Improving the Waste Collection Problem using Sensorized Containers

by

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Abstract

Waste collection is a difficult problem faced by modern society. Environmental issues and increasing population resulting in more waste production and traffic congestion are examples of negative external effects. This thesis provides two useful models related to the waste collection problem. First, the insertion heuristic is used to solve the Vehicle Routing Problem (VRP). Second, the results from the VRP are used to determine where sensors should be implemented in order to decrease the number of overflow events.

The VRP program creates routes for each borough of the city of Rotterdam separately, for every day in one year. Waste accretion is modelled in order to make lists of locations that are eligible to be emptied. This modelling of waste accretion is done using data of inhabitants, waste production and the locations of the waste bins. Using two thresholds, a list with urgent locations and another list with eligible but not urgent locations is constructed. The starting point for a route is the location with currently the highest (estimated) amount of waste. The nearest insertion heuristic is then used to expand the routes until the vehicle's capacity is reached.

Using different numbers of vehicles, different results are obtained. When there are more vehicles available than needed, the program does not use all of them. Overflow occurs less when more vehicles are available. The overflow events are more likely to take place at locations that are either located very far away from their neighbours, have a high standard deviation or a large daily waste accretion. To improve the results, extensions have been added to the VRP including assigning an alternating number of vehicles to a borough and using the forecast of waste accretion to determine which locations should be visited.

Locations with a lot of overflow can be equipped with a sensor, meaning that the actual amount of waste in the bin is known and can be used when creating routes. Results show that significant improvements can be observed when sensors are placed in certain locations, especially when combined with the forecast extension to the VRP. Using the results of this thesis in further work, for example with the addition of a cost-benefit analysis, can lead to useful recommendations for municipalities and waste collection companies.

Preface

This thesis is the last requirement to fulfill the graduation requirements for the degree Master of Science in Operations Research and Quantitative Logistics at the Erasmus University Rotterdam. Deciding to start with a second Master and interrupting my research for the Master Thesis has been a challenge, and I am happy to be able to present to you this finished Master Thesis. I would like to express my gratitude to several people involved in the project.

First of all, I would very much like to thank Dr. Twan Dollevoet, my supervisor from the Erasmus School of Economics, for his supervision. I am very grateful for the opportunity I have been given by Dr. Dollevoet to finish my thesis during my pre-master Political Science. Thank you for taking the time to read and review all my work and for providing me with feedback.

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Lastly, I would like to thank co-reader, Dr. Wilco van den Heuvel, for his time to read and review my work.

I wish you much pleasure reading my Master Thesis.

A.M. Rentier
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Introduction

The collection of waste is an important and difficult problem faced by modern society. Environmental issues arise because of the emissions waste collection vehicles produce. The combination of many stops within a short period of time and engines that have to keep running during loading and unloading leads to a high amount of gas-emissions with air pollution and bad air quality as result. Over the years, the waste collection problem has become even more complex, especially in large cities, with increasing population density and different types of waste that need to be collected.

Other related problems concern the costs of collecting waste, congestion of traffic (especially in larger cities), noise disturbance, health issues and in extreme cases dangerous situations. The waste collection problem has been given a lot of attention over the past years and a substantial amount of improvements has been made. Especially technologies concerning the engines of the vehicles and the type of fuel they use have been improved. However, there is still a lot to gain in the routing and scheduling of the vehicles. More efficient routing leading to less distance travelled, an optimisation of the capacity usage of both bins and vehicles, using less vehicles and making less stops are examples of possible improvements.

1.1. Organization of Dutch Waste Collection

The collection of general waste in the Netherlands is the responsibility of the municipalities. They can either decide to collect the waste with their own service or ensure it is taken care of by third parties. The collection of waste is done with vehicles specially equipped for this task. Over the past years, a number of municipalities decided to switch to more eco-friendly vehicles. For example, both Rotterdam and Amsterdam make use of hybrid vehicles, Breda and Amsterdam have plans to start making use of vehicles powered by hydrogen in 2019 and municipalities in the province of Utrecht are using vehicles running on biogas. However, there is no national protocol for making waste collection more sustainable.

Different types of waste bins are used in Dutch society. Roughly, there are two main-types of bins available for household waste. In some municipalities, every household possesses its own bins for each different type of waste. Usually, the households are responsible for emptying their bins in a way that they need to transport them to a known location, for example the end of the street, such that they can be emptied by trucks. In bigger and more crowded cities, larger containers can be used that are located at a fixed location, accessible for a certain group of inhabitants that live close to this location who can easily access the bin, sometimes using a personal card. These containers can be situated (partly) underground and are emptied with a special type of truck.

1.2. Improving Waste Collection

Traditionally, waste collection operators rely on fixed routes with pre-determined pick-up frequencies, a so-called static planning approach. However, new technological innovations can provide us with real-time data about the waste accumulation at certain locations and improve the efficiency when collecting waste. When planning the routes beforehand, routes are constructed without using real-time data about the fill-level of the waste-bins. It may thus be possible that a bin is emptied without being (almost) full. Using sensors in bins, up-to-date data can be obtained, which can be used in dynamic scheduling and routing to decrease the number of stops and the distance traveled.

The purpose of this thesis is to present a model for the city of Rotterdam in order to analyse both the placing of sensors and construction of routes and improving these results using the real-time data of the sensors. Since over 2200 different locations in the city have general waste bins, a lot of different options for sensor placing are available. The main objectives in this case are minimizing the number of overflow-events, where bins are so full waste cannot be thrown in any more, minimizing the distance the vehicles travel and minimizing the costs for placing sensors. Taking these objectives into account, the central research question will be: How can sensor placement improve the waste collection by optimizing routes for waste collection vehicles?

1.3. Thesis Outline

The thesis is structured as follows: in Chapter 2 literature on the Capacitated Vehicle Routing Problem is reviewed, as well as literature on waste collection and sensorized containers. Chapter 3 contains a problem description followed by Chapter 4 explaining the solution method and Chapter 5 describing the data. The results for both parts of the model including some extensions and improvements are presented in Chapter 6. The conclusions are presented in Chapter 7 and followed by the discussion in Chapter 8.

2

Literature Review

This chapter provides an overview of relevant literature for this thesis. Since the objective of the thesis consists of two parts, namely optimizing the routes for waste-collection in addition to placing sensors in a cost-optimal way, literature on all aspects has been reviewed. First, a general overview on literature about optimising vehicle routing problems will be addressed before discussing specific literature about waste-collection itself. Lastly, literature regarding sensor-placing or using sensorized containers will be reviewed.

2.1. Vehicle Routing Problem

Vehicle Routing Problems (VRPs) have been studied widely since the first description in 1959 by Dantzig and Ramser. Many extensions of the VRP have been described in literature ever since, such as the Capacitated Vehicle Routing Problem (CVRP) where capacity constraints are added to the VRP. An extensive overview of the types of CVRPs has been supplied by Toth and Vigo [2002].

Since VRPs contain a Traveling Salesman Problem (TSP), the problem is NP-hard (Cordeau et al. [2007]). Different methods for solving (C)VRPs are available. The solution methods are divided over two main categories: exact solution methods and heuristics. Often used exact solution methods include branch-and-bound algorithms, branch-and-cut algorithms and dynamic programming. Heuristic approaches are divided between classical heuristics and meta-heuristic approaches such as simulated annealing and tabu-search (Toth and Vigo [2002], Laporte [2009]). Heuristic methods are researched intensively because solving the VRP with additional constraints can be time-consuming using exact methods.

Toth and Vigo [2002] divide classical heuristic methods over three categories: constructive methods, such as the savings algorithm proposed by Clarke and Wright [1964], two-phase methods and improvement heuristics. Rosenthal et al. [1977] analyse several heuristics for the TSP which can be seen as a VRP with only one vehicle. The cheapest and nearest insertion heuristics are methods where the result is at most two times as long as the optimal tour. The class of insertion heuristics is mentioned also in the work of Solomon [1987] who investigates insertion heuristics for the VRP with time-window constraints (VRPTW). In Solomon's [1987] analysis, insertion heuristics perform very well on practical problems and show a very stable behaviour. In Bramel and Simchi-Levi [1995], two versions of location based heuristics (LBH), applied to an approximation of the CVRP, namely the capacitated concentrator location problem (CCLP), are compared to several other methods from the literature such as tabu-search and Clarke and Wright's savings algorithm. One of the LBHs, the seed tours heuristic (ST), leads to generally better outcomes compared to findings in the literature from other methods with roughly the same running time.

2.2. Waste Management

A lot of research has been done regarding the optimization of waste collection VRPs. Since the vehicles for waste-collection usually have a maximum capacity, the problem is often treated as a CVRP. Important for the solution method is the type of waste that is collected. Kim et al. [2006] as well as Elbek and Wøhlk [2016] and Faccio et al. [2011] used the division into three major areas of waste proposed by Golden et al. [2002]. The three areas consist of commercial, residential and roll-on-roll-off waste collection. Residential waste collection involves the waste from private homes and usually yields routes with many stops and short distances in between those stops. The difference between commercial and roll-on-roll-off waste collection is the capacity of the bins. Both Elbek and Wøhlk [2016] and Faccio et al. [2011] deal with waste collected in bins along the streets and treat their problem therefore as a special case of residential waste collection.

Solving the VRP for waste-collection is done using various solution methods. Meta-heuristics are used for example in the research by Benjamin and Beasley [2010], who solve the problem using time windows and driver rest periods. They use three different methods, Tabu Search, Variable Neighbourhood Search and Variable Neighbourhood Tabu Search. Kim et al. [2006] studied a similar waste collection vehicle routing problem using an algorithm that makes use of Solomon's insertion algorithm. Elbek and Wøhlk [2016] use Variable Neighourhood Search as well.

2.3. Modelling Waste

In order to create routes for waste collection, fill-levels of waste bins need to be used as input. Most of the literature so far does not use real-time data and therefore models are used to estimate the current amount of waste present in every bin. Important factors influencing the accretion rate of waste are the number of inhabitants, the time of the year, GDP per capita and lifestyle (Faccio et al. [2011], Nuortio et al. [2006]). The quantity of waste is modelled as a stochastic variable for example by Elbek and Wøhlk [2016], who assume the daily filling follows a normal distribution, as do Coelho et al. [2014], Johansson [2006] in her analytical model and Bogh et al. [2014]. Nuortio et al. [2006] also treat the waste accumulation as being stochastic but base their estimations upon historical weight and route. Deterministic data is used for example by Kim et al. [2006].

2.4. Sensorized containers

Current waste collection routes can be improved using real-time data. Faccio et al. [2011] aim to use real-time data considering the waste-level of the bin and real time position and replenishment level of the vehicle when constructing their routes. They make use of real time input consisting of the bins replenishment level, bins visited, location of vehicles and vehicles replenishment level. However, in their model they assume every bin to be equipped with sensors. They conclude that the benefits of the proposed routing approach are higher than the costs for the implementation of the traceability technology.

Johansson [2006] uses data of 3000 Swedish containers containing level sensors and wireless communication equipment and evaluates different policies for scheduling and routing using data from the bins with sensors. Dynamic routing and scheduling yield better results than static scheduling and routing. However, the investment costs of sensors is not considered.
Both Vicentini et al. [2009] and Rovetta et al. [2009] studied sensorized containers in the area of Pudong, Shanghai as parts of an overarching project. Vicentini et al. [2009] focus on the technology needed in order to acquire information from the containers but they do not investigate how the information from the sensors can be used in the waste collection problem.

3
Problem Description

The general subject of this master-thesis is to present a model that will determine the best locations to place sensors in waste-bins in order to obtain as much cost reduction as possible compared to the costs of investing in these sensors. In order to present a solution for the sensor-placing problem, a Capacitated Vehicle Routing Problem (CVRP) needs to be considered first. The CVRP will be explained in more detail in this chapter as well as the assumptions that are made.

The problem has different objectives to take into account. At one side, customer satisfaction is an important part of the problem. Municipalities want to minimize the overflow of waste-bins to reduce the nuisance for their inhabitants. At the same time, the company collecting the waste wants to have as low costs as possible. Costs can be reduced by driving less kilometers, an optimisation problem that can be modeled as a vehicle routing problem. Costs can also be reduced by making less stops, and emptying less bins, possibly resulting in less routes or vehicles. Lastly, costs can be reduced by minimizing the number of times bins have overflow, since this can possibly result in penalties. Planning which locations to visit can be done based on estimates on how much bins are filled or on real-time data supplied by sensors inside the bins. Sensors in bins can give us real-time data which can be used to improve the routes. However, placing sensors will yield costs as well, so a cost-benefit analysis needs to take place in order to determine where sensors need to be placed and how many in order to reduce the costs as much as possible. The model provided in this thesis can be used to perform such a cost-benefit analysis.

3.1. Waste Collection

The waste is collected with vehicles that can empty the bins one by one with equipment attached to the vehicle. Since a limited number of vehicles is available, not all locations can be visited every day, so it needs to be decided which locations will be visited and emptied based on estimates considering the fill level of every bin. Installing a sensor in a bin will give us a real-time notion of the fill level of the bin. It is important to empty the bin before it overflows, but also to not empty bins that are not full at all. In order to decide which bins will be emptied, two thresholds to determine if the bins are eligible to be visited are applied to the estimates of the fill level of the bins. The first threshold, α, determines whether a bin is full enough to possibly visit and empty the bin. The second threshold, β, higher than α, determines if a bin is an urgent location, meaning it has to be visited soon in order to prevent the bin from overflowing. Bins less than α percent full will not be visited and thus cannot be emptied.

3.1.1. Locations

The set of locations that is used for the research consists of all places in the city of Rotterdam where waste bins are located (see Section 5). They are defined through x- and y-Rijkscoördinaten[1]. The locations are scattered over twelve different boroughs, which each consist of different neighbourhoods. For every location, the address, coordinates and the number and type of bins are defined.

[1]https://www.kadaster.nl/rijksdriehoeksstelsel

3.1.2. Bins

The bins in Rotterdam are divided into two categories, underground and half-underground. At one location, it is possible to have bins for paper, glass, general waste, plastic, clothes, etc. A vehicle collecting waste will only visit bins that contain the same type of waste, but can in theory empty multiple bins at one location if they contain the same type of waste. Multiple bins collecting the same type of waste at the same location will be treated in this model as being one large bin with the capacity of multiple bins. Moreover, it is assumed that both types of bins, underground and half-underground, can be emptied by the same vehicles and that the capacity of all types of bins throughout the city is equal.

For all bins, an estimated fill level can be calculated using the mean accretion per day. It is assumed that the filling at each location is stochastic and assumed to be distributed normally following Coelho et al. [2014] and Elbek and Wøhlk [2016]. However, the estimate of waste in a bin will only take the mean accretion per day into account and will differ from the actual amount of waste in a bin. The actual amount of waste inside a bin can be known when a sensor is placed within the bin. Placing sensors is therefore modelled as knowing the actual (modelled) amount of waste instead of the estimated amount of waste inside the bin.

