based on the current location of the trucks (e.g. depot, emptying a container), the spare capacity of the trucks and the location of the job.

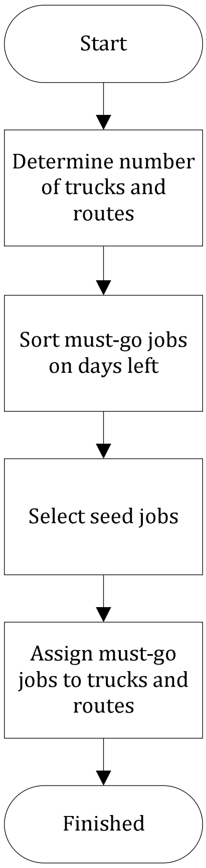


Figure 18 Advanced planning heuristic

6.6.4 May-go jobs

When all must-go jobs are scheduled, there may be some space left in the trucks to empty other containers. By adding *may-go jobs* to the trucks, we try to increase the occupancy rate of the trucks and the route efficiency. We can add *may-go jobs* both after the basic and the advanced method. However, we assume that adding may-go jobs will have more effect with the advanced heuristic because the advanced heuristic spreads the *must-go jobs* over the different trucks. This leaves more space in those trucks to insert *may-go jobs.*

For selecting *may-go jobs*, we do not use all remaining containers, but only the containers with a *days left* that is at most one day larger than the current *must-go day*. In case also balancing is used, we consider only containers with a *days left* a most one day larger than the new must-go day (NMGD). We use this rule for two reasons, one is to reduce the computation time and the other reason is that when a container is far from full, we do not want to insert it in the current schedule.

Once we have a list of all containers with a *days left* between the current *must-go day* and the current *must-go day* plus one (or between the NMGD and NMGD+1 in case we use balancing), we can select the containers to add as a *may-go job.* We loop over all trucks and decide per truck whether there are any *may-go jobs* that can be inserted. We do this based on a ratio of the additional time it takes to empty the container (both travel and handling time) to the expected refuse volume in the container. A small ratio indicates a high amount of refuse compared to the additional time; this means the smaller the ratio, the better. However, we do not select the container with the smallest ratio, but we compare the current ratio of a container with a smoothed historical ratio of that container, which is based on previous emptyings, to select the container with the best improved ratio. Hence, this procedure ensures we select the container that improves the most with respect to the historical ratio. A large improvement indicates it is beneficial to include that container in the current route instead of emptying it at a later time. Once we have selected a container, we insert it in the current route of the trucks and check the remaining capacity in the truck and the time of the day to see whether it is possible to add more containers. If one truck is full, we continue with adding *may-go jobs* to other trucks.

Figure 19 and Figure 20 show graphs of the smoothed ratios of a number of underground containers. We made these graph based on some preliminary simulation runs. Figure 19 displays the values of containers at unfavorable locations, which are locations with (almost) no other containers in the neighborhood. This means that to empty these containers, the truck driver has to deviate much from his route. Figure 20 shows the ratios for containers at more favorable locations, which are locations close to other container locations. We expect the smoothed ratios to differ for favorable and unfavorable locations, which is supported by the two graphs.

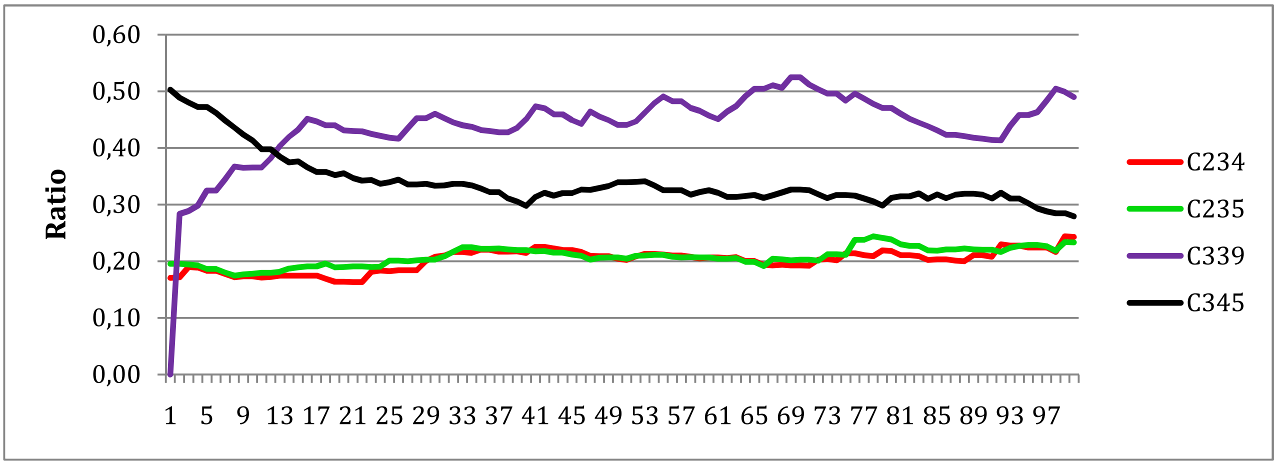


Figure 19 Smoothed ratios for containers at unfavorable locations

Figure 19 shows four containers, of which containers C234 and C235 are at the same location. As we would expect, two containers at the same location have almost the same ratios. The small differences occur as a result of the amount of refuse in the containers. When this differs, the ratio changes. Both Figure 19 and Figure 20 show it takes a few weeks before the smoothed ratios reach a steady value. This is because the smoothed ratios are based on historic emptying ratios, therefore, it takes a number of emptyings before these ratios flatten out. For containers C339 and C345 this is the largest, because these are in the most remote locations.

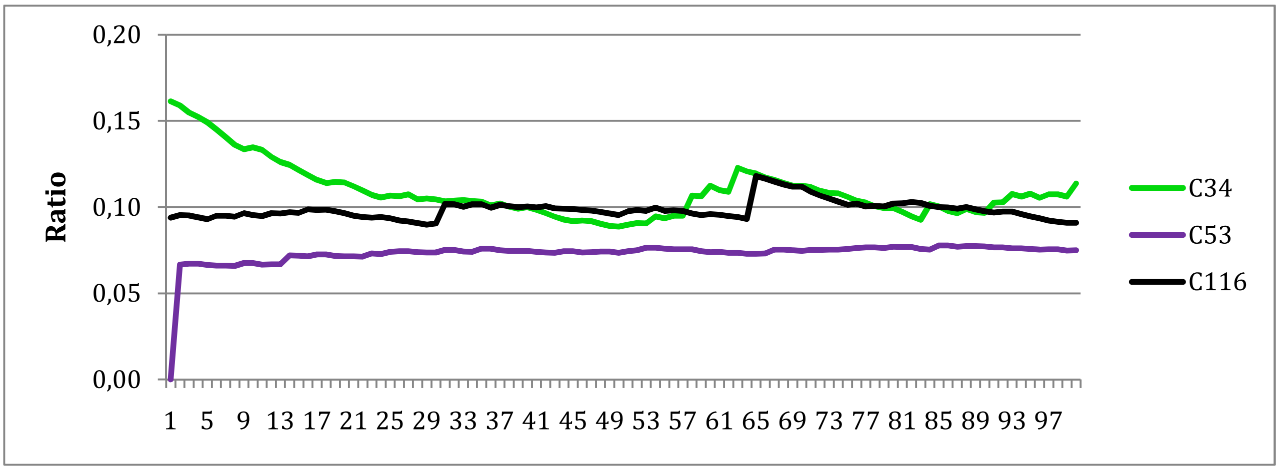


Figure 20 Smoothed ratios for containers at favorable locations in Enschede

Comparing Figure 19 with Figure 20, we see the ratios in Figure 20 are much lower. This is of course logical, because containers at a location with more containers in the neighborhood require less additional driving than containers at remote locations. This results automatically in smaller ratios. The results of the two graphs also support our choice to select *may-go jobs* based on their improvement compared to the historic smoothed ratio. Otherwise, when we would select containers based on their current ratio, containers at distant locations would never be selected.

6.6.5 Rescheduling

Next to the four elements we described in Sections 6.6.1 to 6.6.4, we will also use an option to reschedule the planning during the day. We include this option to evaluate whether a more dynamic planning leads to better results, as stated in Chapter 5. For rescheduling our planning at mid-day, all planned jobs of all trucks currently in use, will be deleted and will then again be assigned to the available trucks using the same planning methodology as is used in the morning. It is important not to delete any jobs a truck currently completes (non-preemption). This aspect of non-preemption is also described in literature by for example Kubale (1996). He observes that non-preemption leads to better schedules. In our case, using non-preemption is reasonable. When a truck is currently fulfilling a job, either emptying a container or driving to a container, it would not be efficient to stop this job and finish it later, based on the new schedule. The travel times and handling times for emptying the containers are relatively small and therefore preemption will not be useful.

6.7 Conclusion

This chapter provided insight into the problem of developing a planning methodology. All relevant variables are presented, together with assumptions that are necessary to model the problem. We presented the heuristic we developed and introduced a number of performance indicators to evaluate the different planning options on. Our heuristic consists of four components, which might or may not be used. We have the possibility to balance the workload, add *may-go* jobs, choose between the basic or the advanced method for assigning the containers to trucks, and decide whether to reschedule our planning during the day.

When using the basic planning heuristic, the number of trucks to use is not known in advance and therefore it uses one truck for as many jobs as possible before using another truck. The advanced heuristic uses the number of trucks determined with the basic heuristic and determines a seed job to improve the efficiency of the routes. Because the advanced heuristic knows the number of trucks necessary to complete all *must-go* jobs, it assigns jobs to all trucks simultaneously. In this way, the jobs will be better spread among the different trucks and therefore we assume the schedules using the advanced heuristic will be more efficient than the schedules of the basic algorithm.

We will test the different options of our heuristics in the simulation model to find out whether they are suited for Twente Milieu. With this model we have the ability to test effect of balancing, adding *may-go* jobs, and to see whether the basic or the advanced option gives the best results in the case of Twente Milieu. The next chapter will further outline the simulation model.

7 Simulation model

This chapter outlines the simulation model we use to test the effects of using a dynamic planning methodology for emptying the underground containers. With the simulation model, we evaluate the two heuristics discussed in Chapter 6. To do so, Section 7.1 gives the experimental design with the experimental factors and Section 7.2 outlines the structure of the simulation model. Section 7.3 explains how we calculated the distances between the containers. Section 7.4 explains how we validated our model and Section 7.5 shows how we calculated the warm-up period and the number of runs. Section 7.6 shows the visualization used to make the simulation model more accessible. Section 7.7 then gives some other important aspects of the simulation model and Section 7.8 concludes this chapter.

7.1 Experimental design

We decided not to include the underground containers located in Almelo in our simulation model, because there is no information available about these containers and the containers are emptied by trucks departing from the depot located in Almelo. This will not affect the outcomes of the planning model used for the underground containers in the other municipalities, because they are emptied from the depot in Hengelo. We will only use the 378 containers located in the municipalities Hengelo, Enschede, Hof van Twente, Losser, and Oldenzaal.

To evaluate the different planning options as discussed in Chapter 5 and to assess the differences between the two planning heuristics we presented in Chapter 6, we use a number of experimental factors in our simulation model. These experimental factors give insight into the operation and the robustness of the different solution possibilities.

To see how a planning methodology performs, we will test its behavior while we vary the circumstances under which it has to perform. We chose seven factors to use in the experiments. These experimental factors are:

1. The number of containers
2. Control rule
3. Updating of the schedule during the day
4. Use of *may-go* jobs
5. Use of balancing
6. Uncertainty in the sizes of the deposits made by households

With these six factors we will do a number of experiments to see which planning methodology works best in the case of Twente Milieu. To see the effects of the factors, we will vary the values of these factors. Table 6 shows the different values for all factors, and briefly explains the reason why we choose these values. As Table 6 shows, the six factors lead to a total number of 3*2*2*2*2*3=144 possible different scenarios when we would use a full factorial design. However, we will use a fractional factorial design. Because the available time is limited, we will start with 378 containers and evaluate all combinations using the five other experimental factors. Based on the results of these simulations, we will decide which combinations are interesting to evaluate using a larger number of containers. However, it might also occur that we find some interesting results that need further analysis. This will then lead to some additional experiments.

Factor	Values	Explanation	Number
Number of containers	378, 1000, 1500	Currently, Twente Milieu operates 378 containers in Hengelo and Enschede. This number will grow to a maximum of around 1500 containers. We will also use one intermediate step to see how the planning model deals with an increased number of containers. We will increase the number of containers by duplicating the existing containers, because we expect the new containers to be at similar location as the old ones, which means the dispersion will be comparable to the current situation.	3
Control rule	Basic, advanced	We simulate two different planning rules, basic and advanced, as stated in Chapter 6, to find out whether a more advanced planning heuristic leads to better results.	2
Updating type	Never, at mid-day	This factor is introduced to see whether a more dynamic way of planning, by updating the schedule more often, leads to better outcomes.	2
Use of *may-go* jobs	No, yes	*May-go* jobs are used to increase the occupancy rate of the trucks. We verify whether this leads to better results	2
Balancing	No, yes	By balancing, the workload should be spread better throughout the week. It is possible to do some additional containers if the next day is expected to be very busy. See Section 6.6.1	2
Uncertainty	0.95, 1, 1.05*variance in deposit sizes	This factor is used to evaluate the sensitivity of the planning method. We check in which way the results are affected by increasing or decreasing the variance of the deposit sizes.	3
		Total	**144**

Table 6 Values of experimental factors

7.2 Structure of simulation model

The simulation model consists of numerous methods that are used to execute the planning heuristic as outlined in Chapter 6. In this section, we will outline the structure of the simulation model. We will not go into detail on all the different methods, because Chapter 6 already gave a clear indication of the different functions and steps in the planning heuristic. These are all translated into the simulation model methods to find out which planning option works best for Twente Milieu. Figure 21 gives the structure of the simulation model, with the most important elements of the model. These are the Event Controller, Settings, Data, Network, and Planning. Figure 21 is a simplified version of the simulation model; a more detailed overview is attached in Appendix E. The schedule included in Appendix E gives a graph of all relevant methods we included in our simulation model, which are used to execute for example the balancing option and the basic heuristic.

The Event Controller contains functions to start and stop the simulation. It includes options to increase or decrease the simulation speed and offers the possibility to set the simulation run length. Also, there are functions to pause and reset the simulation. With resetting it, all parameters, such as the day number, are set back to their initial values.

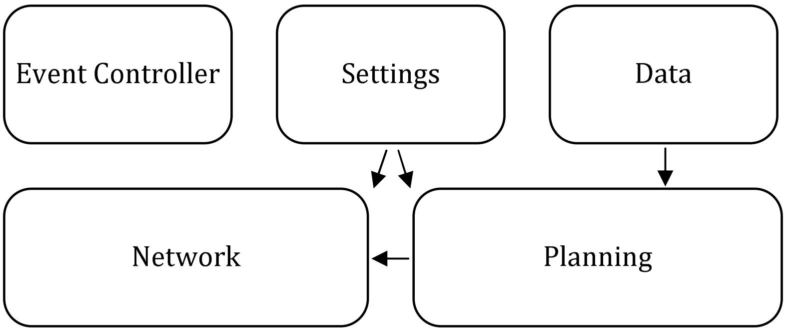


Figure 21 Structure of simulation model

Another important part of the simulation model is the Settings frame. This frame contains information about for example the start and end times of the working day, the number of runs, the travel and handling costs, the *must-go day,* and the capacity of the trucks. All these parameters are used as input in methods, for example when calculating whether a certain truck can empty any more containers, based on its remaining capacity, the expected volume of refuse in a certain container, and the time of the day. These methods are all included in the Planning frame, which we will discuss later in this section.

Next to these settings, the Settings frame includes the scenario table. This table contains all scenarios that have to be tested. In this table it is possible to indicate whether to use the options such as balancing, and the basic or advanced planning heuristic.

One final important aspect of the Settings frame is the option to set the type of network to use. While constructing and testing the simulation model and the methods in it, we used a random network. This network offers the possibility to clearly evaluate the constructed routes and see whether the constructed routes seem logical and whether the heuristic works as it is supposed. Another option is to select the Twente Milieu network, this shows a map of the area Twente Milieu operates in, with all containers marked on that map.

The Network frame shows the network as selected in the Settings frame and displays the routes that are constructed in the Planning frame. This section is only meant to visualize the routes, but does not add to the actual working of the model. However, it does help to understand how the heuristic works and how the routes are constructed.

The next important section in the simulation model is the Data Section. This contains tables with the real data from Twente Milieu such as the customer settings and depot settings. The table with customer settings contains information for each container on:

- the average number of deposits per day
- the average deposit size and variance
- the handling time to empty the container
- container size
- container location

The table with depot settings contains similar information, but then for the two depots, which are the Twente Milieu location Hengelo and Twence:

- the type of depot (parking or emptying)
- the initial number of trucks at that location
- the handling time (if any)
- the address

Next to these two tables, the data section also contains information about the container locations and the distances between the containers. These data tables are used when calculating the routes. The distance tables give the distance in time and in kilometers for every possible container combination. This leads to a matrix of 520*520 with all containers emptied by Twente Milieu. For calculating these distances, we first had to know all locations of the containers. These locations are collected in the addresses table. When increasing the number of containers, we duplicate the existing containers; this means that we can still use the existing distance matrix. Section 7.3 describes exactly how we calculated the distances.

Finally, the Planning frame is the most important frame in the simulation model. This frame contains the methods that actually execute all steps necessary to develop an emptying schedule. It is divided into different sections, with methods for planning and control, network information, truck movements, and network information. The planning and control methods calculate the schedule, while the other methods determine for example the start and end times of the truck movements. Also, the Supplier frame keeps track of the performance of the different planning methodologies. This is necessary to be able to evaluate all options and determine which option works the best in our case. The Planning frame uses settings from the Data section and the Settings section for calculating a schedule.

In Appendix F, we included screenshots of our simulation model. These show the frames discussed in this section and visualize the structure of the simulation model.

7.3 Distance calculation

For realistic simulation results it is important to calculate the distances between the different containers. With a dynamic emptying schedule, there are no fixed routes and therefore the distance between all possible container combinations should be calculated both in time and in kilometers. By doing these calculations in advance and using the resulting distance table in the simulation model, the simulation speed is increased compared to calculating the distances in the simulation model itself.

For calculating the distances, we first generate a list of all containers and the corresponding addresses. Twente Milieu has a list of all containers with an indication of the location by the use of a street-name, crossing of two streets or a closely located building. We converted these indications to street-names with house numbers. For almost all container locations we were able to generate a corresponding street-name and house number. Only for a small number of containers this was not possible because there was no clear indication to derive the exact location from. For these containers, the middle of the street was used as the location, which means that the conversion sometimes deviates a little from the real locations. This difference will be small, because the streets are mostly short, and therefore this will not result in large errors in the distance calculation.

Next, we were able to determine the GPS-coordinates of these locations with this list of container addresses. We used a Google Maps driven application to determine the distances in time as well as in kilometers. In these computations we assume a symmetric distance matrix. This was done to lower the number of calculations, but is also a reasonable assumption. One-way streets are mainly located in residential areas and city centers, but because the distances are small and therefore the travel times short, the deviation as a result of using a symmetric distance matrix is offset by the handling times of emptying a container. In the end, we got a 520*520 matrix displaying the distances between all possible container combinations.

7.4 Model verification

To ensure the simulation model works as it is supposed to, we need to verify our model and check whether all desired functionalities are included, whether the input data is correct and processed accurately, and whether the methods in our simulation model work correctly.

As input data we used the number of deposits per container per day and the deposit sizes for the different containers from the Twente Milieu databases. We verified these values by also weighing the amount of refuse in the underground containers for one week. The data analysis in Chapter 3 describes how we collected and verified these data. It shows that the historic average retrieved from the database matches the real observations. However, one remark we have to make, is that not all underground containers are digital, which means we do not have up-to-date information about the complete set of containers. For the containers that are not in the databases yet, we used the averages of all other containers.

Next, we verified the distance table used in the model using Google Maps. We randomly selected some addresses from the table and compared these with distance calculations from Google Maps. During this research, we made the assumption that the distance matrix was symmetric. For the addresses we verified, we saw that this assumption does not lead to large deviations. Our verification also showed that the larger the distance between two locations, the smaller the differences between the way there and back. This is explained by the presence of one way streets in city centers, where the distances are relatively small. Our verification shows that there are some slight deviations, but our distance calculation works well overall. The differences we did find are offset by the handling times at the containers.

