Use of domain knowledge to optimize the performance of an IoT-based waste collection service

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Image: Rotterdam Named Europe's Best City By The Academy Of Urbanism (https://www.archdaily.com/568231/rotterdam-named-europe-s-best-city-by-the-academy-of-urbanism)

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Use of domain knowledge to optimize the performance of an IoT-based waste collection service

by

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Preface

This thesis report is the final product of the research performed for my master's degree in Transport and Planning at TU Delft. The objective of this research was to develop a solution approach, derived from the knowledge and requirements of the domain, to solve the IoT-based waste collection problem. In hopes that this research will be of value for future research and real-life applications, I must admit that the road in carrying it out was quite challenging but simultaneously tremendously rewarding. Managing a project of this size was a useful experience that I will carry along in my future endeavors. Looking back at the whole journey, I can see how much I grew as a researcher, an engineer, and a person above all, and how much I have learned.

My research would not have reached the same quality was it without the help of my thesis committee and the support of the people around me. I would first like to thank my thesis committee chair Lóri Tavasszy for his invaluable contribution in steering my research in the correct direction at critical points with his constructive criticism. Goncalo, thank you for your advice on how to proceed with my model development when I was stuck in an endless loop at the development of the first clustering phase, as well as for your valuable feedback in structuring and improving my report. I must admit that the course 'CIE4835-Transport Engineering and Optimization' that you teach, sparked my interest in Operations research which is why I chose this project as my final thesis assignment. Michiel, thank you for your untiring support and guidance throughout this journey, as well as for introducing me to the Rotterdam municipality thus making this research project a reality. Thank you for always listening to me so enthusiastically and believing in me.

I am grateful to my supervisors at Rotterdam municipality Daan van den Elzen and Jos Streng for their constant support, and their genuine interest in my work. Thank you, Daan for always being available for any questions, for welcoming me to the waste collection team of the municipality, and for arranging for me a tour with one of your drivers to better experience the whole waste collection process. It has been a great learning opportunity! Thank you, Jos, for being so encouraging about this work and always coming up with new ideas about the model's possible application.

Finally, I would like to thank my family and friends for their constant support, which has been of immeasurable importance to me during this project, and also throughout my studies in the Netherlands. I am extremely grateful to my parents, Lefki and Iasonas, for encouraging me in all my pursuits and always being a solid rock of support for me. Thank you, mom, for teaching me to believe in myself, and as a good captain of my ship to always put my sailors to work to achieve my goals and dreams. My brothers, Giorgos and Antonis, thank you for always being there for me when I needed you. My sister, Myrofora, thank you for always supporting me, being the voice of reasoning, and reminding me of how much I have achieved so far in my life. I want to thank from the bottom of my heart my best friends Athina and Aswin for always being a phone call away, and always being supportive and excited to listen to my new experiences. Lastly, I am grateful to the friends I have made here in the Netherlands, my housemates, and friends from the university, for their presence and for making this whole journey an unforgettable experience.

Sofia Giasoumi
Limassol, May 2022

Executive summary

Installing wireless sensors on a network of waste containers, that monitor at regular intervals their waste fill levels and transmit the data to the cloud of a waste management operator over the internet, describes the Internet of Things (IoT). With this constant stream of data, the dynamic organization of waste collection schedules is enabled as containers are visited for collection only when it is necessary, which consequently leads to demand-responsive services. Domain experts attest that operating a demand-responsive service brings financial and environmental gains to a waste collection service, but it simultaneously introduces complete variability in the system which is undesirable in real-life operations. To solve this problem and consequently optimize the waste collection service's performance, domain experts stress the need for a balanced trade-off between dispatch consistency and flexibility. This means, being able to exploit to the highest degree possible the benefits of demand-responsive operations, while also maintaining a certain level of dispatch consistency when demand varies from day to day.

The objective of this research is to develop a solution approach derived from the knowledge and requirements of the domain, to solve the IoT-based waste collection problem (WCVRP). The WCVRP addressed in this study can be defined as a multi-trip VRP with intermediate facilities. As the problem relates to waste collection, the intermediate facilities refer to disposal facilities that are visited once the effective capacity payload of the vehicles is reached or just before their shift is over. The vehicles must start and finish their routes at the depot empty, hence they are allowed to visit the disposal facilities multiple times to unload the accumulated waste and regain their capacity, before returning to their route or the depot at the end of their shift.

To achieve the stated trade-off and a better organization of the waste collection service a smart solution approach is proposed which is displayed in Figure E.1, the objective of which is to construct routes in such a way that the total traveled kilometers, as well as the total CO2 emissions produced, are minimized. The approach firstly uses a two-phase clustering technique to consecutively assign waste containers to two-level clusters. It subsequently uses a routing model to construct for each of the second-level clusters as many routes as required to accommodate its demand. The first clustering phase operates on the tactical level and employs the K-means algorithm to assign specifically selected containers into monthly-constructed clusters. The containers selected to populate these static clusters are the ones classified as having a monthly 'high' and 'medium' frequency of collection, following the rules imposed by a classification scheme. Required input for the algorithm is the definition of the number of clusters to be constructed, which is determined by examining a range of number of clusters with the combined use of the elbow method and mathematics. Capacity constraints can also be imposed on the clusters to force the assignment of a minimum and/or a maximum number of collection sites.

The second clustering phase aims at the creation of daily container circuits for collection with the employment of the K-nearest neighbor algorithm (KNN). A completely reactive scheduling approach is followed before this phase, realized through a selected scheduling strategy, to schedule the most appropriate containers for collection. The tactical level clusters created at the first clustering phase and the containers scheduled for collection through the scheduling strategy are used as input for this second phase. More specifically, the model identifies which containers already assigned in the tactical level clusters are not scheduled for collection and removes them from the clusters, and uses the remaining assigned containers as an input dataset to train and evaluate the predictive performance of the KNN algorithm. Once the training is over, the algorithm assigns each unassigned container scheduled for collection to the cluster in which the majority of its already assigned neighbor containers belong. To find the optimal number of neighbors for the KNN algorithm, the GridSearch CV tool is used which is restricted to a non-weighted approach, meaning the same weight ("importance") is assigned to all neighbor containers.

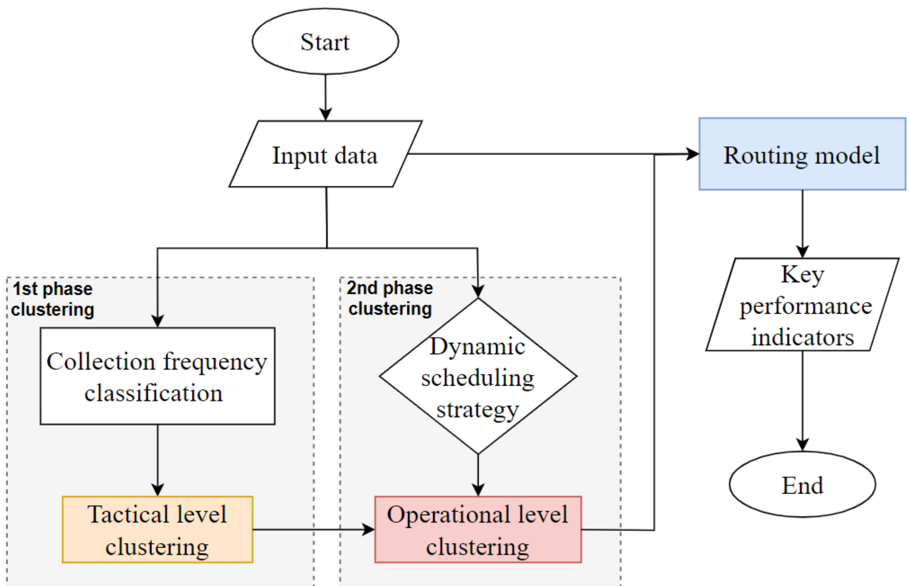

Figure E.1 Flowchart of the proposed solution approach

The routing model uses the travel time and distance matrices between all nodes of the network, and the operational level clusters which indicate which collection sites must be collected on the same route, to construct the waste collection routes. For every cluster, the proposed routing model uses the nearest neighbors algorithm to gradually construct routes starting from every unassigned collection site, and subsequently optimizes each resulting route with a modified 2-Opt algorithm. The classic 2-Opt algorithm does not take into consideration any intermediate facilities that should be inserted in a route at specific positions, such as disposal facility visits, therefore the classic 2-Opt algorithm had to be modified. The modified 2-Opt algorithm uses the initial solution without disposal facility visits as a starting point and iteratively looks for improvement opportunities in the neighborhoods of that solution. For each neighborhood of the route, it uses a swapping mechanism to replace two edges of the route with two other edges and then calculates the new travel distance. If the swapping leads to a shorter travel distance, the algorithm proceeds in inserting the visits to the disposal facility at the correct positions in the route and recalculates the new travel distance. If the resulting route's distance is shorter than the travel distance of the initial solution with disposal facility visits, then the current route is updated. The algorithm continues building on the improved route by repeating the procedure until no more improvements can be found.

Once all the routes are constructed and optimized, the model determines which one is the best performing based on two criteria, the total amount of collected weight and the total number of travel kilometers. Preference is given to routes that manage to visit all collection sites assigned in a cluster. Between routes that manage to visit all collection sites, the best route is the one that manages to travel the least number of kilometers. In the case that collection sites remain unassigned, the best route is considered the one with the highest weight over travel distance ratio, which is selected among routes that visit the disposal facility the least number of times. Once the best route is determined, it is further improved based on certain rules which consider the route's number of visits to the disposal facility, as well as the number of collection sites belonging to the examined cluster that are yet to be assigned. The first rule states that, if only one visit to the disposal facility is planned in the route, no further improvement can be achieved. The second rule states that, if no more unassigned collection sites exist in the cluster but the amount of waste collected during the last tour of the route is less than or equal to 1000kg, the second to last visit to the disposal facility of the route can be removed. This is possible as the vehicle is constrained to use only its effective capacity which is only around 85% of its capacity payload. The last rule states that, if there are still unassigned collection sites in the examined cluster and the last tour of the route is partially full, the stated collection sites must be combined in a new route, if and only if their combined weight of waste is lower than the effective vehicle capacity payload.

The solid waste collection service of the Municipality of Rotterdam, in the Netherlands, was used as a case study to demonstrate the applicability of the proposed solution. To test the developed model, the routes it constructed were compared with a sample of routes executed on one specific day. The same containers collected on the examined day were also scheduled for collection in the model, hence no specific scheduling strategy was applied. Since the traversed paths and timelines of the routes executed in real life were unavailable, the routes had to be resolved with Dijkstra's algorithm. Due to this reason, both the model routes (base case) and the real-life executed routes (current case) were constructed towards the minimization of both distance and time. The results of the analysis proved that, under both objectives, the model achieves not only the functional requirements but also an economically and environmentally enhanced performance in comparison to the current case. More specifically, the routes constructed with the model presented a lower number of traveled kilometers, a higher average vehicle capacity utilization, a higher weight over distance ratio, and reduced CO_2 emissions production and fuel consumption.

Solving towards distance, led to a lower number of travel kilometers and a higher weight over travel kilometers ratio, which is a very important indicator in describing the efficiency of the whole waste collection system. Solving towards time led to a lower travel time and to an increased usage of highway roads and a decreased usage of city roads, which translates to reduced city traffic and a location shift of the produced emissions (see Figure E.2). Solving towards time also resulted in a lower amount of produced emissions in comparison to solving towards distance, but with an almost negligible difference of around 1.5%. For both studied objectives, all the above were achieved with the construction of a larger number of shorter but fuller routes, which led to an increased average vehicle capacity utilization.