3.2. Capacitated Vehicle Routing Problem

The capacitated vehicle routing problem differs from a general vehicle routing problem in the sense that the vehicles have a limited capacity for carrying goods, or in this case, waste. A consequence is that vehicles need to return to the depot when they are full before being able to visit another location. The goal of the Vehicle Routing Problem in our case is to create an optimal set of routes for a fleet of vehicles that minimizes the distance and overflow in order to pick up waste from a given set of locations. Since the problem is solved for each borough separately, these vehicles cannot visit different boroughs during one route.
The following constraints apply to the CVRP:

- A route starts and ends at the depot
- The total waste picked up in a route cannot exceed the vehicle capacity
- All locations on one route have to be located in the same borough

3.2.1. Routes

In order to collect waste, a set of routes needs to be constructed such that the total distance traveled is minimal. It is assumed that by minimizing the distance, the costs will be minimized as well. A route will be represented as follows: an empty vehicle will start at the depot and visit several locations in one borough until the capacity of the vehicle is reached, before returning to the depot. A route is therefore defined as a sequence of locations and the corresponding amount of waste that is collected at every location.

3.2.2. Vehicles

Different types of vehicles are available for the collection of waste. The vehicles have a maximum capacity, which can differ significantly. It is assumed that all vehicles have the same capacity for all boroughs. Changing this capacity of the vehicles influences the routes, since this determines how many locations can be visited on one route. Furthermore, since some locations contain so many bins that their capacity together exceeds the capacity of one vehicle, it is assumed that a vehicle will go to such a location and take only as much waste as its capacity allows, leaving residual waste at the location for another vehicle to pick it up.

3.3. Sensor Placing

Sensors can be used to give an accurate estimate of the amount of waste inside a bin. Placing sensors in every bin will give a detailed map of which locations to visit before they will overflow, whereas placing sensors in no bins at all will leave the scheduling of emptying bins based on estimates only. It needs to be decided which locations need to be equipped with a sensor, in order to gain as much information as possible. With the data received from the sensors, routes can be optimised.

3.4. Model description

An undirected graph is constructed for every neighbourhood. A node represents a location or the depot and every location is connected to the depot. Since it is possible to visit any location after another in the same borough as long as the capacity of the vehicle is not reached, all nodes are connected to each other. An edge (u, v) represents a trip from node u to node v. All locations are connected to each other and the depot with edges, constructing a complete graph. The weights of the edges represent the distances between two nodes. To make the notation of the model clear, the sets, parameters and variables that are used are stated and explained.

3.4.1. Sets

The set of boroughs consists of all the boroughs in Rotterdam, each of which is divided into smaller neighbourhoods. D is the set of all depots where vehicles can start and end their routes. For every borough b a set of vehicles M_b is available, as well as a set of locations where bins are located within the borough, V_b. The set V_b also includes the depot. For every day t in T, sets of locations $L_{t,b}$ and $K_{t,b}$ with estimated fill levels above α or β will be constructed as well as the set of locations with overflow (based on the actual fill level) on that day $O_{t,b}$. A set of routes $R_{t,b}$ will be constructed every day for every borough.

Set	Description	Indices
B	set of boroughs	b
N_b	set of neighbourhoods in borough b	n_b
V_b	set of nodes in borough b	v, u
D	set of depot(s)	d
M_b	set of vehicles for borough b	m
T	set of days	t
$L_{b,t}$	set of locations with estimated fill level above α on day t for borough b	i, j
$K_{b,t}$	set of locations with estimated fill level above β on day t for borough b	k
$O_{b,t}$	set of locations with overflow on day t for borough b	o
$R_{b,t}$	set of routes on day t for borough b	h

3.4.2. Parameters

Multiple parameters are needed to complete the model. The distance between two nodes u and v is $z_{u,v}$. The capacities of the vehicles, δ, and bins, q are parameters which are determined beforehand. Since the waste accretion is given in kilos and the capacities are stated in cubic meters, a conversion factor a is introduced of 500[2] kilos per cubic meter. In order to determine which bins need to be emptied, thresholds concerning the fill level are introduced, where α represents the minimum fill level a bin needs to have before being eligible to be emptied and β the fill level to qualify a bin as an urgent location that needs to be visited as soon as possible in order to prevent overflowing. Since vehicles have a maximum capacity and locations are visited based on estimates, b is introduced as the maximum percentage a vehicle can be filled in the planning. Every location j has been assigned a mean waste accretion μ_j per day to determine the estimated waste level at a location and a standard deviation σ_j used to determine the actual waste accretion (see Chapter 5).

[2]https://www.lne.be/sites/default/files/atoms/files/Overzichtstabelafvalstromen

Parameter	Description
δ	capacity of vehicles in m^3
q	capacity of bins in m^3
a	number of kilos per m^3 waste
α	minimum fill level to be emptied
β	fill level to qualify as urgent location
b	percentage vehicle can be filled
$c_{u,v}$	costs for travelling distance $z_{u,v}$ between node u and v
μ_j	mean daily waste accretion of location j
σ_j	standard deviation of the daily waste accretion of location j
r	rewarding costs incurred when a location is visited
p	penalty costs incurred when a location is not visited

3.4.3. Variables

For every location, the estimated amount of waste is represented by $e_{j,t}$ and the exact amount of waste by $s_{j,t}$. The total waste collected at a location j during a route on day t is $w_{j,t}$. After the routes for a day t have been constructed, the indicator $y_{j,t}$ indicates whether a certain location j is visited on day t. The variable z_j indicates if a location j has been equipped with a sensor or not. If this is the case, the estimated amount of waste at location j equals the exact amount of waste at that location.

Variable	Description
$x^m_{i,j,t} = \begin{cases} 1 & \text{if vehicle } m \text{ visits } j \text{ after } i \text{ on day } t \\ 0 & \text{otherwise} \end{cases}$	
$y_{j,t} = \begin{cases} 1 & \text{if } j \text{ is visited on day } t \\ 0 & \text{if } j \text{ is not visited on day } t \end{cases}$	
$z_j = \begin{cases} 1 & \text{if } j \text{ is sensorized} \\ 0 & \text{if } j \text{ is not sensorized} \end{cases}$	
$e_{j,t}$	estimated amount of waste at location j at day t
$s_{j,t}$	exact amount of waste at location j at day t
$w_{j,t}$	waste collected at location j at day t
$\phi^m_{j,t}$	expected amount of waste vehicle m carries when leaving location j on day t

3.5. Mixed Integer Programming Formulation

Using the above described sets, parameters and variables, a Mixed Integer Programming (MIP) formulation can be stated. A MIP problem is a special form of a Linear Programming (LP) problem, where certain variables are required to be integers. This MIP formulation describes the planning of the routes on a certain day $t \in T$ for a certain borough $b \in B$ and has to be solved for every day t in the planning horizon T. When solving the routing problem, the variables z_j, $e_{j,t}$ and $s_{j,t}$ are assumed to be given (in this paragraph). This MIP formulation does not describe the allocation or implementation of sensors, but only the planning of the routes to pick up waste from a given set of locations. Furthermore, this formulation does not allow bins to be partially emptied.

The objective is stated in equation (3.1) and describes the minimization of total costs. These costs consists of three parts: costs incurred when travelling from node i to node j ($c_{i,j}x^m_{i,j,t}$), penalty costs p incurred whenever a location j in $K_{b,t}$ is not visited and rewarding costs r incurred when a location j in $L_{b,t}$ is visited on a certain day.

Equations (3.2), (3.3), (3.4) and (3.5) represent the constraints. A flow constraint is introduced in equation (3.2), which indicates that the number of vehicles leaving a certain location j must equate the number of vehicles arriving at location j. The constraint given by equation (3.3) constrains the maximum waste a vehicle can pick up on a route; this can not be more than its capacity. Equation (3.4) states that if a location is visited (on a certain day), there must be a vehicle arriving at that location. Equation (3.5) prevents the occurrence of cycles by demanding that the total amount of waste picked up by a vehicle cannot decrease. The set $L'_{b,t}$ is introduced as the union of $L_{b,t}$ and the depot d. Lastly, both $x^m_{i,j,t}$ and $y^m_{j,t}$ have to take a binary value.

$$\text{minimize} \sum_{i \in L'_{b,t}} \sum_{j \in L'_{b,t}} \sum_{m \in M_b} c_{i,j} x^m_{i,j,t} + \sum_{j \in K_{b,t}} p(1 - y_{j,t}) + \sum_{j \in L_{b,t}} r(1 - y_{j,t}) \tag{3.1}$$

$$\sum_{i \in L'_{b,t}} x^m_{i,j,t} = \sum_{i \in L'_{b,t}} x^m_{j,i,t} \qquad \forall j \in L'_{b,t}\ \forall m \in M_b \tag{3.2}$$

$$\phi^m_{j,t} \leq \delta b \qquad \forall j \in L_{b,t}\ \forall m \in M_b \tag{3.3}$$

$$y_{j,t} = \sum_{i \in L'_{b,t}} \sum_{m \in M_b} x^m_{i,j,t} \qquad \forall j \in L_b \tag{3.4}$$

$$\phi^m_{j,t} \geq \phi^m_{i,t} + e_{j,t} - M(1 - x^m_{i,j,t}) \qquad \forall i \in L'_{b,t}\ \forall j \in L_{b,t}\ \forall m \in M_b\ M \gg 0 \tag{3.5}$$

$$x^m_{i,j,t} \in \mathbb{B},\ y_{j,t} \in \mathbb{B} \qquad \forall i \in L'_{b,t}\ \forall j \in L'_{b,t}\ \forall m \in M_b \tag{3.6}$$

4
Solution Method

The problem will be solved in two steps. First, a solution to the CVRP will be constructed using the nearest insertion heuristic as proposed by Rosenthal et al. [1977]. Next, an analysis on placing sensors in bins will be executed by simulating the real-time data of sensors to see if the routing can be improved.

4.1. Waste accretion

Every day, before constructing any routes, the accretion of waste is modelled. A distinction has to be made between the estimated amount of waste at a location and the actual amount of waste at a location, representing locations without and with sensors. The estimated amount of waste at any location grows with the same amount everyday, the mean (see Section 5.3). The actual accretion of waste is assumed to be stochastic and distributed normally. The standard deviation and mean of the location are used to determine the waste accretion at a location on a certain day. The estimated amount will therefore grow with the same amount of waste everyday, while the actual amount of waste accretion can differ daily. If a certain location has not been visited for a few days, the difference between the estimated amount of waste and the actual amount of waste can differ substantially, resulting for example in overflow while the estimates do not account for overflow or bins that are visited when they are not full enough yet. Using sensors in these bins can therefore improve the routes.

4.2. Classifying Locations

Before the routes are constructed, the amount of waste at all locations is examined. Different lists of locations are produced to decide which locations are eligible to be visited:

- A list of locations with a fill rate above α; these locations have reached the minimum fill rate to be emptied and are possible locations to add to routes (PL-list)
- A list of locations with a fill rate above β; these locations are urgent ($urgent$-list)
- A list of locations with overflow; a penalty may be incurred for these locations ($overflow$-list)

Note that locations in the $overflow$-list also appear on the $urgent$-list and in the PL-list. The $overflow$-list is mainly used to keep track of the locations that frequently have overflow. These locations might be equipped with a sensor in the second part of the model. The $urgent$-list is also part of the PL-list.

After classifying the locations, the routes will be constructed. Every day, a completely new set of routes will be planned. Every route will start and end at the depot, and the total amount of waste that is picked up cannot exceed the capacity of the vehicle. Since the routes are planned using the estimated amount of waste and not the exact amount of waste, a buffer is used to prevent the vehicles from overflowing. Vehicles can thus be planned to pick-up an estimated amount of waste not exceeding 90% of their capacity.

4.3. Constructing Routes

After the waste-accretion modelling, a set of routes is created daily and limited by the number of capacitated vehicles available. This number of vehicles differs per borough as the CVRP is solved for each borough seperately. The set of routes is thus constrained by the number of vehicles assigned to each borough. Assuming an unlimited number of vehicles is likely to lead to no overflow, but this case will still be considered to see how this influences the total distance travelled.

Per day, a maximum number of routes can be constructed equal to the available number of vehicles. Since some locations have the same mean, those locations will all have overflow at the same day if they are considered to be empty at the start of the routing problem. In order to prevent all bins to be full on the same day, a start amount of waste between 0 and the maximum capacity of a bin is randomly assigned to every location at the start of the program. The start amount is the same for both the estimated and exact amount of waste at a location. However, at the start of each day the waste accretion is modelled, so before the first routes are constructed the estimated and exact amount of waste will differ already.

4.3.1. Initializing a Route

Since every route needs to start and end at the depot, a route is initialized as a subtour consisting of the depot to depot trip only. A starting point for the route is chosen from the $urgent$-list. If the Nearest Insertion Heuristic is used to choose the first location to insert, all locations close to the depot will be used as starting points. The method chooses the location from the $urgent$-list with the highest estimated amount of waste as starting point f. If the $urgent$-list is empty, f will be the location closest to the depot from the PL-list. Adding the starting point f results in an initialization of a route consisting of the trip from the depot to the starting location and the return trip. Now the route can be expanded. A subtour T consisting of the depot d and f will be the input for the nearest insertion heuristic.

4.3.2. Nearest Insertion Heuristic

Given a graph (N, d) where all nodes are connected to each other, a tour T on a subset $S \subset N$ will be called a subtour of (N, d). A one node subset is treated as a tour without edges (Rosenthal et al. [1977]). Define the distance $d(T, u)$ between a subtour T and node u as min$\{d(x, u)$ for x in $T\}$. The Nearest Insertion Heuristic consists of the following steps:

1. Start with a subtour T and find a node u such that $d(T, u)$ is minimal.
2. Find nodes v and z in the subtour T such that $d(v, u) + d(u, z) - d(v, z)$ is minimal and insert u between v and z.
3. If all cities are inserted, stop. Otherwise, return to Step 1.

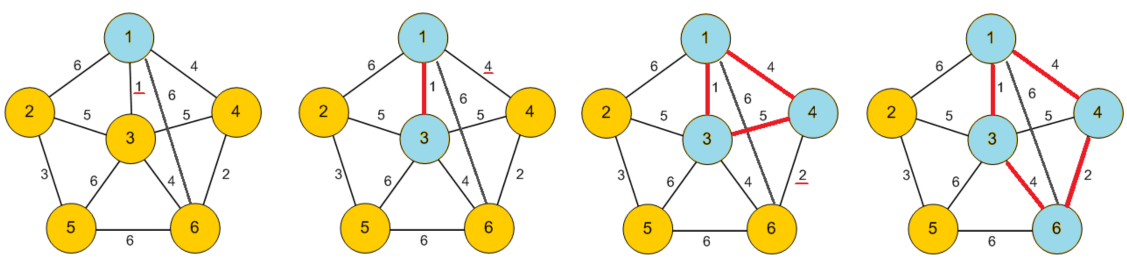

Figure 4.1: Example Insertion Heuristic

4.3.3. Applying Nearest Insertion Heuristic

After a starting point has been chosen to visit after the depot, the nearest insertion heuristic is used to expand the route until either the capacity of the vehicle has been reached, or until all locations are assigned to a route, meaning that the $urgent$- and PL-lists are empty.

When adding a location to a route, the distance is checked between all locations v already part of the route, including the depot d, and all locations u available to be added. The available locations are either part of the PL-list or the $urgent$-list. The location u with the lowest distance to any location $v \in T$, will be added to the route unless picking up the (estimated) amount of waste at location u violates the vehicle capacity constraint. In that case, no other locations are considered and the program ends and returns the route without adding a new location.