Finally, we verified our simulation model by stepping through it. We did this while constructing the various methods, but also when the complete model was finished. By stepping through, we were able to follow all procedures and calculations, and we would see it if there are any errors. We also verified whether the model correctly processes our input data. For example, we checked the calculation of the distribution of the deposit sizes. We used a Gamma distribution, with an alpha and a beta factor. We checked the calculation of the alpha and beta by stepping through the methods, and the calculation works as we supposed. We also built in some checkpoints, which would show whether there are any unwanted results occurring in our simulation model.

7.5 Warm-up period and calculation of number of runs

Another way is to calculate the warm-up period and the number of runs. This ensures that the results of the simulations are trustworthy. A warm-up period is needed to ensure the simulated system is in a stable state when the actual simulation run is started. In our case this means for example that it takes a few days or weeks before the amount of refuse in the containers is stable and representative for the real situation, and it takes some time to generate requests and emptying of the containers. The number of runs is important to ensure reliable results, if the number of runs is too small, we cannot say the outcomes are a result of our planning heuristic or just the result of pure luck.

The warm-up period indicates after which time the system comes into a steady state. In our case, the warm-up period is necessary for determining the smoothed ratios used for adding *may-go jobs* to routes and the warm-up period is also needed to create realistic amount of refuse in the underground containers. At the start of the simulation, we use a uniform distribution between 0 and 0,5 times the container capacity to put a start amount of refuse in it. It takes a while before the amount of refuse in the containers represents the actual situation. For calculating the warm-up period, we used Welch's graphical procedure as described in Law (2007). Appendix G gives the steps in the procedure, and also shows the resulting graph indicating the warm-up period. Using Welch's procedure, we estimated the warm-up period should be 10 weeks or 70 days. We choose the run length to be 220 days, because the run length needs to be larger than the warm-up period.

Next, we calculated the number of runs using the sequential procedure, which is described in Law (2007). For reliable simulation results, we have to perform a number of different runs. The different runs are independent of each other, and therefore, we can compare the results and calculate what number of runs is needed to get valid simulation results. The calculations for determining the number of runs is included in Appendix H. We performed the simulation runs in the calculations with the simplest version of our heuristic, without for example balancing or adding *may-go* jobs to our plan. The minimum number of runs following from the procedure should be three. To ensure the results are also valid when we use other scenarios, we will perform four runs for each experiment. Law (2007) suggest to use at least five runs for each experiment, but we choose to use only four, because the experiments with 1500 containers are very computational intensive. However, since our runs are very large, this will not influence our results.

7.6 Visualization

To make the simulation model more accessible for usage, we added some visualization. This does not contribute to the actual output of the model, but it increases the understanding of the operation of the model. Since it supports the understanding of how the heuristic works and how the routes are constructed, we added a map to our model that displays the developed routes.

The map in our simulation model contains all container locations of the Twente Milieu containers and is only used for visualization of the routes. Displaying a part of a 3D globe on a 2D map requires some transformations and to make the map accurate, we had to use a map projection. We used the Universal Transverse Mercator coordinate system (UTM) to do this. This system uses the Transverse Mercator projection, which is a cylindrical projection, shown in Figure 22. Only the meridian that touches the cylinder is accurate. The cylindrical projection provides the possibility to choose every meridian and therefore makes it possible to project any part of the world accurately on a 2D map. This map is accurate for locations within 15 degrees of the meridian.

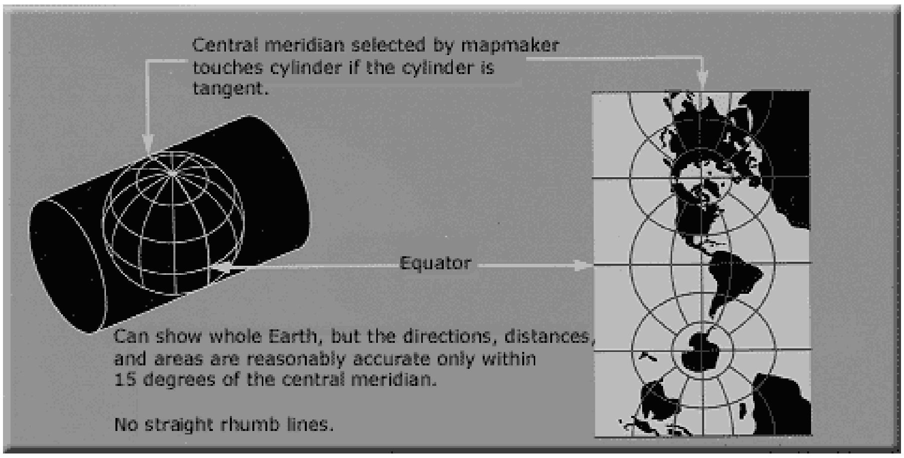


Figure 22 Transverse Mercator projection (TMP, 2010)

The UTM coordinate system divides the earth into 60 zones, which are 6° of longitude in width and centered over a meridian of longitude. Each of these zones are based on the Transverse Mercator projections. The zones are numbered in a eastern direction, the Netherlands are in zone 31 and 32. For the exact locations of the containers, or any other location on earth, the UTM zone is combined with the easting and northing coordinate pair. The easting is the position eastwards of the central meridian of the zone, measured in meters. The central meridian has a value of 500.000 meters, to avoid negative numbers. The northing gives the distance north or south from the equator. To make a distinction between locations on the northern and the southern hemisphere, 'N' or 'S' is used (UTM, 2010) (TMP, 2010). In our case, the projection is somewhat more easy, because all container locations are in zone 32 and this makes the conversion from XY coordinates to GPS more easy.

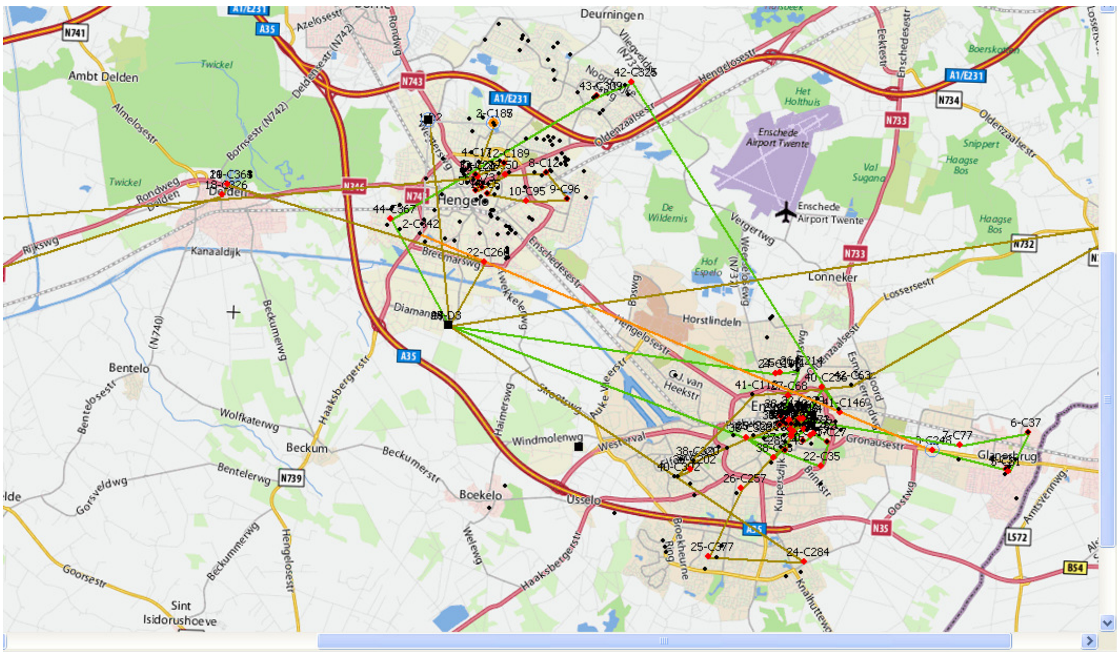


Figure 23 Simulation map

Figure 23 shows the map we used in the simulation model with a schedule for a day. The routes on the map might seem somewhat illogical, but that is a result of the straight lines used for drawing. Drawing actual routes would take too much calculation time. Another point that is of influence on the routes is the fact that they are based on travel times instead of distance. This also might result in some illogical route pictures, whereas they make sense when looking at the actual travel times.

The different colors of the routes indicate the difference between planned routes and already driven routes. Parts of the route that are already finished are grey, while the part of the route the truck is currently driving, is indicated by an orange line. When a truck is emptying a container, this is indicated by an orange dot. As Figure 23 shows, the containers are marked as black dots, and as red dots if they are marked as *must-go jobs*. When multiple trucks are used, each truck has its own color. Figure 23 shows there are two trucks in use, one is indicated by green lines, the other by brown lines.

7.7 Simulation settings

Next to all issues we discussed in this chapter, there are some other points that are important to mention before continuing to the results of our simulation model.

As stated in Section 7.1, we decided to exclude the underground containers located in Almelo for our simulation model, because there is no information available about these underground containers and they are emptied by trucks departing from a depot in Almelo.

In Section 6.3 we introduced a number of parameters we will use in our simulation model. Table 7 gives the values of these parameters we will use in our simulation model. Not all values of the parameters can be given in a table. For example, for the distances between the locations we constructed a large matrix with all locations and the corresponding distances between the locations. We added this matrix to our simulation model, it is too large to include in this report.

Parameter	Value
C	378, see Appendix C
D	3, see TM-depots table in simulation model
L	236, see TM-adresses table in simulation model
N_l	Different per location, see TM-adresses table in simulation model
D_{ij}	Different per container, see distance matrix in simulation model
TT_{ij}	Different per container, see time matrix in simulation model
HTT	2700 seconds
SD	7:30 o'clock
ED	16:00 o'clock
CAP	4.800 liter
RPD	11
RS_i	Different per container, see Appendix C
RSV_i	Different per container, see Appendix C
X_i	Depends on last emptying
$E(G_i)$	Equals (X_i* RS_i)
DL_i	Equals (CAP- $E(G_i)$)/(RPD* RS_i)
HT	250 seconds
R	Differs with the number of containers, maximum set to 10
SF	5
AC	18.000 liter
CAPT	90.000 liter

Table 7 Values for simulation parameters

7.8 Conclusion

This chapter described the simulation model we will use to evaluate the different planning options. We set a number of experimental factors which we will vary, to see how our planning heuristic reacts to different circumstances. The experimental factors are:

1. The number of containers
2. Control rule
3. Updating of the schedule during the day
4. Use of *may-go jobs*
5. Use of balancing
6. Uncertainty in the sizes of the deposits made by households

With these factors, we will perform experiments to find out which combination of factors will lead to the best results for Twente Milieu. We will not use a full factorial design, but a fractional factorial design when simulating the different experiments. We start with experiments using 378 containers, and based on those results, we will evaluate the most interesting options for an increased number of containers.

The structure of our simulation model consists of a number of key elements. The most important element is the Planning frame. This frame contains all methods used to execute the steps of our heuristic. The methods in this frame control, among others, the truck movements, new deposits to containers, and the container emptyings. Other key elements are the Event Controller, the Settings frame, the Data section, and the Network frame.

In the Network frame, we included some visualization to make the simulation model more accessible for usage. We included a map that displays all containers, the scheduled routes, and the current location of a truck. For displaying this map in the Network frame, we used a Universal Transverse Mercator projection. This projection makes it possible to display a part of a 3D globe on a 2D map.

Another essential aspect described in this chapter is the model verification and the calculation of the warm-up period and the number of runs. We calculated the warm-up period and the number of runs using Welch's method and the sequential procedure and found out for valid results, the warm-up period should be 10 weeks and we have to perform 4 runs. We will perform runs of 220 days each.

8 Results

Chapter 7 gave the experimental design, and in this chapter, we discuss the results of our simulation experiments. We start this chapter with determining the best seed selection rule in Section 8.1, and continue with evaluating the use balancing, the addition of *may-go jobs,* rescheduling, and the effect of variance in Sections 8.2 to 8.5. Next, we look at combinations of balancing, using *may-go jobs,* and rescheduling in Section 8.6 and analyze the effect when the number of containers would grow to 1500 in Section 8.7. Section 8.8 concludes on the best option for Twente Milieu.

The tables we use in this chapter to display the results of the various options show values for the total costs, the service level and the fill level. In this chapter, we use the definitions stated as in Section 6.5 for these three performance indicators. Also, we used *t-test* with a 95% confidence level to check whether found differences between scenarios are significant.

8.1 Seed selection rule

In Chapter 6 we discussed the different possibilities for selecting seed jobs, either using a seed on insertion costs or a seed on distance. These possibilities can be used either per truck or per route. Before continuing with the actual simulations, we want to check whether there is a difference between these methods of seed selection and which option we should use during our simulation experiments. Therefore we performed an initial simulation run to decide on the best seed selection rule. In this initial run, we only used the advanced heuristic, because the basic heuristic cannot use all different seed options.

Scenario		Costs	Service Level	Fill Level
Advanced and balancing	Seed on distance per truck	4.856.856	0,955	0,832
	Seed on distance per route	4.894.054	0,953	0,771
	Seed on insertion per truck	4.877.322	0,955	0,822
	Seed on insertion per route	4.878.122	0,951	0,778

Table 8 Results for simulation on seed selection

Table 8 shows the summarized results of our simulation. We performed four runs of every scenario and the numbers given in Table 8 are the averages of these four runs. To be able to make a good comparison, we used a *t-test* to check whether the differences are significant. On costs as well as on the fill level, the *seed on distance per truck* performs the best. On the service level, there are only minor differences between the options. We can state with a confidence level of 95% that the option of the *seed on distance per truck* significantly outperforms the second and fourth options on the fill level. The other results are not significantly different. These results are remarkable, because we would expect the *seed on distance per route* to perform best. This option uses seeds for each route instead of only for the first route. These results might be explained because at the start of a day, all trucks are located at the same location. At this point, it makes sense to select a seed job for each truck to ensure they are spread over the complete area. During the day, when a truck visits Twence and starts a new sub-route, all other trucks are at different locations, which leaves less need to spread the trucks. At this point in time, the trucks are already spread. We will continue our other simulation experiments using the *seed on distance per truck* option, because based on our initial simulation runs, it performs the best.

8.2 Balancing

One option we described in Chapter 6 was to use balancing, this option is meant to spread the workload between the days and to increase the service level, as described in Section 6.6.1. Figure 24 shows a graph of the number of containers emptied per day for three weeks, both with and without the use of balancing. Figure 24 shows that balancing does have the effect of leveling the workload throughout the week. Still, Mondays are the busiest days of the week, but the difference with the other days is less than in case we use no balancing. With balancing, the number of containers emptied per day varies between 45 and 78, while when we do not use balancing, it differs between 23 and 118 container per day.

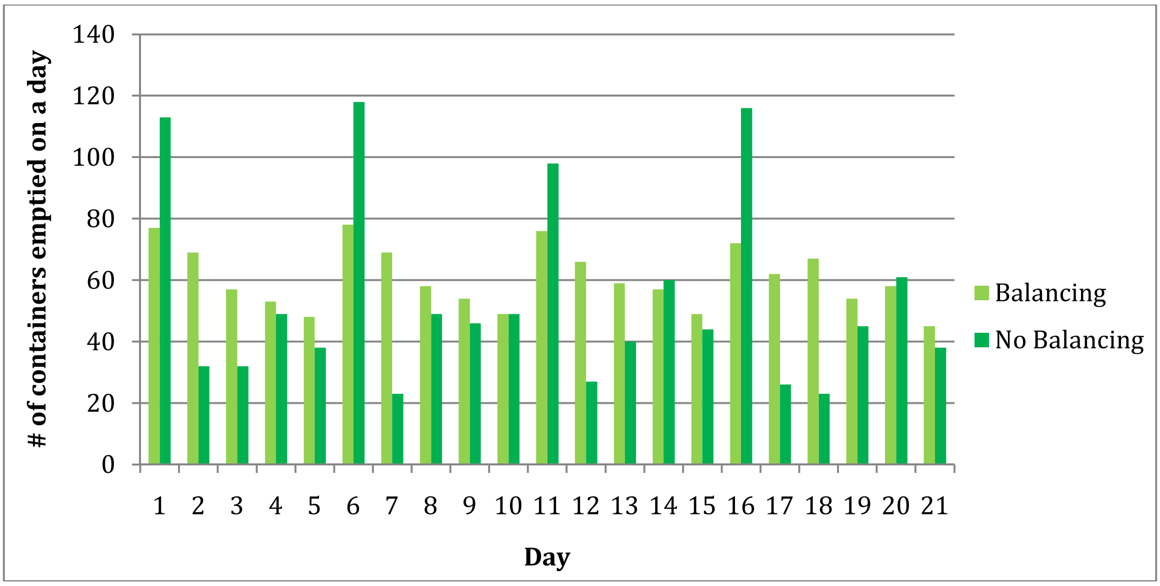


Figure 24 Number of containers emptied per day

Table 9 gives the results of the simulation runs we did to test whether balancing leads to better results. We performed four runs and Table 9 shows the average results of these four runs. We performed these runs for the case of 378 containers as well as for the higher number of 1000 containers.

In the case of 378 containers, using balancing leads to a significant higher service level, both with the basic and the advanced planning heuristic. The fill level also increases, but not as much as the service level. Using balancing leads to a higher number of containers that is emptied. The fact that the costs are slightly lower, is a result of the much lower penalty costs. The handling and travel costs are somewhat higher, because the number of containers emptied is also higher. We can conclude that balancing leads to more efficiency, which is also supported by the maximum number of trucks used, without balancing, this is four, while with using the balancing option, the maximum number equals 3. The average output ratio at the emptying of the containers lies around 82%.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No balancing	4.880.919	0,8140	0,7610
		Balancing	4.879.667	0,9553	0,7813
	Advanced	No balancing	4.920.887	0,8140	0,7708
		Balancing	4.855.345	0,9550	0,8323

1000 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No balancing	10.998.074	0,8115	0,8333
		Balancing	10.961.603	0,9548	0,8150
	Advanced	No balancing	11.251.659	0,8093	0,8275
		Balancing	11.045.861	0,9513	0,8478

Table 9 Results for simulation on balancing

We also simulated a situation with 1000 containers, to see whether our heuristic is able to deal with a larger number of containers. Table 9 shows similar results for 1000 containers as with 378 containers. The costs are of course higher, but this is the result of the much higher number of containers that is emptied. When operating 1000 containers, balancing also leads to a large increase in the service level, but no significant differences on the other two criteria.

When looking at the difference between the basic and the advanced heuristic, we cannot state that one of the heuristics outperforms the other. The advanced heuristic achieves better results on the fill level. This is explained by the simultaneous scheduling of all trucks, this ensures the containers are more equally spread among the trucks, which leads to higher fill levels. On the service level and the costs, the differences between the basic and the advanced heuristic are only minor, the results do not clearly indicate which heuristic performs best.

8.3 Adding may-go jobs

The second option we evaluated, is the use of may-go jobs. With the may-go jobs, we wanted to increase the occupancy rate of the refuse truck and also increase the route efficiency. Table 10 shows the results of the simulation, both for 378 and 1000 containers.

Table 10 shows that especially on the fill levels, large improvements are realized with the addition of may-go jobs to the schedules. This means that the use of the may-go jobs works the way we meant it. By the addition of the may-go jobs, we managed to create better filled schedules. These results occur both with 378 and 1000 containers, in both cases, the fill level is higher than without the addition of the may-go jobs. However, in the situation with 1000 containers, the improvement is not as large as with the 378 containers. This can be explained by the larger number of containers. With this higher number, the schedules will be more efficient because there are more possibilities to add containers. This leave less room for improvement.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No may-go	4.880.919	0,8140	0,7610
		May-go	4.554.067	0,8533	0,9140
	Advanced	No may-go	4.920.887	0,8140	0,7708
		May-go	4.594.320	0,8558	0,9085

1000 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No may-go	10.998.074	0,8115	0,8333
		May-go	10.662.907	0,8303	0,8930
	Advanced	No may-go	11.251.659	0,8093	0,8275
		May-go	10.935.371	0,8280	0,8840

Table 10 Results for simulation on adding may-go jobs

Again, we do not observe a clear difference between the basic and the advanced heuristic. However, when we use may-go jobs the basic heuristic seems to perform better than the advanced heuristic. Especially when we simulated with 1000 containers, the basic heuristic gives slightly better results. In Chapter 6, we assumed the use of may-go jobs would have more effect in combination with the advanced heuristic. Our results do not show this effect, a reason might be that may-go jobs just fill every truck, regardless whether the must-go jobs are equally spread over all trucks or clustered in the first used trucks.

Table 10 also shows the service levels are much lower than when we use balancing, this is because the addition of may-go jobs is meant to increase the fill level, while the use of balancing is meant to increase the service level. Section 8.6 analyzes the use of a combination of these two elements.

8.4 Adjustment during the day

Another option we developed, is the adjustment of the schedules during the day. We use this option to find out whether a more dynamic way of planning leads to better schedules for Twente Milieu. In our heuristic, we reschedule at 11.30, after a half-day work. Table 11 displays the results of the simulation results on rescheduling for both 378 and 1000 containers.