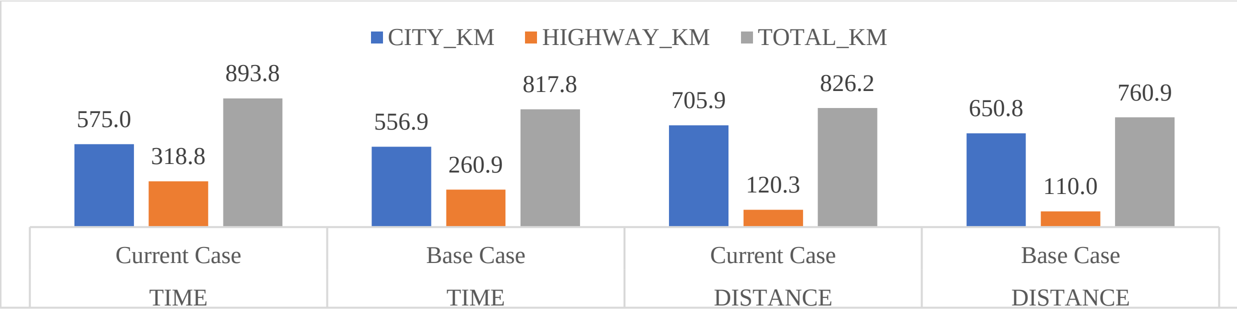

Figure E.2 Current case vs base case – traveled kilometers

To evaluate the model sensitivity, several configurations of different parameters used at the tactical level clustering were examined. The parameters examined were the range of number of clusters used in the Elbow method to find the optimal number of clusters and combinations of different minimum and maximum capacity constraints. The results of the sensitivity analysis proved that the solutions of the model are robust, with the values of the selected KPIs fluctuating within just a range of ±4% when compared to the initial solution. As only one day's routes were used for this analysis, no hard conclusions can be drawn on the real effect of the two examined parameters on the model's sensitivity. It is therefore suggested that more days that present different characteristics are examined, to get a better idea of the fluctuation range of the KPIs values and thereby the model's sensitivity to the examined parameters.

Three dynamic scheduling strategies were selected for examination to demonstrate how can the developed model be used. Each of the examined strategies makes use of the priority classification of the containers to determine if they should be scheduled for collection. The examination and comparison of the selected scheduling strategies proved that certain strategies perform better than others under different KPIs, see Figure E. 3.

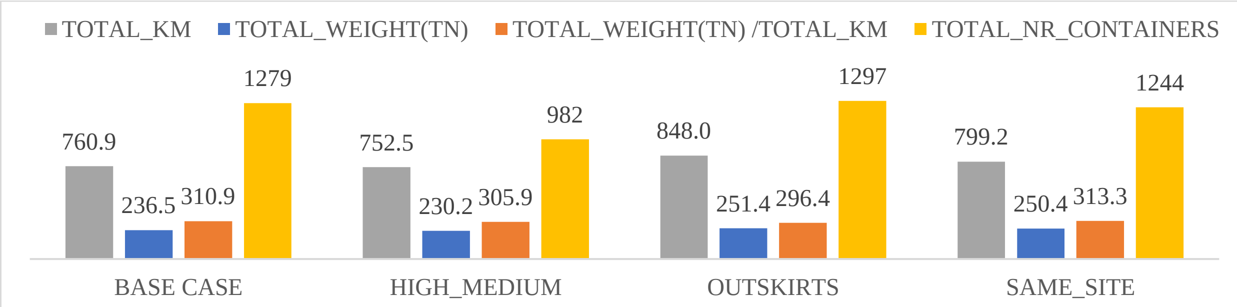

Figure E. 3 Examination of scheduling strategies performance

The 'HIGH_MEDIUM' strategy, which schedules for collection only the 'high' and 'medium' priority containers, achieves the highest average container capacity utilization, travels the least number of kilometers but also collects the least amount of waste. As the least number of containers is scheduled for collection with this strategy, it is suggested that is followed on days that present relatively low waste generation. The 'SAME_SITE' strategy, which schedules for collection all 'high' and 'medium' priority containers and additionally all the containers located at those collection sites, achieves the highest weight over travel kilometers among the rest of the strategies. This strategy proves that savings can be achieved by collecting all the containers located at a collection site, as no additional kilometers need to be traveled other than for the trips to and from the disposal facility for unloading. This strategy is proposed to be followed on days with higher waste generation, but specifically on Mondays and Fridays to deal with the reduced operations of the weekend. The 'OUTSKIRTS' strategy, which schedules for collection all 'high' and 'medium' priority containers, and all the containers located on the outskirts of a city if at least one of them needs servicing, achieves the highest average vehicle capacity utilization in comparison to the rest of the strategies, but performs the worst for almost every examined KPI. Despite not performing the best, this strategy still shows potential. It is recommended that a policy is examined in combination with the 'OUTSKIRTS' strategy, in which the residents of the outskirts are informed in advance about the arrival of the waste collection vehicle so that they can dispose their waste on time. This will aid in collecting a higher amount of waste while traveling the same amount of kilometers, therefore to an even higher vehicle capacity utilization and weight over travel kilometers ratio.

Overall, the strategies performed as expected, but it is acknowledged that a different set of priority classification rules would have led to completely different outcomes. Undeniably, to concretely conclude on the behavior of each, they should be tested under various classification rules and on multiple days which present different waste generation patterns. Furthermore, to show their full potential, they should be examined for several consecutive days as the fill level and accumulation period of each container, which is used for their priority classification, is affected by the previous day's executed schedule.

In general, the developed model can be used by any waste collection service which presents the same characteristics and imposes the same constraints as the formulated WCVRP the model is intended to solve. The model is equipped with multiple tunable parameters and uses a variety of user-imposed rules to construct the final solution, which enables its generalizability and transferability to new data and situations. It is important to recognize nevertheless its limitations, as it is focused on the attainment of specific requirements, and it does not aim to address everything that takes place during waste collection scheduling or routing.

Its main limitations are derived from its deterministic behavior. To be more specific, the time spent to service each container as well as the time spent at the disposal facility for unloading are assumed to be static variables, while the duration for both these activities is stochastic in reality. Furthermore, the moment the vehicle visits the disposal facility for unloading is assumed to be the moment it reaches an accumulated weight of 9000kg of collected waste. This is again not very realistic, as the vehicle volume capacity is usually the main indicator used to send the vehicle for unloading and not its weight capacity. Except for the assumed parameter values mentioned before, to achieve a deterministic model behavior and ensure the model's results reproducibility the algorithms employed in the model are set to be deterministic. More specifically, a seed was fed to the K-means algorithm to keep the starting points constant with every model run, while to ensure reproducibility of the train and test data used in the KNN algorithm an arbitrary seed with a specific split ratio (80% train data, 20% test data) was used.

Except from the investigation of the three examined scheduling strategies, the model can further be used to understand the transport mechanisms of waste and how the road network is utilized by the waste collection vehicles. Among others, important aspects to be considered should be the routes' compactness, which regards the overlapping of routes, and the identification of the most frequently used roads. With information on the network usage, a timely concept to be examined would be the calculation of CO_2 emissions production per resulting waste collection area, which would aid in understanding the impact of the waste collection routes. Applying the model for a consecutive number of days can enable the identification of underused containers, or containers in hard-to-reach locations on the network which cause the formation of inefficient routes, which can thereafter be moved to more beneficial locations to better exploit them.

The city of Rotterdam has already been able to put some of the findings of this research into practice, demonstrating a proof of concept. To be more precise, they adopted the idea of clustering for a specific set of containers during real operations, which enabled the assignment of drivers to it and validated that efficiency gains can be achieved with the cluster-focused routes. The city of Rotterdam further states that the research's results provided insights into how to further improve the current dynamic routing process and better articulate the city's needs in future tenders for this kind of planning tools. For the longer term, the city of Rotterdam wishes to analyze the potential efficiency gains from a combined collection of household and domestic waste. They recognize that the first step towards this goal has already been taken with this research, which made available a tool that plans and analyzes the process of household solid waste collection.

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Chapter 1 Introduction

1.1 Context

Internet of Things (IoT) is the most prevalent technological advancement that is continuously revolutionizing the way we live. Its integration into waste management allowed for the creation of a cyber-physical system that holds the potential of reshaping the waste collection service toward more demand-responsive, efficient, and dynamic operations (Pardini et al., 2019). This system integrates sensing and networking on waste containers with the use of appropriate wireless sensors, connecting them as such to the Internet as well as to each other. These sensors monitor at regular intervals each container's waste fill level, and other physical characteristics (e.g. temperature), and transmit the data to the cloud of the waste management operator.

The use of this technology has been on the rise, witnessed in smart cities all around the globe (Neffati et al., 2021) as organizations are gradually realizing this technology's potential in addressing some of their most pressing priorities. A prime example of a metropolitan city adopting this ground-breaking technology is the city of Rotterdam in the Netherlands, which has established this technology in its waste collection operations since 2017. As early adopters of this technology, the waste collection department of Rotterdam attests to the multiple benefits of this innovation and shares some useful insights from their day-to-day operations.

With access to real-time information on the status of each container, IoT technology is proven particularly beneficial where the containers are situated in remote locations or where they experience highly variable fill rates. The containers which usually experience the latter are located in densely populated areas, meaning they serve a large number of people, and are located in collection sites with multiple containers. With the use of this technology, the dynamic organization of waste collection is enabled as containers are collected only when it is necessary. This ensures that the servicing needs are met, and the waste is collected in a timely fashion, which consequently translates to a reduction of overfill phenomena and collection of partially full containers. These are two of the most transparent indicators of inefficient waste collection management. The former poses an array of hazards to human health and deteriorates citizen satisfaction, while the latter incurs higher operational costs and strains unnecessarily the environment with avoidable pollution emissions.

In addition to the above, the constant waste generation data stream transmitted by the installed sensors can aid in the identification of seasonal trends or events, and therefore to an appropriately adapted waste collection service. The waste collection department of Rotterdam can attest to this statement as the unprecedented increase in household waste generation during the COVID-19 pandemic could be easily monitored and assessed, and the waste collection crews of the department were able to composedly respond to it.

1.2 Problem definition

The waste collection department of Rotterdam, as experts in the domain of IoT-based waste collection, express the need and interest for an improved method of scheduling and planning their operations. Specifically, they would like to reduce the complete variability which is associated with the current demand-responsive operations as it has proven to be a significant issue, and concurrently increase the dispatch consistency of the waste collection routes without hindering the enabled flexibility. Complete variability is undesirable for several reasons such as administrative inconvenience, the need for enhanced internal communications, and driver unfamiliarity with site-specific inconveniences e.g. road works, blocked containers, etc., among others.

Furthermore, they would like to achieve a more economically and environmentally enhanced operations performance. This translates to a maximization of the amount of collected waste in such a way that the total travel kilometers and CO2 emissions produced are minimized. By achieving these objectives the department's efficiency will be increased, lesser resources will be wasted, and better service will be provided to the citizens.

1.3 Research objectives

The objective of this research is to develop a solution approach to solve the IoT-based waste collection problem, which is derived from the knowledge and requirements of the domain. The use of the knowledge of the domain is significant as it ensures that the model is tailored and applicable to a real-life IoT-based waste collection service. The overarching objective of the approach is to maintain dispatch consistency and flexibility when the containers' location and demands vary from day to day, as well as to attain an economically and environmentally enhanced waste collection performance.

1.4 Research questions

The problem definition and research objective lead to the formulation of the following main research question:

"How can the knowledge of the domain be used to improve the performance of an IoT-based waste collection service?"

The following sub-questions guide us in addressing the main research question:

1. What are the functional requirements of an IoT-based waste collection service as derived from the knowledge of the domain?
2. What scheduling strategies have been proposed to schedule containers for collection?
3. How has the waste collection problem been approached in literature?
4. What solution approaches are employed in literature to solve the waste collection problem?
5. What solution approach is proposed to reach the stated functional requirements?
6. How does the developed model perform?

1.5 Research approach

In this chapter an introduction of the studied topic was given, the necessity for this research was outlined, and the leading research objectives and questions were presented. The research approach adopted to address the sub-questions and compose an answer to the main research question is displayed in Figure 1.1 which also provides an overview of the report's structure.