Next, the location needs to be inserted into the current route. A location can never be inserted before the first visit to the depot or after the last visit to the depot. When inserting a certain location u between v_1 and v_2, the distance between v_1 and v_2 ($d(v_1, v_2)$) does not have to be executed anymore, but the distances from v_1 to u ($d(v_1, u)$) and u to v_2 ($d(u, v_2)$) are added. The program inserts location u in the route such that $d(v_1, u) + d(u, v_2) - d(v_1, v_2)$ is minimal.

After inserting a location into a route, the program will again search for a location that is closest to any location already on the route, until the vehicle is full or all lists of locations are empty. Next, the location is deleted from the PL-list and possibly from the $urgent$-list if it was part of that list.

Before adding a new location to the route, it is checked whether emptying the bins at the location will not exceed the vehicle's capacity. If so, the new location will not be inserted and the route is returned to the list of routes. The next route will be initiated. If all lists of locations are empty, no locations have to be visited and the program will stop and return the current set of daily routes.

4.3.4. Visiting a Location

When a location is added to a route, both the estimated and the actual amount of waste are set to zero, since a vehicle will always empty a bin completely (which equals the actual amount of waste), except when the total amount of waste at a location is more than the available capacity of a vehicle. In that case, the vehicle takes as much as its capacity allows and leaves some residual waste at a location.

4.4. Extensions to the CVRP

In order to improve the CVRP, some extensions are added to the program to see if the results of the CVRP can be improved. Two different extensions are considered. First, it is considered if using a varying number of vehicles on different days improves the solution of the CVRP.

The second extension considers the forecasted accretion that will occur on the day the routes are executed. So, instead of planning the routes only based on their current fill level, the expected accretion is also taken into account. When making the PL-list and $urgent$-list, the current waste volume plus half the expected daily accretion is used to determine whether a location has surpassed the thresholds α and β. This might improve the results, because locations that are just below β on one day, can have overflow the next day if they have a large accretion rate. By taking this accretion into account, these nearly full locations can be visited before they flow over.

4.5. Sensor Placement

After creating waste-collection routes, placement of sensors will be analysed in order to improve the routes. When a sensor is placed at a certain location, it is assumed that the real-time fill level of the bins at that location is known. These fill levels are the exact amount of waste, modelled as stochastic variables and distributed normally. After the sensor placement, the program is run with and without sensors, with the same daily accretion amounts and start fill levels to calculate the improvement.

Assigning sensors to bins can decrease the number of overflow events and also decrease the number of visits to bins with a fill rate below α. Improvement can also be seen when the distance that is travelled lessens. On the other side, it is also possible that the distance travelled increases, if the locations equipped with a sensor have to be visited more often than the estimate would suggest because the actual fill level is higher than expected.

Sensors can be placed in every bin, but placing sensors in all bins will lead to high costs for placing, maintaining and repairing them. The results of the CVRP are used to determine the sensor placement policy. After running the CVRP for different boroughs with varying numbers of available vehicles, data about overflow events is available. In some boroughs, the overflow events are concentrated in certain locations, whereas other boroughs have a more evenly spread pattern of overflow. The placement of the sensors is analysed using two different methods, an ad-hoc method and the Simulated Annealing heuristic.

4.5.1. Ad-Hoc Method

Certain characteristics of a location are related to the number of times a locations has overflow during a year, most importantly the distance to the closest neighbour, the standard deviation of the waste accretion at the location and the mean daily accretion. Since the nearest insertion heuristic chooses the locations to visit based on distance, it can be intuitively explained that the locations far away from other locations are chosen very seldom to be included in a route. The only way that they are visited is when there are no other available locations, or when they are chosen as a starting point for a route. A high standard deviation and a high mean of the waste accretion can cause a location with an estimated fill level below β on a certain day to suffer from overflow on the next day. Knowing the exact fill level using a sensor can possibly prevent this from happening and these locations might thus be good candidates for a sensor. Based on such characteristics of the bins and the outcome of the CVRP it is decided in which bins to place a sensor.

4.5.2. Simulated Annealing Heuristic

The Simulated Annealing heuristic is a local search metaheuristic based on the physical process of annealing that consists of melting a material and then slowly cooling it again. The cooling process should be executed carefully in order to reach a perfect state with certain specific properties. Applying this to the sensor placement problem, the physical states of the annealing process correspond to the different solutions that the problem can have. In this case, a solution x represents a yes or no for all locations, indicating whether they do or do not have a sensor. For this solution, the solution value $s(x)$ can be determined by running the CVRP program. The solution value is a weighted combination of the total distance travelled in the CVRP program and the number of overflow events.

The heuristic that is used consists of the following steps:

1. Start with an initial solution and determine the solution value. The (overflow-)results from the CVRP section can be used to decide an initial solution. Set the optimal solution x^* to the initial solution.
2. Set T to a start value and decide the number of iterations I.
3. Find a direct neighbour solution x'. This means only one sensor can be added or removed from the solution. Running the CVRP program with the candidate solution x' and calculate the solution value.
4. Decide whether to accept the new solution. The candidate solution x' is always accepted if its solution value $z(x')$ is better than solution value $z(x)$ of the current solution x, and will be accepted with a certain probability p if it is worse.
5. Update T.
6. Check whether the current solution value $z(x)$ is better than the so far best solution value $z(x^*)$. In that case, update the best solution.

7. Repeat steps 3 to 6 I times.

Since the objective is to both minimize total distance travelled and number of overflow events, the solution value is calculated at the total distance (in kilometers) plus 0.5 times the number of overflow events. This means effectively that one overflow event is viewed as costing the same as travelling 0.5 kilometer. The Simulated Annealing heuristic is known for its ability to escape local minima because it can accept solutions worse than the current solution. These solutions are accepted with a certain probability p that depends on the difference between the current and the candidate solution as well as on T:

$$p(x, x', T) = -\mathrm{e}^{\frac{-\Delta(x,x')}{T}} \tag{4.1}$$

Here, $\Delta(x, x')$ denotes the difference between the objective values of x and x'. In every iteration, T will be decreased with a certain factor, thus lowering the probability to accept a worse solution.

5 Data

In order to make the results as useful as possible, data is collected about the waste collection of Rotterdam. The municipality of Rotterdam provides data about the locations of the waste collection bins, its boroughs and neighbourhoods and their inhabitants. Unfortunately, no historical data about the waste accretion has been obtained, but combining the available data is assumed to lead to accurate estimates.

5.1. Available Data

The data that is used is publicly available on the Rotterdam Open Data platform[1] and contains the locations of permanent bins for all types of waste in the city of Rotterdam. For every location the exact location is defined through Rijkscoördinaten, an address is stated and the borough and neighbourhood it is situated in are given. This results in a list of more than 3200 locations positioned throughout the city. Extracting the locations for general waste only, about 2200 locations remain. One depot is added to the list of locations, representing a real depot of a waste-collecting company that is considerably close to the city of Rotterdam. This depot is used for all boroughs. It is assumed that there is no depot located in the city itself.

Next to the locations, data about the waste production in the city of Rotterdam provided by the CBS (Centraal Bureau Statistiek[2]) was used and combined with numbers about the population to predict the waste-production. An overview of the waste-production per person over the last few years can be found in Figure 5.1.

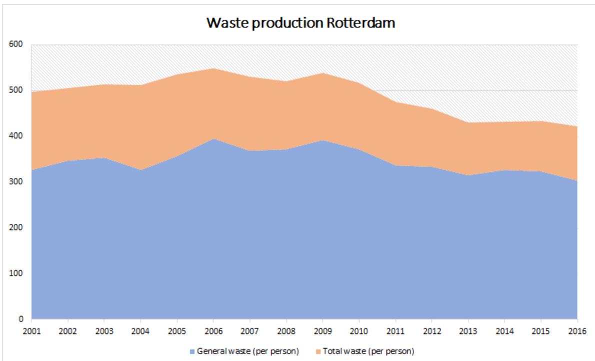

Figure 5.1: Annual waste production per person in Rotterdam

[1] http://rotterdamopendata.nl/dataset/vuilcontainers
[2] http://statline.cbs.nl/Statweb/

5.2. Assumptions and Data Pre-Processing

Since the density of both inhabitants and waste-bins is very different depending on the different boroughs and neighbourhoods, the data-set is split into different smaller sets all representing one borough. Two boroughs have such a small population, because they are mostly industrial area, that they are excluded. This resulted in ten sets representing the following boroughs: Centrum, Charlois, Delfshaven, Feijenoord, Prins Alexander, Kralingen-Crooswijk, Hillegersberg-Schiebroek, Ijsselmonde, Noord and Overschie (see Figure 5.2).

Figure 5.2: Boroughs of Rotterdam

Each of the boroughs is divided into multiple neighbourhoods. The waste-production given by the CBS is the mean amount of kilos general waste that is produced per year per person in Rotterdam. It is assumed that the inhabitants of Rotterdam will deposit their generated waste in a bin that is located in their own neighbourhood. Combining the population numbers of the different neighbourhoods with the numbers of waste-bins in that neighbourhood and the expected amount of waste produced per year per person, a mean waste-accretion per day per bin in a certain neighbourhood can be calculated. Note that these means are different for every neighbourhood even if they are located in the same borough. An example for the borough Delfshaven is given in Figure 5.3, where for each neighbourhood the number of inhabitants, number of bins and mean accretion per day per bin are stated.

Figure 5.3: Delfshaven inhabitants, bins, daily waste accretion per bin

5.2.1. Distance Matrices

Because one of the objectives of the research is to minimize the distance traveled, the distances of the locations to other locations and the depot have to be known. As mentioned before, for every location where bins are situated, Rijkscoördinaten are given. For every borough a Euclidean distance matrix is constructed using the Rijkscoördinaten of the locations and the depot.

5.2.2. Data Usage

From the ten available boroughs, four boroughs will be analysed using the previously introduced model because of time constraints. The boroughs that are chosen are Centrum, Charlois, Kralingen-Crooswijk and Prins-Alexander. These four boroughs are chosen because they have substantially varying numbers of locations and bins. An overview of the data for these four boroughs can be found in Table 5.1.

Table 5.1: Summary of Data for Analysed Boroughs

Borough	Acreage (km^2)	Inhabitants	Locations	Bins
Centrum	4.9	32442	155	313
Charlois	11.9	63764	450	700
Kralingen-Crooswijk	12.9	51955	342	559
Prins Alexander	18.6	94120	254	363

5.3. Modelling Waste-Accretion

Now that a mean waste accretion per day per bin is determined, this can be used to model the waste-accretion per location. A distinction needs to be made between the estimated and exact amount of waste in the bin. This represents the difference between bins with sensors and bins without. For bins with a sensor, the exact amount of waste inside is known, for bins without a sensor only the estimate is available which consists of the mean waste accretion per day times the number of days it has not been emptied.

As mentioned in the previous chapter, the exact waste-accretion is assumed to be stochastic and distributed normally. The exact amount of waste that is added to a bin is modeled using the mean and a standard deviation that are assigned to the location. The standard deviation is uniformly random chosen and between 5 and 25 percent of the mean. Locations with more than one bin are treated as locations with one large bin, also having a standard deviation between 5 and 25 percent of the mean. Since the standard deviation might have an impact on the overflow of a certain location, two different datasets are constructed with different standard deviations assigned to the locations.

5.4. Assigning Vehicles

Considering the number of inhabitants in a borough and the estimated waste production per year, an estimation of the number of vehicles that are needed to pick the waste up in one borough can be calculated. This estimation is the lower bound for the number of vehicles that need to be assigned to a certain borough. The estimated waste production per year is calculated by multiplying the mean waste production per person with the number of inhabitants in a borough. Dividing this by the capacity of a vehicle leads to an estimated lower bound of the number of vehicles needed to pick up all produced waste.

Since bins will be emptied completely when they are visited and not partially, and it is not always known how much waste is inside the bins at a location, a planned route will probably not pick up exactly as much waste as the capacity of the vehicle is. In addition, the planned routes will need to take a buffer into account since a certain location may contain more (or less) waste than estimated. The actual number of vehicles assigned to a certain borough will thus be higher than the above-mentioned lower bound.

6
Results

For four boroughs, the VRP program results will be discussed in the first section. After the VRP-results, the results for implementing the sensors will be discussed.

6.1. Results VRP

For four boroughs, different scenarios are calculated. First, the VRP program is executed with three different numbers of vehicles: too many vehicles, too few vehicles and just enough vehicles. These classifications are based upon the number of overflow-events that occur when running the program with that particular number of vehicles. Using too many vehicles will result in no or very little overflow, using too little vehicles will result in a lot of overflow and using just enough vehicles will lead to some overflow, but generally not so much. Sometimes the difference in number of overflow events when using one vehicle extra or less is significant. This aspect will be further investigated using an extended version of the VRP program where the number of vehicles is not the same for every day. Furthermore, the VRP program will be executed using the expectations for the next day to determine which locations will be visited on that day.

The results will be determined in part by the capacity of the bins and vehicles. In this model, the vehicles have a capacity of 18m^3, where the bins have a capacity of 4m^3. Bins can only be emptied when they have reached fill level α, which is in this model 60%, so the number of bins emptied on one route is limited to a maximum of 7.5. Since some locations contain multiple bins, routes do not have to make the same number of stops as the number of bins they empty.

Charlois

Charlois is one of the larger neighbourhoods in Rotterdam, and has 450 different locations for waste collection. In total, 700 bins are situated in Charlois, distributed over the 450 locations. Multiple bins on one location are treated as one larger bin. The Charlois VRP-program is run with 7, 8 and 15 vehicles on two different datasets. All programs are executed 10 times for two different datasets, where the only difference between the two datasets is the standard deviation assigned to the different locations. The program with 7 vehicles leads to between 900 and 2200 overflow events on a yearly basis, meaning 3.7 locations have overflow on one day on average, which is around 0,8% of all locations in the Charlois borough (see Table A.2). Using a maximum of 7 vehicles a day, the results show that in all runs except one (run 7, dataset 1, see Table A.2) all 7 vehicles are used every day the program runs. The second dataset performs slightly better looking at the number of overflow events, but the distance that is travelled daily and per route is shorter looking at Dataset 1. In both datasets, two locations (1727 and 1712) are obvious outliers looking at the number of overflow events compared to other locations. An overview of the top ten overflow locations can be found in Table A.3.

Using 8 vehicles, the number of overflow events decreases drastically; on average, 9.3 overflow events on a yearly basis. Not all available vehicles are used everyday, on average 7.47 routes are constructed a day. The distance travelled per day and per route is higher than in the program using 7 vehicles.