Table 11 shows that the effects of rescheduling are only minor. For the basic algorithm, the effects are even negative. The only real positive results occur for the advanced heuristic with 1000 containers, in this specific situation, the costs are lower and the fill levels are higher than without the rescheduling. The service level and the fill level are low in this case, but that is the result of only using rescheduling and no balancing or may-go jobs. We will analyze these combinations in Section 8.6.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No rescheduling	4.880.919	0,8140	0,7610
		Rescheduling	5.145.029	0,8183	0,6828
	Advanced	No rescheduling	4.920.887	0,8140	0,7708
		Rescheduling	4.915.589	0,8205	0,7925
1000 containers	**Scenario**		**Costs**	**Service Level**	**Fill Level**
	Basic	No rescheduling	10.998.074	0,8115	0,8333
		Rescheduling	11.436.814	0,8148	0,7868
	Advanced	No rescheduling	11.251.659	0,8093	0,8275
		Rescheduling	10.762.257	0,8128	0,9745

Table 11 Results for simulation on rescheduling

The minor results for the rescheduling options can be explained by the fact that the rescheduling option reschedules all trucks and always at 11.30, independent of the situation. It might be more beneficial to reschedule for example only one truck, when we assume the next scheduled job will not fit into this truck. Another option is to reschedule all trucks at the moment we assume one truck will not be able to perform its next scheduled job. Therefore, we changed our rescheduling heuristic and inserted an option to reschedule only one truck or all trucks, only when we assume the capacity is not sufficient for the next job. We now have three rescheduling options:

1. Rescheduling all trucks at 11.30 o'clock. This is our old rescheduling option.
2. Rescheduling 1 truck when we assume the next job will not fit into the truck
3. Rescheduling all trucks when we assume the next job will not fit into a truck

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No rescheduling	4.880.919	0,8140	0,7610
		Rescheduling 1	5.145.029	0,8183	0,6828
		Rescheduling 2	4.928.816	0,8105	0,7515
		Rescheduling 3	5.087.857	0,8160	0,6993
	Advanced	No rescheduling	4.920.887	0,8140	0,7708
		Rescheduling 1	4.915.589	0,8205	0,7925
		Rescheduling 2	4.994.046	0,8135	0,7568
		Rescheduling 3	4.968.779	0,8155	0,7713

Table 12 Results for simulation on new rescheduling strategies

Table 12 shows the results of our new simulations. It shows that rescheduling only one truck works better than rescheduling all trucks. However, we still cannot say that using rescheduling leads to better schedules. To be sure, we also tested rescheduling option 2 while also using balancing, but this also does not lead to better results, see also Table 13. Therefore, we think rescheduling during the day does not contribute to better schedules.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	Balancing	4.879.667	0,9553	0,7813
		Balancing + Rescheduling 2	4.911.733	0,9485	0,7743
	Advanced	Balancing	4.855.345	0,9550	0,8323
		Balancing + Rescheduling 2	5.020.195	0,9548	0,7745

Table 13 Results for simulation using rescheduling option 2 with balancing

A reason that rescheduling does not improve our schedules might be that we use deterministic times. This means there is no uncertainty at this point that might cause deviations from our initial schedule. When we would use stochastic travel times, there will be more uncertainty, and therefore more deviation from the initial schedules. This could lead to better results using the rescheduling option. Therefore, we would recommend to further investigate the use of rescheduling when using stochastic travel times.

8.5 Variance in deposit size

Another factor we want to investigate, is the influence of variance on the simulation outcomes. Therefore, we performed a number of experiments with a higher and lower variance in deposit size. We varied the standard deviation both to 95% and 105% of the actual standard deviation.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	No variance	4.880.919	0,8140	0,7610
		Variance 0.95	4.881.314	0,8135	0,7610
		Variance 1.05	4.881.327	0,8135	0,7610
	Advanced	No variance	4.920.887	0,8140	0,7708
		Variance 0.95	4.920.429	0,8138	0,7708
		Variance 1.05	4.920.767	0,8130	0,7708

Table 14 Results for simulation on variance in deposit size

Table 14 shows that there is no influence of more variance in deposit sizes on the simulation outcomes. This is explained by the portfolio effect. Increasing the variance results in more deviation, but because the deviations go both higher and lower than the original values, the effect fades out, resulting in no visible changes in the simulation outcomes.

Therefore, we decided to change the mean deposit sizes, instead of the standard deviation, to investigate whether this has a larger influence. The results of these simulation are shown in Table 15. We tested the scenario of using both the balancing option and the addition of may-go jobs and used three different variance factors to vary the mean deposit size: 0,05, 0,1, and 0,2. We used these values to create a uniform distribution between (1-variance factor) and (1+variance factor). We then randomly draw a number from this distribution which we use to determine new values for the alpha and beta of our Gamma-distribution for determining the deposit size. This new way of increasing uncertainty thus affects the alpha and beta factors used to determine the deposit sizes. The higher the number, the higher the uncertainty in mean deposit size, the maximum value for this factor would be 1.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	Balancing + May-go	4.769.880	0,989	0,939
		Balancing + May-go MV 0,05	4.766.696	0,989	0,937
		Balancing + May-go MV 0,1	4.767.354	0,986	0,936
		Balancing + May-go MV 0,2	4.788.195	0,985	0,934
	Advanced	Balancing + May-go	4.772.516	0,976	0,944
		Balancing + May-go MV 0,05	4.762.873	0,974	0,943
		Balancing + May-go MV 0,1	4.782.141	0,976	0,937
		Balancing + May-go MV 0,2	4.785.044	0,973	0,938

Table 15 Results for simulation on mean variance

However, Table 15 shows that the results are still not heavily affected by the increased uncertainty. The results deteriorate only slightly when we increase the mean-factor. This means our simulation results are only slightly sensitive to variation in the input data.

8.6 Combinations

Next, we also simulated combinations of the options we evaluated in the previous sections. We did this both with 378 and 1000 containers. Table 16 and Table 17 show the results of these simulations. The rescheduling option is in this case the rescheduling of all trucks at 11.30 o'clock, because we investigated the other rescheduling options after we finished all simulations.

378 containers	Scenario		Costs	Service Level	Fill Level
	Basic	Balancing	4.879.667	0,9553	0,7813
		May-go	4.554.067	0,8533	0,9140
		Balancing + May-go	4.769.880	0,9888	0,9390
		Balancing + May-go + Rescheduling	4.823.991	0,9833	0,9050
	Advanced	Balancing	4.855.345	0,9550	0,8323
		May-go	4.594.320	0,8558	0,9085
		Balancing + May-go	4.772.516	0,9755	0,9443
		Balancing + May-go + Rescheduling	4.848.212	0,9808	0,9600

Table 16 Results for simulation of combinations with 378 containers

For the basic algorithm with 378 containers, the combination of using balancing together with the addition of may-go jobs gives significant better results on the service and fill level than when using only balancing or only may-go jobs. The costs for using balancing and may-go jobs are higher than using only may-go jobs, but this is the result of emptying more containers. The combination of the balancing and may-go empties around 1000 containers more, which results in higher travelling and handling costs. On the other hand, the penalty costs are lower, and the combination uses one truck less. This indicates the combination of using balancing and may-go jobs leads to more efficient schedules. When we then look at the combination of balancing, may-go jobs and rescheduling, we see no significant differences with the case of using only balancing and may-go jobs. We already stated this in Section 8.4, rescheduling does not increase the results, this probably is the result of the deterministic travel times we use.

For the advanced algorithm, the results are similar to the basic algorithm. The combination of using balancing and may-go jobs together outperforms the use of only one of the two options. The combination of all three options for the advanced algorithm does also not lead to better results. There is not much difference between the results of the basic and the advanced algorithm, on costs and service level, the basic algorithm scores slightly better, while the advanced heuristic gets the best results for the fill level.

1000 containers	Scenario		Costs	Service Level	Fill Level
	Basic	Balancing	10.961.603	0,9548	0,8150
		May-go	10.662.907	0,8303	0,8930
		Balancing + May-go	10.698.812	0,9673	0,8863
		Balancing + May-go + Rescheduling	10.951.269	0,9670	0,8925
	Advanced	Balancing	11.045.861	0,9513	0,8478
		May-go	10.935.371	0,8280	0,8840
		Balancing + May-go	10.871.016	0,9650	0,9008
		Balancing + May-go + Rescheduling	10.580.129	0,9780	1,0310

Table 17 Results for simulation of combinations with 1000 containers

Table 17 shows the results of using combinations of options when we use 1000 containers. Again, the combination of balancing and may-go jobs outperforms the options where we use only one of the two options. Also, the use of rescheduling does not improve the results much. However for the advanced heuristic, the addition of the rescheduling option does increase the results, but Table 17 also shows an average fill level of 1,03. This is of course impossible, and it shows the rescheduling option does not work entirely as supposed. The new scheduling options, as described in Section 8.4, works better.

What is also interesting to see, is whether our new developed heuristic works better than the current planning methodology used by Twente Milieu. Therefore, Figure 25 displays the output ratios at the moment of emptying a container. These results are reached using the advanced heuristic with the combination of balancing and may-go jobs with 378 containers. We simulated for a year, and Figure 25 shows about 2.600 emptyings during that year. The total number of emptyings in that year was much higher, around 13.000, but that would make the graph unreadable. Figure 25 shows the average output ratio at emptying lies at 78 percent, and almost all containers have an output ratio above 60 percent. This indicates the deviation is less than in the current situation. For comparison, see also Figure 7 in Section 3.2. Although there are a number of containers that have an output ratio above 100 percent, the percentage of containers that is emptied too late lies little above 2 percent.

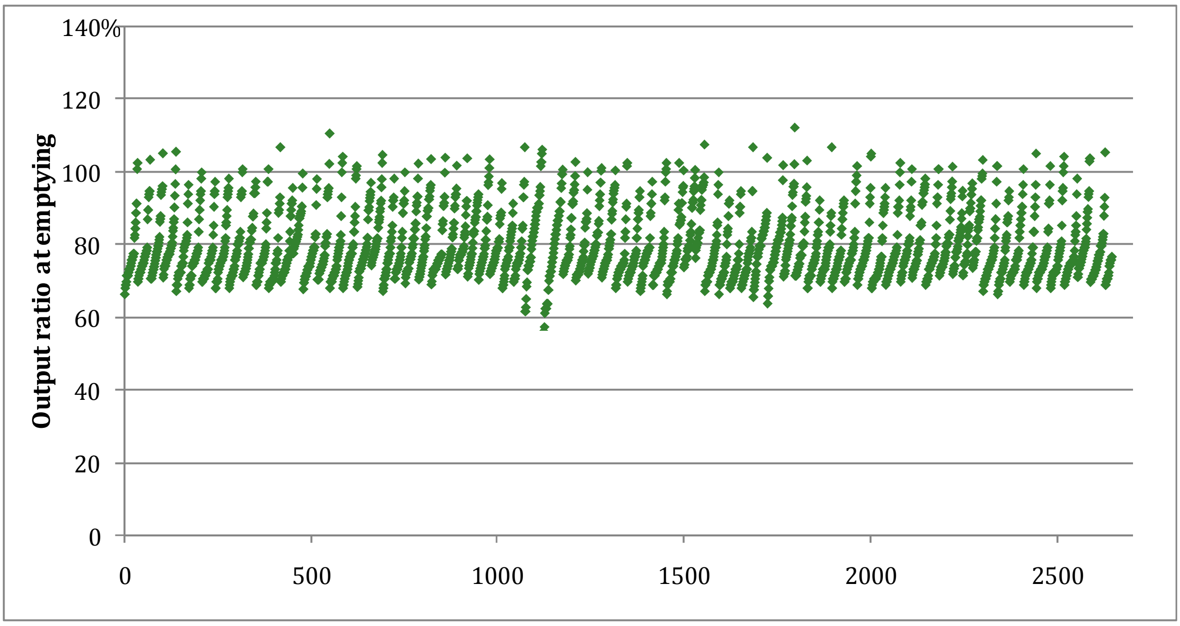


Figure 25 Output ratio at emptying of the containers

To really be able to compare the new planning methodology with the current planning methodology, we also made a new box plot displaying the average output ratio and the number of emptyings for each container. Again, we used the advanced heuristic in combination with balancing and the addition of may-go jobs. We simulated for a year with 378 containers. Compared to Figure 7, the new box plot in Figure 26 shows much more the ideal horizontal line. There is not much deviation and all output ratios lie around the 80 percent line. This is a large improvement compared to the current situation, where the average output ratios deviate between 20 and 100 percent. Also, the number of emptyings deviates less using our new planning methodology. Most containers are emptied between 25 and 50 times in a year. Figure 26 shows a number of containers that are emptied between 50 and 60 times. Most of these containers are located in the centre of Enschede, and are also used by companies. One remarkable point in Figure 26 are the two containers that are only emptied 8 and 12 times in a year. These marks are probably the result of an error in the input data. In the data analysis we performed in Chapter 3, these two containers also had a very low number of emptyings in 2009, respectively 4 and 18 times.

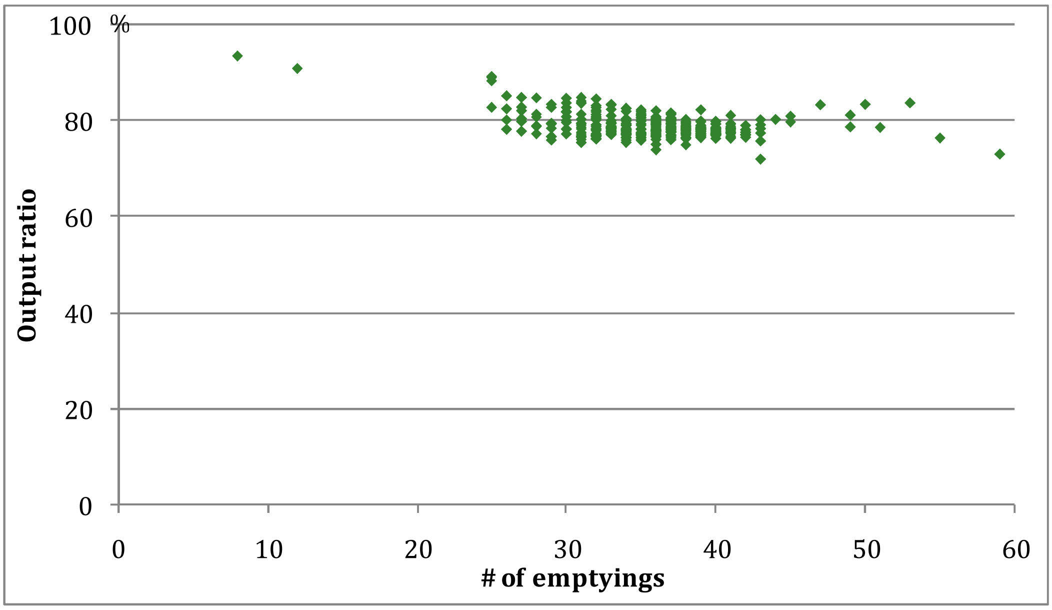


Figure 26 Box plot of the output ratio versus the number of emptyings, using the advanced heuristic, balancing and the addition of may-go jobs.

8.7 1500 Containers

Finally, we performed a number of simulations using 1500 containers. Table 18 shows the results we got from these simulations. Again, the rescheduling option reschedules all trucks at 11.30 o'clock. We did not perform all possible scenarios with 1500 containers, due to the large computation time.

1500 containers	Scenario		Costs	Service Level	Fill Level
	Basic	Balancing	15.547.393	0,9528	0,8300
		Balancing + May-go	15.400.762	0,9638	0,8660
		Balancing + May-go + Rescheduling	15.780.716	0,9650	0,8680
	Advanced	Balancing	15.889.105	0,9483	0,8283
		Balancing + May-go	15.746.433	0,9580	0,8603
		Balancing + May-go + Rescheduling	14.991.032	0,9660	1,0445

Table 18 Results for simulations with 1500 containers

These results show the combination of multiple options leads to significant better results, the costs are lower, while the service level and the fill level are higher. Only for the basic heuristic, the combination of all three options does not lead to better results. For the basic heuristic, the combination of balancing and may-go jobs leads to the best results. Another remarkable point is the fill level of 1,04, this again shows that the rescheduling option does not work entirely as supposed. A fill level higher than one might occur when the real refuse volumes of containers are higher than expected.

8.8 Conclusion

In this chapter, we evaluated all options of the heuristic we described in Chapter 6. We evaluated all options separately, but we also evaluated a number of combinations. We tested our configurations with the basic and the advanced heuristic, and with three different amounts of containers. One observation we can make, is that the total costs are not linear, Figure 27 shows this. When the number of containers increases, the total costs also increase, but with a smaller factor. This is logical, because the additional containers are located in the same area, which results in relatively lower travelling costs. Also, because the number of containers is higher, the schedules will become more efficient. This is a result of a larger choice in containers to add to a route.

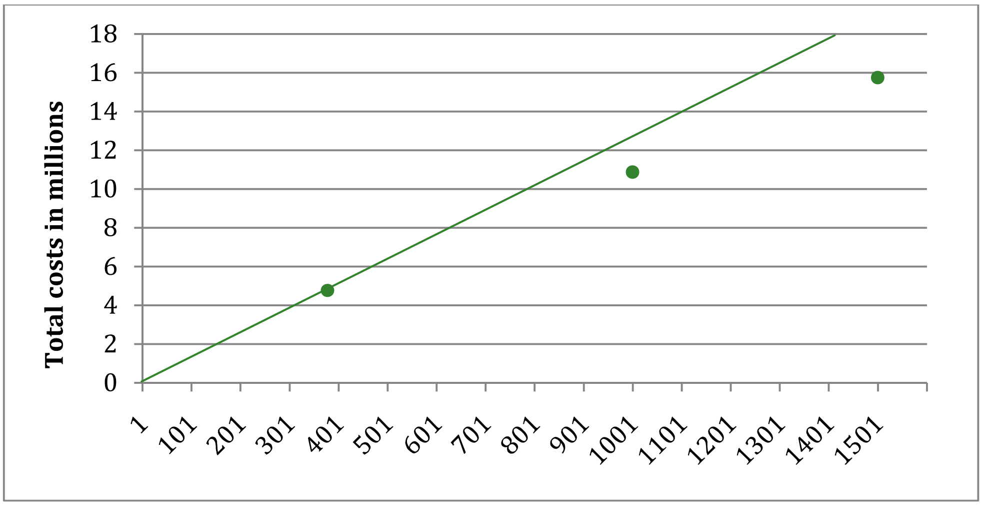


Figure 27 Total costs for the advanced heuristic with balancing

Looking at the number of trucks to use, this also does not increase linearly. The option using balancing and may-go jobs uses with 378 containers 2 trucks, while with 1000 containers 5 trucks are used, and with 1500 7 trucks are used. This supports our statement that the schedules become more efficient with the number of containers.

When we look at the differences between the basic and the advanced heuristic, we cannot state that the advanced heuristic performs better than the basic heuristic. Figure 28 and Figure 29 give the overall results for the use of balancing for both the basic and the advanced heuristic. The two figures both show that the service level does not depend on the number of containers. The fill level is slightly negative influenced by the number of containers, but the difference is only small. For all numbers of containers, the fill level lies around 0,9. The assumption we made earlier, about the advanced heuristic would lead to better results, is not supported by our simulation results. This might be a result of the relatively short distances between the containers. When the distances are small, a more advanced scheduling and routing methodology might not lead to large improvements compared to a more simple way of planning.