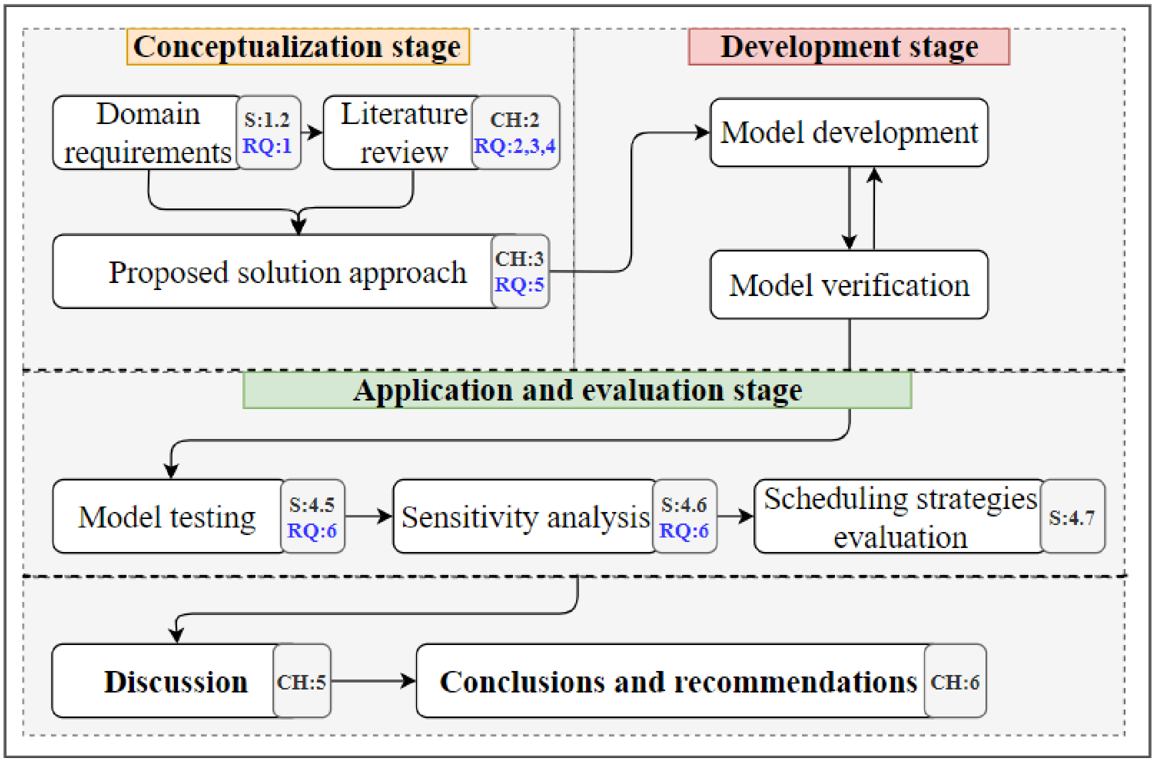


Figure 1.1 Research approach

At the conceptualization stage, domain experts were interviewed to understand what functional requirements they put forward for the scheduling and planning of an IoT-based waste collection service. A brief overview of the requirements is presented in Section 1.2, while more relative information can be found in Section 4.3, addressing thereby in detail research sub-question 1. Once the requirements were known, an extensive literature review was performed to gain a deeper understanding of the field and notice the relevant methods and techniques employed to solve the waste collection vehicle routing problem (WCVRP). A review of the relevant literature is provided in Chapter 2 which discusses various proposed dynamic scheduling strategies, how the waste collection problem has been generally approached, and different solution approaches developed to solve the WCVRP, answering respectively research sub-questions 2, 3, and 4.

Chapter 3 addresses research sub-question 5 as it gives an outline of the solution approach proposed to solve the IoT-based WCVRP, which is derived from the findings of the literature review and the requirements set forth by the domain experts. The WCVRP problem is formally formulated and modeled in Section 3.1, followed by the explanation of the proposed solution approach in Section 3.2. The overall approach consists of three sub-models, the consecutive development of which started once all the necessary data was collected. During the development stage, the model was verified to ensure that it was performing by the initial modeling assumptions and that its outputs were sound and logical. To do so, bottom-up testing was performed, testing the sub-models first and then the overall model.

Chapter 4 uses the waste collection service of Rotterdam as a case study to demonstrate the applicability of the developed model. This chapter presents the city’s waste collection system and its current planning methodologies in Section 4.1 and Section 4.2 respectively. Subsequently, it describes the requirements and objectives the service articulates for its future operations as an IoT-based waste collection service in Section 4.3, thereby addressing in detail research sub-question 1. Section 4.4 presents the results of testing the developed model on the selected case study, and Section 4.5 presents the results of a sensitivity analysis performed to understand the model's sensitivity to certain parameters. The findings of Section 4.4 and Section 4.5 together address research sub-question 6 which concerns the evaluation of the developed model's performance. Section 4.6 finally demonstrates how can the developed model be used to investigate and evaluate three different scheduling strategies. In Chapter 5 the findings of the research are interpreted and discussed, and the limitations of the model are outlined. Lastly, Chapter 6 formulates the conclusions of the research, addresses the research questions, and provides recommendations for model improvement, future research, and the waste collection service of Rotterdam.

Chapter 2 Literature review

To construct optimal waste collection routes traversing by a selected set of containers can be referred to as the waste collection vehicle routing problem (WCVRP), for which numerous models and approaches have been proposed in the existent literature. This chapter gives an overview of the various approaches aiming to solve different components of the waste collection problem. Section 2.1 presents the dynamic scheduling strategies proposed in the literature thereby addressing sub-question 2. This is followed by a discussion regarding the WCVRP and its multiple variants in Section 2.2 which answers respectively sub-question 3. In Section 2.3, an overview of the solution methodologies employed in the literature to solve the problem is provided, answering as such sub-question 4. In Section 2.4, a variety of performance indicators used to quantify the performance of the proposed approaches is presented, and finally, Section 2.5 concludes on the necessity of this research.

2.1 Dynamic scheduling strategies

Researchers have proposed a blend of dynamic scheduling strategies which utilize the enabled dynamicity brought by the IoT in the waste collection context. These strategies form a set of rules with specific objectives that guide the planning process into higher efficiency operations. For the evaluation of such strategies, waste generation data are required which, depending on the research objectives, may be real or synthetic. This section firstly explains under what circumstances each category of data is used, and secondly, it elaborates on the different dynamic scheduling strategies studied in the literature.

2.1.1 Real data vs synthetic data

Researchers studying the dynamic waste collection problem often use a case study to clarify their findings and to demonstrate the practical effect of their method. They apply their solution to a real-life problem or a hypothetical one with invented data (Beliën et al., 2014). These hypothetical problems often represent scenarios developed to analyze the sensitivity of collection strategies or small instances to benchmark developed heuristics solutions to exact-solution mathematical models. The scenarios' tunable parameters can relate to the waste collection service, the container network characteristics, and the waste generation itself. We see, for example, researchers experimenting with different values of containers' capacity, vehicle capacity, and fleet size to test their methodologies (Anagnostopoulos et al., 2015; Omara et al., 2018; Amal et al., 2018). In addition, some authors construct simple grid or circular networks of containers, subject to different sizes, to propose the most appropriate strategies (Johansson, 2006; Vonolfen et al., 2011; Markov et al., 2016; Akhtar et al., 2017; Omara et al., 2018; Neffati et al., 2021). Lastly, researchers examine the effect of their proposed solutions under a variety of waste generation patterns. These are either constructed by drawing waste deposits and arrival rates from distributions (Johansson, 2006; Vonolfen et al., 2011; McLeod et al., 2013; Mes et al., 2014; Akhtar et al., 2017; Omara et al., 2018; Hannan et al., 2018; Heijnen, 2019; Neffati et al., 2021) or by adopting predefined waste generation patterns (Arribas et al., 2010; Abdallah et al., 2019). In most of the cases, due to data unavailability, the mean and standard deviations of the distributions are drawn from the literature.

Real-life problems are conversely accompanied by a real container network under specific service characteristics and real waste generation data. For specific case studies the data are provided in the form of historical waste generation rates on the container level (Zsigraiova et al., 2013), while in others the data are retrieved by real-time traceability devices (Faccio et al., 2011; Markov et al., 2016; Christodoulou et al., 2016; Hua et al., 2016; Ramos et al., 2018; Wu et al., 2020). Some authors use the real-time data to perform predictions for the next collection day, rather than to blindly react to them on the same collection day (Abdallah et al., 2019; Ferrer & Alba, 2019). In other cases, the waste data are provided on an aggregated level. Simple disaggregation techniques are then utilized to transform the data to the desired level (Teixeira et al., 2004; Nuortio et al., 2006; de Oliveira Simonetto & Borenstein, 2007; Arribas et al., 2010; Expósito-Márquez et al., 2019). Lastly, studies exist which focus explicitly on route optimization, thus ignoring the actual amount of accumulated waste in the containers and consecutively losing the benefits of targeted container collection (Karadimas et al., 2005; Strand et al., 2020). In these cases, the vehicle capacity planned for a route is overestimated as it schedules all the containers for collection, and assumes they are full.

With the adoption of dynamic scheduling strategies, which containers should be collected and at what moment in time (usually which day) becomes an option. Depending on the goals of the research, completely reactive scheduling or predictive-reactive scheduling approaches are proposed. With each approach, various trigger rules and ranking methods are examined to define the containers' eligibility for (possible) collection.

2.1.2 Reactive scheduling vs predictive-reactive scheduling

The two main scheduling categories examined in the literature are completely reactive scheduling and predictive-reactive scheduling. In the former, no firm scheduling is generated in advance, and decisions are made locally in real-time, while in the latter schedules made for a rolling horizon are revised in response to real-time events (Ouelhadj & Petrovic, 2009). Logically, the predictive-reactive scheduling could offer a significantly improved *global* system performance, in comparison to the completely reactive scheduling, as the latter acts in a myopic way due to decisions made only in real-time.

Waste generation data is stochastic by nature, which could make predictive-reactive scheduling more relevant for waste collection as, often conservatively, sufficient vehicle capacity can be always ensured. IoT technology reduces, on the other hand, most of the randomness and uncertainty associated with waste generation data, as it allows real-time access to the information regarding the actual amounts generated in the network. Thus transforming, for an instance in time, this stochastic variable to a deterministic. It is important to note here that the "instance in time" is the moment when the collection schedule is constructed, not en-route but prior. A few studies have delved into real-time rerouting as they pay particular concern to the possibility of immediate waste collection of for example high-priority waste containers (Anagnostopoulos et al., 2015; Wu et al., 2020) or due to reaction to unexpected events.

From the literature we observe that researchers often use the benefits of real-time information as a solid basis to construct completely reactive schedules, thus eliminating the need for a rolling horizon plan (Abdallah et al., 2019; Akhtar et al., 2017; Anagnostopoulos et al., 2015;

Christodoulou et al., 2016; Faccio et al., 2011; Neffati et al., 2021; Omara et al., 2018). It is quite a striking fact that all the authors mentioned above deal with the collection of solid waste and try to minimize an objective that is most often traveled distance or time and fleet size.

Ferrer & Alba (2019) also follow a completely reactive scheduling technique with the objective of distance minimization, but they instead focus on recyclable waste collection. They state that it is crucial, especially for selective collection in which the waste volume is lesser than solid waste, the planning of collection routes to be optimal as the side effects caused by these trips could outweigh the benefits of the collection. McLeod et al. (2013) adopted in their research a one-day look-ahead period approach to construct routes for textile collection, aiming at maximizing profit. Acknowledged limitation of their model is the inability to delay collections to increase profit as the rolling horizon is not long enough.

Expósito-Márquez et al. (2019) present a similar problem to the work of McLeod et al. (2013) in which they aim to maximize the amount of recyclable waste collected in the containers, all while minimizing the risk of overflows. To achieve their objectives, they use instead a predictive-reactive scheduling technique to construct routes for a rolling horizon. Mes et al. (2014) use a predictive-reactive schedule to solve an inventory routing problem with the multi-objective of minimizing costs while maximizing citizen satisfaction. The authors associated in this case citizen satisfaction to a time-dependent penalty cost related to overflown containers. Along similar lines is the work of Johansson (2006) which demonstrates the advantages of dynamic schedules over static, over a time horizon, when considering overflown containers penalty in cost minimization. Ramos et al. (2018) study three operational management approaches which are formulated under the following three combinations: 1. reactive scheduling aiming at cost minimization 2. reactive scheduling aiming at profit maximization 3. predictive-reactive scheduling aiming at profit maximization. They proved that the best approach was the latter with improvements both in profit maximization as well as cost minimization. Based on the above, it can be derived that predictive-reactive scheduling is the most efficient approach when the aim is to maximize an objective.