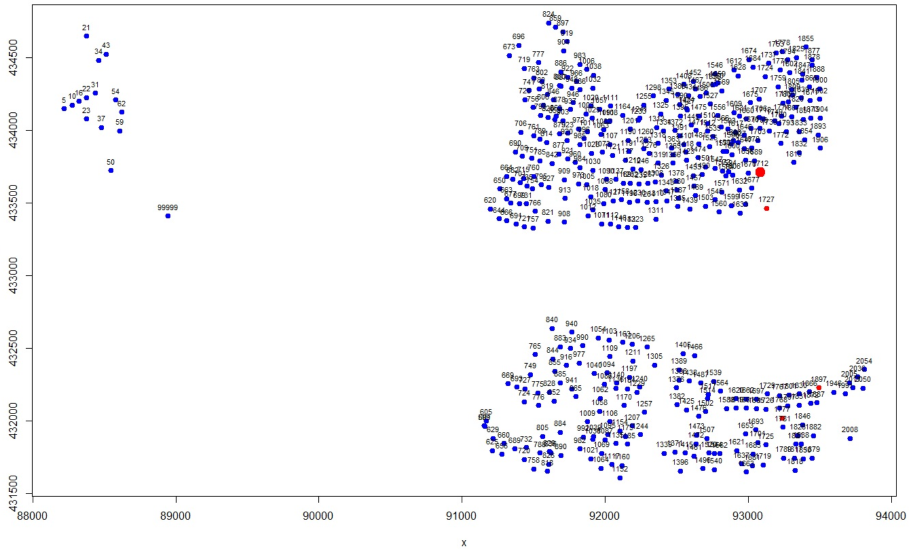

Figure 6.1: Example of overflow in Charlois in one year using 8 vehicles

In Table A.5, all locations with more than one overflow-event in total are shown. The locations 1712 and 1727 are still the locations with the most overflow (see Figure 6.1, where red dots mean that the location has suffered from overflow and a large dot means the location had overflow more than ten times (in a year)). One explanation for these two locations to have so much more overflow than the other locations is the fact that their mean waste accretion is a lot higher than other locations and they are the only two locations located in that particular neighbourhood.

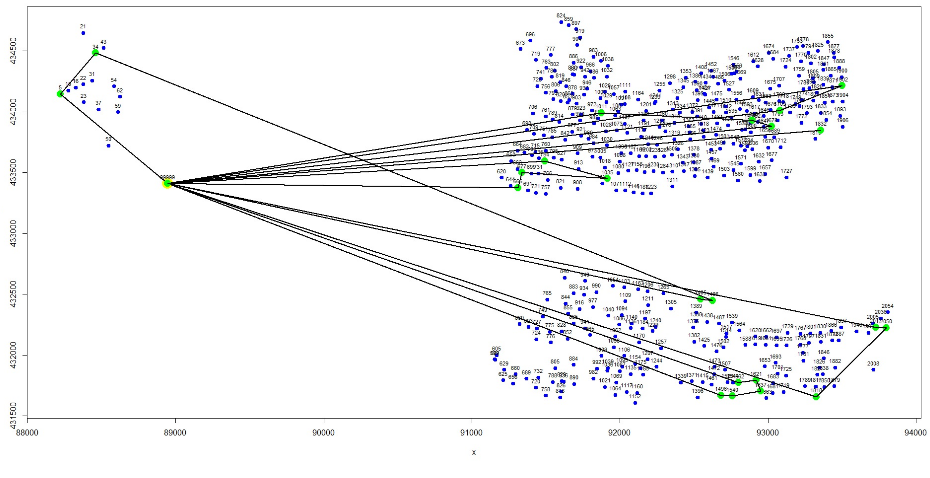

Figure 6.2: Example of set of routes in Charlois using 7 vehicles on one day

The last program used 15 vehicles. Not all vehicles are used everyday, since the program stops as soon as the lists with available locations are empty. On average, 7.67 vehicles are used when the first dataset is used, and 6.63 when the second dataset is used. The average number of vehicles used on a daily basis is thus very close to the number of vehicles used before. Interestingly, for dataset 2, the average number of vehicles is lower than 7 vehicles, while the total number over overflow events over ten runs was 3. Because the program can adjust the number of vehicles daily, based on the number of urgent locations, the number of overflow events becomes almost zero, while the used number of vehicles does not increase a lot. The distance per route is higher than the programs with 7

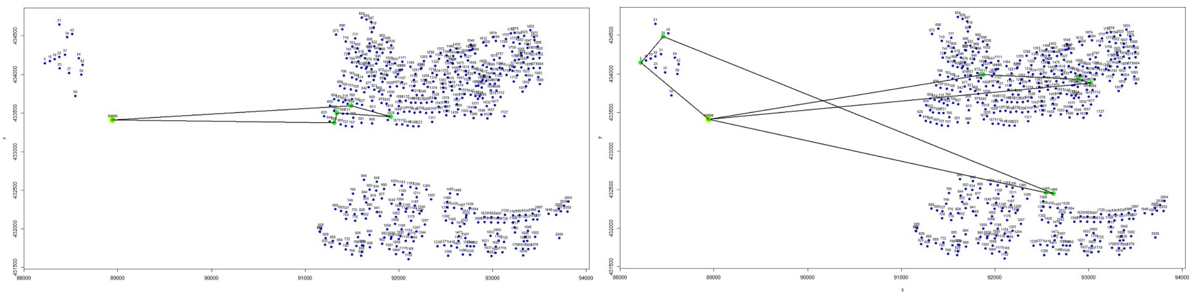

Figure 6.3: Detail of routes in Charlois using 7 vehicles on one day

or 8 vehicles. Since the program with 15 vehicles can always visit all locations that have reached the threshold to be emptied, the first routes will be chosen in such a way that the distance is minimized, but the last routes consist of routes that might be further apart from each other. An example of a set of daily routes is shown in Figures 6.2 and 6.3. Table 6.1 gives an overview of the above described results.

Table 6.1: Summary of Charlois VRP Results

Number of available routes	**Overflow per year**	**Distance per route (km)**	**Total distance per year (km)**
Dataset 1			
7	1420.8	7.5	19264
8	10.3	8.2	22332
15	0.4	8.3	23356
Dataset 2			
7	1259.3	7.5	19276
8	8.3	8.2	22334
15	0.3	8.6	20715

Centrum

For the borough Centrum, the program is run using 4 vehicles, 5 vehicles and 15 vehicles on two datasets where the only difference between the datasets is the standard deviation assigned to the locations. Using 4 vehicles will result in 90 to 100 overflow events on average on a yearly basis (see Table A.8). Almost half of the overflow events occurs at the same location (see Table A.9). A possible explanation might be that this location is far away from any neighbouring locations, and will not be chosen by the heuristic to be inserted into a route. An example of the overflow after one year is shown in Figure 6.4, where red dots mean that the location has suffered from overflow and a large dot means the location had overflow more than ten times (in a year). It is clear that location 1959 is far away from other locations and has more overflow. Figure 6.5 shows a set of routes in the Centrum neighbourhood during one of the days where 4 vehicles are used.

Using 5 vehicles decreases the number of overflow events drastically, going from roughly 90 to 100 a year to 28 (a decrease of around 70%). Not all 5 vehicles are used everyday since the average number of vehicles that is used is 4.3 (see Table A.10). The distance per route is slightly higher when using more vehicles. With 15 vehicles, the distance per route increases a little bit (roughly 50 meters), but the number of overflow events decreases further and now only takes place in one location, the same location as named before, 1959 (see Table A.12 and A.13). The number of vehicles used is 4.4 per day on average, where the number of vehicles that is used differs a lot between days. Because the number of vehicles assigned to the Centrum neighbourhood is rather small, adding or removing one vehicle from the program relatively has a large impact on the capacity. Running the program with 3 vehicles leads to around 42,000 overflow events, nearly 115 locations per day, which is more than 75% of the locations in Centrum.

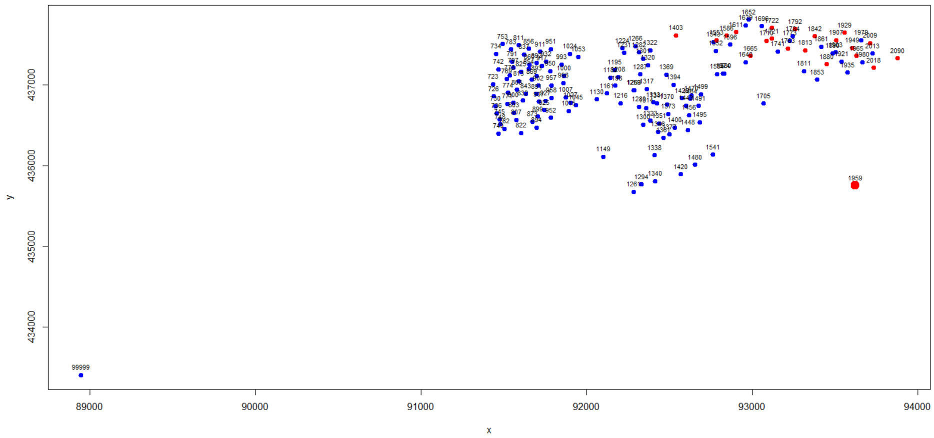

Figure 6.4: Example of overflow in Centrum in one year using 4 vehicles

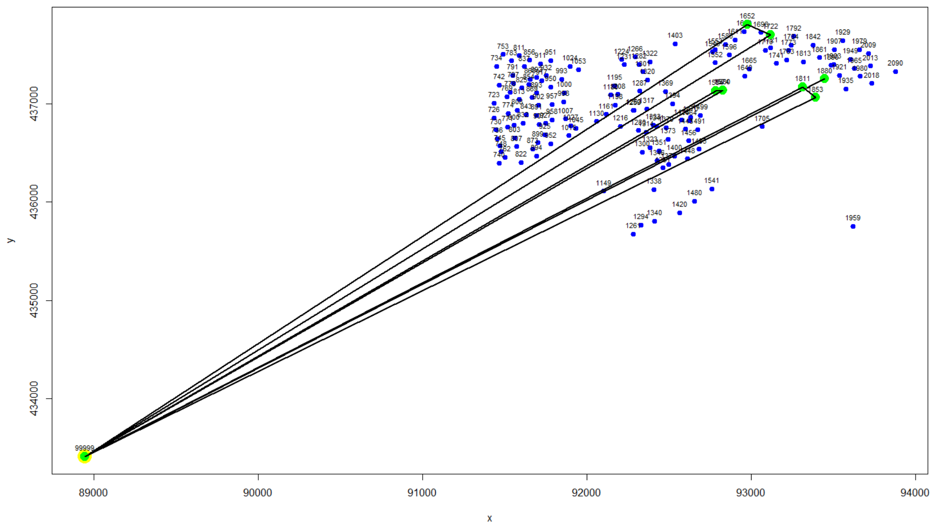

Figure 6.5: Example of set of routes in Centrum using 4 vehicles on one day

Table 6.2: Summary of Centrum VRP Results

Number of available routes	Overflow per year	Distance per route (km)	Total distance per year (km)
Dataset 1			
4	99.7	10.9	15966
5	28.1	11.2	17608
15	7.5	11.2	17912
Dataset 2			
4	91.5	11.0	15994
5	28.2	11.2	17570
15	10.4	11.2	18664

Prins Alexander

The borough Prins Alexander, located in the northeast of Rotterdam, has 364 bins distributed among 254 locations. The VRP program is executed using 6, 7 and 15 vehicles. Using 6 vehicles (see Table A.14), more than 11000 overflow events occur on a yearly basis, more than 30 a day (which is almost 12% of all locations in the borough). Adding one more vehicle eliminates almost all overflow (see Table A.15), leading tot an average of 4 overflow events on a yearly basis. The average route is 700 to 800 meters longer compared to the routes in the program with 6 vehicles. On average, the program uses 6.5 vehicles per day. When 15 vehicles are available, on average 6.7 vehicles are used per day and the length of the routes is comparable to the route when using 7 vehicles (see Table A.16). An example of the routes that are created can be found in Figures 6.6 and 6.7.

In Figure 6.6 all 7 routes are shown for a certain day in the program, while Figure 6.7 shows the first route on the left and the second and third route on the right to give a clearer example. It can be observed that the first route consists of three locations located very close to each other (note that not all locations have to be visited, therefore the routes have to be constructed considering all eligible locations), and the second and third route visit locations also relatively close to each other. In Figure 6.6 the last routes seem to visit locations that are not very close to each other, but this is a consequence of the heuristic: all close eligible locations are already visited and locations further away still need to be visited and will be included in the routes.

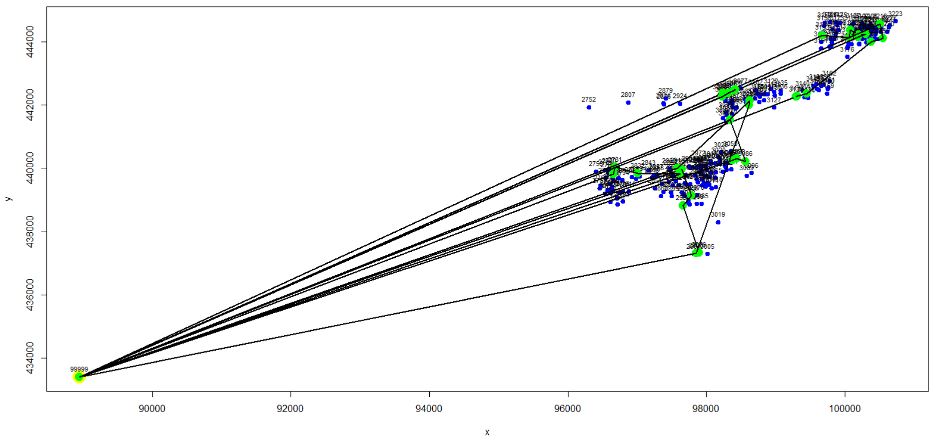

Figure 6.6: Example of set of routes in Prins Alexander using 7 vehicles on one day

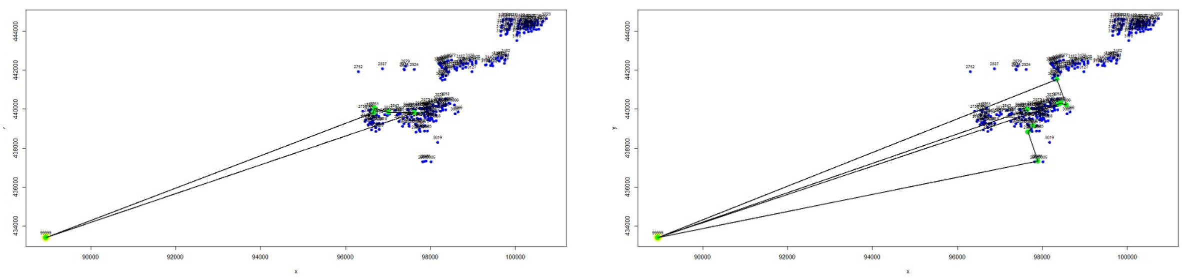

Figure 6.7: Detail of routes in Prins Alexander using 7 vehicles on one day

In contrast to the previous boroughs, there are no locations that have significantly more overflow than other locations as can be concluded after the VRP program is executed. The overflow events in the borough Prins Alexander are divided among a lot of different locations and are not centered in certain locations. Therefore, no tables with overflow events are given for Prins Alexander. An overview of the results for 6, 7 and 15 vehicles is given in Table 6.3. The distance per year differs depending on the number of vehicles that are available. Going from 6 to 7 routes per day, on a yearly basis more than 6000 extra kilometers are travelled, leading to a drastic decrease of overflow events. With 15 vehicles, even less overflow occurs (see Table A.16), but the total distance travelled is almost the same compared to the results for 7 vehicles.