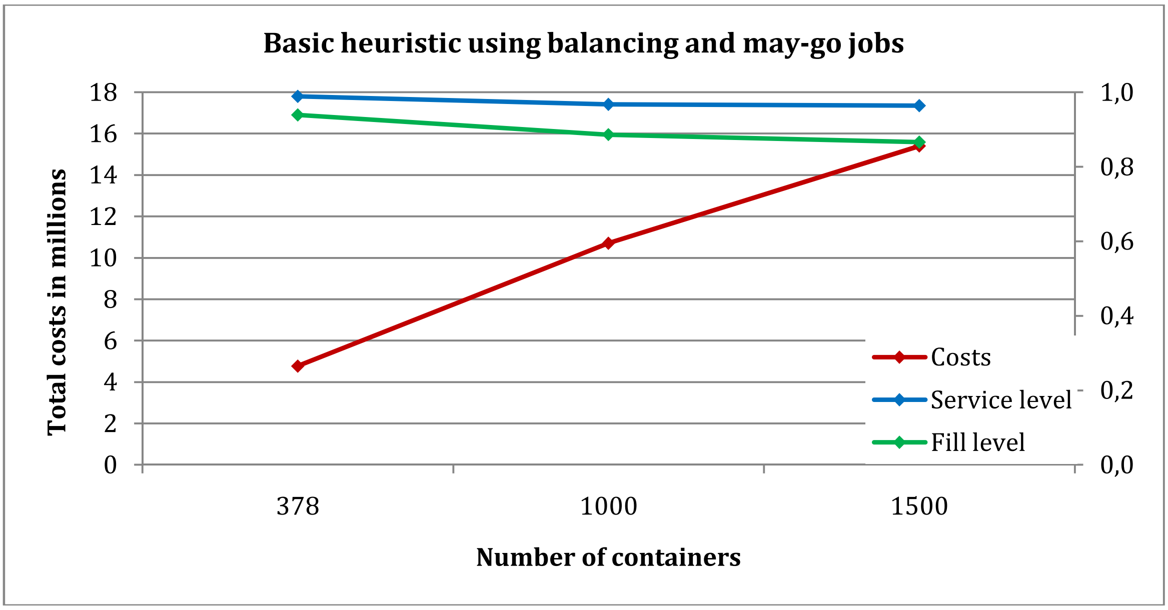


Figure 28 Overall results for basic simulations

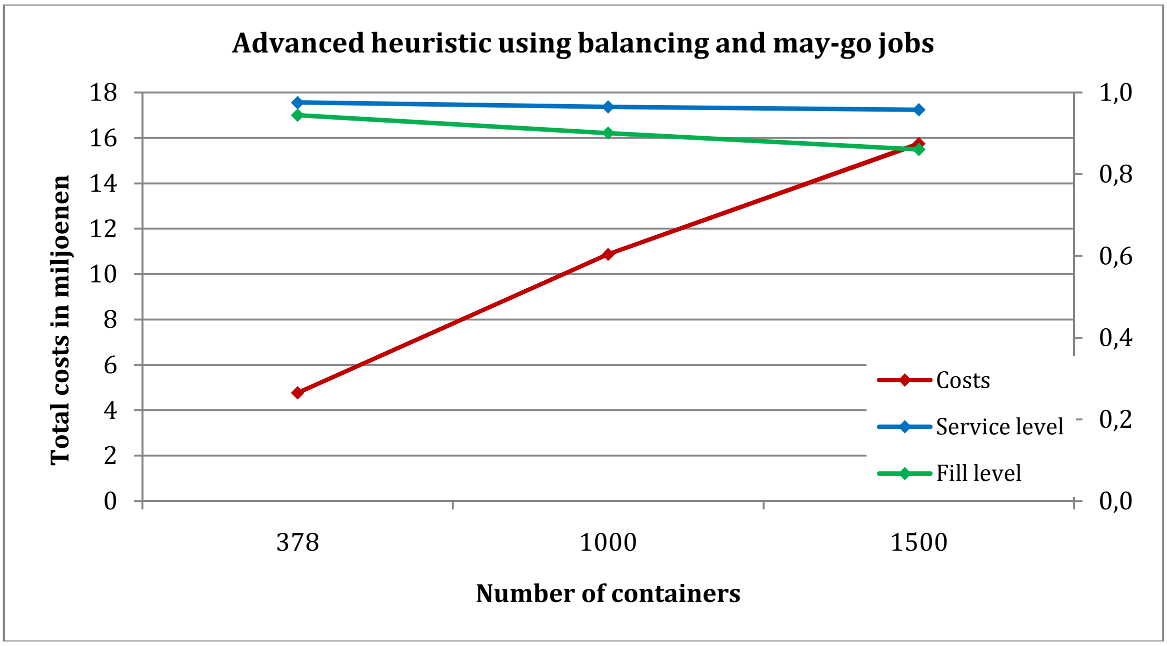


Figure 29 Overall results for advanced simulations

Based on our findings, we think the best configuration to empty the underground containers of Twente Milieu is to use balancing and may-go jobs. We do suggest to use the advanced heuristic. Although our simulations did not lead to a clear difference between the basic and the advanced option, we do think the advanced heuristic offers more flexibility in planning the emptying of the containers. When we look at the output ratio of this combination, we see the average output ratio lies around 78 percent. This is much higher than the current output ratio of 50 to 60 percent, but somewhat lower than when we use no balancing or may-go jobs. In that case, the average output ratio lies around 85 percent, but the service level is much lower.

We finish this chapter with the conclusion that our simulation model also gave some remarkable results. For one, the rescheduling option had no effect on the results. We assumed rescheduling during the day would increase the outcomes, but the simulation results did not support this hypothesis. A reason that there was no effect might be our choice to use deterministic travel times. This choice leads to less variation than when we would have decided to use stochastic travel times and might be a reason that the rescheduling option does not have the desired effect. Another reason that the rescheduling option had no visible effect might be that the emptying process is less dynamic as expected. When the number of deposits and the deposit sizes do not fluctuate much, there will not be much deviation from the initial plan and therefore, the rescheduling will not lead to better results. Also, when we used our rescheduling in combination with balancing and may-go jobs for 1000 and 1500 containers, the fill levels raised above 100 percent. This is another reason to improve the rescheduling option. Another remarkable point is we found no clear difference between the basic and the advanced heuristic. We still assume the advanced heuristic is more flexible, but we cannot support this with our simulation results. Finally, varying the standard deviation and the mean of the deposit sizes had only little effect. Only when we varied the mean deposit size with a large factor, results were visible. It might be that our model is hardly affected by variance, but this is worth further investigation. Therefore, we recommend additional research on these areas.

9 Conclusions and recommendations

In this chapter, we will draw conclusions and give recommendations based on the results of our research. Section 9.1 gives an answer to our problem statement and outlines the results and remarkable points we encountered during our research. Section 9.2 provides recommendations to Twente Milieu how to increase the results of using a dynamic planning and also gives a number of recommendations for further research.

9.1 Conclusions

In this report, we analyzed the options to use a dynamic planning methodology to reduce to CO_2 emission at Twente Milieu. To do so, we used the following research question:

In what way could a dynamic planning methodology for emptying the underground refuse containers be used to lead to both company-economic benefits as well as to a reduction of CO_2 emission?

We started our research with evaluating the current situation at Twente Milieu. This was necessary to get insight in the type of organization and to gain understanding on which other planning methodologies would fit Twente Milieu. We also did a data analysis, to evaluate the quality and usefulness of the data Twente Milieu collects in its databases. Evaluating the current way of working led us to the following conclusions:

- Currently, routes are driven intuitively by the truck drivers
- There are no fixed routes, which gives problems when another driver has to take over the route
- The current way of charging for each emptying does not stimulate less frequent emptying of the containers
- The use of digital containers leads to a better insight in the amount of refuse deposited and therefore also facilitates a better emptying schedule
- The underground containers are, on average, only 50 to 60 percent full at emptying
- The average deposit size is 41 liter
- The introduction of 'Diftar' will probably lead to larger and lesser variance in deposit size
- The alignment of containers at apartment buildings is of influence on the refuse volumes in them

Based on the analysis of the current situation, combined with a literature study, we distinguished four different planning methodologies to evaluating for use at Twente Milieu.

- Current way planning methodology
- Daily planning
- Daily planning with periodic rescheduling
- Continuous rescheduling

These options vary between almost static and very dynamic, and they all have their own advantages and disadvantages. Based on our research, we expected the third option to be the best choice for Twente Milieu. To validate our choice, we used a simulation model to test and compare the second and third planning option.

We developed a heuristic, which we used in our simulation model. Figure 30 shows the basic elements of this heuristic. In our simulation model, we evaluated whether the use of the elements 'Balancing' and 'Add may-go jobs' lead to better results. These two components are optional. Also, we investigated whether there is a difference between the basic and the advanced planning heuristic.

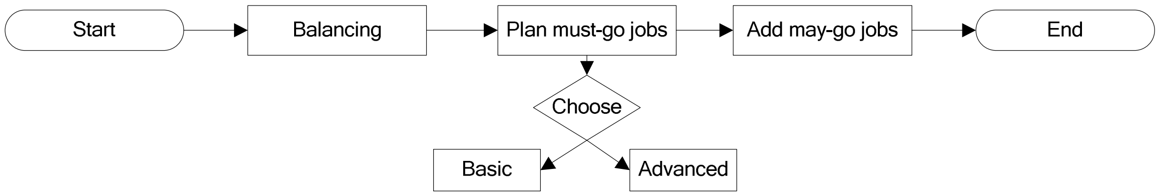


Figure 30 Basic elements of planning heuristic

In our simulation model, we also evaluated the effect of rescheduling during the day and the ability of our heuristic to deal with a larger number of containers and with more uncertainty in the deposit sizes. .

Based on the results of our simulation model, we suggest a planning methodology which uses both balancing and the addition of may-go jobs, combined with the advanced heuristic. The advanced heuristic fills all necessary trucks with jobs simultaneously, which offers more flexibility than the basic heuristic that fills only one truck at a time with jobs. Next to this conclusion, the simulations also offered a number of other insights:

- While increasing the number of containers, the costs and the number of trucks to use do not increase linear with the number of containers. When the number of containers grows, the schedules will become more efficient as a result of a larger choice of containers to add to a route. Also, the travelling costs will be relatively lower, because the additional containers are located in the same area.
- The service level and the fill level are not influenced by a larger number of containers.
- Using balancing influences the service level positively, while it has no major influence on the fill level.
- The option to use may-go jobs has a large positive influence on the fill level.
- Adding more uncertainty to the deposit sizes only has a minor impact on the simulation outcomes, we varied the standard deviation and also used uncertainty on the mean of the deposit sizes. This might be explained by the portfolio effect.
- We assume more uncertainty in the deposit sizes will have more influence when we use stochastic travel times instead of deterministic travel times.
- We did not find a significant difference between the basic and the advanced heuristic. However, we do think the advanced heuristic will be more flexible and better able to deal with, for example, stochastic travel times.
- Rescheduling during the day does not improve the results. This might be an indication that the emptying process at Twente Milieu is less dynamic as expected. When the actual amount of refuse in the containers does not deviate much from the expected amount of refuse, rescheduling will not increase the schedules. Another reason might be the deterministic travel times we used. When we would use stochastic travel times, there will be more uncertainty, which might increase the effect of rescheduling.

9.2 Remarks and recommendations

In our research, we analyzed in what way a dynamic planning methodology can contribute to the reduction of CO_2 emission at Twente Milieu. As stated, we think the combination of using balancing and the addition of may-go jobs will lead to the best results. However, there are some remarks and recommendations we would like to make based on our research.

We recommend Twente Milieu to actively work on improving the quality of the data on underground containers. Using a dynamic planning methodology requires reliable and accurate data and we recommend to validate and improve the quality. For example, it would be useful to have accurate information on the difference in deposit sizes between the different containers. This influences the number of deposits a container can handle before it is full. When this data is precise, this will increase the usefulness of the dynamic planning methodology. In our simulation, we did not have accurate data on all containers. When precise information about all containers is used as simulation input, the results will also be more accurate. Of course, the quality of the data will increase in the future, because the number of digital containers increases and Twente Milieu will start using weighing tools on its trucks in 2011.

Another remark we need to make, is the influence of Diftar on the refuse volumes in the underground containers. Diftar will be implemented in 2012 and means that every households has to pay for the number of deposits they make. We assume this will lead to larger deposits with less variance in deposit sizes. It might be worth full to investigate the influence of larger deposit sizes on the planning methodology more extensively.

In our research, we did not include the containers in Almelo. We decided to exclude these containers, because there is no information available on the refuse volumes. Also, the underground containers in Almelo are emptied from the depot in Almelo, which made it easy to exclude only Almelo. This did not conflict with the emptying of the other containers. However, when Almelo is included, it might be possible to create better schedules. Some of the containers in far away locations such as Markelo or Goor could then be emptied either from Hengelo or from Almelo. This increases the flexibility and possible reduces detours in routes. When the underground containers in Almelo are changed to digital containers, or if there is information on the deposit sizes and refuse volumes in the containers, it might be interesting to see the effect of including Almelo in our simulation model.

In our research, we looked at each container individually. However, at many locations there are multiple underground containers placed. It is arguable to look at all containers at the same location together. Only when all containers of the group are almost full, the group is eligible for emptying. Working with groups of containers might further reduce the amount of kilometers driven to empty the containers. On the other hand, it might irritate users if they have to try a number of containers before they find one that is available for refuse disposal.

Finally, a limitation of our model is that we used deterministic travelling times. Of course, in reality, the time to travel from one container to another is stochastic. We recommend extending our model with the implementation of stochastic handling times. This makes our model more realistic, and it probably will increase the use of rescheduling.

Based on our conclusions and the remarks we made in this section, we make the following suggestions for further research:

- Include the containers located in Almelo in the schedules. It will be interesting to see the influence of these additional containers and an additional depot. Adding the containers in Markelo and Goor to the cluster of containers in Almelo. It would be interesting to see whether this combination leads to better results than the current cluster.
- Use stochastic travel times to evaluate the influence of more uncertainty on the simulation results.
- During 2010, many underground containers are replaced by new digital containers. This offers the possibility to increase the quality of the data. When the data on the containers is better, it would be possible to determine the average number of deposits for each container individually. This will increase the results of our simulation model.
- We also recommend to evaluate whether looking at container locations instead of individual container changes the results of our research. We assume it will lead to more flexibility and probably a reduction in the kilometers driven by the refuse trucks.
- In our simulation model, the rescheduling option did not achieve the results we hoped for. This might a result of the situation at Twente Milieu being less dynamic than

supposed, but it would be good to evaluate whether there are other options to use rescheduling.

- When the travel times are stochastic, and there is more accurate information about all containers, we assume varying the deposit sizes will have more effect. Studying the influence of uncertainty on our new planning model might lead to new insights for the rescheduling option.

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Appendix

Appendix A – List of definitions

- *Underground container* A container used by multiple households for the disposal of household refuse. The container is dug into the ground in such a way that only the lid is visible.

- *Static planning* We consider a planning to be static if it is based on average historic data on refuse volumes rather than on the expected actual amounts of refuse in a container. Because the historic averages remains the same for every day or week, the planning also does not change between days or weeks.

- *Dynamic planning* We consider a planning to be dynamic if it is not static. This means a dynamic planning is based on the expected actual amount of refuse in a container. Because the expected amount of refuse varies between days and weeks, a dynamic planning might be different for each day or week.

- *Output ratio* The output ratio gives the expected amount of refuse in the underground containers, expressed in a percentage. In this report, we distinguish two different ways to calculate the output ratios.

  Registered output ratio This output ratio is based on the databases of Twente Milieu and corresponds to the number of times the container lid was opened. This number thus gives the amount of deposits made to the container. This is the estimation Twente Milieu uses for the refuse volume in their underground containers

  Calculated output ratio This output ratio is calculated based on combination of information from the Twente Milieu databases and the registered amount of waste dumped at Twence, together with the assumption that one cubic meter of refuse weighs 110 kilos.

- *Route* The route of a truck is its schedule for a day. A route may contain several trips to Twence and therefore it may consist of a number of sub-routes. The total route consists of all sub-routes and the route from Twence to the depot.

- *Sub-route* A sub-route is the trip a truck makes along a number of containers and which ends at Twence.

- *Days left* The *days left* is calculated for each container and indicates after how many days a container is expected to be full. The *days left* might be different for each container, because it is based on the average number of deposits per day and the average deposit sizes for that specific container.

- *Must-go-day* The *must-go-day* is a non-fixed level that indicates which containers should at least be emptied on a certain day. If the *must-go-day* is for example 2, this means that all containers that have a *days left* of 2 or less, should be emptied on this day. The *must-go-day* might be adjusted, for example to balance workload over the week.

- *Must-go job* The *must-go job* is a container which has a *days left* equal or less than the *must-go-day.* All *must-go jobs* have to be served on a certain day. The number of *must-go jobs* deviates from one day to another.

- *May-go job* The *may-go job* is a container that is included in a route after all *must-go jobs* are planned. *May-go jobs* are used to increase the occupancy rate and are selected based on their ratio of additional travel time and additional amount of refuse. We only consider containers with a *days left* that is maximum one day more than the *must-go-day* as possible *may-go jobs.*

Appendix B – Calculations data analysis

The average weight of refuse per container is calculated by combining the data on the emptying with the total weight dumped at Twence. We did this by dividing the total volume (in kilograms) dumped at Twence on a certain day by the number of containers that was emptied on that same day. This results in the average amount of refuse per container.

Next, we calculated for each container individually the volume in kilograms and in cubic meters. We did this based on the number of deposits for an individual container. This number is used to calculate the fraction of the total volume that should come from the individual container. Together with the assumption that 1 cubic meter of refuse weighs 110 kilograms and the fact that the container size is 5m^3, the actual output ratios can be calculated.

The registered output ratios are taken from the databases of Twente Milieu and represent the number of times users dispose their refuse to the container. The databases register these numbers per container, so with this information we were able to determine the average registered output ratios.

The standard deviations, which are also given in the tables in Chapter 6, are calculated with the formula presented in Excel. These outcomes give an indication of the diffusion of the calculations. When the standard deviation is high, the diffusion of the different numbers is also high. For example, the two sequences 1,2,3,4,5,6,7,8,9 and 4,5,6,4,5,6,4,5,6 both have an average of 5, but the standard deviation of the first sequence is much higher than the second sequence.

Appendix C – Output ratios containers Enschede

Street	No. of emptyings	Average output ratio (registered)	Standard deviation	Average output ratio (calculated)	Standard deviation	Weight (calculated)	Weight (Actual)	Deposit size (liter)
Amundsenstraat	45	52,49	14,67	40,56	12,43	223,10	280	38,64
Amundsenstraat	50	55,62	16,53	43,54	13,45	241,00	300	39,39
Begoniastraat	52	110,15	14,12	84,29	20,19	463,60	450	38,26
Beltstraat 78	54	42,46	16,50	34,12	11,54	187,68	170	40,18
Beltstraat 78	54	44,02	17,04	37,63	14,67	206,96	220	42,74
Beukinkstraat 160	52	47,96	12,42	36,99	9,98	203,40	320	38,55
Borneostraat	50	46,82	54,00	33,35	34,54	183,40	80	35,61
Borneostraat	50	115,04	41,59	93,11	39,26	512,10	370	40,47
Bosuilstraat	52	74,04	16,63	56,13	15,42	308,70	193	37,90
Bosuilstraat	51	76,63	13,43	60,65	16,67	333,50	348	39,57
Boulevard 1945 105	51	22,02	15,09	16,16	11,46	91,60	170	37,82
Boulevard 1945 105	51	77,73	29,80	62,01	24,97	341,00	220	39,88
Boulevard 1945 500	51	21,90	14,56	17,08	12,56	93,30	85	38,73
Boulevard 1945 500	51	55,37	19,09	41,94	17,17	230,70	95	37,88
Boulevard 1945 500	51	73,29	22,59	54,98	17,11	302,40	195	37,51
Boulevard 1945 500	52	87,90	27,46	65,76	18,33	361,70	405	37,41
Brammelerstraat 14	130	58,80	26,33	71,16	86,23	395,10	375	61,09
Brammelerstraat 14	135	75,90	22,36	82,33	52,69	457,00	525	54,73
Brinkstraat 268	51	69,41	21,73	51,45	15,01	282,90	300	37,05
Buitenweg	51	66,47	12,82	51,45	11,67	282,60	240	38,65
Bultsbosweg 2	49	27,45	14,73	20,99	10,87	115,40	60	38,22
Bultsbosweg 2	48	88,58	20,84	68,72	17,58	378,00	320	38,79
Celebestraat	3	83,00	45,92	55,23	43,71	303,80	155	33,27
Celebestraat	3	142,67	73,11	58,48	54,49	321,60	365	20,49
Celebestraat	2	122,00	48,08	87,17	62,30	479,40	455	35,72
De Heurne 2	100	36,60	17,37	35,39	19,07	194,70	180	48,36
De Heurne 25	99	42,06	19,59	41,51	24,12	228,30	380	49,34
De Heurne 79	51	50,22	19,36	39,10	16,45	215,10	130	38,94
De Heurne 79	47	67,19	23,86	108,90	17,26	274,30	140	37,11
Dotterbloemstraat 10	52	29,04	11,23	22,41	9,79	123,25	100	38,59
Dr A.H.J. Coppesstraat	37	56,81	26,42	96,55	24,66	243,20	115	38,92
Dr Benthemstraat	27	31,63	20,45	22,54	15,29	124,00	208	35,64
Dr Benthemstraat	27	108,74	42,56	80,20	28,98	441,00	268	36,87
Dr Benthemstraat	25	111,80	36,71	81,98	34,78	450,90	398	36,66
Esmarkelaan 14	48	39,77	16,75	31,15	14,75	171,33	295	39,16
Esmarkelaan 9	48	66,35	18,22	52,80	19,46	290,40	295	39,79
Fridtjof Nansenstraat	49	59,94	21,74	36,84	13,25	202,60	240	30,73
Fridtjof Nansenstraat	49	65,35	22,00	46,64	17,81	256,50	320	35,68
Fridtjof Nansenstraat	48	46,48	16,25	50,45	19,68	277,50	310	54,28
Getfertweg	48	63,92	14,24	50,20	13,79	276,10	210	39,27
Getfertweg	48	94,79	19,63	73,83	18,41	406,00	250	38,94
Gronausevoetpad	1	36,00		26,44		145,40	85	36,72
Haverstraatpassage 90	103	55,56	27,99	56,37	34,74	310,03	360	50,73
Haverstraatpassage 90	88	71,27	29,99	72,12	38,03	396,68	410	50,60
Hengelosestraat 104	47	64,60	18,89	44,38	22,15	341,04	300	48,00
Hofstraat 3	100	35,82	17,55	34,53	20,61	189,91	105	48,20
Hofstraat 3	103	39,27	17,81	38,83	20,76	213,54	175	49,43
Hofstraat 3	63	40,03	15,20	39,16	19,31	215,35	215	48,90