In summary, we observe that the type of material that is to be collected affects, most of the time, the objectives of the research, which in their turn point towards the direction of a specific dynamic scheduling approach. Recyclable waste is often associated with profit, which is why the most popular objective of operators and researchers is its maximization. This indicates that the use of a predictive-reactive scheduling technique is the most beneficial for this kind of problem. That is not to say that this technique is not beneficial for solid waste collection as the objective may be the maximization of capacity utilization, that is for containers as well as vehicles, or of overall collected amount of waste. On the other hand, solid waste poses an array of dangers and annoyingness to the public if left unattended for too long. In this situation we see that operators and researchers focus mostly on dealing with the problem at hand in a reactive manner, therefore collecting waste on time all while considering cost-efficient operations.

2.1.3 Trigger for collection

Some authors develop scheduling strategies in which containers are selected for collection based on their "attractiveness" in the whole system and not just on a prefixed fill level. Ramos et al. (2018), for example, select containers for collection based on their fill levels, aiming simultaneously at waste quantity maximization, and travel distance minimization. They of course set a service level to guarantee a mandatory collection to prevent containers from overflowing. Others, base the container selection on future predictions. Abdallah et al. (2019) developed an algorithm that obtains the fill-level for each container and adds the expected level increase of the following day. It finally selects containers for collection if the total fill level is larger than the container capacity minus a safety margin. Vonolfen et al. (2011) developed a function that predicts the number of days a container will be full by taking into account the current fill level of the container and the probability distribution increment of the next day. According to this function, the containers with the least number of days to become full are selected for collection. Heijnen (2019) proposes an approach in which containers are selected for collection if the desired number of days (DED) before collection falls into a predefined rolling horizon. The DED is determined by finding the day before the overflow probability of a container exceeds an allowable threshold.

More common among researchers is the use of a simplified approach in which a static predefined minimum fill-level rule is imposed to select the containers to be attended to each day (Zsigraiova et al., 2013; Anagnostopoulos et al., 2015; Ramos et al., 2018; Ferrer & Alba, 2019). Some researchers endeavor to prove, under a variety of scenarios, which minimum fill level would lead to more optimal operations. For example, Hannan et al. (2018) and Akhtar et al. (2017) showed that for a capacitated WCVRP, solved with a particle Swarm Optimization Algorithm (PSO) and a modified Backtracking Search Algorithm (BSA) respectively, the best collection results can be achieved with a static 70-75% minimum fill-level. Neffati et al. (2021) proved that a 70% fill level is optimal for a scenario of low arrival rates to the containers, as the percentage of overfilled containers is close to zero, while for variable arrival rates the 70% threshold is comparable with a fixed collection frequency of three times per week. Faccio et al. (2011) demonstrated that the optimal threshold fill level is a function of a predefined oversize risk parameter (% of allowed overfilled containers) and an observed waste generation pattern.

Other studies adopting the simplified approach, also include in the selection containers which have not yet reached the threshold fill level. These extra containers are considered as they are located close to the already generated routes, and/or are expected to be full soon (Johansson, 2006; Mes et al., 2014; Christodoulou et al., 2016; Omara et al., 2018). The purpose of adding the extra containers is to increase the vehicle capacity utilization and the overall amount of collected waste. Omara et al. (2018) evaluate three collection strategies in this regard: 1. Containers reaching a threshold fill level 2. Containers reaching a threshold fill level plus containers adjacent to an already constructed route 3. Containers reaching a threshold fill level plus containers adjacent to an already constructed route that have reached a minimum threshold fill level. They proved that the second collection strategy performs the best in smaller container networks in terms of cost and delay, while the first collection strategy performs the best in larger networks. Mes et al. (2014) examine the inclusion of extra containers based on their attractiveness which is described as an additional travel time to waste volume ratio. To maintain a balanced workload between routes, the authors consider a limit on the maximum number of extra containers which can be collected per day.

Overall, it is generally acknowledged that while the vehicle capacity utilization and amount of collected waste may be improved with the addition of extra containers, it might also lead to unnecessarily long routes or a disproportionate workload for the following days. To better define the containers' eligibility for collection, researchers have developed a variety of ranking rules presented analytically in the next section.

2.1.4 Container ranking and collection rules

Researchers usually classify containers to different priority levels by establishing certain threshold fill levels, referred to by various definitions (Johansson, 2006; McLeod et al., 2013; Ferrer & Alba, 2019). Johansson (2006) considers that containers with a 100% fill level trigger a “red alarm”, which must be collected within 24 hours, while the ones with a fill level exceeding 75% trigger a “yellow alarm”. The author makes special use of this classification to introduce a special rule for Fridays which considers the collection of “yellow alarm” containers in an endeavor to avoid overfull containers during the weekends. McLeod et al., (2013) define containers with a fill level above 75% as “must-be-visited” which are also subject to a penalty to discourage overflows, above 50% as “may-be-visited” and less than 50% as “should-not-be-visited” as they are considered to not contain sufficient amount of waste to warrant a visit. Ferrer & Alba (2019) consider the estimated container fill levels to classify the containers as “mandatory” if the fill level is greater than 80%, and “optional” if it is higher than 50%.

A hybrid classification method can be seen in the work of Christodoulou et al. (2016). It regards not only the estimated container fill levels but also the waste accumulation period. The authors have defined an upper threshold on the number of days a container can remain unattended which is based on the seasonal period and the area type. In this context, they calculate the priority of each container on a rank from 4 to 1, with 4 indicating the highest priority corresponding to the day-imposed limit. The rest of the ranking priorities are defined only based on predefined fill level thresholds which can be parameterized by the administrator.

Another way to distinguish containers for collection is based on the expected number of days till they are full. Mes et al. (2014) use optimal learning techniques to tune two parameters that represent thresholds on the number of working days a container must be full to consider it a “must-go”, a “may-go” or a “no-go”. These adjustable parameters are specific to every day of the week, for example on Friday the containers which are expected to be full before Monday morning should be considered as “must-go” and be collected. Vonolfen et al. (2011) make the distinction between high and low priority containers in their research. The priority of a container is calculated considering both its location (and interaction with other containers) and its characteristics. Regarding its location, various factors are considered, tunable by a learning strategy, which form a weighted sum. Regarding its characteristics, the refill threshold and refill barrier are examined for an overpass. The former refers to the expected number of days before becoming full and the latter to the free space of the container. Similar to Vonolfen et al. (2011), Wu et al. (2020) and Anagnostopoulos et al. (2015) classify the containers to high or low priority, primarily according to their location in the network, and secondarily by the amount of accumulated waste. Containers that are located close to hospitals, fuel stations, schools, etc. are considered a high priority, irrespective of their accumulated amount of waste.

2.2 Waste collection vehicle routing problem

As observed from the previous section, a plethora of dynamic scheduling strategies is suggested in the literature that aim in reaching higher levels of efficiency. The smart selection of containers to be collected daily constitutes the steppingstone towards significant cost reductions and service quality improvement. The problem then comes down to the construction of optimal waste collection routes traversing by the selected containers, known as the WCVRP. Many variations and specializations of the WCVRP exist, depending on the problem characteristics and the often conflicting goals and constraints (Dotoli & Epicoco, 2017). The WCVRP variants encountered in the literature are presented in the following sections by elaborating on the considered constraints, problem characteristics, and sought-after objectives.

2.2.1 Constraints

Waste collection VRP is generally more difficult to solve than a classical VRP (Han & Cueto, 2015) as on the one hand more constraints must be taken into account, and on the other hand, multiple collection sites need to be considered on the same route (Dotoli & Epicoco, 2017). Depending on the level of realism that is to be adopted, the number of imposed constraints grows linearly.

At the outset, the refuse vehicles are typically subject to constrained capacities, meaning that the accumulated amount of waste of any route must not exceed the vehicle's capacity. The moment the vehicles reach their capacity they must visit a specific disposal facility to empty their load before returning to the depot. This capacity-constrained VRP is referred to as CVRP, which constitutes the most popular VRP variant among researchers studying the WCVRP (McLeod et al., 2013; Son, 2014; Anagnostopoulos et al., 2015; Christodoulou et al., 2016; Akhtar et al., 2017; Hannan et al., 2018; Omara et al., 2018; Ferrer & Alba, 2019). In the case that multiple trips are allowed to be performed in a route, the CVRP transforms to a multi-trip VRP (Multi-T VRP). This corresponds to more realistic operations as the vehicle can visit the disposal facility multiple times to unload their accumulated waste and regain their capacity, before returning to their route or the depot at the end of the day (Babaee Tirkolaee et al., 2019; Kim et al., 2006).

Temporal constraints can also be imposed on the waste collection routes, representing either the shift's legal duration (Kim et al., 2006; Arribas et al., 2010; Faccio et al., 2011; Zsigraiova et al., 2013; Abbatecola et al., 2016), the drivers' break (Kim et al., 2006; Buhrkal et al., 2012), or the time windows in which containers can be collected throughout the day (Kim et al., 2006; Nuortio et al., 2006; McLeod et al., 2013). The VRP problem is then referred to as a VRP with time windows (VRPTWs). In specific cases, the number of stops allowed in a route is bounded above a threshold so that a workload balance can be achieved (Kim et al., 2006; Buhrkal et al., 2012). For the same reason, added constraints can be imposed on the number of times a refuse vehicle is allowed to visit a disposal facility (Son, 2014; Abbatecola et al., 2016).

2.2.2 Physical infrastructure and fleet

The variance of the fleet and the complexity of the physical infrastructure (e.g., number of depots and treatment/disposal facilities) can affect the computational complexity of the problem as an advanced resource allocation is required. In most instances, the researchers adopt a simple network setup in which the depot also acts as the disposal facility. This implies that the collection routes have as an origin and destination the depot.

To respond more accurately to reality, researchers are also adopting more complex network setups, transforming thus the classical VRP to a VRP with intermediate facilities (VRP-IF). We see, for example, researchers adopting networks consisting of one depot and one separate disposal facility (Mes et al., 2014; Omara et al., 2018; Strand et al., 2020). Others take it a step further and consider multiple depots and disposal facilities in their studies, solving as such a multi-depot VRP. Buhrkal et al. (2012), Christodoulou et al. (2016), and Kim et al. (2006) assume a route sequence of one vehicle starting and ending at the same depot, considering disposal operations at the nearest disposal site.

Similarly to the previous, De Oliveira Simonetto & Borenstein (2007) consider multiple sorting units in their model, but in contrast, they aim to assign a balanced number of collection vehicles to them to avoid an excessive number of collection trips in some and idleness in others. Markov et al. (2016), on the other hand, solve a multi-depot VRP in which they assume a route sequence in which the origin depots are fixed, but the destination depots are not, as they state that it is not always optimal for a vehicle to return to the depot it started from. It can then be understood that the complexity of solving a multi-depot VRP grows exponentially as the right time to empty the vehicles as well as to choose the best disposal facility should be determined. In this case, it may not be optimal to only visit the disposal facility when the vehicle becomes full, but earlier if the situation allows, to minimize the total driven distance.

Despite the wide practical applications of the problems described above, many important realistic features are often omitted. Most of the studies regarding the waste collection VRP assume a homogeneous fleet which is often not realistic. It is usual that the fleet of a service is slowly expanding, acquiring throughout time vehicles with different capacities and related costs. Although it may be beneficial to have a homogeneous fleet in regard to operational, maintenance, and training costs, the network topology may be requiring some vehicle diversity. For instance, certain container sites may be associated with their own dependencies, such as mountainous terrain or narrow streets (Christodoulou et al., 2016; Markov et al., 2016). Specific containers may be compatible with only certain collection vehicles, as their network similarly to the vehicle fleet is slowly expanding (Ferrer & Alba, 2019). Furthermore, the remoteness of container locations may affect the choice of a collection vehicle due to the incurring costs. Considering these site dependencies, certain authors approach the WCVRP as a VRP with a heterogeneous fleet in their effort to associate vehicles to routes in the most beneficial way (Zsigraiova et al., 2013; Son, 2014; Amal et al., 2018; Babaee Tirkolaee et al., 2019).