Table 6.3: Summary of Prins Alexander VRP Results

Number of available routes	Overflow per day	Overflow per year	Distance per route (km)	Total distance per year (km)
Dataset 1				
6	30.3 (11.8 %)	11048	25.6	56131
7		4	26.4	62654
15		1	26.2	64131
Dataset 2				
6	33.6 (13.2 %)	12277	25.6	56123
7		4.3	26.3	62409
15		0.4	26.4	64203

Kralingen-Crooswijk

For Kralingen-Crooswijk, the VRP program is executed on one dataset using 6, 7 and 15 vehicles (see Table A.17, A.18, A.19). Kralingen-Crooswijk is a borough large in acreage, but has a lake and forest located in it so that the number of vehicles that is used is less than used for the borough Charlois, which is smaller in acreage. Looking at the results, it is clear that using 6 vehicles leads to a lot of overflow, around 7 locations a day. Adding only one vehicle can almost prevent all overflow from happening. It is interesting to notice that when 15 vehicles are available, the overflow completely disappears and the distance per route only increases with roughly 100 meters. On average, 6.6 routes are planned for each day when there are 15 available. The overflow in the borough Kralingen-Crooswijk is evenly distributed among different locations and does not have any clear outliers. An overview of the results for Kralingen-Crooswijk is given in Table 6.4.

Table 6.4: Summary of Kralingen VRP Results

Number of available routes	Overflow per day	Overflow per year	Distance per route (km)	Total distance per year (km)
Dataset 1				
6	6.97 (2.03 %)	2545	14.2	31206
7		0.7	14.7	34644
15		0	14.8	35852

6.2. Extensions to the VRP

6.2.1. Alternating Number of Vehicles

For some boroughs, the difference in results when adding one vehicle is substantial. For Charlois and Kralingen-Crooswijk, as can be seen in Table 6.1 and 6.4, when one vehicle more is available on a day the overflow decreases drastically but the total distance travelled per year increases (for example with 11% in Kralingen-Crooswijk). Moreover, when the number of available routes is 15, in Charlois the daily average used is 7.5, and 6.6 in Kralingen-Crooswijk, leading to almost no overflow events on a yearly basis. An alternating number of vehicles might decrease the number of overflow events while not increasing the total distance travelled a lot.

Charlois

For the borough Charlois, the previous results show that when 7 vehicles are used a lot of overflow occurs, but when 8 vehicles are used the number of overflow events drastically decreases and the actual average number of routes on a day is 7.5. However, the mean distance per route is 600-700 meters higher when using 8 vehicles compared to the program using 7 vehicles. To see if these results can be improved, the number of vehicles is alternated between days. On even numbered days, 7 vehicles are available, on odd numbered days there are 8 vehicles available.

The alternating program uses on average a little less vehicles per day than the program where 8 vehicles are available on every day. The number of overflow events is roughly double the number of overflow when using 8 vehicles, but the distance per route is slightly less. However, on a yearly basis, the total distance travelled by the alternating program is about 500 kilometers less compared to the program with 8 vehicles.

Table 6.5: Summary of Charlois VRP Extension Results

Number of available vehicles	**Number of routes per day**	**Overflow per year**	**Distance per route (km)**	**Total distance per year (km)**
7	7	1421	7.54	19264
7/8	7.4	21.4	8.12	21833
8	7.5	10.3	8.20	22332

Kralingen-Crooswijk

For Kralingen-Crooswijk, the program is executed using 6 and 7 vehicles alternately and using 7 vehicles once every three days. As the number of vehicles available per day increases, the total distance per year also increases, while the number of yearly overflow events decreases. Using 7 vehicles once every three days leads to 1251 km less distance travelled on a yearly basis compared to having 7 vehicles available every day (3.75% decrease). However, the average number of yearly overflow events is 30 times larger than when 7 vehicles are used. Using 6 and 7 vehicles alternately decreases the yearly distance with 740 kilometers compared to using 7 vehicles every day and still only leads to 2.4 overflow events on a yearly basis. An overview of the results based on ten runs for each different number of vehicles can be found in Table 6.6.

Table 6.6: Summary of Kralingen-Crooswijk VRP Extension Results

Number of available vehicles	**Number of routes per day**	**Overflow per year**	**Distance per route (km)**	**Total distance per year (km)**
6	6.00	2545	14.25	31206
6/6/7	6.28	21.4	14.57	33393
6/7	6.34	2.4	14.65	33904
7	6.45	0.7	14.73	34644

6.2.2. Using Forecast

The results of the VRP program can possibly improve by considering the forecasted accretion of the next day when planning a route. For the boroughs Charlois and Centrum, the results using forecast are compared to the results without using forecast.

Centrum

In Table 6.7 the results over the VRP (average on ten runs) with and without forecast are shown. Using the same number of routes on a day, the total distance per year increases with 34 km (an increase of 0.21%) while the overflow decreases with 42 instances per year, a decrease of more than 42%.

Table 6.7: Centrum using Forecast

Forecast	Number of vehicles	Overflow per year	Distance per route (km)	Total distance (km/year)
without	4	99.7	10.94	15966
with	4	57.7	10.96	16000

Charlois
For Charlois, the results are compared for 7 routes a day. The same trend can be observed as above. The overflow per year decreases with 38%, while the distance per route and the total distance per year increase only a little.

Table 6.8: Charlois using Forecast

Forecast	Number of vehicles	Overflow per year	Distance per route (km)	Total distance (km/year)
without	7	1421	7.54	19236
with	7	869	7.55	19298

6.3. Results Sensor Placement Ad Hoc Method
After the results of the VRP program, it is analysed if implementing sensors can improve the waste collection. Adding a sensor to a certain location means that it is possible to use the actual amount of waste in the bins at these locations instead of an estimate when constructing the routes. The results for the VRP with sensors are constructed as follows: first, the program is run without any sensors, where the waste-accretion at every location for every day is saved, as well as the start-amount of waste of every location; next, the program is run again with sensors, using saved waste-accretion and start amount of waste as in the program without sensors, so that the difference between results can not be explained by differences in start amount of waste or waste accretion. In the results, the routes for the first few days are thus very similar, since only the locations with a sensor have a different amount of waste, and routes without any sensorized locations will be the same. After a few days, the program with sensors will make different routes because it has more information about the sensorized locations.

6.3.1. Implementing Sensors at All Locations
Prins Alexander
Since the VRP results for the borough Prins Alexander show that there are no locations with significantly more overflow than other locations, the program is executed with sensors on and off at all locations to see if this improves the results. The results can be found in Table A.20. In the first ten runs, 6 vehicles are available. Averages over ten runs are given in Table 6.9. For 6 vehicles, both the total distance travelled per year as well as the overflow per year decreases. However, the number of overflow events is still very high. When 7 vehicles are available, the results when sensors are used are better than without sensors. In all runs, the number of vehicles used per day is lower with sensors, as is the total distance travelled in a year which is more than 450 kilometers less on a yearly basis.

Table 6.9: Prins Alexander All Locations Sensorized Averages

Vehicles	Sensors	Number of routes per day	Total distance (km/year)	Distance per route (km)	Overflow per year
6	off	6	56139	25.64	11516
	on	6	56025	25.60	10571
7	off	6.51	62623	26.37	5.3
	on	6.41	62153	26.57	4.4

6.3.2. Implementing Sensors at Locations with Overflow

Charlois

Using the results from Table A.2 and Table A.3, sensors are implemented at the locations with the most overflow in the ten runs of the VRP program using 7 and 8 vehicles. In Table 6.10, the results using 8 vehicles for Dataset 1 with and without sensors are shown.

Table 6.10: Charlois Sensorized Locations based on Overflow for 8 vehicles (average over 10 runs)

Sensors	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year
0	2726.1	22279	8173	12.2
2	2724.5	22338	8199	7.0
5	2724.2	22331	8197	6.8
10	2727.3	22406	8215	6.6
20	2724.5	22355	8205	5.9
30	2724.0	22381	8216	5.2

For all runs, the program has less overflow when sensors are used. As can be observed in Figure 6.8, the overflow slowly decreases as the number of sensors increases. Using only two sensors, at the two locations with the most overflow, the overflow per year decreases with more than 42% while the distance per route and total distance per year slighly increase. However, while the decrease of overflow between 0 and 30 sensors is 57%, the increase in distance is only 0.5%. The slight increase in distance can be a result of the sensorized locations, since the program has accurate information about these locations and can be forced to visit these locations more often than it would be visiting based on estimates.

Figure 6.8: Charlois Sensorized Locations based on Overflow for 8 vehicles (average over 10 runs)

Looking at the results for 7 vehicles (see Figure 6.9), the results are slightly different than with 8 vehicles. The overflow per year only decreases when 5 or 10 sensors are implemented, but the decrease is not as significant as in Figure 6.8. The total distance per year does however decrease more when more sensors are used.

Table 6.11: Charlois Sensorized Locations based on Overflow for 7 vehicles (average over 10 runs)

Sensors	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year
0	2555	19288	7549	1386
2	2555	19263	7539	1406
5	2555	19269	7542	1343
10	2555	19249	7534	1361
20	2555	19234	7528	1457
30	2555	19221	7523	1497

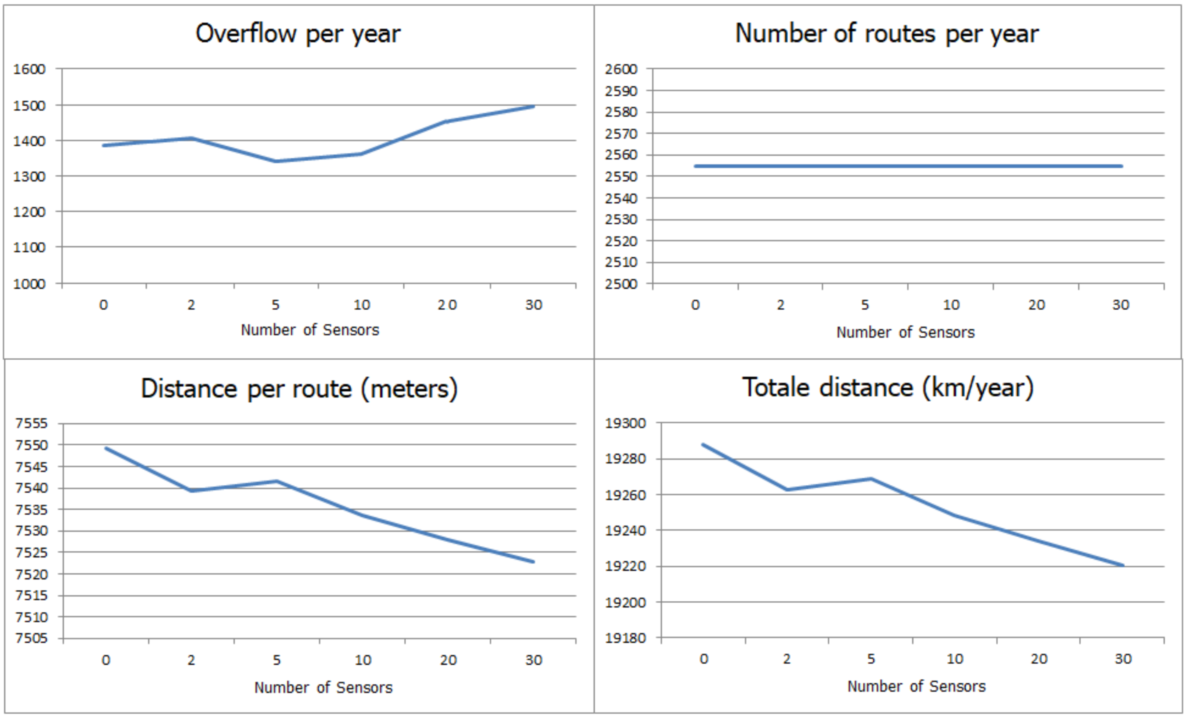

Figure 6.9: Charlois Sensorized Locations based on Overflow for 7 vehicles (average over 10 runs)

Extension VRP based on Forecast

Again, it is determined whether the results can be improved using the forecast of accretion. The average results over ten runs can be found in Table 6.12. The results with and without forecast are compared in Figure 6.10. For every number of sensors, the overflow per year is significantly lower when the forecast is used. On average (over all number of sensors), the decrease is more than 400 overflow events, more than 30% less than the overflow without using the forecast. The total distance is a little bit more when using the forecast, but the difference is lower than 100km on a yearly basis for all number of sensors.

Table 6.12: Charlois Sensorized Locations based on Overflow for 7 vehicles using forecast (average over 10 runs)

Sensors	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year
0	2555	19340	7570	869
2	2555	19341	7570	978
5	2555	19356	7576	904
10	2555	19318	7561	992
20	2555	19313	7561	1085
30	2555	19298	7553	1033

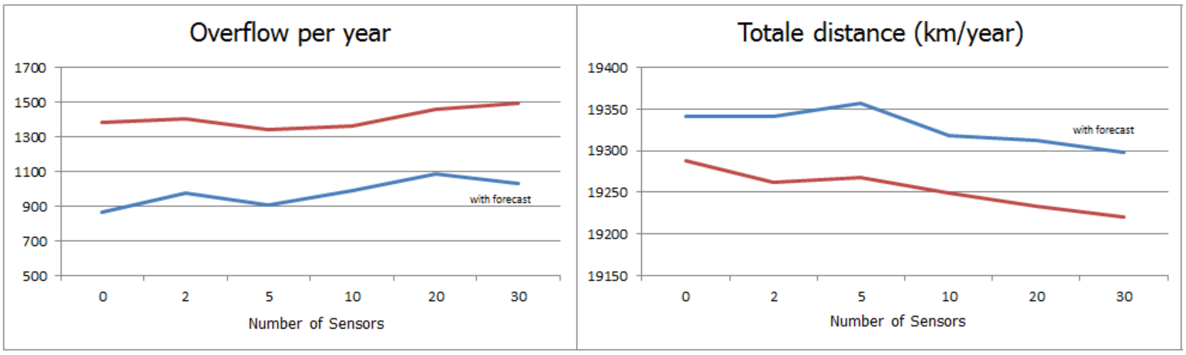

Figure 6.10: Charlois Sensorized Locations based on Overflow for 7 vehicles using Forecast (average over 10 runs)

Centrum

For the borough Centrum, there is one location with a lot of overflow (see Tables A.9, A.11, A.13). An analysis is performed on adding a sensor to this location, 1959. In Table 6.14 the results are shown with and without the sensor (average over ten runs). The overflow per year decreases with 32% over all locations, and with 63% at the sensorized location. This only accounts for 11 extra kilometers on a yearly basis, which is negligible on the total yearly distance. An impression of the overflow is shown in Figure 6.11, where the decrease in overflow at location 1959 can be observed clearly.

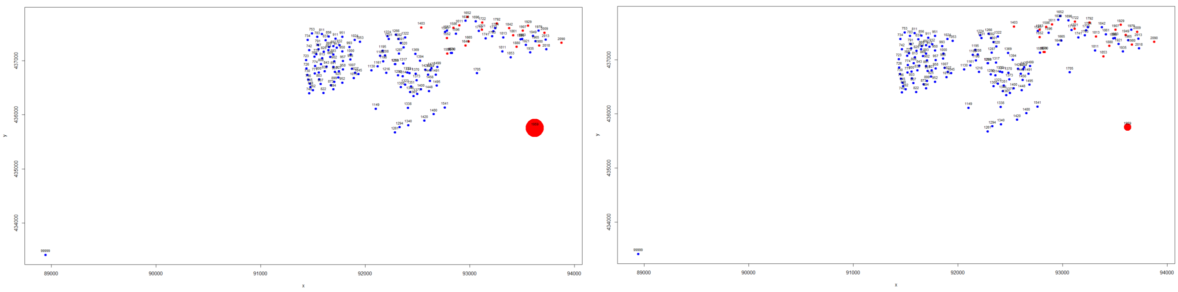

Figure 6.11: Yearly overflow in Centrum without (left) and with sensor

Table 6.13: Centrum Sensorized Location based on Overflow for 4 vehicles (average over 10 runs)

Sensors	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year (at sensorized location)
0	1459.5	16011	10970	107.1 (66.8)
1	1459.6	16022	10977	73.3 (25)

Extension VRP based on Forecast

Since adding the sensor does not remove all overflow at the sensorized location, there is still room for improvement. Using the accretion forecast, the same sensor analysis is executed. The total overflow per year is considerably lower when using the forecast. Even without using a sensor, the overflow is almost 50% lower compared to the overflow when the forecast is not used. When a sensor is implemented at location 1959 only 6.6 overflow events per year remain, less than 10% of the 57.7 overflow events occurring without the sensor.