Hofstraat 39	8	24,13	6,49	21,22	6,94	116,72	105	43,97
Hofstraat 39	8	24,13	6,49	21,22	6,94	116,72	175	43,97
Hulsbeekgaarde	28	74,64	33,63	60,94	29,23	102,31	170	12,46
Hulsbeekgaarde	30	67,63	26,73	60,94	29,23	335,20	200	45,06
Hulsbeekgaarde	30	79,17	27,71	61,17	22,46	336,50	220	38,64
Hulsbeekgaarde	25	84,80	30,80	67,89	26,36	373,40	210	40,03
Hulsbeekgaarde	29	98,00	30,55	77,84	26,92	428,10	250	39,71
J.J. van Deinselaan	49	58,59	15,21	45,72	13,13	251,40	180	39,01
J.J. van Deinselaan	51	76,84	12,64	59,74	14,22	328,50	220	38,86
Jan van Elburgstraat	50	98,64	20,15	78,14	21,25	429,80	390	39,61
Jan Vermeerstraat	25	65,80	20,35	52,67	18,88	289,70	365	40,02
Korte haaksbergerstraat 36	56	81,91	26,88	64,55	23,61	355,01	300	39,40
Korte haaksbergerstraat 36	54	98,19	27,34	78,89	28,17	433,90	365	40,17
Korte Haaksbergerstraat 43	105	51,12	21,46	50,29	27,21	276,60	180	49,19
Korte Haaksbergerstraat 43	105	65,60	23,40	65,43	33,62	359,90	230	49,88
Korte Hengelosestraat 15	79	64,42	29,21	57,34	25,31	319,58	230	45,10
Kroedhofteplein 16	52	73,90	14,34	56,78	17,16	312,27	330	38,41
Kuipersdijk 55	3	116,67	89,07	81,08	67,67	445,92	365	34,75
Kuipersdijk 55	2	131,00	35,36	92,31	6,64	507,68	410	35,23
Lippekerkstraat 172	27	34,26	7,31	25,89	6,44	142,42	85	37,79
Marthalaan 8	52	67,50	14,72	52,25	13,86	287,26	160	38,69
Mooienhof 177	50	18,76	9,20	14,61	7,59	80,36	200	38,94
Mooienhof 177	50	73,86	35,16	56,80	26,04	312,41	240	38,45
Mooienhof 177	50	81,02	29,42	61,29	20,65	337,07	350	37,82
Mooienhof 2	52	45,46	23,96	36,21	20,63	199,13	115	39,82
Mooienhof 2	52	62,65	24,81	48,85	20,52	268,69	340	38,99
Nassaustraat	47	40,11	11,28	31,93	9,74	175,63	170	39,81
Nassaustraat	48	51,94	12,69	40,63	11,34	223,46	190	39,11
Noorderhagen 36	111	64,68	30,26	64,03	37,83	355,71	275	49,99
Noorderhagen 36	109	64,17	29,67	66,38	38,16	368,83	300	52,25
Noorderhagen 58	107	77,18	27,70	76,33	33,22	419,82	350	49,45
Oldenzaalsestraat 2	95	65,31	33,65	66,41	41,31	365,30	180	50,85
Oldenzaalsestraat 2	100	69,58	31,65	70,56	40,32	388,10	390	50,71
Oldenzaalsestraat 44	50	129,14	29,25	98,85	26,90	543,86	390	38,29
Oldenzaalsestraat 81	50	51,30	15,92	39,14	12,68	215,26	375	38,15
Oliemolensingel 26	24	82,75	11,24	60,31	11,93	331,71	250	36,44
Oude Markt 31	101	68,58	24,14	68,22	32,69	375,23	525	49,74
Parallelweg	48	24,46	17,74	19,14	14,96	105,25	70	39,12
Parallelweg	50	60,86	22,66	47,51	20,14	261,30	80	39,03
Parallelweg	47	97,87	35,68	76,48	27,11	420,65	100	39,07
Parallelweg	50	107,84	35,94	82,45	31,04	453,49	410	38,23
Parallelweg	46	172,70	35,63	133,93	28,80	736,63	500	38,78
Robert Scottstraat	48	52,71	17,51	41,65	14,27	229,05	60	39,51
Robert Scottstraat	47	82,28	28,49	64,95	19,10	357,20	180	39,47
Roerstraat	52	99,27	16,27	76,05	18,52	418,25	390	38,30
Roomweg	52	67,77	24,65	52,19	23,21	287,03	163	38,50
Roomweg	52	67,77	24,65	52,19	23,21	287,03	237	38,50
S.L. Louwesstraat 181	50	65,34	17,13	50,63	14,35	278,46	180	38,74
S.L. Louwesstraat 2	50	90,38	28,76	69,37	21,41	381,50	310	38,37

Schiestraat	52	57,83	13,72	44,70	16,52	245,83	263	38,65
Schurinksweg	50	49,20	22,84	38,08	19,68	209,44	160	38,70
Schurinksweg	49	105,00	19,42	78,58	19,48	432,18	430	37,42
Shackletonstraat	46	51,35	15,30	39,23	10,98	215,77	280	38,20
Shackletonstraat	49	61,61	19,98	48,89	15,27	268,89	295	39,67
Stationsplein	52	64,85	12,85	49,08	11,77	269,94	205	37,84
Sterkerstraat 2	51	66,41	13,40	51,54	12,29	284,55	300	38,95
Themislaan	50	27,74	11,29	21,61	9,73	118,87	50	38,96
Themislaan	50	82,78	18,38	65,45	18,45	359,97	330	39,53
Tulpstraat	51	101,29	19,99	75,95	16,59	417,72	298	37,49
Van Heekplein 52	102	65,72	18,17	63,35	27,32	348,40	210	48,19
Van Lochemstraat 1	51	38,45	16,92	29,30	13,56	161,15	195	38,10
Van Lochemstraat 1	52	51,02	15,24	39,83	12,82	219,06	240	39,03
Van Lochemstraat 110	52	23,23	22,93	16,73	18,34	102,81	50	40,23
Van Lochemstraat 110	52	79,65	20,32	62,77	18,82	350,84	300	40,04
Van Loenshof 56	53	89,53	24,59	68,58	20,22	377,17	378	38,30
Walstraat 35	95	30,17	17,52	29,00	17,30	159,51	125	48,07
Walstraat 35	94	40,18	28,83	41,05	36,55	225,80	200	51,09
Walstraat 35	93	50,10	28,83	51,15	35,53	281,04	200	51,00
Wethouder Beverstraat 60	47	55,57	19,24	65,16	18,87	358,35	405	58,62
Wethouder Gerbertstraat	26	23,62	10,57	29,79	18,46	163,82	200	63,06
Wethouder Gerbertstraat	25	36,32	12,66	41,90	13,62	230,45	200	57,68
Wilhelminastraat 125	48	83,23	32,88	64,39	29,59	354,13	260	38,68
Windbrugstraat	101	38,20	15,36	43,51	60,23	239,00	240	56,88
Windbrugstraat	101	38,63	20,24	45,32	52,84	249,20	285	58,64
Zonstraat 1	28	54,00	13,15	39,31	11,79	216,20	175	36,40
Zuiderhagen 16	46	111,87	39,21	85,10	31,69	468,10	560	38,04

Table 19 Data underground containers in Enschede (March 2010)

Appendix D – Data underground containers Twente Milieu

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
1	Adriaen van Ostadestraat	Enschede	52,2084444	6,8599223	41,30	7,00	12	20,49
2	Ahuislanden	Enschede	52,1892633	6,8958269	41,30	7,00	12	105,07
3	Ahuislanden	Enschede	52,1892633	6,8958269	41,30	7,00	12	62,99
4	Ahuislanden	Enschede	52,1892633	6,8958269	41,30	7,00	12	11,04
5	Aletta Jacobsstraat 168	Almelo	52,3561078	6,6603609	41,30	7,00		
6	Aletta Jacobsstraat 168	Almelo	52,3561078	6,6603609	41,30	7,00		
7	Aletta Jacobsstraat 29	Almelo	52,3560894	6,6609091	41,30	7,00		
8	Algonquin	Hengelo	52,268577	6,7864633	41,30	7,00		57,00
9	Algonquin	Hengelo	52,268577	6,7864633	41,30	7,00		57,00
10	Amundsenstraat	Enschede	52,2118247	6,9665707	39,39	6,78	45	52,49
11	Amundsenstraat	Enschede	52,2118247	6,9665707	38,64	7,28	50	55,62
12	Anemoonstraat	Almelo	52,3430729	6,6666986	41,30	7,00		
13	Apollolaan	Almelo	52,3583275	6,6414928	41,30	7,00		
14	Archimedesstraat 9	Hengelo	52,2569001	6,8029499	41,30	7,00		57,00
15	Assinklanden	Enschede	52,1902252	6,9007787	41,30	7,00	12	58,54
16	Assinklanden	Enschede	52,1902252	6,9007787	41,30	7,00	12	46,30
17	Assinklanden	Enschede	52,1902252	6,9007787	41,30	7,00		57,00
18	Avenue 14	Almelo	52,3314249	6,6571047	41,30	7,00		
19	Avenue 14	Almelo	52,3314249	6,6571047	41,30	7,00		
20	B P Hofstedestraat	Hengelo	52,263859	6,7948982	41,30	7,00	27	36,29
21	B P Hofstedestraat	Hengelo	52,263859	6,7948982	41,30	7,00	27	36,29
22	Bartokstraat 9	Almelo	52,3620529	6,6342618	41,30	7,00		
23	Beekstraat	Hengelo	52,2644283	6,7911448	41,30	7,00	24	47,00
24	Beekstraat	Hengelo	52,2644283	6,7911448	41,30	7,00	24	47,00
25	Beekstraat	Hengelo	52,2644283	6,7911448	41,30	7,00	24	47,00
26	Beethovenlaan	Almelo	52,3576883	6,6379994	41,30	7,00		
27	Begoniastraat	Enschede	52,224906	6,9045608	38,26	5,41	52	110,15
28	Begoniastraat 8	Hengelo	52,2634858	6,780398	41,30	7,00		57,00
29	Bela Bartokstraat	Hengelo	52,2684801	6,8139599	41,30	7,00		57,00
30	Bela Bartokstraat	Hengelo	52,2684801	6,8139599	41,30	7,00		57,00
31	Belgradostraat 49	Hengelo	52,2910298	6,8137543	41,30	7,00	12	46,30
32	Beltstraat 50	Enschede	52,2173163	6,8938503	31,00	7,00		57,00
33	Beltstraat 78	Enschede	52,2161294	6,8943415	42,74	5,09	54	44,02
34	Beltstraat 78	Enschede	52,2161294	6,8943415	40,18	4,96	54	42,46
35	Bentelobrink	Enschede	52,1925143	6,8732558	41,30	7,00	12	69,86
36	Betuining	Almelo	52,3345041	6,6599895	41,30	7,00		
37	Betuining	Almelo	52,3345041	6,6599895	41,30	7,00		
38	Beukenstraat	Goor	52,2343923	6,6023284	41,30	7,00	24	20,21
39	Beukinkstraat 1	Enschede	52,2200095	6,9028349	41,30	7,00	10	53,00
40	Beukinkstraat 160	Enschede	52,2176049	6,9025809	38,55	4,89	52	47,96
41	Beukweg 22	Hengelo	52,2701881	6,7919903	41,30	7,00		57,00
42	Bloemenstraat 1	Oldenzaal	52,3135939	6,9225073	41,30	7,00	24	62,01
43	Bloemenwaaier	Almelo	52,334135	6,6576932	41,30	7,00		
44	Boddenstraat 2	Almelo	52,3588672	6,6603554	41,30	7,00		
45	Boekelose Stoomblekerij	Enschede	52,2056525	6,8036162	41,30	7,00		57,00
46	Bokhorstlanden	Enschede	52,1922672	6,9018355	41,30	7,00	2	82,92
47	Bontweverij	Enschede	52,2184226	6,9037405	41,30	7,00		57,00
48	Border	Almelo	52,3332697	6,6590669	41,30	7,00		
49	Borneostraat	Enschede	52,2150406	6,8932158	40,47	5,09	50	46,82
50	Borneostraat	Enschede	52,2150406	6,8932158	35,61	5,09	50	115,04
51	Bornsestraat 7	Hengelo	52,2672054	6,7916781	41,30	7,00		57,00
52	Bornsestraat 7	Hengelo	52,2672054	6,7916781	41,30	7,00		57,00

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
53	Bosuilstraat	Enschede	52,2328755	6,8977414	39,57	4,37	51	76,63
54	Bosuilstraat	Enschede	52,2328755	6,8977414	37,90	6,71	52	74,04
55	Boulevard 1945 105	Enschede	52,2175786	6,8962076	39,88	5,00	51	77,73
56	Boulevard 1945 105	Enschede	52,2175786	6,8962076	37,82	5,00	51	22,02
57	Boulevard 1945 500	Enschede	52,2164421	6,9082028	37,41	4,06	51	73,29
58	Boulevard 1945 500	Enschede	52,2164421	6,9082028	37,51	4,06	51	21,90
59	Boulevard 1945 500	Enschede	52,2164421	6,9082028	37,88	4,06	51	55,37
60	Boulevard 1945 500	Enschede	52,2164421	6,9082028	38,73	4,02	52	87,90
61	Brahmsstraat	Hengelo	52,267958	6,8125602	41,30	7,00		57,00
62	Brahmsstraat	Hengelo	52,267958	6,8125602	41,30	7,00		57,00
63	Brammelerstraat 14	Enschede	52,2210424	6,8929413	54,73	9,85	135	75,90
64	Brammelerstraat 14	Enschede	52,2210424	6,8929413	61,09	9,96	130	58,80
65	Brasemstraat	Hengelo	52,2944988	6,8163718	41,30	7,00	13	74,56
66	Breemarsweg 368	Hengelo	52,2538496	6,7754374	41,30	7,00	4	24,79
67	Breemarsweg 572	Hengelo	52,2570371	6,7628146	41,30	7,00	4	21,87
68	Brinkstraat 268	Enschede	52,2114434	6,9061284	37,05	3,98	51	69,41
69	Bronforelstraat 28	Hengelo	52,2921397	6,8207282	41,30	7,00		57,00
70	Bronforelstraat 29	Hengelo	52,2935844	6,8152797	41,30	7,00		57,00
71	Brugstraat 105	Almelo	52,3616224	6,6606315	41,30	7,00		
72	Brugstraat 105	Almelo	52,3616224	6,6606315	41,30	7,00		
73	Buitenweg	Enschede	52,2145743	6,8755189	38,65	4,96	51	66,47
74	Bultsbosweg 2	Enschede	52,2194551	6,9733567	38,79	7,35	49	27,45
75	Bultsbosweg 2	Enschede	52,2194551	6,9733567	38,22	7,43	48	88,58
76	Burgemeester Jansenplein 1	Hengelo	52,2658074	6,7915511	41,30	7,00		57,00
77	Burgemeester Jansenplein 1	Hengelo	52,2658074	6,7915511	41,30	7,00		57,00
78	Canadian Grenadier	Hengelo	52,2685456	6,7875599	41,30	7,00		57,00
79	Canadian Grenadier	Hengelo	52,2685456	6,7875599	41,30	7,00		57,00
80	Castorweg	Hengelo	52,2750672	6,8072619	41,30	7,00		57,00
81	Celebesstraat	Enschede	52,2143723	6,894408	20,49	9,57	3	142,67
82	Celebesstraat	Enschede	52,2143723	6,894408	35,72	9,57	3	83,00
83	Celebesstraat	Enschede	52,2143723	6,894408	33,27	9,57	2	122,00
84	Cesar Franckstraat	Hengelo	52,2700992	6,8204697	41,30	7,00		57,00
85	Cesar Franckstraat	Almelo	52,3623269	6,641997	41,30	7,00		
86	Chopinstraat 34	Almelo	52,3612249	6,6363485	41,30	7,00		
87	Christiaan Huygenslaan	Hengelo	52,2547373	6,7818151	41,30	7,00	4	59,37
88	Christiaan Huygenslaan	Hengelo	52,2547373	6,7818151	41,30	7,00	9	46,94
89	Clematisstraat 17	Almelo	52,3426413	6,6737172	41,30	7,00		
90	Clematisstraat 53	Almelo	52,342164	6,6737058	41,30	7,00		
91	Coldstream	Hengelo	52,2676972	6,7871704	41,30	7,00		57,00
92	Coldstream	Hengelo	52,2676972	6,7871704	41,30	7,00		57,00
93	Colensostraat	Hengelo	52,2678334	6,8008049	41,30	7,00		57,00
94	Colonnade 24	Almelo	52,3310803	6,6602406	41,30	7,00		
95	Colonnade 4	Almelo	52,3302007	6,6600627	41,30	7,00		
96	Colonnade 4	Almelo	52,3302007	6,6600627	41,30	7,00		
97	Colonnade 56	Almelo	52,3320864	6,6604357	41,30	7,00		
98	Colonnade 56	Almelo	52,3320864	6,6604357	41,30	7,00		
99	Cornelis Dopperstraat	Hengelo	52,2811927	6,8320464	41,30	7,00	16	55,31
100	De Heurne 2	Enschede	52,2196039	6,8988557	48,36	10,11	100	36,60
101	De Heurne 25	Enschede	52,2207153	6,8987924	49,34	10,17	99	42,06
102	De Heurne 79	Enschede	52,2224763	6,8995172	37,11	5,00	47	67,19
103	De Heurne 79	Enschede	52,2224763	6,8995172	38,94	5,35	51	50,22
104	De Hoven 69	Almelo	52,358762	6,6628358	41,30	7,00		
105	De Kerkegaarden	Goor	52,2339124	6,5808127	41,30	7,00	25	36,05
106	De Wetstraat 13	Hengelo	52,2659401	6,7951904	41,30	7,00		57,00