2.2.3 Objective functions

All the researchers trying to solve a WCVRP follow a clear objective in their approaches. This objective leads to the formulation of a model which optimally solves the problem or leads to near-optimal solutions, depending on the adopted solution approach and the network size and characteristics.

The minimization of distance, costs and time are among the most popular objectives used by researchers. Time and distance minimization are straightforward as the goal is to reduce the total travel distance or time of all vehicles of the system. Some studies considering distance minimization as the leading objective are those of Hannan et al.(2018), Abdallah et al.(2019), Neffati et al.(2021) while the work of Amal et al.(2018) considers purely the minimization of the total waste collection time. Zsigraiova et al. (2013) optimized the route's construction in their model under both objectives and concluded that optimizing for time, rather than distance, produces larger reduction values of the operating variables of total time, distance, and fuel consumption.

Cost minimization is contrarily rather ambiguous, as every researcher can consider in their study different types of costs. The main advantage of minimizing costs, nevertheless, is that different types of goals can all be expressed in terms of the same monetary unit. The most frequently considered costs include the transport-mileage cost, usually expressed in EUR/km or on some occasions in EUR/h (Mes et al., 2014), and the employment cost expressed in EUR/h. In certain studies, additional costs are assumed, such as a fixed cost per vehicle (Markov et al., 2016; Ramos et al., 2018), a fixed handling cost per container (Omara et al., 2018), or a variable handling cost per container expressed in EUR/h (Mes et al., 2014).

Some researchers try to optimize the waste collection problem from a completely different perspective, that of maximization. Son (2014) solved the WCVRP with the single objective of maximizing the amount of collected waste. Similarly to Son (2014), McLeod et al. (2013) and Ramos et al. (2018) focused on maximizing the collected waste, while considering that a price market is associated with each recyclable container. Their objective was therefore to maximize profit, defined as the difference between the revenues and the transportation costs. This specific type of routing problem relating to profit maximization can be referred to as the Vehicle Routing Problem with Profits (VRPP).

Next to the aforementioned costs, we see researchers employing various types of cost penalties that are formulated based on their predefined objectives. Markov et al. (2016), for example, study a VRP with intermediate facilities in which they allow vehicles to start and end their shift at the most convenient depot. To incentivize the relocation to the origin depot they employ a cost component in the objective function expressed in travel distance and time. Babaee Tirkolaee et al. (2019) attach, on another approach, hard and soft time windows on each container site to indicate their priority of service. This indirectly means that an exit from a hard window is impossible, while an exit from a soft window will inflict a cost penalty. Another time-related cost penalty can be found in the work of Johansson (2006), which is incurred with the collection overdue of overflown containers during a prespecified amount of time on weekdays and the weekend. Overflown container-related penalties are also considered in the works of Omara et al. (2018) and Mes et al. (2014) who express this penalty per unit of a kilo of overflow waste, and per unit of volume of overflow waste respectively.

The minimization of environmental effects is rarely studied in the literature. The authors who decided to study it approached it from multiple aspects. Strand et al. (2020) consider the minimization of carbon dioxide emissions in function of the reduced travel time to construct the most efficient waste collection routes. In addition, they developed a real-time optimization function to automatically assign unplanned container requests to a truck by considering minimal emissions. Anagnostopoulos et al. (2015) study a dynamic waste collection architecture, which focuses on minimizing the time required to serve high priority areas and keep the average expected performance at a high level. The authors state that containers in such areas should be depleted the soonest to minimize the risk of fire and the effect of waste on the environment and human lives. Expósito-Márquez et al. (2019) study the eco-efficient VRP (Ee-VRP) which has an objective the maximization of container capacity utilization. The authors develop a solution approach that gives priority to high-filled containers thus allowing the reduction of fuel consumption, as well as the number of overflowing containers.

Some researchers follow a multi-objective approach aiming at the simultaneous optimization of multiple objectives. Faccio et al. (2011) worked on optimizing the route construction towards minimized covered distance and required vehicle fleet. Vonolfen et al. (2011) follow a similar approach to Faccio et al. (2011), all while maintaining a certain service level determined by the number of overfilled containers over time. Cortinhal et al. (2016) on the contrary, aim to partition a service territory into an optimal number of sectors such that each can be covered by one feasible vehicle trip, whilst minimizing the total routing time and the workload time imbalance per sector.

Kim et al. (2006) developed a clustering-based waste collection algorithm, similar to Cortinhal et al. (2016), aiming to minimize the required fleet size and total routing time. The authors' higher motive was, however, to improve the workload balance of the constructed routes as well as the route compactness, which indicates the extent to which the constructed routes are overlapping. Similarly, Arribas et al. (2010) aimed to address in their study tactical decisions, such as solid waste collection zone definition and vehicle fleet design, all while considering the minimization of total travel time.

De Oliveira Simonetto & Borenstein (2007) followed a bi-objective optimization approach. The first objective regards the determination of the daily amount of solid waste to be sent to each recycling sorting unit to achieve more balanced workload and the second objective regards the construction of minimum transport cost routes. Wu et al. (2020) focused on obtaining the optimal paths of each collection vehicle with the objective of minimizing the total distance, total greenhouse gas (GHG) emissions, and total comprehensive costs including vehicle costs and GHG emissions costs.

2.3 WCVRP solution approaches

An extensive set of solution approaches have been deployed to solve the variants of WCVRP mentioned in the previous sections. This indicates that no perfect method exists to tackle this problem in its holistic nature. The focus is instead placed on distinctive features of the problem. This is mainly because the WCVRP is an NP (non-deterministic polynomial) hard combinatorial optimization problem which is hard to solve.

The solution approaches can be distinguished into two categories. The first employs mathematical programming techniques to solve small network instances to optimality, but at the expense of exponentially increasing computation time. And the second addresses heuristic and metaheuristic methodologies which do not guarantee optimality but yield good results in a shorter execution time. This category also proves to be the most widespread among researchers as heuristics are often simple to describe and implement, which leads to their easy adaptability.

Irrespective of the choice of an exact or inexact solution approach, the WCVRP complexity can be reduced by reducing the problem size. This approach, usually referred to as a cluster-first route-second approach, partitions the 'customers set' into individual smaller instances which are solved separately into complete routes.

In the following subsections the clustering techniques employed by researchers to partition the 'customers set' of a WCVRP into individual smaller instances are presented, followed by a description of the general and historically well studied methods for solving the WCVRP.

2.3.1 Clustering techniques

Clustering is in general the task of segregating points with similar characteristics and assigning them into clusters. For waste collection the points assigned to clusters are the waste containers, with rules imposed by the geography of the area, the practitioners, as well as by the characteristics of the containers themselves.

In most of the instances, purpose of the clustering is to reduce the solution space and lead to faster and possibly better solutions. For a further reduction of the solution space and acceleration of the performance of the algorithms, we see researchers aggregating containers into "super" containers under the condition that they belong in the same location and bear the same time windows (Buhrkal et al., 2012; Christodoulou et al., 2016).

Considering all the clustering benefits enlisted, multiple researchers are adopting the cluster-first route-second approach in their studies to enhance the applicability of their solutions to real-life operations. Some authors use real-time fill levels of containers to allocate them to clusters formed before every collection. The objective is to include containers which's waste level exceeds a predefined threshold level (Akhtar et al., 2017; Hannan et al., 2018; Ramos et al., 2018). The k-means algorithm is popular among researchers as it allows containers to be assigned to clusters using as an only criterion the distance (Anagnostopoulos et al., 2015; Hua et al., 2016).

Some researchers aim in the construction of clusters that are subject to constraints such as vehicle capacity, shift duration, traffic temporal conditions, or a balanced number of containers. To achieve those constraints they develop various clustering techniques. Abbatecola et al. (2016) use the farthest container from the depot as a cluster starting point and consequently populate it with the containers located close to it until the vehicle capacity is reached. Other studies are following an approach in which an initial clustering solution is obtained which is consequently improved. To construct the initial solution a certain number of containers must be selected to act as the cluster centroids. These can be selected based on the least potential costs (Kim et al., 2006), iteratively based on predefined criteria (Cortinhal et al., 2016), or randomly (Arribas et al., 2010). The rest of the containers are assigned to the formulated clusters according to the shortest distance, always respecting the considered constraints. When a cluster is closed, e.g. the shift duration is exceeded, the containers are assigned to the second nearest cluster that can accommodate them, etc.

To improve the initial feasible solution Arribas et al. (2010) and Cortinhal et al. (2016) apply local improvement methods, such as cluster centroid re-election, type 1-OPT, and type 2-OPT operations. The last two aim in reassigning one container to another cluster and exchange a pair of containers from different clusters respectively. Kim et al. (2006) use the initial solution to recalculate the centroids of the created clusters and use them to calculate the “grand centroid”, which as the name suggests represents the centroid of the cluster centroids. The containers are then sorted on a descending order based on the distance between them and the grand centroid and are consecutively assigned to the cluster closest to them. Just like Arribas et al. (2010), the authors consider a one-move improvement method to reassign containers to nearer clusters in an effort to reduce the clusters overlapping.

2.3.2 Methods to solve the WCVRP

Various methods have been developed in literature able to produce initial feasible solutions. It is common practice, nevertheless, that the initial solutions are improved with local improvement methods. We see a plethora of insertion heuristics and swarm intelligence algorithms trying to solve the WCVRP, and various algorithms aiming to improve the initially obtained solutions. Most encountered local improvement methods in literature are neighborhood search algorithms and general heuristic methods, such as genetic algorithm, simulated annealing, and tabu search, which are combined with various local search enhancement methods.

Insertion heuristics

Insertion heuristics are often preferred by researchers due to their simplistic nature. One route is built at a time, usually starting from an arbitrary container, and is iteratively populated by containers selected under certain criteria, and until the predefined constraints are met. Sometimes the seed containers selected are the ones with the largest minimum distance from the depot so that the constructed routes are spread afar with a more balanced workload (Mes et al., 2014). The farthest insertion heuristic, adopted in the work of Abbatecola et al. (2016) to solve a traveling salesman problem (TSP), works similarly. The depot and the farthest container from the depot are inserted first into the route. Then in iterative nature, the container further away from the containers already inserted in the route is selected for insertion and placed into the route at the point causing the shortest increase in the total length.

A common criterion used to insert containers in a route is the shortest distance or time, meaning that the nearest neighbor containers are iteratively prolonging the constructed route (Faccio et al., 2011; Mes et al., 2014; Heijnen, 2019; Neffati et al., 2021). Vonolfen et al. (2011) used the cheapest insertion algorithm to construct initial routes which they later optimized with a push-forward insertion heuristic (PFIH). Another criterion used to insert containers in the route is the quantity of waste they hold. In the work of Expósito-Márquez et al. (2019) the containers with the highest quantities have a higher probability of being inserted in the route as the objective of their research is to maximize the amount of recyclable waste collected. Next to the above, researchers are also devising ratios of various quantities to be used as an insertion criterion. Teixeira et al. (2004) for example, calculated for all uncollected containers the ratio between the “urgency of collection” and the cost of insertion, while Mes et al. (2014) considered a relative ratio, between the additional travel time and quantity of waste to a historical average ratio, to insert “maygo” containers in the already constructed routes.

Swarm intelligence algorithms

Researchers also focus on metaheuristic algorithms based on swarm intelligence to solve the WCVRP. A swarm consists of a large number of homogenous, unsophisticated agents that interact locally among themselves and their environment without any central management but managing to yield an “intelligent” global behavior. Examples of these algorithms are the ant colony optimization (ACO) and the particle swarm optimization (PSO). Karadimas et al. (2005) and Hua et al. (2016) utilized the ant colony optimization algorithm (ACO) to construct the optimal routes of the collection vehicles. Hannan et al. (2018) modified a PSO algorithm to solve the WCVRP and then improved the initial routes with inter-route (2-opt*, Or-opt-1), and intra-route (2-opt, Or-opt) improvement methods.