Table 6.14: Centrum Sensorized Location based on Overflow using Forecast for 4 vehicles (average over 10 runs)

Sensors	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year (at sensorized location)
0	1459.6	16000	10963	57.7 (53.5)
1	1458.9	16010	10975	6.6 (3.2)

6.4. Results Sensor Placement Simulated Annealing

Using the Simulated Annealing Heuristic, an optimal sensor placement solution is searched for. The heuristic has 150 iterations and in every iteration the VRP simulation is run for 150 days. In every iteration a neighbouring solution (candidate solution) is analysed: one location is randomly chosen, and at this location a sensor is added if there was not one already, and removed if the location already had a sensor. With this candidate solution, consisting of a vector with zeros and ones where a one represents a placed sensor at a location, the VRP simulation described before is executed for 150 days. Routes are planned for these 150 days, and for the locations that have a sensor now again the exact amount of waste is known. The total distance travelled in kilometers in all routes in the 150 days and the number of overflow events divided by two combined gives the solution value.

If the candidate solution is not accepted, the current solution does not change, and the next neighbouring solution is considered. At the end every iteration, T (usually an indicator for temperature) is decreased by applying $T_{n+1} = 0.95T_n$. This influences the acceptance probability, which depends on the difference between the candidate and current solution and T (see Equation 4.1). The initial solution consists of no sensors at all, and in every iteration one sensor can be either added or removed. Effectively this means that it would take at least as much iterations as there are locations to arrive at a solution where all locations have a sensor.

Centrum

In Table 6.15, the obtained solutions that are found in ten different runs of the Simulated Annealing program for the Centrum borough are presented. The number of sensors that are used in the best solution varies a lot, differing from 0 in run 1 and 5 (which means the initial solution was the best solution found) to 72 sensors used in run 7 and 10.

Figure 6.12 shows the different candidate, current and best solutions for two different runs. The horizontal axis represents the number of iterations, while the vertical axis represents the solution value, consisting of the total number of kilometers travelled in the 150 days that the program runs and the 0.5 times the number of overflow events. On the left side of Figure 6.12 the results are shown for run 5, on the right hand side for run 7. In run 5 the initial solution is actually the best obtained solution. The heuristic proposes a new candidate solution in every iteration, represented by the red line in the

Table 6.15: Centrum 4 vehicles 150 days 150 iterations

Run	Initial Solution	Best Solution	Number of Sensors (best solution)
1	6552	6552	0
2	6599	6552	37
3	6558	6531	20
4	6553	6551	12
5	6556	6556	0
6	6612	6550	36
7	6582	6530	72
8	6567	6520	20
9	6580	6546	8
10	6582	6529	72

figure. It is clear to see that the heuristic actually accepts a worse solution multiple times. In run 7, the best solution gradually improves (see the two right graphs in Figure 6.12).

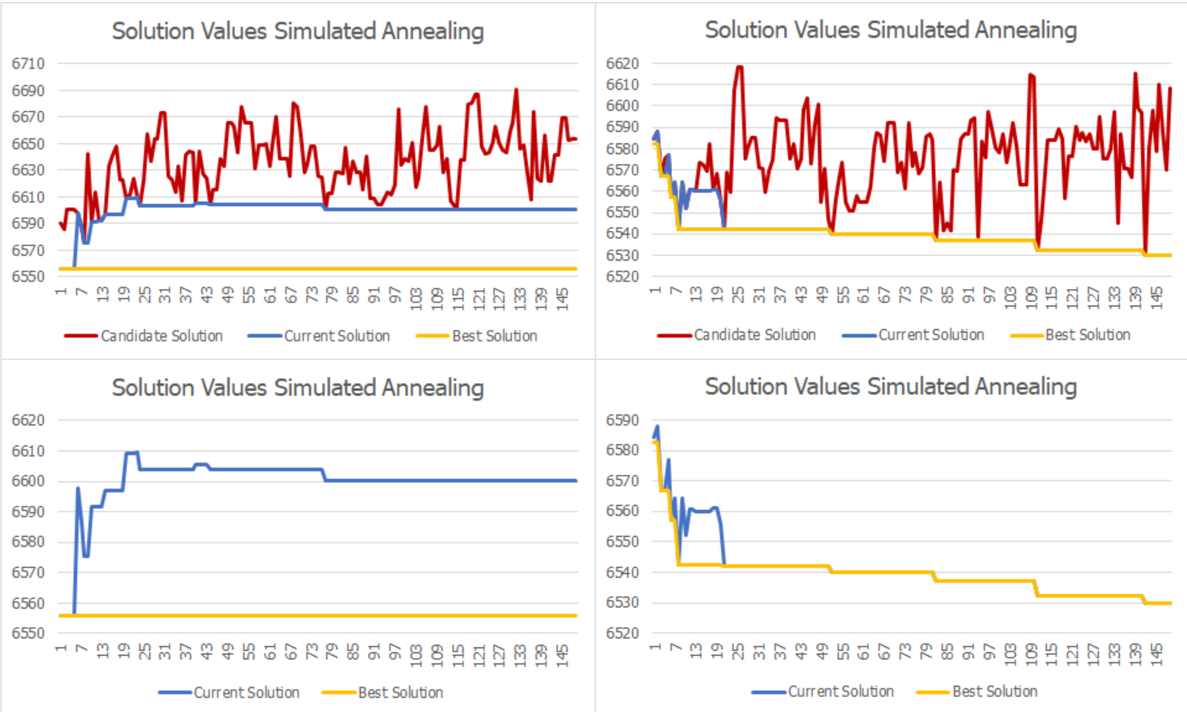

Figure 6.12: Centrum Simulated Annealing results for 4 vehicles (150 iterations)

In Figure 6.13 (left), the solution value and number of sensors used to obtain that solution value are plotted against each other. The blue line represents the number on sensors that are placed at various locations (see vertical axis on the right), while the red line represents the solution value. There does not seem to be a clear relation. Adding more sensors does not necessarily lead to a lower solution value, although it can be observed that lower solution values are obtained when more sensors are placed. A possible explanation for the absence of any clear relation might be that not all sensors are valuable, only for certain locations a sensor can have added value. Figure 6.13 (right) shows the number of sensors compared to the number of overflow events. An increase in number of sensors seems to lead to a decrease of overflow events, confirming earlier observed trends (see Section 6.3.2).

Comparing the best obtained solutions of all ten runs, it can be analysed which locations are equipped

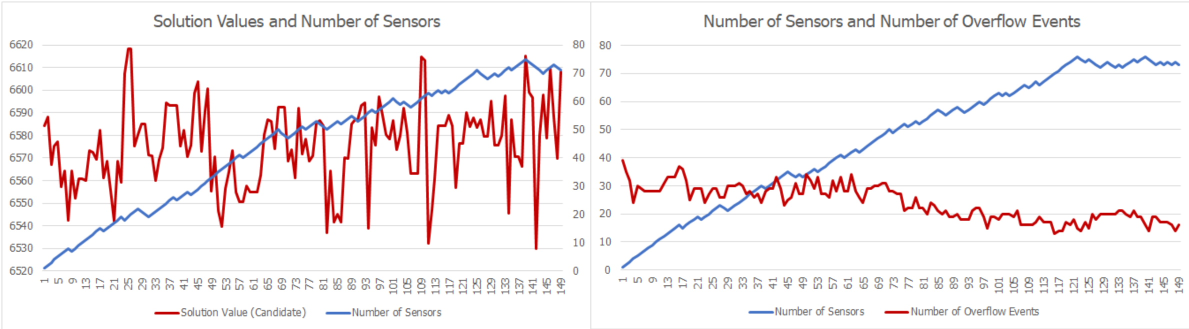

Figure 6.13: Centrum Solution Values for Different Number of Sensors

with a sensor. Figure 6.14 shows the number of times a location has a sensor in a best solution. The locations with a blue colour never have a sensor, and a light grey colour indicates they have a sensor in one of the solutions. This number increases with the intensity of the color and size of the dot, and the maximum is represented by the location with a red colour, which has a sensor in 50% of the best solutions. Interestingly, this was not the location with the most overflow in the earlier runs of the Centrum borough (see Figure 6.4).

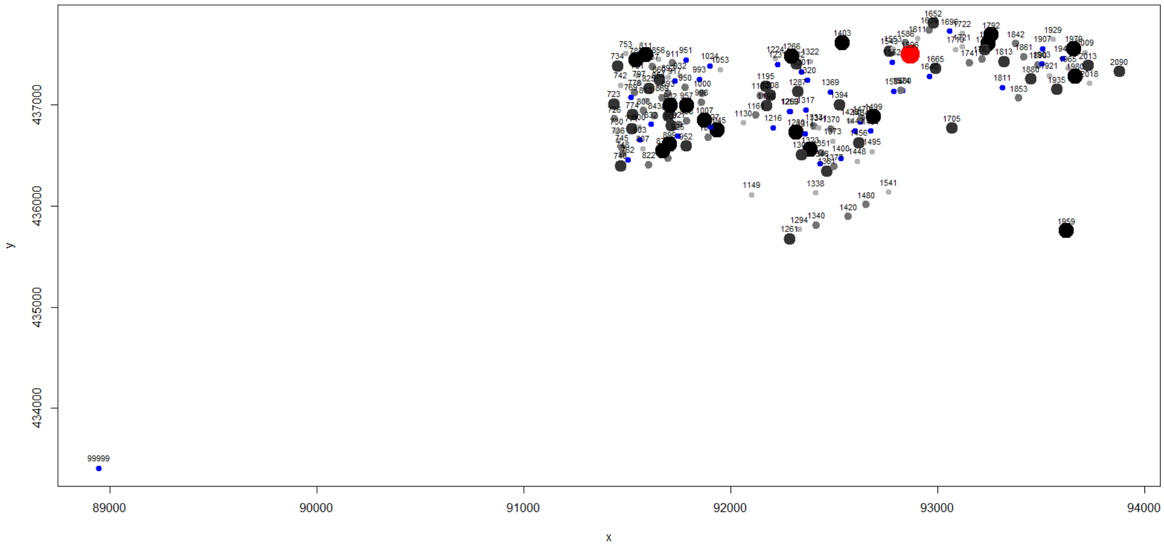

Figure 6.14: Centrum Placement of Sensors in Optimal Solutions

Using the results of the Simulated Annealing method, it is found that location 1596 appeared in 50% of the best solutions. This result can be used when deciding where to place a sensor. To see if the results for the VRP improve when implementing a sensor at location 1596 the program is executed again with this sensor. As can be seen in Table 6.16, the total distance per year decreases with 13 kilometers, with an average decrease of 5 overflow events per year. The sensorized location itself does not have many overflow events, and when sensorizing the location this is minimized to zero.

Table 6.16: Centrum Sensorized Location Simulated Annealing for 4 vehicles (average over 10 runs)

Sensors (at 1596)	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year (at sensorized location)
0	1459.8	16014	10970	108.7 (2)
1	1459.6	16001	10962	103.4 (0)

6.5. Comparing Methods

The results of both methods that are discussed in the section above each return a location that might be suitable for sensorizing. The average results over ten runs of sensorizing one of these locations are compared in Table 6.17. The Ad-Hoc method sensorizes location 1959, and this results in a significant drop in overflow, both at the sensorized location as well as at other locations. With the Simluated Annealing method, location 1596 is returned most often as part of the best solution found after 150 iterations. Implementing a sensor at this location results in a lower distance per year, and a very small drop in overflow events, but the decrease in overflow events is significantly smaller than with the Ad-Hoc method.

Table 6.17: Centrum Sensorized Location Compare Methods for 4 vehicles (average over 10 runs)

Method	Number of routes per year	Total distance (km/year)	Distance per route (m)	Overflow per year (at sensorized location)
Ad-Hoc	1459.6	16022	10977	73.3 (25)
Simulated Annealing	1459.6	16001	10962	103.4 (0)

7 Conclusion

7.1. Vehicle Routing Problem

The VRP has been executed for four different boroughs, with varying numbers of vehicles. The number of vehicles that are needed for a certain borough to get an acceptable number of yearly overflow events is related to the number of locations in a borough and the number of bins these locations contain. In Table 7.1 it can be seen that a borough with a higher number of locations and bins needs more vehicles to limit the number of overflow events on a yearly basis.

Table 7.1: Overview Results VRP

Borough	Number of vehicles available	Number of locations	Number of bins	Overflow per year
Centrum	4	155	313	100
Centrum	5	155	313	28
Kralingen	6	342	559	2545
Kralingen	7	342	559	1
Prins-Alexander	6	254	364	11048
Prins-Alexander	7	254	363	4
Charlois	7	450	700	1421
Charlois	8	450	700	10

In all boroughs it is clear that using less vehicles leads to shorter routes. Because less routes can be planned, there are more locations available in the PL- and $urgent$-list that the insertion heuristic can choose, leading to denser routes. This does however, have a negative effect on the number of overflow events. The total distance travelled per year differs a lot between the neighbourhoods because of the location of the depot. Since every route consists of a trip from the depot to the borough and back, the average distance to the depot from a borough influences the total distance travelled a lot. The total distances travelled per year can therefore not be compared.

For all four boroughs, one scenario is considered where the number of vehicles available leads to quite some overflow. This might indicate that the number of available vehicles is structurally too low to collect all waste. This happens for example in Kralingen-Crooswijk (Table A.17) and in Prins Alexander with 6 vehicles (Table A.14).

Adding more vehicles and thus making it possible to create more routes does decrease the number of overflow events in all four boroughs, and increases both the mean distance per route and total distance per year. Interestingly enough, having 15 vehicles available does not lead to an enormous increase in routes. Simply because the program can decide every day how many routes it needs to visit all eligible locations, almost all overflow is removed (for all four boroughs there is less than 1 overflow event on average per day when 15 vehicles are used). The increase in total distance on a yearly basis is relatively small, between 2 and 6%, compared to the results with enough vehicles to have relatively little overflow (see Tables 6.1, 6.2, 6.3 and 6.4). The number of vehicles used by the VRP program fluctuates a lot when 15 vehicles are available, but because it can adjust the number of routes to the number of urgent locations, the overflow can be prevented. This idea is further explored in the extension with alternating numbers of vehicles.

7.2. Overflow

As mentioned before, the number of overflow events depends mostly on the number of routes that are created on a daily basis. When using too few vehicles, a lot of overflow occurs. The distribution of the overflow events on the locations in a borough can indicate the locations that could benefit from the implementation of a sensor. In the borough Charlois and Centrum, there are locations that have significantly more overflow events during a year than the other locations in the neighbourhood. Sometime these locations even have overflow when 15 vehicles are used. For Kralingen-Crooswijk en Prins-Alexander the overflow seems to be distributed more evenly over the different locations.