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
107	De Wetstraat 13	Hengelo	52,2659401	6,7951904	41,30	7,00		57,00
108	De Wetstraat 13	Hengelo	52,2659401	6,7951904	41,30	7,00		57,00
109	De Wetstraat 13	Hengelo	52,2659401	6,7951904	41,30	7,00		57,00
110	Debussystraat	Hengelo	52,2711664	6,8211001	41,30	7,00		57,00
111	Deldenerstraat 203	Hengelo	52,2666005	6,7748955	41,30	7,00		57,00
112	Deldenerstraat 203	Hengelo	52,2666005	6,7748955	41,30	7,00		57,00
113	Deldenerstraat 26	Hengelo	52,2666903	6,7904996	41,30	7,00		57,00
114	Diepenbrockstraat 125	Almelo	52,3597047	6,6422794	41,30	7,00		
115	Diepenbrockstraat 31	Almelo	52,3589167	6,6442895	41,30	7,00		
116	Dinant Dijkhuisstraat	Hengelo	52,2805978	6,8310052	41,30	7,00	14	42,26
117	Dinant Dijkhuisstraat	Hengelo	52,2805978	6,8310052	41,30	7,00	14	32,50
118	Diogenesstraat 9	Hengelo	52,2567068	6,803398	41,30	7,00	1	54,17
119	Dotterbloemstraat	Almelo	52,3453229	6,6663216	41,30	7,00		
120	Dotterbloemstraat 10	Enschede	52,2279192	6,9155008	38,59	5,41	52	29,04
121	Dr A H J Coppesstraat	Enschede	52,236728	6,8875681	38,92	6,78	37	56,81
122	Dr A Kuyperstraat	Hengelo	52,2721418	6,7896766	41,30	7,00		57,00
123	Dr Benthemstraat	Enschede	52,2253501	6,8948581	36,66	6,57	27	108,74
124	Dr Benthemstraat	Enschede	52,2253501	6,8948581	36,87	5,88	25	111,80
125	Dr Benthemstraat	Enschede	52,2253501	6,8948581	35,64	6,57	27	31,63
126	Drienerstraat 47	Hengelo	52,2651572	6,798479	41,30	7,00		57,00
127	Drienerstraat 47	Hengelo	52,2651572	6,798479	41,30	7,00		57,00
128	Duindoornstraat 2	Almelo	52,3420875	6,6748433	41,30	7,00		
129	Duindoornstraat 51	Almelo	52,3419993	6,6747969	41,30	7,00		
130	E Du Perronstraat 1	Hengelo	52,2636237	6,8272452	41,30	7,00		57,00
131	Emmastraat	Enschede	52,2172599	6,883937	41,30	7,00	19	84,34
132	Emsdettenplein	Hengelo	52,2927822	6,8042227	41,30	7,00		57,00
133	Emsdettenplein	Hengelo	52,2927822	6,8042227	41,30	7,00		57,00
134	Enschedesestraat 1	Hengelo	52,2652242	6,7933426	41,30	7,00		57,00
135	Enschedesestraat 1	Hengelo	52,2652242	6,7933426	41,30	7,00		57,00
136	Enschedesestraat 1	Hengelo	52,2652242	6,7933426	41,30	7,00		57,00
137	Enschedesestraat 62	Hengelo	52,2637937	6,797396	41,30	7,00	29	60,14
138	Eskerplein 11	Almelo	52,3660074	6,6790835	41,30	7,00		
139	Esmarkelaan 14	Enschede	52,2135827	6,9509738	39,16	7,37	48	39,77
140	Esmarkelaan 9	Enschede	52,2164647	6,9512414	39,79	7,36	48	66,35
141	F Zernikestraat	Hengelo	52,2543015	6,7850276	41,30	7,00	4	50,62
142	Ferdinand Bolstraat	Enschede	52,208596	6,8588942	41,30	7,00		57,00
143	Ferdinand Bolstraat	Enschede	52,208596	6,8588942	41,30	7,00		57,00
144	Folie	Almelo	52,3331207	6,6619139	41,30	7,00		
145	Franz Lisztstraat	Hengelo	52,2683944	6,8101275	41,30	7,00		57,00
146	Fred van Eedenstraat	Almelo	52,3408384	6,6596184	41,30	7,00		
147	Fridtjof Nansenstraat	Enschede	52,211443	6,9673286	35,68	7,35	49	65,35
148	Fridtjof Nansenstraat	Enschede	52,211443	6,9673286	30,73	7,42	49	59,94
149	Fridtjof Nansenstraat	Enschede	52,211443	6,9673286	54,28	5,17	48	46,48
150	Frits ten Brinkstraat 47	Almelo	52,3665493	6,6855348	41,30	7,00		
151	Ganzenmarkt 1	Oldenzaal	52,3123094	6,930077	41,30	7,00	24	28,51
152	Garenboom 37	Almelo	52,3653783	6,6832607	41,30	7,00		
153	Garenboom 93	Almelo	52,3645439	6,6805364	41,30	7,00		
154	Garenboom 93	Almelo	52,3645439	6,6805364	41,30	7,00		
155	Gerdastraat	Hengelo	52,2562559	6,7668861	41,30	7,00		57,00
156	Gerrit de Veerstraat	Enschede	52,2137586	6,9694235	41,30	7,00		57,00
157	Gerrit Peuscherstraat	Hengelo	52,2847372	6,8233932	41,30	7,00	14	34,52
158	Getfertplein	Enschede	52,2118316	6,8902849	41,30	7,00		57,00
159	Getfertweg	Enschede	52,2128771	6,8908099	38,94	5,19	48	94,79

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
160	Getfertweg	Enschede	52,2128771	6,8908099	39,27	5,19	48	63,92
161	Gieskesstraat 18	Hengelo	52,260639	6,7971655	41,30	7,00	1	39,17
162	Golsstraat	Hengelo	52,2588745	6,7988125	41,30	7,00		57,00
163	Golsstraat	Hengelo	52,2588745	6,7988125	41,30	7,00		57,00
164	Golsstraat	Hengelo	52,2588745	6,7988125	41,30	7,00		57,00
165	Graeshoek	Enschede	52,1955904	6,8557477	41,30	7,00	3	82,78
166	Graeshoek	Enschede	52,1955904	6,8557477	41,30	7,00	12	22,25
167	Grand Canal 15	Almelo	52,3309314	6,6593532	41,30	7,00		
168	Grand Canal 15	Almelo	52,3309314	6,6593532	41,30	7,00		
169	Grand Canal 36	Almelo	52,335319	6,6600293	41,30	7,00		
170	Graskom 2	Almelo	52,3327793	6,6586853	41,30	7,00		
171	Graskom 2	Almelo	52,3327793	6,6586853	41,30	7,00		
172	Grenoblestraat	Hengelo	52,2949688	6,8048659	41,30	7,00		57,00
173	Griegstraat	Hengelo	52,2688231	6,8156021	41,30	7,00		57,00
174	Griegstraat	Hengelo	52,2688231	6,8156021	41,30	7,00		57,00
175	Griegstraat 13	Almelo	52,3635012	6,6380119	41,30	7,00		
176	Groene Bruglaan	Almelo	52,3812928	6,6619033	41,30	7,00		
177	Groene Bruglaan	Almelo	52,3812928	6,6619033	41,30	7,00		
178	Gronausevoetpad	Enschede	52,2203321	6,910516	36,72	7,00		57,00
179	Gronausevoetpad	Enschede	52,2203321	6,910516	36,72	7,00		57,00
180	Grundellaan	Hengelo	52,262681	6,8078103	41,30	7,00		57,00
181	Grundellaan	Hengelo	52,262681	6,8078103	41,30	7,00		57,00
182	H C Pootstraat 3	Hengelo	52,2633145	6,8213009	41,30	7,00		57,00
183	H C Pootstraat 3	Hengelo	52,2633145	6,8213009	41,30	7,00		57,00
184	H C Pootstraat 3	Hengelo	52,2633145	6,8213009	41,30	7,00		57,00
185	H C Pootstraat 3	Hengelo	52,2633145	6,8213009	41,30	7,00		57,00
186	H C Pootstraat 3	Hengelo	52,2633145	6,8213009	41,30	7,00		57,00
187	H Leefsmastraat	Hengelo	52,2788309	6,7885525	41,30	7,00		57,00
188	H Leefsmastraat	Hengelo	52,2788309	6,7885525	41,30	7,00		57,00
189	H Leefsmastraat	Hengelo	52,2788309	6,7885525	41,30	7,00		57,00
190	Hagenstraat 7	Almelo	52,3568234	6,6634129	41,30	7,00		
191	Hans Vonkstraat	Hengelo	52,2842308	6,8299078	41,30	7,00	26	33,91
192	Hans Vonkstraat	Hengelo	52,2842308	6,8299078	41,30	7,00	23	30,00
193	Havenkade	Almelo	52,3598728	6,6566643	41,30	7,00		
194	Haverstraatpassage 7	Enschede	52,2197095	6,8979289	41,30	7,00		57,00
195	Haverstraatpassage 7	Enschede	52,2197095	6,8979289	41,30	7,00		57,00
196	Haverstraatpassage 90	Enschede	52,2207238	6,8966028	50,60	10,13	88	71,27
197	Haverstraatpassage 90	Enschede	52,2207238	6,8966028	50,73	10,18	103	55,56
198	Haverweg	Hengelo	52,2593504	6,8091015	41,30	7,00		57,00
199	Haverweg	Hengelo	52,2593504	6,8091015	41,30	7,00		57,00
200	Hedeveld 2	Almelo	52,3664644	6,6839508	41,30	7,00		
201	Hedeveld 28	Almelo	52,3661974	6,6834995	41,30	7,00		
202	Hedeveld 54	Almelo	52,3658905	6,6834396	41,30	7,00		
203	Helweg	Enschede	52,2008389	6,8395784	41,30	7,00		57,00
204	Helweg	Enschede	52,2008389	6,8395784	41,30	7,00		57,00
205	Hendrik Jan van Heekplein 1	Enschede	52,2182161	6,8970261	48,19	12,76	63	67,11
206	Hengelosestraat 104	Enschede	52,2252853	6,8831606	48,00	6,73	47	64,60
207	Hennepstraat 4	Hengelo	52,2590189	6,8100938	41,30	7,00		57,00
208	Hennepstraat 4	Hengelo	52,2590189	6,8100938	41,30	7,00		57,00
209	Heraklesstraat 13	Hengelo	52,2522955	6,8023157	41,30	7,00	1	64,17
210	Hermelijnstraat	Hengelo	52,2871289	6,8160429	41,30	7,00	13	22,18
211	Het Jannink	Goor	52,2310974	6,583864	41,30	7,00	13	49,04
212	Het Jannink	Goor	52,2310974	6,583864	41,30	7,00	13	49,04

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
213	Hiltjesdamhof	Goor	52,2414646	6,5751899	41,30	7,00	28	50,57
214	Hofstraat 3	Enschede	52,219813	6,8964099	48,90	10,37	63	40,03
215	Hofstraat 3	Enschede	52,219813	6,8964099	49,43	7,00		57,00
216	Hofstraat 3	Enschede	52,219813	6,8964099	48,20	7,00		57,00
217	Hofstraat 39	Enschede	52,2194572	6,8975145	43,97	13,76	103	39,27
218	Hofstraat 39	Enschede	52,2194572	6,8975145	43,97	13,69	100	35,82
219	Horstweg 16	Hengelo	52,2606096	6,7644202	41,30	7,00	4	52,08
220	Hortensiastraat 47	Almelo	52,342047	6,6758991	41,30	7,00		
221	Hulsbeekgaarde	Enschede	52,2222449	6,8971986	39,71	6,59	29	98,00
222	Hulsbeekgaarde	Enschede	52,2222449	6,8971986	40,03	6,79	28	74,64
223	Hulsbeekgaarde	Enschede	52,2222449	6,8971986	38,64	7,21	25	84,80
224	Hulsbeekgaarde	Enschede	52,2222449	6,8971986	12,46	4,96	30	79,17
225	Hulsbeekgaarde	Enschede	52,2222449	6,8971986	45,06	4,96	30	67,63
226	Ikarosstraat	Hengelo	52,2513032	6,802588	41,30	7,00		57,00
227	J H W Robersstraat	Enschede	52,2118104	6,8647092	41,30	7,00		57,00
228	J J van Deinselaan	Enschede	52,2079095	6,9064885	38,86	5,01	51	76,84
229	J J van Deinselaan	Enschede	52,2079095	6,9064885	39,01	5,09	49	58,59
230	Jacobastraat	Hengelo	52,2573534	6,7739629	41,30	7,00	30	45,19
231	Jan van Elburgstraat	Enschede	52,2011307	6,7987321	39,61	4,65	50	98,64
232	Jan van Galenstraat	Hengelo	52,2705899	6,7989645	41,30	7,00		57,00
233	Jan van Galenstraat	Hengelo	52,2705899	6,7989645	41,30	7,00		57,00
234	Jan van Galenstraat	Hengelo	52,2705899	6,7989645	41,30	7,00		57,00
235	Jan van Galenstraat	Hengelo	52,2705899	6,7989645	41,30	7,00		57,00
236	Jan van Galenstraat	Hengelo	52,2705899	6,7989645	41,30	7,00		57,00
237	Jan Vermeerstraat	Enschede	52,2119236	6,8605057	40,02	3,94	25	65,80
238	Joke Smitstraat	Almelo	52,3565041	6,6595388	41,30	7,00		
239	Jupiterstraat	Hengelo	52,2747493	6,8150189	41,30	7,00		57,00
240	Kattenhoek	Hengelo	52,2633376	6,7929182	41,30	7,00		57,00
241	Kattenhoek	Hengelo	52,2633376	6,7929182	41,30	7,00		57,00
242	Kerkstraat	Hengelo	52,2580834	6,7865349	41,30	7,00	4	72,71
243	Kolkstraat 26	Almelo	52,3510676	6,6634358	41,30	7,00		
244	Koppelboerhoek	Enschede	52,1932432	6,8567597	41,30	7,00	11	44,24
245	Korte Haaksbergerstraat 36	Enschede	52,2198428	6,8925842	40,17	6,22	54	98,19
246	Korte Haaksbergerstraat 36	Enschede	52,2198428	6,8925842	39,40	6,29	56	81,91
247	Korte Haaksbergerstraat 43	Enschede	52,2195443	6,892389	49,88	10,10	105	65,60
248	Korte Haaksbergerstraat 43	Enschede	52,2195443	6,892389	49,19	10,10	105	51,12
249	Korte Hengelosestraat 15	Enschede	52,2216838	6,8930125	45,10	9,60	79	64,42
250	Kortelandstraat 2	Enschede	52,2184465	6,9014199	41,30	7,00	11	22,80
251	Kroedhofteplein 16	Enschede	52,2298774	6,8921579	38,41	5,41	52	73,90
252	Krommendijk	Almelo	52,374634	6,6900899	41,30	7,00		
253	Krommendijk	Almelo	52,374634	6,6900899	41,30	7,00		
254	Kuipersdijk 55	Enschede	52,2152102	6,8962631	35,23	5,31	2	131,00
255	Kuipersdijk 55	Enschede	52,2152102	6,8962631	34,75	11,17	3	116,67
256	Landweer 20	Almelo	52,3656944	6,6870283	41,30	7,00		
257	Langelermaatweg	Hengelo	52,2559216	6,7931894	41,30	7,00		57,00
258	Langestraat 70	Delden	52,2620073	6,7086822	41,30	7,00	16	36,09
259	Leuvenstraat 13	Hengelo	52,2947103	6,8070524	41,30	7,00		57,00
260	Lijsterweg	Hengelo	52,2683154	6,8021847	41,30	7,00		57,00
261	Lipperkerkstraat 172	Enschede	52,2223999	6,911747	37,79	4,18	27	34,26
262	Londenstraat 1	Hengelo	52,297932	6,7971704	41,30	7,00		57,00
263	Londenstraat 170	Hengelo	52,2957877	6,8050662	41,30	7,00		57,00
264	Londenstraat 170	Hengelo	52,2957877	6,8050662	41,30	7,00		57,00
265	Loofgang 14	Almelo	52,331894	6,6623213	41,30	7,00		

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
266	Loofgang 14	Almelo	52,331894	6,6623213	41,30	7,00		
267	Loofgang 46	Almelo	52,3308418	6,6621063	41,30	7,00		
268	Loofgang 46	Almelo	52,3308418	6,6621063	41,30	7,00		
269	Louis van Gasterenstraat	Hengelo	52,287053	6,8408065	41,30	7,00	14	37,98
270	M T Steynstraat 4	Almelo	52,3449325	6,6591632	41,30	7,00		
271	Maasstraat 60	Almelo	52,3506948	6,6756513	41,30	7,00		
272	Magnoliastraat 104	Almelo	52,341294	6,6744957	41,30	7,00		
273	Magnoliastraat 142	Almelo	52,341283	6,6746678	41,30	7,00		
274	Magnoliastraat 42	Almelo	52,341312	6,6742149	41,30	7,00		
275	Magnoliastraat 66	Almelo	52,341305	6,6743236	41,30	7,00		
276	Marathonlaan 15	Hengelo	52,2531542	6,8020439	41,30	7,00		57,00
277	Markveldebrink	Enschede	52,1902646	6,8696109	41,30	7,00	12	105,35
278	Markveldebrink	Enschede	52,1902646	6,8696109	41,30	7,00	12	48,47
279	Markveldebrink	Enschede	52,1902646	6,8696109	41,30	7,00	3	23,89
280	Marssteeg 20	Hengelo	52,2659036	6,7882916	41,30	7,00		57,00
281	Marssteeg 20	Hengelo	52,2659036	6,7882916	41,30	7,00		57,00
282	Marthalaan 8	Enschede	52,2187006	6,9124239	38,69	4,89	52	67,50
283	Mastbos	Enschede	52,2047855	6,8655665	41,30	7,00	12	60,28
284	Mauritsplein	Hengelo	52,2558304	6,7990022	41,30	7,00		57,00
285	Mauritsplein	Hengelo	52,2558304	6,7990022	41,30	7,00		57,00
286	Mauritsplein	Hengelo	52,2558304	6,7990022	41,30	7,00		57,00
287	Mennistenhoek 51	Almelo	52,3519369	6,6635214	41,30	7,00		
288	Mennistenhoek 51	Almelo	52,3519369	6,6635214	41,30	7,00		
289	Mina Krusemanstraat	Enschede	52,2166832	6,8816436	41,30	7,00	10	46,83
290	Mina Krusemanstraat	Enschede	52,2166832	6,8816436	41,30	7,00	10	23,50
291	Mina Krusemanstraat	Enschede	52,2166832	6,8816436	41,30	7,00	2	7,92
292	Mina Krusemanstraat	Enschede	52,2166832	6,8816436	41,30	7,00		57,00
293	Mooienhof 177	Enschede	52,2171307	6,8962917	37,82	4,96	52	62,65
294	Mooienhof 177	Enschede	52,2171307	6,8962917	38,45	4,61	52	45,46
295	Mooienhof 2	Enschede	52,2164125	6,9000631	38,94	3,68	50	18,76
296	Mooienhof 2	Enschede	52,2164125	6,9000631	38,99	3,68	50	81,02
297	Mooienhof 2	Enschede	52,2164125	6,9000631	39,82	3,68	50	73,86
298	Mozartlaan	Hengelo	52,2690207	6,8154089	41,30	7,00		57,00
299	Mozartlaan 82I	Hengelo	52,2702068	6,8189194	41,30	7,00		57,00
300	Mussenstraat	Hengelo	52,2653843	6,8074236	41,30	7,00		57,00
301	Nassaustraat	Enschede	52,2165731	6,8874784	39,11	5,24	48	51,94
302	Nassaustraat	Enschede	52,2165731	6,8874784	39,81	4,11	47	40,11
303	Nico Werkmanstraat	Hengelo	52,2791319	6,7928368	41,30	7,00		57,00
304	Nico Werkmanstraat	Hengelo	52,2791319	6,7928368	41,30	7,00		57,00
305	Nico Werkmanstraat	Hengelo	52,2791319	6,7928368	41,30	7,00		57,00
306	Nije Allee 4	Almelo	52,3352399	6,6640556	41,30	7,00		
307	Nije Allee 54	Almelo	52,3329544	6,663792	41,30	7,00		
308	Noordachtereschweg	Markelo	52,2459499	6,4957354	41,30	7,00	27	47,04
309	Noorderhagen 36	Enschede	52,2218083	6,895271	49,99	10,12	109	64,17
310	Noorderhagen 36	Enschede	52,2218083	6,895271	52,25	10,08	111	64,68
311	Noorderhagen 58	Enschede	52,221498	6,8975048	49,45	13,19	107	77,18
312	Ockeghemstraat	Hengelo	52,2713762	6,8172722	41,30	7,00		57,00
313	Oelerweg 181	Hengelo	52,2554602	6,7736355	41,30	7,00	4	64,17
314	Oelerweg 181	Hengelo	52,2554602	6,7736355	41,30	7,00	4	41,25
315	Oelerweg 181	Hengelo	52,2554602	6,7736355	41,30	7,00	4	37,08
316	Oldemeulehoek	Enschede	52,1944483	6,8565399	41,30	7,00	12	54,24
317	Oldenzaalsestraat 2	Enschede	52,2187023	6,9003784	50,71	9,59	100	69,58
318	Oldenzaalsestraat 2	Enschede	52,2187023	6,9003784	50,85	9,69	95	65,31