Son (2014) developed a hybrid method to solve the WCVRP in which a binary gravitational search algorithm is used to construct the initial routes, which are later optimized by chaotic particle swarm optimization (CPSO). CPSO is an extension of the PSO algorithm that incorporates the passive congregation and chaos theory in an effort to avoid local optima as well as to increase its performance. Wu et al. (2020) used a PSO algorithm to obtain initial optimal routing solutions which they then optimized with three local search operators: swap, reverse, and insert. To decide whether to accept the new solutions the authors employed the simulated annealing (SA) algorithm which accepts solutions better than the original, as well as solutions worse than the original under a calculated possibility.

Neighborhood algorithms

Neighborhood algorithms proceed to a systematic change of neighborhood within local search heuristics, which usually use one kind of neighborhood structure. An example of the application of multiple neighborhood algorithms can be found in the work of Nuortio et al. (2006). The authors firstly apply a hybrid insertion heuristic to construct their initial routes based on the cheapest insertion method. They later improve these solutions with a guided variable neighborhood threshold metaheuristic (GVNT), which concurrently allows the acceptance of solutions worsening the objective value and serves as a stopping criterion. Overall, this algorithm integrates seven well-known improvement neighborhoods used for intra-route and inter-route reordering.

Markov et al. (2016) developed a multiple neighborhood search (MNS) heuristic which starts by constructing feasible initial solutions based on the cheapest insertion heuristic and then applies an iterative improvement procedure accepting infeasible intermediate solutions. The authors considered the swap, reinsert and 2-opt operators for intra-route and inter-rout reordering, which are successively applied until a maximum number of iterations or a maximum number of non-improving iterations has been reached. Buhrkal et al. (2012) used a greedy algorithm to construct initial routes and an adaptive large neighborhood search (ALNS) algorithm to optimize them. The neighborhood that ALNS employs is defined implicitly through several destroy and repair methods which are probabilistically chosen based on their past performance. The authors also use in their research a simulated annealing acceptance criterion such that an improving solution is always accepted but a worse solution is accepted under a calculated probability.

Simulated annealing

Simulated annealing (SA) as a stochastic global search optimization algorithm can escape from local optimums and lead to an optimal global solution. Similarly to Wu et al. (2020), other researchers have employed SA to improve their initial solutions and achieve the global optimum. Babaee Tirkolaee et al. (2019) developed a random generator algorithm to generate initial routes which are later optimized with a SA algorithm employing local search methods such as displacement, replacement, 2-Opt, and Or-opt. The authors accepted all solutions better than the original, in addition to worse solutions if a randomly generated associated number in the range [0,1] was lesser than a prespecified algorithmic value. Buhrkal et al. (2012) extended the known Solomon's insertion algorithm and used it to construct initial routes starting from some seed containers. These are chosen based on two starting criteria: the farthest stop from the depot or the stop that has the earliest due time. The authors then improve the constructed routes by a SA meta-heuristic using the CROSS exchange local search method.

Tabu search

Opposite to randomizing approaches such as simulated annealing, Tabu search (TS) is a meta-heuristic that is based on the principle of intelligent solution search, embracing as such efficient and systematic forms of direction like memorizing and learning (Kamboj & Sengupta, 2009). Arribas et al. (2010) and Zsigraiova et al. (2013) employed a tabu search metaheuristic approach to solve the WCVRP while McLeod et al. (2013) employed in addition three local search operators (container addition, container removal, and container swap) to optimize their solutions.

Evolutionary algorithms

To evolve a population of solutions, evolutionary algorithms apply biologically inspired operations such as selection, crossover, and mutation. Strand et al. (2020) approached the routing creation as a traveling salesman problem and solved it by implementing the multi-objective evolutionary algorithm NSGA-II. Amal et al. (2018) used the modified Dijkstra algorithm to construct initial collection routes and consequently a genetic algorithm to optimize them.

2.4 Performance indicators

To quantify the performance of their solution, researchers use an abundance of performance indicators. These indicators can describe the economic, environmental, and computational performance of a solution. They usually measure the solution's performance versus a set of predefined objectives, incumbent solutions, or standard problem instances. This process of confirming that the model achieves its intended purpose is known as model validation.

2.4.1 Economic performance

As already mentioned, the KPIs used to describe the performance of a solution may be derived from the objectives of the problem the solution is aiming to achieve. Unsurprisingly then, the most popular KPI used in the WCVRP is the total travel distance, as the most popular optimization objective refers to the minimization of that.

Following is the time, characterized under multiple forms. Researchers are mostly interested in determining the total working duration of the constructed routes, that including the travel time between the depot, the collection area, and the dumping site, as well as the service time, indicating the time needed to service the containers (Amal et al., 2018; Anagnostopoulos et al., 2015; Arribas et al., 2010; Expósito-Márquez et al., 2019; Zsigraiova et al., 2013). There are papers though which consider only the traveling time (Cortinhal et al., 2016; Zsigraiova et al., 2013), or the travel and service time spent specifically in the collection area (Abdallah et al., 2019; Ferrer & Alba, 2019).

Some researchers focus on the level of a route considering, for example, the average tour duration (Son, 2014), or the average shift time occupation (Teixeira et al., 2004). An interesting route-level indicator is the response time, used in the work of Anagnostopoulos et al. (2015), which represents the average time that a truck needs to serve high priority containers. Closely related to the time indicators is the workload duration balance. This measure is related to the fairness among the collection crews as smaller values point to more balanced workload durations. Kim et al. (2006) and Cortinhal et al. (2016) use this indicator in their studies and define it as the difference between the duration of the longest and the shortest route.

The total amount of collected waste is often used by researchers to show the overall efficiency of their solution. This indicator is used to compare proposed solutions with incumbent situations (Christodoulou et al., 2016; Expósito-Márquez et al., 2019; Ferrer & Alba, 2019), proposed algorithms with ones that exist in the literature (Son, 2014), and generally different collection strategies (McLeod et al., 2013; Anagnostopoulos et al., 2015; Hannan et al., 2018, 2018).

The service efficiency can also be evaluated by the capacity utilization, of either the infrastructure or the fleet. The vehicle capacity utilization refers to the amount of waste carried per unit of vehicle capacity (Teixeira et al., 2004; Johansson, 2006; Vonolfen et al., 2011; Christodoulou et al., 2016; Hannan et al., 2018; Ramos et al., 2018), while the container capacity utilization indicates the fill level of the containers before collection (Teixeira et al., 2004; Johansson, 2006; Expósito-Márquez et al., 2019). Another indicator related to container capacity utilization is the number of overfilled containers, as demonstrated in the work of Neffati et al. (2021), which depicts how many containers had been overflown in a period of time.

Researchers often use rate indicators to compare two different quantities that have different units of measure. These indicators give an initial idea of how a system performs on average. Some of these rate indicators include the distance, time or cost per kilo of collected waste (Mes et al., 2014; Expósito-Márquez et al., 2019), or from a different perspective the weight of collected waste over a travel distance (Hannan et al., 2018; Ramos et al., 2018).

2.4.2 Environmental performance

The environmental performance is mainly evaluated based on CO2 emission production (Abdallah et al., 2019; Amal et al., 2018; Strand et al., 2020) and fuel consumption (Zsigraiova et al., 2013; Anagnostopoulos et al., 2015; Christodoulou et al., 2016; Amal et al., 2018; Expósito-Márquez et al., 2019). In majority of the studies those indicators are calculated by considering only the driving time, but certain few include in addition the time the vehicle is idling, as its engines still operate at high revolutions to lift the waste container and compress their content.

A monetary value can sometimes be attached to these two indicators to be complementary to other related costs. Some studies focus on estimating those through a more detailed analysis which considered multiple factors and parameters. The basis for this is the approximately linear relation of CO_2 emission production to fuel consumption. More specifically, the total CO_2 emission production can be calculated by multiplying the fuel consumption (L), by an emission coefficient (kg CO_2/L). The emission coefficient measures the trucks' efficiency in converting the fuel consumed into carbon emissions.

The fuel consumption can also be expressed per ton of waste (Akhtar et al., 2017; Hannan et al., 2018), or per travel kilometer (Wu et al., 2020). In this case, to calculate the CO_2 emissions the total amount of collected waste and the total travel kilometers should be considered respectively. In general, the fuel consumption can be calculated by taking into account the truck weight, its waste load, the road type, the travel distance, and the average travel speed (Neffati et al., 2021). Bala et al. (2021).

2.4.3 Computational performance

It is quite often, when researchers are developing a new heuristic or mathematical model, that they compare apart from their approach's outcomes with that of others, the computation time as well. The reason behind this lies in the fact that heuristics don't guarantee optimality, rather a fair solution in a shorter execution time than that of an exact algorithm. Therefore, the purpose of this comparison is to examine the speed of convergence, rather than convergence itself. For small problem instances, the total computation time can be used to compare the solutions' performance, which exhibits the time devoted to constructing the final routes of the collection vehicles (Nuortio et al., 2006; Anagnostopoulos et al., 2015; Cortinhal et al., 2016). It is usual though that a stopping criterion is employed for the solution of a problem instance, as especially for a mathematical model the problem can be proven intractable, due to its size and number of constraints and characteristics. A limit can be imposed also on the computation time or the number of allowed iterations (Markov et al., 2016; Ferrer & Alba, 2019). For the former, a maximum preset CPU time is allowed, for when is reached it means that the optimal solution is not found, but the value of the best feasible obtained solution is reported instead (Abbatecola et al., 2016; Babaee Tirkolaee et al., 2019). The values defining the stopping criteria are usually obtained through experimentation.

2.5 Conclusions

This chapter gave an overview of the various approaches proposed in the literature to solve different aspects of the WCVRP. More specifically, it presented various dynamic scheduling strategies, it discussed the WCVRP and its multiple variants, and it reported a variety of solution methods to solve the WCVRP, addressing thereby research sub-questions 2, 3, and 4.

Through the literature review, a deeper understanding of the field was gained, and most importantly, it was investigated if and to what extent the requirements set by the domain experts, as discussed briefly in the problem definition in Section 1.2, were taken into consideration. A vast number of solution approaches exist to solve the WCVRP under different topologies, objectives, and constraints. It has been understood though, that the solution approaches which adopt clustering techniques to solve the IoT- based WCVRP, most closely reach the predefined requirements of dispatch consistency and flexibility. Nonetheless, no proposed clustering technique has been encountered in the literature to achieve a trade-off between the two required states, as explained below.

The clustering techniques proposed in the literature follow an array of rules to perform the ‘customer’ assignment to the most beneficial cluster, which can either lead to the creation of completely static or variable clusters. If the rule dictates that the container assignment to clusters must be performed before any scheduling strategy is applied, meaning all the containers must be used, the clusters constructed are static, ensuring the operations dispatch consistency. At the same time, the rigid boundaries of the clusters may impose limitations on the routing efficiency and flexibility as the waste demands vary daily.

On the other hand, if only the containers scheduled for collection are assigned to clusters, as selected by the rules of a scheduling strategy, the constructed clusters will vary daily to accommodate the uncertain demand. Studies adopting this approach have been observed to also impose constraints on the cluster formation such as vehicle capacity, shift duration, balanced size, time windows, etc. It can be understood that with this approach full dispatch flexibility can be achieved, which is nonetheless inconvenient due to practical reasons. In addition, with the imposition of the individual constraints to construct the containers cluster, it can be inferred that inefficient or infeasible routes may be constructed as it is usual in real life to consider multiple constraints at the same, e.g. vehicle capacity and shift duration.

Overall, it can be concluded that no approach has been reported in the literature to achieve the stated requirements set forth by the domain experts for the IoT-based WCVRP. The relevance and timely importance make this an interesting research gap to address. To address the identified gap, a solution approach to solve the IoT-based WCVRP is proposed in Chapter 3.

Chapter 3 Methodology

This chapter aims to give an outline of the proposed solution approach, as mentioned in the previous chapter, which thereby addresses research sub-question 5. Firstly, the WCVRP problem is formally formulated and modeled in section 3.1, followed by the presentation of the proposed solution approach in section 3.2. The chapter is concluded in section 3.3 with a short discussion about the solution approach, the necessary assumptions that frame it, and its expected outcomes.