For both Centrum and Charlois, the top overflow locations are the same on both datasets. In Charlois, locations 1712 and 1727 have a very high mean waste accretion of 356.04 kg per day since they are the only two locations with bins in that neighbourhood. Since a bin has a capacity of 2000 kg, the waste level can go from under 90% (which means it is not an urgent location) to overflow the next day. In Centrum the same thing occurs. Location 1959 is responsible for 50% of all overflow in the program with 4 vehicles and for almost all overflow in the program with 5 vehicles. The accretion per day is 305.74, which is again very high. These locations with a high daily accretion are also located relatively far from other locations. See for example Figure 6.11 in Section 6.3.2.

The last characteristic that might have an effect on the number of overflow events at a location is the assigned standard deviation. To investigate this, the VRP is run on two datasets with different standard deviations for the boroughs Centrum, Charlois and Prins-Alexander. It seems there is some evidence for this hypothesis. For example in Table A.3, location 1073 has a standard deviation of 25% in Dataset 2 and is the fourth highest overflow location while it is not even in the top ten for Dataset 1. The same can be observed in Table A.9 where location 1907 has a standard deviation of 24% on Dataset 1 and is among the top ten overflow locations while it is not for Dataset 2.

In conclusion, it seems that the most overflow happens at locations that are located far away from others, because they have a high accretion rate and because the insertion heuristic chooses locations on a route that are located close to others. Furthermore, it can be concluded that locations with a high standard deviation are more likely to have overflow.

7.3. Extensions

To improve the results of the VRP, two extensions are investigated: alternating number of vehicles, where a different number of vehicles is available on each day, and using forecast to decide which locations are eligible to visit.

7.3.1. Alternating Number of Vehicles

Looking at the results for alternating numbers of vehicles in Tables 6.5 and 6.6 it can be concluded that an alternating number of vehicles can be an effective way to compromise between having too much overflow and using too many vehicles. For both boroughs, the number of overflow events gradually decreases when the average number of routes per day increases, whereas the total distance per year gradually increases. Depending on the costs that are assigned to overflow as well as to using a vehicle, a cost-benefit analysis can be made to decide which scenario is optimal.

7.3.2. Using Forecast

The problem of locations being not urgent on one day and flowing over the next day because of their large accretion rate might be solved by considering their daily accretion when planning the routes. In the VRP this is done by taking the amount of waste inside a bin plus half of the expected waste accretion of the day when checking if a location has passed the α and β thresholds. This can help to make a distinction between locations that have the same fill level on a certain day, but that have different accretion rates, such that the locations with the largest waste accretion are visited faster. The results show that using the forecast does in fact improve the results significantly. For the Centrum borough, without any sensors, the overflow per year decreases by more than 42% while the total distance a year only increases 34 km, only 0.2% of the total. For Charlois the same pattern can be observed, the overflow is significantly lower while the total distance travelled in a year increases with a negligible amount. It can thus be concluded that using the forecast to plan the routes improves the results compared to only taking into account the current waste levels.

7.4. Sensorizing Locations

Different approaches for sensorizing locations have been considered. The runs are executed without sensors, while saving the start amount of waste assigned to each bin and the actual accretion for every location on every day. The results could therefore only be influenced by the presence of sensors.

7.4.1. Ad-Hoc Method

All Locations

For Prins Alexander, there were no locations with considerably more overflow than others, so the program is executed with sensors at all locations. Implementing sensors at all locations leads to less overflow and less distance travelled for both 6 and 7 vehicles. The decrease in overflow is 8% for 6 vehicles and 17% for 7 vehicles. The program using only 6 vehicles might not be able to have such a large improvement because there are just not enough vehicles available to visit all urgent locations, even with the information provided by the sensors.

Overflow Locations

For Charlois an extensive analysis is done comparing different scenarios of sensor placements, for both 7 and 8 vehicles. The sensors are implemented in the locations with the most overflow in the VRP results. When using 8 vehicles, it is clear that the overflow can be decreased significantly, even when only two sensors are implemented. The total distance travelled per year stays virtually the same, for two sensors the increase of the total distance per year is 0.26%. Adding more sensors gradually decreases the overflow while gradually increasing the total distance travelled per year but only with a very small, perhaps negligible, amount (see Figure 6.8).

For 7 vehicles, no trend can be observed when increasing the number of sensors. When using 5 sensors, the overflow per year decreases from 1386 to 1343 per year. The total distance decreases when sensors are used. The VRP has been limited by the number of vehicles and was not able to visit all overflow locations, which explains the (still) very high number of overflow locations. By using the information from the sensors, unnecessary stops can be prevented, resulting in lower distance travelled. Using the forecast does again clearly improve the overflow results. In Figure 6.10 the results are presented for the program with and without sensors. For every number of sensors, the program using the forecast to plan the routes has less overflow. The increase in total distance per year is minimal, namely less than 100 km (around 0.5%).

For the Centrum neighbourhood, it is recommended to equip location 1959 with a sensor. The overflow decreases with 32% while the total distance travelled does not significantly increase. When using the forecast, the results are even better when implementing the sensors. The overflow per year goes from 57.7 to 6.6. Moreover, the results using forecast but without any sensors are also better than without using the forecast, because the yearly overflow decreases from 99.7 to 57.7, so it is recommended to always use the forecast.

7.4.2. Simulated Annealing

The Simulated Annealing heuristic is applied to the Centrum borough in order to look for the best way to implement sensors in this borough. It is clear to see that the heuristic is able to improve the initial solution significantly after 150 iterations in most of the runs. Since the solution value consists of the distance travelled and the number of overflow events, the heuristic seeks to minimize both. Figure 6.13

shows that there is no clear connection between the solution value and the number of sensors that are used in a solution. However, minima and maxima become more extreme, and best solutions found in different runs use a large number of sensors. This might indicate that not all locations are useful to equip with a sensor, but only certain locations, a hypothesis that might be further investigated in the future. A connection between the number of sensors and number of overflow events does appear to exist, meaning that when the number of sensors increases and the solution value does not, the distance travelled has to increase as well (with decreasing number of overflow events). This increase is possibly caused by the information from the sensor, urging vehicles to visit sensorized locations instead of nearer other locations with only an estimated fill level.

Analyzing the results of the best solution returned by the method shows that some locations are significantly more often part of the best solution while others are never sensorized in the best solution at all (see Figure 6.14). Comparing the results of the Ad-Hoc method and the Simulated Annealing method shows that placing the one sensor found by the Ad-Hoc method causes a larger decrease of overflow events than placing the sensor found by the Simulated Annealing method, while the latter results in a (negligible) smaller distance per year and per route.

7.5. Concluding Remarks & Recommendations

The VRP results show that with small adjustments a lot of improvement can be achieved. Having some extra vehicles available to be used dynamically in order to assist boroughs on a tough day can decrease the number of overflow events and prevents the snowball effect from happening (where there are not enough resources to visit all overflow locations and the overflow increases more and more). For every borough there is a minimum number of vehicles and when the available amount of vehicles is below this minimum, it is hard to improve the results using extensions or sensors. Using the forecast to plan the routes is a strong recommendation since this improves the results in all cases.

Overflow occurs mostly in locations with large accretion rates and isolated locations far away from neighbouring locations. Equipping these locations with a sensor can significantly improve the results as it did in Charlois (two sensors, 42% decrease of overflow events) and Centrum (one sensor, 32% of overflow decrease) without significantly increasing the total distance travelled. It is thus recommended to implement sensors in these locations that are either remote from others or have a high accretion rate. The Simulated Annealing method shows some promising results in locating the best locations for sensor placement and it is recommended to apply the heuristic to different boroughs. Since some locations seem to never be equipped with a sensor, it could be interesting to restrict the locations eligible for a sensor to find out if the solution improves faster and more.

8
Discussion

8.1. Discussion

Although the proposed methods generate some promising results, there is always room for improvement. By choosing the insertion heuristic as method for constructing routes, the results are influenced significantly. For example, the locations with the most overflow events in this model are the most remote locations, because they are not likely to be inserted into a route by the insertion heuristic. Furthermore, whenever adding the location found by the insertion heuristic exceeds the vehicle's capacity, the program terminates and the route is saved. Trying to insert other locations might decrease the number of routes.

The construction of the routes is also in a large part dependent of the parameters. Especially the thresholds α and β, determining which locations are eligible to be emptied, have a large impact on the locations that are visited on a certain day. Choosing these thresholds differently and repeating the analysis can be an interesting extension of the research. Adding a third threshold, as proposed by Elbek and Wøhlk [2016], to determine whether a location should be emptied when it is visited could be an addition to the model. This threshold is useful for locations without a sensor, that will not be emptied when their fill level is below this third threshold which is checked when the location is visited.

A number of simplifications has been applied to the problem. Assuming a universal capacity for both bins and vehicles, might not be a truthful representation of reality. Using Euclidean distances simplifies the calculation of the distance that needs to be travelled but can result in distances significantly different from real life. Treating multiple bins on one location as one large bin, has two consequences that should be improved. First, when the total waste at a location with multiple bins exceeds the capacity of a vehicle, the vehicle takes as much waste a possible. In reality, this is not possible, since a bin can not be emptied partially. Therefore, an integer number of bins has to be emptied. Furthermore, when adding a sensor to a location with multiple bins, in order to gather information about the waste levels of all bins, sensors have to be placed in each bin separately.

8.2. Further Work

8.2.1. Extending the VRP

To make the results more applicable in reality, some suggestions for extensions are proposed. At the moment, the routes are planned for 365 days. Taking weekends and holidays into account, as well as time constraints applying for example to the personnel could be implemented. In this model, no scheduling is executed assigning the routes to the personnel for example. It is assumed that one vehicle completes one route a day, but it might well be possible that one vehicle can do multiple routes a day, which should be scheduled.

8.2.2. Cost-Benefit Analysis

No cost-benefit analysis can be executed since the costs of for example placing sensors, driving, picking up waste and having overflow are not known. Furthermore, the historical data of the locations, where for example the mean accretion and standard deviation can be derived from are now based on estimates. However, adding this information to the program and methods of this thesis can definitely result in a strong and useful recommendation for any waste-collecting company or municipality. When costs are known, the consideration between implementing sensors, using more vehicles or having more overflow can be used to result in a more substantiated recommendation.

8.2.3. Sensor Placement

While the Ad-Hoc method and Simulated Annealing heuristic show some promising results, more research is needed in order to find out which locations to equip with a sensor. Knowing more about the actual costs of sensor placement, maintenance etc. could contribute significantly to the analysis. For example the solution value used in the Simulated Annealing method, depends on the number of overflow events and total distance travelled, and knowing the exact costs of these parts of the solution could lead to another ratio used for calculating the solution value. Furthermore, the Simulated Annealing method could be applied to more boroughs and could be expanded using more iterations and different acceptance probabilities.

A

Appendix

A.1. Boroughs and Neighbourhoods

Table A.1: Overview Boroughs

Borough	Neigbourhood	Inhabitants	Bins	Mean estimated waste per day per bin (kg)[1]
Centrum	Cool	5068	81	55,56
	Kop van Zuid	2073	6	305.74
	Nieuwe Werk	1480	12	109.14
	Oude Westen	9356	122	67.86
	Stadsdriehoek	14447	94	136.01
Charlois	Carnisse	11082	153	64.10
	Heijplaat	1130	15	66.66
	Oud Charlois	13255	156	75.19
	Pendrecht	11655	134	76.97
	Tarwewijk	12313	160	68.10
	Zuidplein	1207	3	356.04
	Zuidwijk	12193	109	98.99
Delfshaven	Schiemond	5037	31	143.79
	Bospolder	7151	74	80.88
	Delfshaven	6763	70	85,50
	Oud Mathenesse	7074	69	90.72
	Tussendijken	7077	108	57.99
	Spangen	10385	146	62.95
	Middelland	11820	86	121.63
	Nieuwe Westen	19223	164	103.73
Feijenoord	Afrikaanderwijk	8221	94	77.39
	Bloemhof	13681	115	105.28
	Feijenoord	7193	76	83.75
	Hillesluis	11862	121	86.75
	Katendrecht	4601	67	60.77
	Kop van Zuid - entrepot	8351	43	171.86
	Noordereiland	3293	40	72.85
	Vreewijk	13804	58	210.61

[1] Using mean waste production 323kg per person per year (CBS) and 365 days a year

Borough	Neigbourhood	Inhabitants	Bins	Mean estimated waste per day per bin (kg)
Hillersberg -Schiebroek	Hillegersberg Noord	7768	39	176.26
	Hillegersberg Zuid	7943	103	68.24
	Molenlaankwartier	7902	12	582,73
	Nieuw Terbregge	3554	32	98.28
	Schiebroek	16277	121	119.04
Ijsselmonde	Beverwaard	11704	52	199.18
	Groot IJsselmonde	27668	133	184.09
	Lombardijen	13587	99	121.45
	Oud IJsselmonde	5977	20	246.46
Kralingen -Crooswijk	De Esch	4351	27	142.61
	Kralingen Oost	7786	38	181.32
	Kralingen West	15658	227	61.04
	Nieuw Crooswijk	2723	43	56.04
	Oud Crooswijk	8151	112	64.40
	Rubroek	8211	83	87.54
	Struisenburg	5075	31	144.87
Noord	Agniesebuurt	4059	44	81.63
	Bergpolder	7951	95	74.06
	Blijdorp	10082	111	80.38
	Liskwartier	7569	88	76.11
	Oude Noorden	16918	205	573.03
	Provenierswijk	4620	56	73.01
Overschie	Kleinpolder	6684	61	109.50
	Overschie	7548	61	96.97
Prins Alexander	Lage Land	10569	76	123.06
	Nesselande	12303	90	120.97
	Ommoord	24999	7	102.22
	Oosterflank	10512	91	75.19
	Prinsenland	9760	39	87.54
	's Gravenland	8190	6	143.79
	Zevenkamp	16095	55	258.96

A.2. Results VRP

A.2.1. Charlois

Table A.2: Charlois VRP Results for 7 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2555	52602.14	7514.59	1463
2	2555	52865.67	7552.24	2141
3	2555	52724.43	7532.06	1443
4	2555	52992.37	7570.34	1271
5	2555	52740.03	7534.29	1118
6	2553	52858.44	7557.12	1768
7	2555	52914.05	7559.15	1166
8	2555	52812.53	7544.65	993
9	2555	52570.56	7510.08	1719
10	2555	52702.31	7528.90	1126
Average	7.0 (per day)	52778.25	7540.34	1420.8 (per year)
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2555	52744.92	7534.99	1146
2	2555	52766.32	7538.05	1253
3	2555	52673.20	7524.74	974
4	2555	52793.91	7541.99	952
5	2555	52890.03	7555.72	1740
6	2555	52834.01	7547.72	1022
7	2555	52790.40	7541.49	2105
8	2555	52657.94	7522.56	1422
9	2555	52586.25	7512.32	1262
10	2555	53368,26	7624.04	717
Average	7.0 (per day)	52810.52	7544.36	1259.3 (per year)