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
319	Oldenzaalsestraat 44	Enschede	52,2197253	6,9002707	38,29	4,70	50	129,14
320	Oldenzaalsestraat 81	Enschede	52,2207475	6,8999448	38,15	4,67	50	51,30
321	Oliemolensingel 26	Enschede	52,2229542	6,9114125	36,44	5,80	27	34,26
322	Oosteres 1	Almelo	52,3602968	6,6713407	41,30	7,00		
323	Oostwal 9	Oldenzaal	52,3144328	6,9309353	41,30	7,00	24	23,37
324	Ootmarsumsestraat 342	Almelo	52,3686235	6,6832341	41,30	7,00		
325	Orangerie 2	Almelo	52,3338615	6,6600488	41,30	7,00		
326	Orangerie 2	Almelo	52,3338615	6,6600488	41,30	7,00		
327	Orangerie 21	Almelo	52,3336343	6,6629459	41,30	7,00		
328	Orangerie 21	Almelo	52,3336343	6,6629459	41,30	7,00		
329	Oude Markt 31	Enschede	52,220477	6,8956233	49,74	10,12	101	68,58
330	P C Boutensstraat 1	Almelo	52,3448047	6,6581384	41,30	7,00		
331	P C Boutensstraat 1	Almelo	52,3448047	6,6581384	41,30	7,00		
332	P C Boutensstraat 161	Almelo	52,3420619	6,6580767	41,30	7,00		
333	P C Boutensstraat 161	Almelo	52,3420619	6,6580767	41,30	7,00		
334	P C Boutensstraat 221	Almelo	52,3414246	6,6590405	41,30	7,00		
335	P C Boutensstraat 221	Almelo	52,3414246	6,6590405	41,30	7,00		
336	P C Boutensstraat 259	Almelo	52,3411083	6,658798	41,30	7,00		
337	P C Boutensstraat 259	Almelo	52,3411083	6,658798	41,30	7,00		
338	P C Boutensstraat 75	Almelo	52,3437201	6,658085	41,30	7,00		
339	P C Boutensstraat 75	Almelo	52,3437201	6,658085	41,30	7,00		
340	Parallelweg	Enschede	52,2229776	6,895762	38,78	6,80	50	107,84
341	Parallelweg	Enschede	52,2229776	6,895762	38,23	6,80	50	60,86
342	Parallelweg	Enschede	52,2229776	6,895762	39,07	6,89	48	24,46
343	Parallelweg	Enschede	52,2229776	6,895762	39,03	4,13	47	97,87
344	Parallelweg	Enschede	52,2229776	6,895762	39,12	4,17	50	107,84
345	Parallelweg Ls 8	Hengelo	52,2593056	6,7967665	41,30	7,00		57,00
346	Parallelweg Ls 8	Hengelo	52,2593056	6,7967665	41,30	7,00		57,00
347	Parterre	Almelo	52,3302603	6,6566837	41,30	7,00		
348	Pastoor Geerdinkstraat	Losser	52,3170007	6,9843247	41,30	7,00		57,00
349	Paul Krugerstraat 49	Hengelo	52,2681187	6,7985119	41,30	7,00		57,00
350	Paul Steenbergenstraat	Hengelo	52,2865178	6,8388445	41,30	7,00	1	26,67
351	Paulinastraat 1	Hengelo	52,2611315	6,7667953	41,30	7,00	4	26,67
352	Peter Rubensstraat	Hengelo	52,2781751	6,7962566	41,30	7,00		57,00
353	Peter Rubensstraat	Hengelo	52,2781751	6,7962566	41,30	7,00		57,00
354	Peter Rubensstraat	Hengelo	52,2781751	6,7962566	41,30	7,00		57,00
355	Peter Rubensstraat	Hengelo	52,2781751	6,7962566	41,30	7,00		57,00
356	Piet Heinstraat	Hengelo	52,2702042	6,8001665	41,30	7,00		57,00
357	Piet Heinstraat	Hengelo	52,2702042	6,8001665	41,30	7,00		57,00
358	Piet Heinstraat	Hengelo	52,2702042	6,8001665	41,30	7,00		57,00
359	Piet Heinstraat	Hengelo	52,2702042	6,8001665	41,30	7,00		57,00
360	Plateau	Almelo	52,3342831	6,6618873	41,30	7,00		
361	Plompstraat	Almelo	52,3444912	6,6672336	41,30	7,00		
362	Plompstraat	Almelo	52,3444912	6,6672336	41,30	7,00		
363	Poolsterstraat 10	Hengelo	52,2752656	6,8107754	41,30	7,00		57,00
364	Poolsterstraat 10	Hengelo	52,2752656	6,8107754	41,30	7,00		57,00
365	Potskampstraat 1	Oldenzaal	52,3156186	6,9347028	41,30	7,00	24	80,69
366	Poulinkstraat 18	Almelo	52,353239	6,6608681	41,30	7,00		
367	Poulinkstraat 69	Almelo	52,3533684	6,6601826	41,30	7,00		
368	Poulinkstraat 69	Almelo	52,3533684	6,6601826	41,30	7,00		
369	Prieel 1	Almelo	52,330485	6,6561562	41,30	7,00		
370	Prinsenstraat 12	Almelo	52,3540049	6,6648474	41,30	7,00		
371	Pruisische Veldweg 1	Hengelo	52,2510045	6,8018081	41,30	7,00	1	59,58

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
372	Pythagorasstraat 13	Hengelo	52,2572969	6,8025436	41,30	7,00	2	52,09
373	Rappersweg 61	Almelo	52,3674008	6,6838935	41,30	7,00		
374	Rappersweg 68	Almelo	52,3667698	6,6838946	41,30	7,00		
375	Ravelstraat	Hengelo	52,2707209	6,8200097	41,30	7,00		57,00
376	Ravelstraat 34	Almelo	52,3630346	6,6357245	41,30	7,00		
377	Rietmolenstraat	Enschede	52,2157985	6,9028981	41,30	7,00	11	10,82
378	Rob de Vriesstraat	Hengelo	52,2845016	6,8400419	41,30	7,00	14	42,94
379	Roberinkstraat	Losser	52,262347	7,0075088	41,30	7,00		57,00
380	Robert Scottstraat	Enschede	52,2123997	6,9675995	39,47	6,74	46	82,52
381	Robert Scottstraat	Enschede	52,2123997	6,9675995	39,51	7,40	48	52,71
382	Roerstraat	Enschede	52,2410611	6,8890875	38,30	5,76	52	99,27
383	Roombeekhofje	Enschede	52,2297731	6,8905935	41,30	7,00		57,00
384	Roombeekhofje	Enschede	52,2297731	6,8905935	41,30	7,00		57,00
385	Roomweg	Enschede	52,2315625	6,8958249	38,50	5,41	52	67,77
386	Roomweg	Enschede	52,2315625	6,8958249	38,50	5,41	52	67,77
387	Rossinistraat 34	Almelo	52,3620478	6,6368709	41,30	7,00		
388	S L Louwesstraat 181	Enschede	52,2070986	6,8639121	38,74	5,01	50	65,34
389	S L Louwesstraat 2	Enschede	52,2100265	6,8637824	38,37	4,95	50	90,38
390	Salamanderstraat	Hengelo	52,2888715	6,8153413	41,30	7,00		57,00
391	Salamanderstraat	Hengelo	52,2888715	6,8153413	41,30	7,00		57,00
392	Saturnusstraat 121	Hengelo	52,2755203	6,8161909	41,30	7,00		57,00
393	Saturnusstraat 121	Hengelo	52,2755203	6,8161909	41,30	7,00		57,00
394	Saturnusstraat 121	Hengelo	52,2755203	6,8161909	41,30	7,00		57,00
395	Saturnusstraat 16	Hengelo	52,273985	6,8157243	41,30	7,00		57,00
396	Schiestraat	Enschede	52,2405875	6,8884562	38,65	5,85	52	57,83
397	Schietspoel	Almelo	52,3656301	6,681053	41,30	7,00		
398	Schubertstraat	Hengelo	52,2723855	6,8189393	41,30	7,00		57,00
399	Schubertstraat	Hengelo	52,2723855	6,8189393	41,30	7,00		57,00
400	Schubertstraat	Hengelo	52,2723855	6,8189393	41,30	7,00		57,00
401	Schulpvijver 2	Almelo	52,3321584	6,6584591	41,30	7,00		
402	Schumannstraat	Hengelo	52,271543	6,8199302	41,30	7,00		57,00
403	Schumannstraat	Hengelo	52,271543	6,8199302	41,30	7,00		57,00
404	Schumannstraat	Hengelo	52,271543	6,8199302	41,30	7,00		57,00
405	Schurinksweg	Enschede	52,2305132	6,897645	37,42	5,04	49	105,00
406	Schurinksweg	Enschede	52,2305132	6,897645	38,70	5,18	50	49,20
407	Sesastraat	Almelo	52,3526312	6,661836	41,30	7,00		
408	Shackletonstraat	Enschede	52,2107439	6,9661291	39,67	7,10	49	61,61
409	Shackletonstraat	Enschede	52,2107439	6,9661291	38,20	5,30	46	51,35
410	Sherwood Rangers	Hengelo	52,2677502	6,790986	41,30	7,00		57,00
411	Sherwood Rangers	Hengelo	52,2677502	6,790986	41,30	7,00		57,00
412	Sherwood Rangers	Hengelo	52,2677502	6,790986	41,30	7,00		57,00
413	Sherwood Rangers	Hengelo	52,2677502	6,790986	41,30	7,00		57,00
414	Sibeliusstraat 13	Almelo	52,3601988	6,6372897	41,30	7,00		
415	Sibeliusstraat 37	Almelo	52,3599718	6,6367136	41,30	7,00		
416	Sibeliusstraat 37	Almelo	52,3599718	6,6367136	41,30	7,00		
417	Siriusstraat	Hengelo	52,2749784	6,8131328	41,30	7,00		57,00
418	Smetanastraat 9	Almelo	52,3611086	6,6338578	41,30	7,00		
419	Socratesstraat 20	Hengelo	52,2561902	6,8046582	41,30	7,00		57,00
420	Somerset	Hengelo	52,2683159	6,7867538	41,30	7,00		57,00
421	Somerset	Hengelo	52,2683159	6,7867538	41,30	7,00		57,00
422	Spiegelstraat	Hengelo	52,2689465	6,8264423	41,30	7,00		57,00
423	Spinnerij 10	Almelo	52,3648393	6,6805127	41,30	7,00		
424	Spoorstraat 31	Hengelo	52,2626327	6,7917156	41,30	7,00	52	61,75

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
425	Spoorstraat 31	Hengelo	52,2626327	6,7917156	41,30	7,00	52	61,75
426	Stadionlaan 20	Hengelo	52,2560955	6,8024289	41,30	7,00	3	55,00
427	Stadshagen	Delden	52,2642352	6,7102984	41,30	7,00	19	62,54
428	Stadshagen	Delden	52,2642352	6,7102984	41,30	7,00	9	59,91
429	Stadshagen	Delden	52,2642352	6,7102984	41,30	7,00	19	40,53
430	Stadshagen	Delden	52,2642352	6,7102984	41,30	7,00	19	18,90
431	Stationsplein	Hengelo	52,2621934	6,7943278	41,30	7,00		57,00
432	Stationsplein	Hengelo	52,2621934	6,7943278	41,30	7,00		57,00
433	Stationsplein	Hengelo	52,2621934	6,7943278	41,30	7,00		57,00
434	Stationsplein	Enschede	52,2216905	6,8898409	37,84	4,08	52	64,85
435	Steenbokstraat	Hengelo	52,2749604	6,8181242	41,30	7,00		57,00
436	Steenbokstraat	Hengelo	52,2749604	6,8181242	41,30	7,00		57,00
437	Steffensweg	Almelo	52,3408633	6,6714533	41,30	7,00		
438	Sterkerstraat 2	Enschede	52,214608	6,8728787	38,95	4,96	51	66,41
439	Stockholmstraat 4	Hengelo	52,2945758	6,7928921	41,30	7,00		57,00
440	Terras 1	Almelo	52,3312253	6,6584842	41,30	7,00		
441	Terras 1	Almelo	52,3312253	6,6584842	41,30	7,00		
442	Terras 36	Almelo	52,3293194	6,6566735	41,30	7,00		
443	Theater 2	Almelo	52,3349346	6,660297	41,30	7,00		
444	Theater 2	Almelo	52,3349346	6,660297	41,30	7,00		
445	Theater 29	Almelo	52,3348135	6,6631992	41,30	7,00		
446	Theater 29	Almelo	52,3348135	6,6631992	41,30	7,00		
447	Themislaan	Enschede	52,2061286	6,9701761	39,53	7,28	50	82,78
448	Themislaan	Enschede	52,2061286	6,9701761	38,96	7,28	50	27,74
449	Theresiastraat 18	Hengelo	52,2601478	6,7641965	41,30	7,00	3	48,33
450	Theresiastraat 72	Hengelo	52,2583628	6,763708	41,30	7,00	4	45,00
451	Thorbeckelaan 152	Almelo	52,3572573	6,6487227	41,30	7,00		
452	Thorbeckelaan 36	Almelo	52,3568914	6,651332	41,30	7,00		
453	Thorbeckelaan 88	Almelo	52,3571038	6,6501818	41,30	7,00		
454	Trijpstraat 1	Hengelo	52,2606866	6,7967007	41,30	7,00	2	19,17
455	Trijpstraat 83	Hengelo	52,259711	6,7961885	41,30	7,00	1	26,67
456	Tulpstraat	Enschede	52,2272316	6,9057327	37,49	5,03	51	101,29
457	Twekkelerplein	Hengelo	52,2575669	6,8014745	41,30	7,00	3	30,56
458	Valeriusstraat 125	Almelo	52,3597729	6,6450976	41,30	7,00		
459	Valeriusstraat 53	Almelo	52,3589068	6,6454604	41,30	7,00		
460	Valeriusstraat 87	Almelo	52,359304	6,6452541	41,30	7,00		
461	Van Lochemstraat 1	Enschede	52,2225477	6,898375	39,03	6,35	51	38,45
462	Van Lochemstraat 1	Enschede	52,2225477	6,898375	38,10	5,16	52	51,02
463	Van Lochemstraat 110	Enschede	52,2221315	6,8978515	40,04	5,05	52	23,23
464	Van Lochemstraat 110	Enschede	52,2221315	6,8978515	40,23	5,05	52	79,65
465	Van Loenshof 56	Enschede	52,2186838	6,8951615	38,30	3,92	53	89,53
466	Veenstraat 78A	Enschede	52,2179537	6,9037072	41,30	7,00	11	40,15
467	Veldkersstraat	Almelo	52,348409	6,667538	41,30	7,00		
468	Veldzicht	Almelo	52,364163	6,6809557	41,30	7,00		
469	Venusstraat 123	Hengelo	52,2756102	6,8143369	41,30	7,00		57,00
470	Venusstraat 123	Hengelo	52,2756102	6,8143369	41,30	7,00		57,00
471	Verdilaan	Almelo	52,360884	6,6379617	41,30	7,00		
472	Verdilaan	Almelo	52,360884	6,6379617	41,30	7,00		
473	Verdilaan	Almelo	52,360884	6,6379617	41,30	7,00		
474	Verdilaan	Almelo	52,360884	6,6379617	41,30	7,00		
475	Vista	Almelo	52,3313598	6,6630942	41,30	7,00		
476	Voorstraat	Goor	52,2362543	6,5876501	41,30	7,00	13	25,96
477	Vriezenveenseweg 176	Almelo	52,3805718	6,6639945	41,30	7,00		

	Container location	City	Latitude	Longitude	Average deposit size (liter)	Standard deviation	Number of emptyings in 2009	Average output ratio at emptying(%)
478	Walstraat 35	Enschede	52,2196483	6,8945312	51,00	9,72	94	40,18
479	Walstraat 35	Enschede	52,2196483	6,8945312	51,09	9,78	95	30,17
480	Walstraat 35	Enschede	52,2196483	6,8945312	48,07	9,07	93	50,10
481	Waterstraat	Goor	52,2314889	6,582642	41,30	7,00	13	2,37
482	Wederiklaan	Enschede	52,2151969	6,9423191	31,00	7,00		57,00
483	Weefgetouw	Almelo	52,3659949	6,6817473	41,30	7,00		
484	Weideweg	Hengelo	52,2706271	6,7804141	41,30	7,00		57,00
485	Weideweg	Hengelo	52,2706271	6,7804141	41,30	7,00		57,00
486	Weideweg	Hengelo	52,2706271	6,7804141	41,30	7,00		57,00
487	Weideweg	Hengelo	52,2706271	6,7804141	41,30	7,00		57,00
488	Weideweg	Hengelo	52,2706271	6,7804141	41,30	7,00		57,00
489	Wemenstraat 17	Hengelo	52,2659542	6,7936316	41,30	7,00		57,00
490	Wemenstraat 17	Hengelo	52,2659542	6,7936316	41,30	7,00		57,00
491	Werninkhofstraat	Hengelo	52,276182	6,7897243	41,30	7,00		57,00
492	Wessex	Hengelo	52,2700983	6,7872057	41,30	7,00		57,00
493	Wethouder Beversstraat 60	Enschede	52,2066778	6,880575	58,62	7,73	47	55,57
494	Wethouder Gerbertstraat	Enschede	52,2055871	6,8791783	57,68	9,36	25	36,32
495	Wethouder Gerbertstraat	Enschede	52,2055871	6,8791783	63,06	9,36	26	23,62
496	Wethouder Kampstraat	Hengelo	52,2503117	6,7945909	41,30	7,00		57,00
497	Weusthagstraat	Hengelo	52,2776054	6,7967867	41,30	7,00		57,00
498	Weusthagstraat	Hengelo	52,2776054	6,7967867	41,30	7,00		57,00
499	Weustinkplantsoen 8	Hengelo	52,260165	6,7779875	41,30	7,00	3	23,89
500	Wierdensestraat	Almelo	52,3556709	6,6382803	41,30	7,00		
501	Wijlre	Almelo	52,3745841	6,69217	41,30	7,00		
502	Wijlre	Almelo	52,3745841	6,69217	41,30	7,00		
503	Wilderinksstraat	Hengelo	52,2584162	6,7748042	41,30	7,00	55	60,06
504	Wilhelminastraat 125	Enschede	52,2206419	6,9037936	38,68	4,84	48	83,23
505	Willem van Otterloostraat	Hengelo	52,2837649	6,8286859	41,30	7,00	16	15,89
506	Willemsgang 10	Almelo	52,3586815	6,664305	41,30	7,00		
507	Windbrugstraat	Enschede	52,2186352	6,8959237	58,64	9,40	101	38,63
508	Windbrugstraat	Enschede	52,2186352	6,8959237	56,88	10,00	101	38,20
509	Wingerd	Almelo	52,3509808	6,6605133	41,30	7,00		
510	Wingerd	Almelo	52,3509808	6,6605133	41,30	7,00		
511	Wintertuin 16	Almelo	52,3297908	6,6617356	41,30	7,00		
512	Wittem	Almelo	52,3751512	6,6932148	41,30	7,00		
513	Wittem	Almelo	52,3751512	6,6932148	41,30	7,00		
514	Ypelobrink	Enschede	52,1927616	6,87042	41,30	7,00	3	66,11
515	Zonstraat 1	Enschede	52,2287268	6,8583154	36,40	3,95	28	54,00
516	Zuiderhagen 16	Enschede	52,220192	6,893546	38,04	5,33	46	111,87
517	Zunabrink	Enschede	52,1948928	6,8749984	41,30	7,00	12	92,60
518	Zwanenbelt 59	Almelo	52,3522955	6,6644195	41,30	7,00		
519	Zwedeweg 10	Enschede	52,2171388	6,8774904	41,30	7,00		57,00
520	Zweersstraat 19	Almelo	52,3595988	6,6441861	41,30	7,00		

Table 20 Data all underground containers Twente Milieu (March 2010)

Appendix E – Structure of simulation model

Figure 31 shows the structure of the simulation model with all methods and decisions whether to use balancing, basic or advanced planning, and use may-go jobs.