3.1 Problem formulation

The waste collection problem addressed in this study can be defined as a multi-trip VRP with intermediate facilities. As the problem relates to waste collection, the intermediate facilities refer to disposal facilities that are visited once the capacity payload of the vehicles is reached, or just before their shift is over. The vehicles are allowed to visit those facilities multiple times, hence multi-trip, to unload the accumulated waste and regain their capacity, before returning to their route or the depot at the end of the shift.

The problem is defined on a directed real-network graph $G = (V, A)$, where the set of nodes $V = V^d \cup V^f \cup V^m$ consists of a depot $V^d = \{0\}$, a disposal facility $V^f = \{1\}$, m nodes $V^m = \{2, \dots, 2 + m\}$, n collection sites $V^c \subseteq V^m$, and the set of arcs is $A = \{(i, j, r) | \, i, j \in V, i \neq j, r \in R\}$, where r denotes the road type with R = {Urban, Highway}. Each collection site $s \in V^c$ represents a set of waste containers situated at the same spot where $s_c = \{1, \dots, c\}$, and has an associated service time st_s and weight of waste w_s. Let t_{ij} and d_{ij} be the travel time and travel distance associated with arc (i, j, r) respectively, and $K = \{1, \dots, k\}$ be the given set of homogeneous vehicles with capacity C and maximum shift duration *T*. $H_{i,k,t}$ is a continuous variable indicating the current driving duration of vehicle k at node i at every time t it traversers it. Let $x_{ijr,k}$ be equal to 1 if arc (i, j, r) is used by vehicle k and 0 otherwise, and $y_{s,k}$ be equal to 1 if collection site $s \in V^c$ is served by vehicle k and 0 otherwise.

The model's objective is to successively determine the membership of waste containers to clusters, created both on a tactical and operational level, such that the total traveled kilometers and total CO2 emissions produced by the routes created to service the operational level clusters are minimized. The total travel kilometers are expressed by (1), where n the number of times arc (i, j, r) is traversed.

$$Minimize \sum_{r \in R} \sum_{k \in K} \sum_{(i,j,r) \in A} d_{ijr} x_{ijr,k} n \qquad (1)$$

The total CO2 emissions are produced while vehicle k is driving, while it serves a collection site s, and while it unloads its waste at the disposal V^f, as expressed by (2.

$$Minimize \; E_{CO2_{driving}} + E_{CO2_{serving}} + E_{CO2_{unloading}} \qquad (2)$$

The work of Bala et al. (2021) is used as a reference to calculate the total amount of CO2 emissions produced while driving as expressed by (3). The amount of CO2 emissions produced on an arc (i, j, r) is the product of its length l, and an emission production factor C_{ir} which depends on the arc's respective road type r and the cumulative weight of waste $Q_{i,k,t}$ the vehicle k carries at the start of the arc at node i each time t it traverses it. It must be noted that $Q_{i,k,t} = Q_{j,k,t}$ for arc (i,j,r) as no additional waste is collected in the in-between. The emission production factor C is given for an empty and a full vehicle, therefore, to translate it according to the cumulative weight of waste Q (4 is applied, where Q_M constitutes the vehicles maximum load capacity. It is important to note that the additional weight of the heavy box and equipment used to collect and compact the waste that the vehicles continuously carry is not considered.

$$E_{CO2_{driving}} = \sum_{r\in R}\sum_{k\in K}\sum_{(i,j,r)\in A} d_{ijr}x_{ijr,k}C_{ir} \tag{3}$$

$$C_{ir} = C_{r,empty} + \frac{\left(C_{r,full} - C_{r,empty}\right) * Q_{i,k,t}}{Q_M} \tag{4}$$

The total CO2 emissions produced while vehicle k serves a collection site s is expressed by (5)(5, where C_{idling} is an emission production factor expressed in CO2 gr /min, and st_s is the service of time of collection site s the calculation of which is explained in more detail in 0.

$$E_{CO2_{servicing}} = C_{idling} * \left(\sum_{k\in K}\sum_{s\,\in\, V^c} st_s y_{s,k}\right) \tag{5}$$

The total CO2 emissions produced while vehicle k unloads its waste at the disposal V^f is expressed by (6), where $ut_{k,df}$ is the total unloading time of vehicle k at a disposal facility, and $n_{k,df}$ the number of visits of vehicle k at the disposal facility.

$$E_{CO2_{unloading}} = C_{idling} * \left(\sum_{k\in K} n_{k,df}ut_{k,df}\right) \tag{6}$$

The formulated problem is subject to:

$$\sum_{j\in V} x_{0jr,k} = 1 \qquad \forall r \in R, k \in K \tag{7}$$

$$\sum_{i\in V} x_{i1r,k} = 1 \qquad \forall r \in R, k \in K \tag{8}$$

$$\sum_{i\in V}\sum_{k\in K} x_{ijr,k} = 1 \qquad \forall r \in R, j \in V^c \tag{9}$$

$$\sum_{i \in V} x_{ijr,k} = \sum_{i \in V} x_{jir,k} \qquad \forall r \in R, j \in V, k \in K \qquad (10)$$

$$\sum_{i \in V^d \cup V^f} Q_{i,k,t} = 0 \qquad \forall k \in K, t \in T \qquad (11)$$

$$Q_{j,k,t} + w_j \leq Q_{i,k,t} + (1 - x_{jir,k})M \qquad \forall j \in V - \{V^f\}, i \in V, r \in R, k \in K, t \in T \qquad (12)$$

$$Q_{i,k,t} \leq C \qquad \forall i \in V, r \in R, k \in K \qquad (13)$$

$$H_{i,k,t} \leq T \qquad \forall i \in V, k \in K, t \in T \qquad (14)$$

$$H_{i,k,t} + st_j + t_{ij} \leq H_{j,k,t} + (1 - x_{ijr,k})M \qquad \forall (i,j) \in V, r \in R, k \in K, t \in T \qquad (15)$$

$$x_{ijr,k} \in \{0,1\} \qquad \forall (i,j) \in V, k \in K, r \in R \qquad (16)$$

$$y_{s,k} \in \{0,1\} \qquad \forall s \in V^c, k \in K \qquad (17)$$

$$Q_{i,k,t} \geq 0 \qquad \forall i \in V, k \in K, t \in T \qquad (18)$$

$$H_{i,k,t} \geq 0 \qquad \forall i \in V, k \in K, t \in T \qquad (19)$$

Constraints (7) and (8) impose that all k vehicles must start and finish their routes at the depot. Constraint (9) ensures that all containers are serviced exactly once, while constraint (10) ensures that the inflow and outflow of all nodes in the graph are equal. Constraint (11) states that all vehicles must be empty at the start and end of the routes before they return to the depot, therefore, the cumulative weight of waste at the depot and disposal facility nodes is set to be zero. Constraint (12) ensures that the cumulative waste carried by vehicle k is successively increasing in the logical order of the planned route for every node visited except the disposal facility. The vehicle capacity constraint is set by (13), which indicates the moment of visit to the disposal facility for unloading, while the allowed shift duration is maintained by (14). It must be noted that only the effective time for collection is considered, hence the preparation and break time are ignored. Constraint (15) ensures that the cumulative time spent driving to and servicing each collection site of a planned route follows a logical progression. Finally, constraints (16), (17), (18), and (19) impose the binary and non-negative variables.

3.2 Solution approach

To solve the WCVRP problem formulated in Section 3.1, the solution approach displayed in Figure 3.1 is proposed. The approach has an overarching objective to construct routes in such a way that a trade-off between dispatch consistency and flexibility is maintained. For this reason, the approach makes use of a two-phase clustering technique to efficiently assign collection sites to clusters and subsequently constructs as many routes as required for each cluster to accommodate its demand.

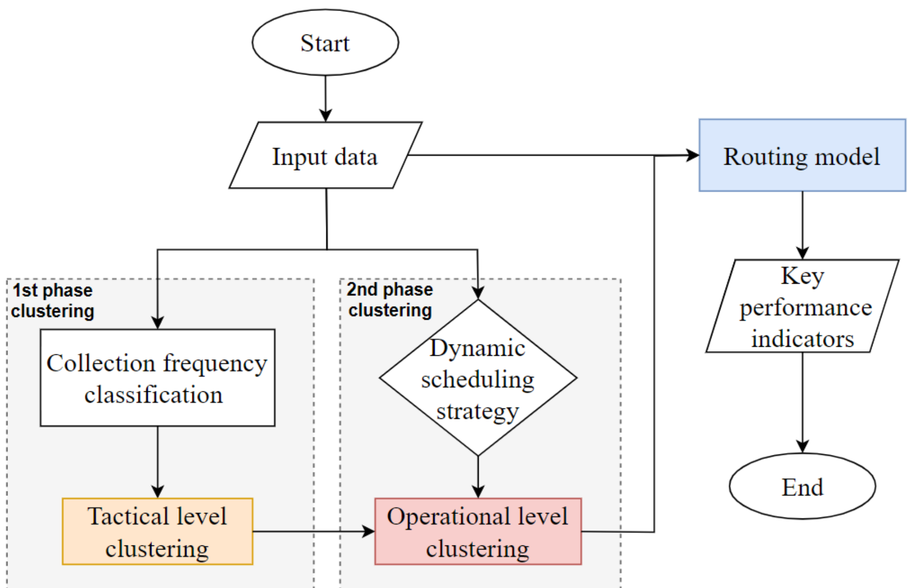


Figure 3.1 Flowchart of the proposed solution approach

To apply the proposed approach, the input data tabulated in Table 3-1 are required. First, the locations of the waste containers, disposal facilities, and depots must be identified to construct the waste collection network, by retrieving information regarding their coordinates and addresses. This network must be subsequently combined with the city's road network, which has road-type associated average speeds, to compute the distance and time matrices between all locations.

To set up the constraints of the problem in the approach, information regarding the maximum shift duration the vehicles are allowed to operate, as well as their maximum weight capacity which indicates the moment of visit at the disposal facility must be provided. To calculate the relevant KPIs, information regarding the waste collection vehicles must be provided such as emissions production factors, fuel consumption factors, and loading/unloading durations.

Lastly, the waste generation data must be provided per waste container along with their respective identification and dimensions. This data includes the container's daily waste fill levels, which when combined with the containers' dimensions and a kg/m^3 conversion rate provide the generated weight of waste. Next, it includes the daily waste accumulation period per container as well as their historical monthly frequency of collection.

Table 3-1 Required input data for the proposed solution approach

Entity	Parameters
Waste collection network	Waste containers' addresses and coordinates
	Disposal facilities and depots' addresses and coordinates
Distance- and time-matrices	Road network with average speeds
Problem constraints	Shift duration
	Maximum weight capacity
Waste collection vehicles	Emission production factors
	Fuel consumption factors
	Loading/Unloading durations
Waste generation data	Waste containers identification and dimensions
	Containers' daily waste fill-levels
	Containers' daily waste accumulation period
	Containers' monthly collection frequency

3.2.1 Two-phase clustering technique

The first clustering phase focuses on the tactical level of planning and aims in the construction of geographically fixed clusters of container sites to resemble independent waste collection areas. It is presumed that the route-associated variability and overlapping will be reduced if the routes are focused on each independent waste collection area. This tactic will enable maintaining dispatch consistency through the drivers' assignment to each of the waste collection areas, which will consequentially lead to increased familiarity and better administration control.

During this phase, the K-means algorithm is employed to assign *specifically* selected containers into clusters. The containers populating those static clusters are selected based on their frequency of collection, which is derived from monthly-based historical data. The month-long time frame was chosen to account for the effect of seasonal trends, events, celebrations, etc. on waste generation, which indirectly affects the containers' frequency of collection. These clusters are formed once per month and remain constant thereafter till the next period. More information on collection frequency classification and tactical level clustering is provided in sub-section 3.2.1.1.