Table A.3: Charlois overflow for 7 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1727	56	4182.67	147.10	0.13
1712	50,1	4151.97	86.13	0.06
884	12,2	3121.25	126.84	0.15
1831	9,7	4598.81	76.35	0.21
1846	9,2	4659.91	81.88	0.09
1897	8,8	4700.23	71.62	0.19
2036	8,6	4944.21	67.32	0.09
1832	8,5	4433.31	79.02	0.07
1946	8,5	4808.64	80.28	0.09
1021	8,2	3393.29	86.09	0.06
Dataset 2				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1727	44.9	4182.67	147.10	0.19
1712	42.2	4151.97	86.13	0.22
884	18.6	3121.25	126.84	0.24
1073	12.0	3065.80	73.48	0.25
855	8.7	2908.95	84.66	0.23
1846	7.9	4659.91	81.88	0.24
1609	7.8	4017.80	47.45	0.21
1991	7.6	4888.41	68.61	0.23
2008	7.2	5006.77	257.00	0.08
1897	7.0	4700.23	71.62	0.19

Table A.4: Charlois VRP Results for 8 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2724	60619.70	8119.70	8
2	2728	61248.55	8194.91	12
3	2729	61136.90	8176.98	19
4	2724	61360.02	8221.88	8
5	2728	61010.95	8163.12	10
6	2713	60183.95	8096.99	15
7	2723	61069.75	8185.99	9
8	2717	61107.40	8209.13	10
9	2734	62118.34	8293.05	6
10	2731	61988.02	8284.74	6
Average	7.48 (per day)	61184.36	8194.65	10.3
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2723	61246.53	8209.69	11
2	2728	61137.63	8180.07	7
3	2735	61418.80	8196.66	9
4	2730	61462.67	8217.54	8
5	2728	61376.78	8212.07	16
6	2723	61232.06	8207.75	3
7	2726	61136.63	8185.94	3
8	2728	61014.68	8163.62	8
9	2728	61820.84	8271.48	8
10	2730	61190.11	8181.10	10
Average	7.48 (per day)	61303.67	8202.59	8.3

Table A.5: Charlois overflow for 8 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1712	7.6	4151.97	86.13	0.06
1727	2.0	4182.67	147.10	0.13
Dataset 2				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1712	6.3	4151.97	86.13	0.22
1727	1.1	4182.67	147.10	0.19
1706	0.6	4184.363	30.64	0.06

Table A.6: Charlois VRP Results for 15 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2796	63839.79	8333.88	1
2	2802	64169.60	8358.99	0
3	2796	63956.05	8349.06	0
4	2793	63506.06	8299.22	0
5	2807	64511.13	8388.52	1
6	2808	64220.50	8347.75	0
7	2805	64052.10	8334.77	0
8	2796	63704.03	8316.16	1
9	2786	64225.93	8414.38	1
10	2794	63702.80	8321.95	0
Average	7.67 (per day)	63988.80	8346.51	0.4
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2798	64107.67	8362.87	1
2	2797	64159.69	8372.65	1
3	2791	63911.01	8358.12	0
4	2246	53363.95	8672.24	0
5	2275	54124.46	8683.71	0
6	2258	53502.40	8648.53	0
7	2250	52908.66	8582.96	1
8	2258	53427.40	8636.40	0
9	2261	53771.40	8680.48	0
10	2268	54260.33	8732.37	0
Average	6.63 (per day)	56753.70	8573.03	0.3

Table A.7: Charlois overflow for 15 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1727	0.3	4182.67	147.10	0.13
1712	0.1	4151.97	86.13	0.06
Dataset 2				
1712	6.3	4151.97	86.13	0.22
1727	1.1	4182.67	147.10	0.19

A.2.2. Centrum

Table A.8: Centrum VRP Results for 4 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of over-flow events**
1	1460	43595.77	10898.94	133
2	1460	43779.19	10944.80	127
3	1460	43862.33	10965.58	71
4	1457	43706.09	10949.02	86
5	1459	43890.24	10980.08	105
6	1459	43752.25	10945.56	79
7	1460	43873.41	10968.35	54
8	1460	43691.07	10922.77	104
9	1460	43704.37	10926.09	114
10	1460	43560.55	10890.14	124
Average	4.00 (per day)	43741.53	10939.13	99.7 (per year)
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of over-flow events**
1	1460	43756.00	10939.00	102
2	1460	44012.68	11003.17	93
3	1460	43834.96	10958.74	55
4	1460	43829.13	10957.28	100
5	1460	43624.61	10906.15	131
6	1460	43770.36	10942.59	103
7	1460	43807.81	10966.16	65
8	1460	43774.89	10943.72	80
9	1459	43807.81	10959.46	113
10	1460	43928.46	10982.11	73
Average	4.00 (per day)	43820.35	10955.84	91.5 (per year)

Table A.9: Centrum overflow for 4 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	53.1	5229.71	940.37	0.20
1880	6.1	5919.96	96.44	0.21
2090	3.9	6299.45	164.09	0.20
1792	2.8	6073.88	89.55	0.18
2009	2.6	6290.33	67.38	0.21
1721	2.3	5891.08	39.54	0.17
1907	2.0	6161.58	104.60	0.24
1949	2.0	6170.12	100.06	0.22
Dataset 2				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	47.9	5229.71	940.37	0.14
1880	4.6	5919.96	96.44	0.09
2090	4.1	6299.45	164.09	0.25
1792	3.2	6073.88	89.55	0.05
1611	2.8	5799.90	71.75	0.20
2009	2.5	6290.33	67.38	0.09
1813	2.4	5939.43	104.44	0.18
1721	2.1	5891.08	39.54	0.24

Table A.10: Centrum VRP Results for 5 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	1585	48253.46	11111.99	34
2	1576	48281.77	11182.01	29
3	1583	48537.75	11191.58	35
4	1585	48701.81	11215.24	37
5	1568	47668.98	11096.42	29
6	1604	49257.93	11208.94	21
7	1566	47818.78	11145.50	28
8	1558	47829.16	11205.16	39
9	1573	48198.42	11184.00	39
10	1566	47874.41	11158.47	24
Average	4.32 (per day)	48242.25	11169.93	28.1 (per year)
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	1574	47953.89	11120.18	36
2	1575	48472.73	11233.36	26
3	1573	48368.43	11223.44	17
4	1558	47561.03	11142.35	17
5	1574	48247.08	11188.17	44
6	1573	48214.68	11187.77	35
7	1570	48039.87	11168.51	34
8	1578	48543.20	11228.31	17
9	1570	48044.25	11169.52	32
10	1565	47925.09	11177.42	24
Average	4.30 (per day)	48137.02	11183.90	28.2 (per year)

Table A.11: Centrum overflow for 5 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	28.2	5229.71	940.37	0.20
1880	0.3	5919.96	96.44	0.21
2090	0.3	6299.45	164.09	0.20
1792	0.2	6073.88	89.55	0.18
1574	0.1	5378.48	7.51	0.25
1949	0.1	6170.12	100.06	0.22
1980	0.1	6101.86	85.82	0.19
2009	0.1	6290.33	67.38	0.21
Dataset 2				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	27.7	5229.71	940.37	0.14
1721	0.1	5891.08	39.54	0.24
1792	0.1	6073.88	89.55	0.05
1880	0.1	5919.96	96.44	0.09
1980	0.1	6101.86	85.82	0.24
2090	0.1	6299.45	164.09	0.25

Table A.12: Centrum VRP Results for 15 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	1601	49050.68	11182.70	12
2	1617	49888.81	11261.23	6
3	1609	49244.16	11170.99	5
4	1517	46613.66	11215.55	8
5	1612	49656.02	11243.45	6
6	1612	49678.18	11248.47	6
7	1606	49026.80	11142.46	8
8	1600	49213.22	11226.77	8
9	1599	49224.64	11236.39	4
10	1603	49140.33	11189.16	12
Average	4.38 (per day)	49073.65	11211.72	7.5 (per year)
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	1585	49544.96	11253.21	13
2	1576	49239.59	11169.95	16
3	1583	49558.42	11235.29	17
4	1585	48885.73	11159.03	3
5	1568	49237.73	11232.36	11
6	1604	49888.92	11150.92	4
7	1566	49442.59	11222.98	8
8	1558	49999.04	11272.17	6
9	1573	49173.88	11196.80	8
10	1566	49942.41	11238.58	18
Average	4.41 (per day)	48137.02	11213.13	10.4 (per year)

Table A.13: Centrum overflow for 15 vehicles on two datasets

Dataset 1				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	7.5	5229.71	940.37	0.20
Dataset 2				
Location	**Mean number of overflow (per year)**	**Distance to depot**	**Distance to closest location**	**Standard deviation**
1959	10.4	5229.71	940.37	0.14

A.2.3. Prins Alexander

Table A.14: Prins Alexander VRP Results for 6 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2190	153573.80	25595.63	9304
2	2190	153872.11	25645.35	11511
3	2190	153978.55	25663.09	12689
4	2189	153996.03	25677.73	9742
5	2190	153865.99	25644.33	13261
6	2190	153560.74	25593.46	11149
7	2190	153718.32	25619.72	10335
8	2190	153845.65	25640.94	11065
9	2190	153687.50	25614.58	13564
10	2190	153726.69	2562.12	7860
Average	6.0 (per day)	153782.54	25631.60	11048 (30.27 p/d)
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2190	153840.79	25640.13	11814
2	2190	153982.81	25663.80	11135
3	2190	153822.98	25637.16	12903
4	2190	154125.00	25687.50	13145
5	2190	153604.35	25600.73	10431
6	2190	153484.31	25580.72	18424
7	2187	153634.64	25640.90	8029
8	2190	153628.01	25604.67	12433
9	2190	153632.12	25605.35	15286
10	2190	153862,72	25643.79	9173
Average	6.0 (per day)	153761.77	25630.47	12277 (33.6 p/d)

Table A.15: Prins Alexander VRP Results for 7 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2367	170895.76	26352.75	3
2	2374	171672.56	26394.48	5
3	2369	171096.76	26361.47	5
4	2371	171220.17	26358.23	3
5	2373	171657.52	26403.29	5
6	2378	171791.12	26116.79	3
7	2379	171867.97	26368.98	4
8	2389	172771.84	26396.70	4
9	2374	171823.19	26417.63	3
10	2374	171754.27	26407.04	5
Average	6.5 (per day)	171655.12	26382.88	4
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2381	172524.76	26447.51	3
2	2358	167774.76	25970.22	2
3	2378	172209.18	26432.44	5
4	2377	170545.51	26188.10	5
5	2370	171106.50	26351.84	3
6	2384	171771.68	26298.94	3
7	2375	171188.88	26309.03	7
8	2365	169666.33	26185.29	9
9	2367	170876.17	26349.73	4
10	2376	172158.97	26446.98	2
Average	6.5 (per day)	170982.27	26298.01	4.3

Table A.16: Prins Alexander VRP Results for 15 vehicles on two datasets

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2432	176207.19	26445.57	2
2	2421	175863.64	26513.93	2
3	2440	176825.59	26451.37	0
4	2419	174604.88	26345.92	1
5	2415	175380.09	26506.72	0
6	2413	174033.43	26324.99	1
7	2431	176081.67	26437.60	1
8	2434	176432.95	26457.69	1
9	2435	176154.90	26405.15	1
10	2421	175441.78	26450.33	1
Average	6.65 (per day)	126021.71	26433.92	1
Dataset 2				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2417	174832.33	26402.07	0
2	2432	176535,45	26494,83	1
3	2432	175820,59	26420,14	0
4	2428	176125,37	26476,83	0
5	2430	176640.92	26532,48	0
6	2430	176207.58	26511.03	0
7	2423	175609.53	26453.77	0
8	2429	176563.33	26531.75	0
9	2423	174550.60	26294.25	1
10	2423	176101.40	26332.25	2
Average	6.65 (per day)	175898.71	26444.94	0.4

A.2.4. Kralingen-Crooswijk

Table A.17: Kralingen-Crooswijk VRP Results for 6 vehicles on one dataset

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2190	85623.01	14270.50	2305
2	2190	85407.45	14234.57	2299
3	2190	85464.53	14244.09	1597
4	2190	85342.34	14223.72	2151
5	2190	85474.54	14245.76	1500
6	2190	85610.25	14268.37	1589
7	2190	85453.19	14242.20	2765
8	2190	85582.14	14263.69	3617
9	2190	85461.96	14243.66	5343
10	2190	85531.15	14255.19	2282
Average	6.0 (per day)	85495.06	14249.18	2544.8 (6.97 p/d)

Table A.18: Kralingen-Crooswijk VRP Results for 7 vehicles on one dataset

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2358	94837.36	14680.08	0
2	2352	94859.66	14720.99	0
3	2350	94565.19	14687.79	0
4	2363	95668.87	14777.46	2
5	2352	94841.14	14718.12	1
6	2345	93954.27	14624.01	1
7	2350	94672.50	14704.45	1
8	2351	95379.14	14807.91	1
9	2346	94675.55	14730.00	1
10	2358	95687.24	14811.64	0
Average	6.4 (per day)	94914.09	14726.24	0.7

Table A.19: Kralingen-Crooswijk VRP Results for 15 vehicles on one dataset

Dataset 1				
Run	**Number of routes**	**Mean distance per day**	**Mean distance per route**	**Number of overflow events**
1	2425	98146.87	14772.62	0
2	2430	98685.18	14823.08	0
3	2429	98139.02	14747.12	0
4	2435	98266.87	14729.94	0
5	2429	98353.95	14779.41	0
6	2426	98278.60	14786.35	0
7	2436	98694.04	14787.90	0
8	2423	97894.15	14746.75	0
9	2419	97745.52	14748.70	0
10	2420	98030.38	14785.57	0
Average	6.6 (per day)	98223.46	14770.75	0

A.3. Results Sensorized Locations

A.3.1. Implementing Sensors at All Locations

Prins Alexander

Table A.20: Prins Alexander All Locations Sensorized for 6 Vehicles

Run	**Sensors**	**Number of routes per day**	**Total distance (km/year)**	**Distance per route (km)**	**Overflow per year**
1	off	6	56138	25.63	12156
	on	6	56047	25.59	10165
2	off	6	56102	25.62	11313
	on	6	56116	25.62	13795
3	off	6	56191	25.66	12738
	on	6	55919	25.53	10787
4	off	6	56304	25.71	7001
	on	6	56290	25.70	5124
5	off	6	56094	25.61	9446
	on	6	56184	25.65	11648
6	off	6	55843	25.53	13102
	on	6	56099	25.62	6437
7	off	6	56172	25.65	11912
	on	6	56047	25.57	12033
8	off	6	56106	25.62	11816
	on	6	55642	25.54	11504
9	off	6	56186	25.66	11389
	on	6	55923	25.54	13342
10	off	6	56257	25.69	14291
	on	6	56042	25.59	10879

Table A.21: Prins Alexander All Locations Sensorized for 7 Vehicles

Run	Sensors	Number of routes per day	Total distance (km/year)	Distance per route (km)	Overflow per year
1	off	6.45	62195	26.41	8
	on	6.38	61902	26.54	5
2	off	6.51	62529	26.31	4
	on	6.41	62158	25.62	4
3	off	6.52	62557	25.66	5
	on	6.42	62321	25.53	3
4	off	6.52	62803	26.40	2
	on	6.41	62132	26.57	4
5	off	6.52	62771	26.40	5
	on	6.43	62310	26.55	5
6	off	6.54	63004	26.41	5
	on	6.39	61903	26.56	7
7	off	6.52	62840	26.43	5
	on	6.41	62190	26.59	4
8	off	6.51	62554	26.32	9
	on	6.41	62114	26.56	4
9	off	6.48	62474	26.43	4
	on	6.40	62171	26.60	3
10	off	6.50	62498	26.36	6
	on	6.42	62327	26.61	5

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