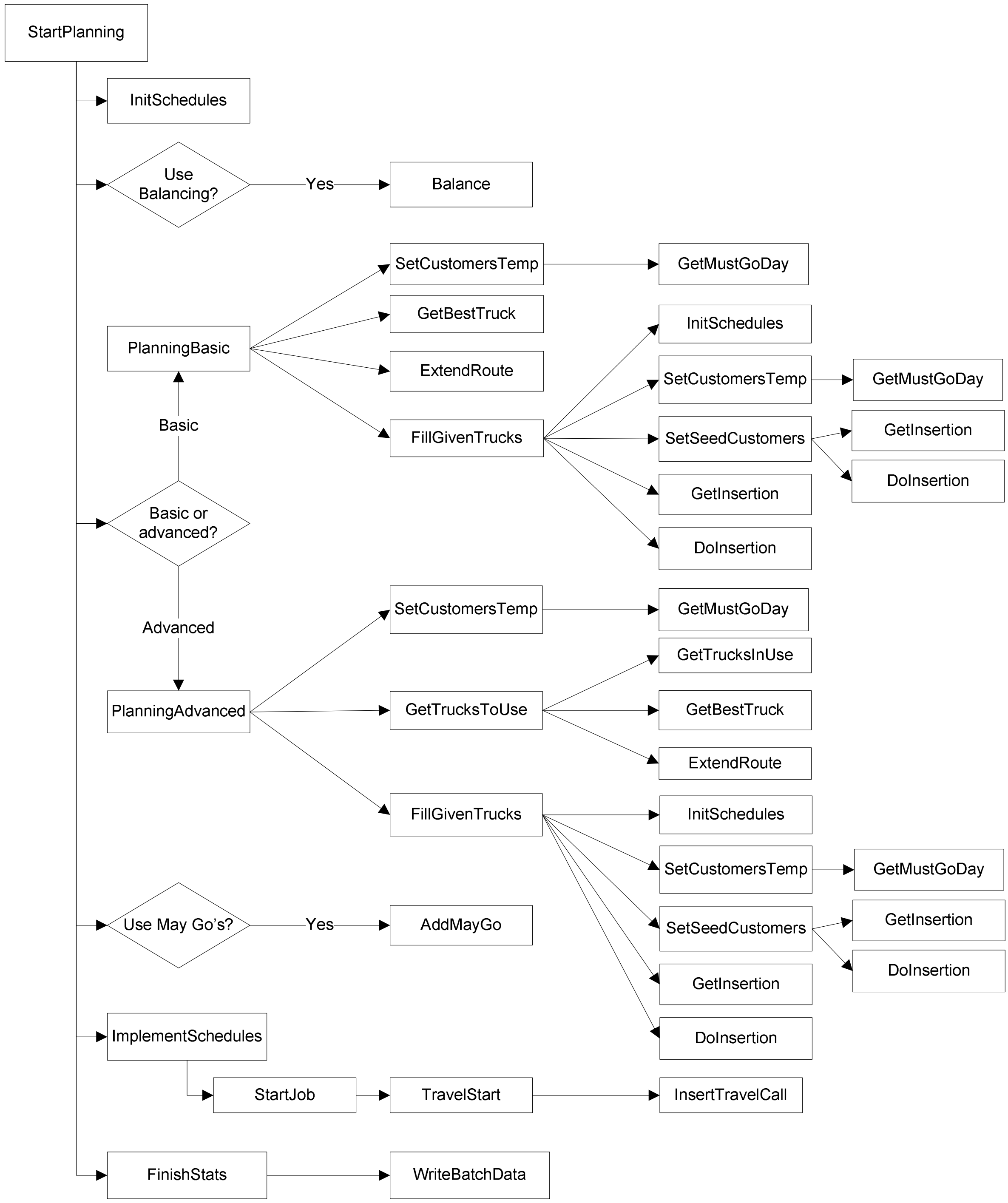

Figure 31 Structure of simulation model

The simulation model starts with initializing all schedules, this means that all current schedules are emptied. At the start of the day, there are no schedules, but for the rescheduling during the day, emptying the schedules is necessary. Only the current job is kept, because, as stated in Chapter 6, we use non-preemption.

After initializing the schedules, we have to decide whether to use balancing or not. The model uses a table with different scenarios, which indicate whether the basic or the advanced planning should be used. This table with scenarios also indicates whether *may-go* jobs should be included and whether trucks should be sent in different directions using seed jobs. Next, we choose either for planning basic or planning advanced.

Both the basic and the advanced heuristic start with determining the *must-go day* for all containers and select the containers that have fewer days left than the *must-go day* to be planned. The basic heuristic then continues with the selection of the first available truck and assigns jobs to that truck. The jobs are assigned based on *cheapest insertion* and only jobs on the *must-go* list are selected for insertion. If a truck is full, which means its capacity is reached or there is no time left in the day, a next truck is selected. These steps are repeated until all *must-go* jobs are scheduled. Only in case not all *must-go* jobs fit in the available trucks, the method *'FillGivenTrucks'* is used. In that case, all current schedules are deleted, the *must-go* list is again created and the most urgent jobs are assigned first. The jobs are inserted with the use of a seed job, this leads to more efficient routes. When the basic heuristic is finished, there is a possibility to fill the trucks with *may-go* jobs. For the basic heuristic this means that, most times, only the last truck gets *may-go* jobs, because this heuristics fill trucks one truck at a time. It is possible that when a truck has no space left for a *must-go* job, it does have space for a *may-go* job, but most space will be available in the last truck.

The advanced heuristic starts with determining the number of trucks and routes that is necessary to complete all *must-go* jobs. Once the number of trucks is determined, the given number of trucks is filled. This is done for all trucks simultaneously, and the trucks are first sent in different directions to increase efficient routes using seed jobs. The *must-go* jobs are one-by-one assigned to the best possible truck and route and when all *must-go* jobs are planned, the routes are extended with *may-go* jobs. For the advanced heuristic the effect of using *may-go* jobs will probably be larger, because they can be inserted in more than one route. The use of the *may-go* jobs will increase the efficiency of the routes.

Once the schedules have been made, the schedules are implemented. This means the trucks will start travelling and the containers are emptied. The constructed routes are drawn on the map.

Finally, our model records the performance of the planning options and writes this in an output file. With these files we are able to compare the different scenarios and decide which one performs best.

Appendix F – Simulation model overview

The simulation model also uses some other visualization, next to the map, for example for the input settings and for the methods used to select containers for emptying and creating of routes. Figure 32 gives the home screen of the simulation model, which gives possibilities to select a network, which might be the Twente Milieu network as displayed in Figure 23 in Chapter 7, or a random network. The random network is used for testing different planning methods. The *customers* frame contains information about the containers, *network* displays the map and planned routes and the *suppliers* frame contains all methods used for planning and rescheduling. Also, the home screen has buttons to start or stop the simulation, and to increase simulation speed. The *settings* button hides a screen which contains all input settings needed to do the simulation. Figure 33 shows this *settings* frame. This frame includes a table with all container locations, size, average number of deposits, and average deposit sizes. It also gives the start and end times of a day and the capacity of the refuse trucks. Figure 34 shows the *suppliers* frame, with all methods used to determine a schedule for each day. It is divided in different sections, of which the planning and control section is the most important. This section determines the actual schedules.

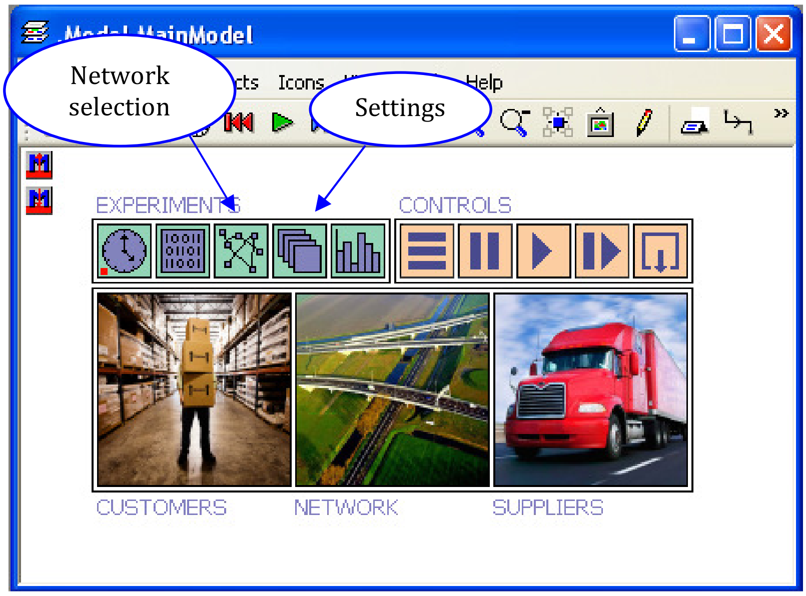

Figure 32 Home screen of simulation model

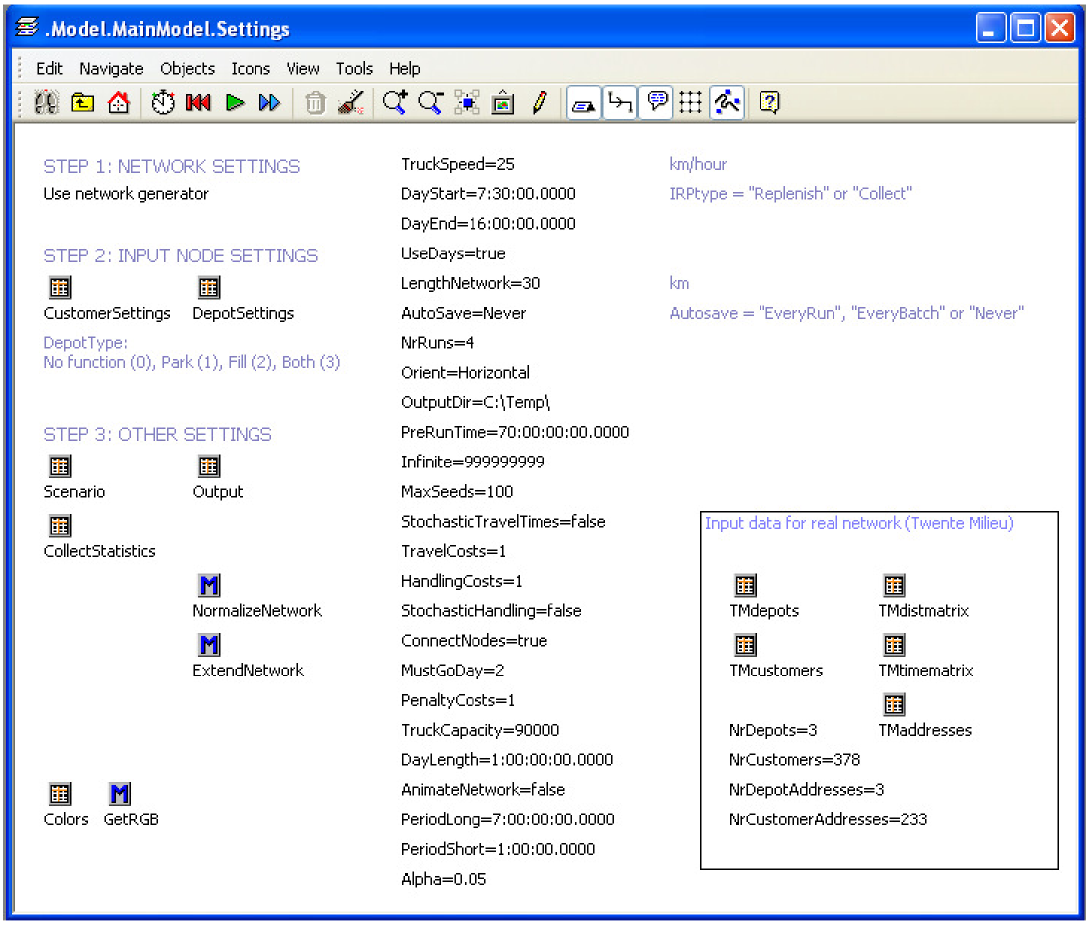

Figure 33 Settings of simulation model

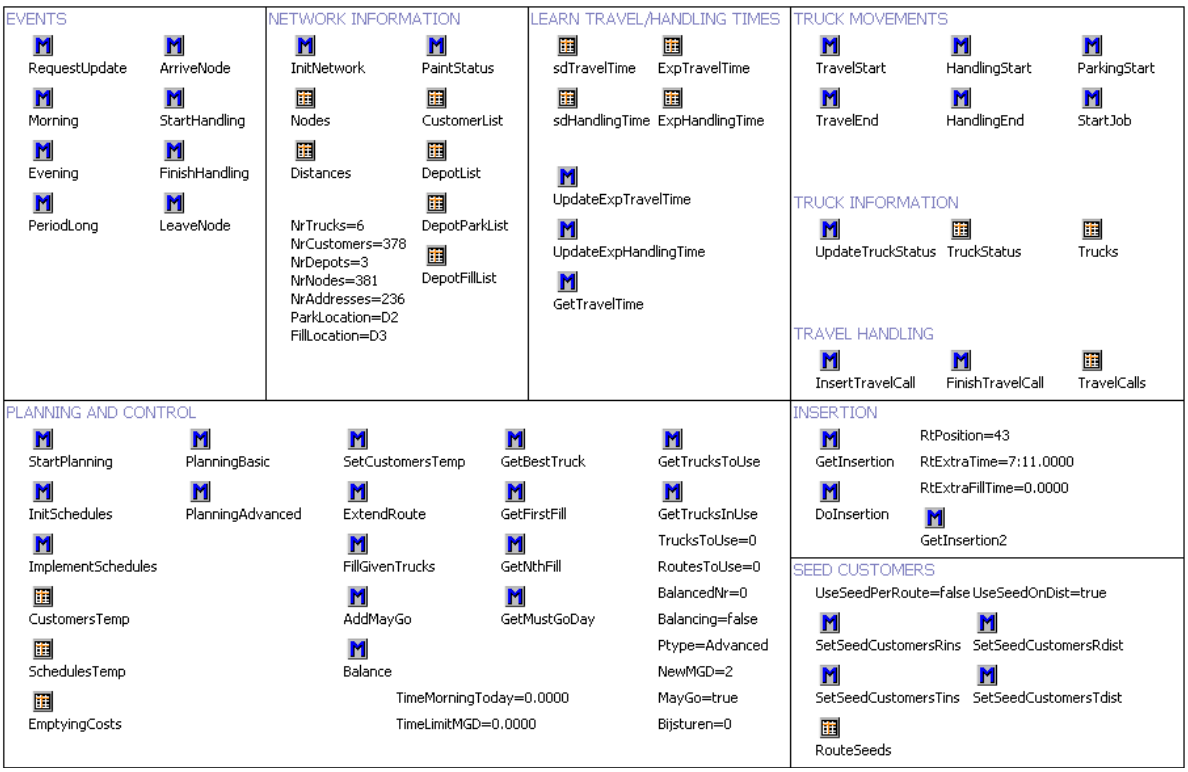

Figure 34 Suppliers frame containing all method used for planning and scheduling

Appendix G – Calculation of the warm-up period

For calculating the warm-up period, we use the four steps of Welch's graphical procedure (Law, 2007). The procedure consists of the following steps:

1. Make n replications of the simulation, each of length m, where m is large. Y_{ji} is the ith observation from the jth replication.
2. Calculate $\bar{Y}_i$, which is the average value of the ith day over n runs.
3. Calculate the moving averages $Y_i(w)$, where w is the window. Choose a value for w such that $w \leq m/4$
4. Plot the moving averages and choose l to be that value of i for which the function appears to converge.

We started with performing five simulation runs with a run length of 500 days each, and calculated the averages for every observation. We continued with calculating the moving averages for an increasing w, and plotted the graphs. We took w=5, 15, 20, and 40. For w=40, the graph is smooth.

Figure 35 shows the graph we used to determine the warm-up period. The two lines give the moving averages for w=5 and w=40. For w=40, the graph becomes constant after 50 days. This means that the warm-up period needs to be 10 weeks, because this graph only shows the weekdays.

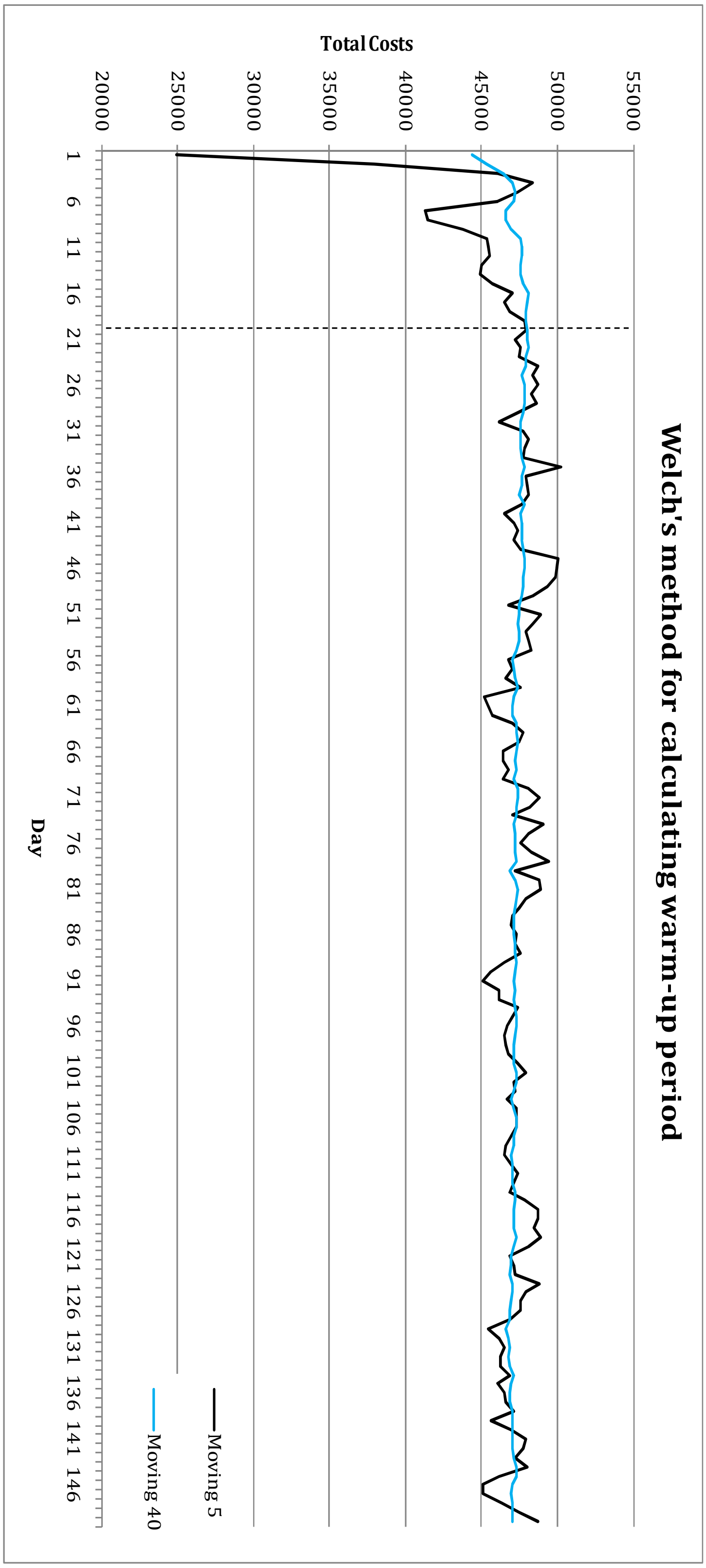

Figure 35 Moving averages for determining warm-up period

Appendix H – Calculation of the number of runs

For calculating the number of runs, we used the sequential procedure, consisting of the following steps:

1. Make *n* replications of the simulation
2. Compute $\overline{X}(n)$ and $\delta(n,\alpha)$ with $\delta(n,\alpha) = t_{n-1,1-\alpha/2}\sqrt{S_n^2 / n}$
3. If $\delta(n,\alpha)/\overline{X}(n) \leq \gamma'$, then stop with confidence interval $[\bar{X}_n - \delta(n,\alpha), \bar{X}_n + \delta(n,\alpha)]$ and *n* is the run length. Otherwise, set *n:=n+1* and make an additional replication

For determining the number of runs, we performed an initial simulation run with 15 replications using the most simple variant of our model, without balancing or the adding *may-go* jobs to our plan. We use the total costs of the different runs, because the total costs are the most important performance indicator, as stated in Section 6.5. Table 21 shows that the number of runs should be at least two. This is a low number, that might be caused by the large numbers in the column 'Total costs', this results in a high average. To be certain we will perform the right number of runs, we also determined the number of runs using the service level and the fill level as indicators. Table 22 and Table 23 show the results when calculating the number of runs using these indicators. This results in a minimum of three runs that is needed for valid results. To be sure the number of runs will be sufficient for the other scenarios as well, we choose the number of runs for our experiments to be four.

N	Total Costs	Average	StDev	Tstatistic	Delta	Error	Runs
1	**4892610**	4892610	0,000	0,000	0,000	0,000	wrong
2	**4875030**	4883820	12430,934	12,706	111687,540	0,023	right
3	**4868337**	4878659	12536,956	4,303	31143,188	0,006	right
4	**4887699**	4880919	11189,897	3,182	17805,470	0,004	right
5	**4911859**	4887107	16892,593	2,776	20974,681	0,004	right

Table 21 Sequential procedure for determining run length

N	Service Level	Average	StDev	Tstatistic	Delta	Error	Runs
1	**0,816**	0,816	0,000	0,000	0,000	0,000	wrong
2	**0,814**	0,815	0,001414214	12,70620473	0,012706205	0,016	right
3	**0,813**	0,814	0,001527525	4,30265273	0,003794583	0,005	right
4	**0,813**	0,814	0,001414214	3,182446305	0,002250329	0,003	right
5	**0,817**	0,815	0,00181659	2,776445105	0,002255595	0,003	right

Table 22 Sequential procedure for determining run length using service level

N	Fill Level	Average	StDev	Tstatistic	Delta	Error	Runs
1	**0,754**	0,754	0,000	0,000	0,000	0,000	wrong
2	**0,776**	0,765	0,015556349	12,70620473	0,139768252	0,183	wrong
3	**0,759**	0,763	0,011532563	4,30265273	0,028648474	0,038	right
4	**0,755**	0,761	0,010230673	3,182446305	0,016279283	0,021	right
5	**0,762**	0,761	0,008871302	2,776445105	0,011015176	0,014	right

Table 23 Sequential procedure for determining run length using fill level