The second clustering phase focuses on the operational level planning and aims at the creation of daily container circuits for collection with the employment of the K-nearest neighbor algorithm (KNN). A completely reactive scheduling approach is followed before this phase, realized through a selected scheduling strategy, to schedule the most appropriate containers for collection. The tactical level clusters created at the first clustering phase and the containers scheduled for collection, as selected by the scheduling strategy, are used as input for this second clustering phase.

The model identifies which containers already assigned in the tactical level clusters are not scheduled for collection and removes them from the set and uses the remaining assigned containers as an input dataset to train and evaluate the predictive performance of the KNN algorithm. Once the training is over, the algorithm assigns each unassigned container scheduled for collection to the cluster in which the majority of its already assigned neighbor containers belong. With the daily re-assignment of containers to clusters, it is presumed that dispatch flexibility can be maintained, as the clusters' boundaries are fluid to respond to the daily demands. More information on the dynamic scheduling strategies examined in the proposed solution approach and the operational level clustering is provided in sub-section 3.2.1.2.

A schematical representation of the proposed two-phase clustering technique is displayed in Figure 3.2. In part A, we see the outcome of the tactical level clustering in which only the specifically selected containers, as chosen based on their frequency of collection, are assigned into geographically fixed clusters. In parts B and C, the process of the operational level clustering is displayed. In part B, the already assigned containers, which are also scheduled for collection on that specific instance, remain in their assigned clusters. In Part C, the rest of the unassigned containers which are also scheduled for collection are identified, and subsequently assigned to the cluster in which the majority of their already assigned neighbor-containers belong.

In part D, the daily circuits of containers to be collected are displayed. For each of the resulting clusters of containers, the routing model will construct as many waste collection routes as required to accommodate its demand. It can be observed that the static clusters (part A) constructed at the tactical level planning serve as fixed geographical areas, the boundaries of which become flexible during the operational level planning to accommodate the daily demands (part D). This is possible as not all the containers are used to construct the tactical-level clusters, therefore dispatch consistency can be maintained while dispatch flexibility is not hindered.

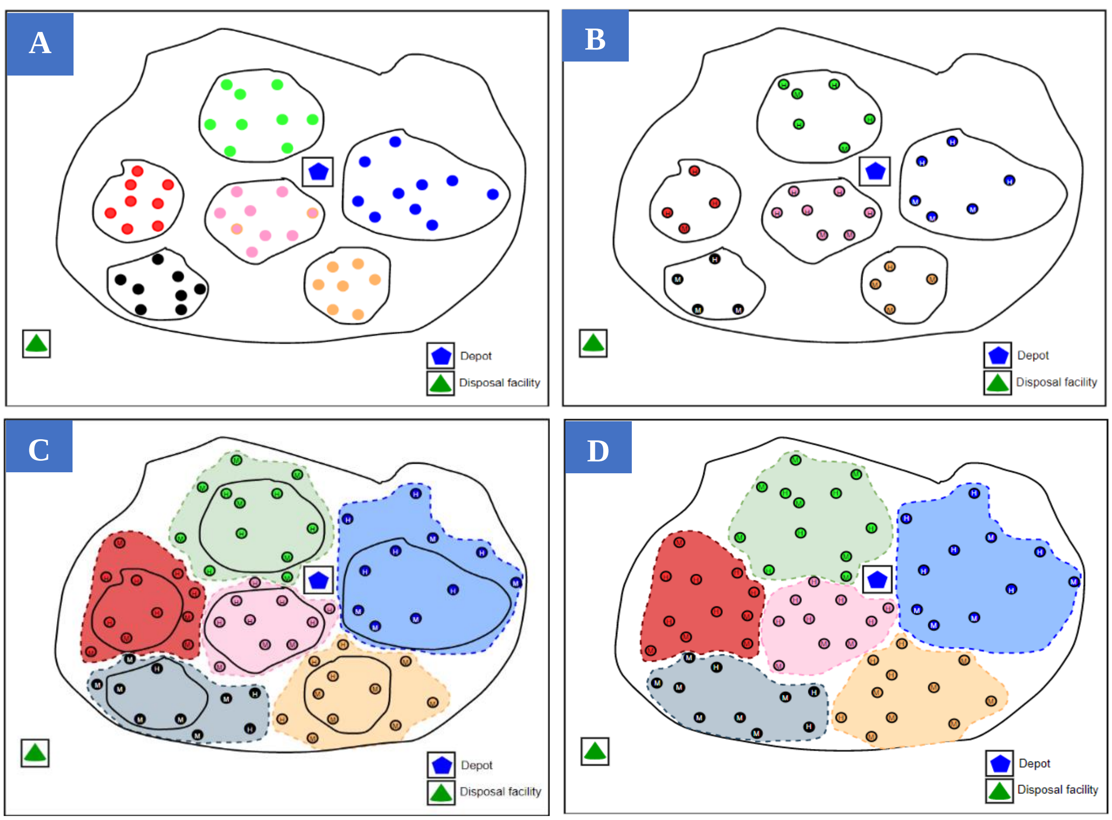


Figure 3.2 Schematical representation of the two-phase clustering technique

The proposed approach was inspired by the work of Zhong et al. (2007) who investigated the construction of routes for local packages delivery. The authors created a two-stage vehicle routing model based on a strategic core area design and operational cell routing, to evaluate the effect on driver familiarity. The two-phase clustering technique proposed in this study adopts similar concepts, such as the design of cluster core areas and the flexible container assignment, but is still very different from the one proposed by Zhong et al. (2007) for multiple reasons.

First, this study focuses on the WCVRP, which is a reverse logistics problem, in comparison to the forward logistics problem the authors are addressing. Reverse logistics comprises the sector of supply chains that collects used products from their typical final destination for further reuse and/or reprocessing, such as recovery or proper disposal. Forward logistics comprises the sector of supply chains in which a series of activities is performed to distribute new products to consumers. Generally, the WCVRP is harder to solve than the traditional VRP as the vehicles must visit the disposal facilities to unload the collected waste, regain their capacity and subsequently continue to their planned routes.

Second, the authors' objective was to construct balanced last-mile delivery routes. For this purpose, they considered the region around the depot as a "flex zone" the customers of which were daily reassigned to achieve a balanced load among the constructed routes. The purpose of this study is to achieve a balanced trade-off between dispatch consistency and flexibility through the construction of the most efficient waste collection routes possible, irrespective of the imbalanced number of containers assigned to each. To achieve the flexible assignment in the proposed approach no 'flex-zone' is considered, rather the constructed clusters are formulated in such a way that their daily boundaries are fluid to accommodate the daily demand.

Furthermore, Zhong et al. (2007) aggregate the customers into "cells" based on their postal code, while in the proposed approach each container is considered on an individual level, which increases the complexity of the problem to be solved. Lastly, it must be stated that the algorithms employed in each solution approach are different, as different are the objectives each study tries to achieve.

3.2.1.1 Tactical-level clustering

Initially, the containers to populate the clusters constructed at the tactical level need to be selected. The criterion used for the selection is the monthly frequency of collection, as derived from historical monthly data. The classification scheme presented in Table 3-2 is used to classify the containers into a 'high', 'medium', and 'low' frequency category. Only the containers classified as 'high' and 'medium' frequency are then selected to populate the static clusters.

Table 3-2 Collection frequency classification scheme

High frequency	Medium frequency	Low frequency
frequency >= 15 t.p.m.	4 t.p.m < frequency < 15 t.p.m	frequency <= 4 t.p.m

*t.p.m. = times per month

The reason why these two categories of containers are selected is twofold. Firstly, under the assumption that the collection frequency of a container is relative to its waste filling rate, these two categories contain containers that require constant service. In this case, the waste fill rate can be affected by the population density of the area the container is in, or by the existence of neighbor containers carrying the same waste type. As the tactical level clustering aims in ensuring dispatch consistency, it is presumed that the use of this type of container to geographically lead the clusters' construction will be beneficial.

Secondly, and in continuance to the above, the spatial distribution of containers in a city made necessary the selection of both 'high' and 'medium' frequency containers for the tactical level clustering. To explain, more containers are located in a city center than in the outskirts, due to the respectively higher population density and size. For the same reasons, the city center-based containers have substantially higher fill rates than the ones in the outskirts. With the application of the proposed classification scheme, it is expected that the majority of the 'high' frequency containers would be located in the city center and just a few in the outskirts. If only the 'high' frequency containers were selected for the tactical level clustering, due to the uneven distribution in the area, and specifically the small number of the scattered ones in the outskirts, the resulting clusters would not be representative of the areas. To minimize the problem, the 'medium' frequency containers are also considered to create a more uniform distribution in the whole area and create more representative clusters.

K-means algorithm

The k-means algorithm implementation in Scikit-learn, a machine learning library for python, is employed to perform the tactical level clustering of the selected containers. The k-means algorithm is an unsupervised clustering algorithm that uses an iterative technique to group unlabeled points into a 'K' number of clusters. The objective of the algorithm is to assign points to clusters such that the inertia, otherwise known as within sum of squares (WSS), is minimized and the capacity constraints, if any, are respected. Inertia is calculated by initially measuring the squared Euclidean distance between each container and its assigned cluster centroid, and by finally summing all the squared distances across all the clusters.

Important to note here is that standardization of the data is performed before any clustering process to ensure that the variables are comparable, especially when they are measured on different scales or when their mean value and/or standard deviation are largely different. The variables used for the waste containers clustering are their longitude and latitude coordinates, denoted as X and Y. Even though these variables have the same measuring scale (degrees), their mean value and standard deviation are largely different, hence they are scaled to ensure that they have a standard deviation of one and a mean value of zero.

A good model balances intra-cluster homogeneity and inter-cluster heterogeneity, which translates to a low inertia value and a low number of clusters. However, these two variables are conflicting, as when the number of clusters increases, the value of inertia decreases. It then becomes a question of what the optimal number of clusters for a specific dataset should be if the K-means algorithm requires this information as an input.

The Elbow method is employed to answer the previously listed question. In this method, a range of number of clusters is examined by running the K-means algorithm and calculating the inertia value for each. When plotting the inertias as a function of the number of clusters, an elbow-looking curve is formed, see the blue curved line in Figure 3.3, with lower inertia values for the larger number of clusters. The point at which the graph rapidly changes and creates an elbow shape, almost parallel to X-axis, indicates the optimal number of clusters. Of course, the lower the inertia the better the model fit is, but the risk of overfitting increases as well. Hence the optimal number of clusters is indicated by the sharp change in the curvature of the plot.

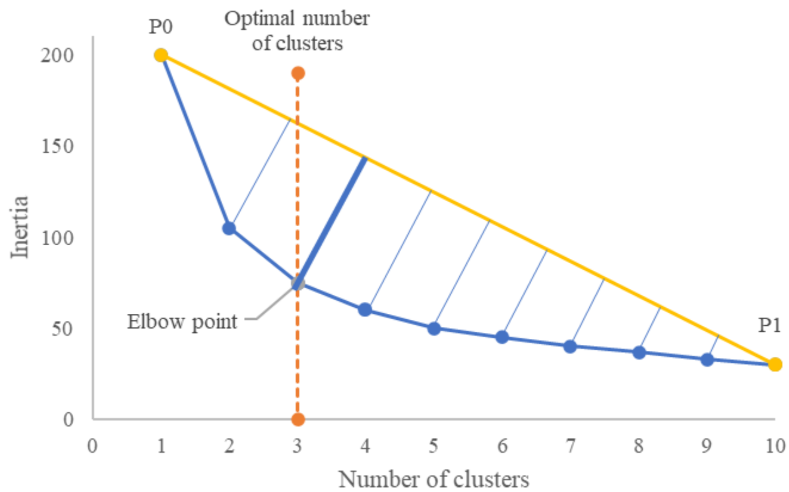


Figure 3.3 Optimal number of clusters identified with elbow method and mathematical method

As sometimes the point at which the elbow occurs is not easily identifiable, mathematics is employed in combination with the elbow method to give a more precise answer. In theory, the point with the largest perpendicular distance to the line drawn between points P_0 and P_1, see the yellow line in

Figure 3.3, indicates the optimal number of clusters. Points P_0 and P_1 indicate respectively the start and end of the examined range of potential number of clusters. The perpendicular distances are calculated by the well-known line-to-point distance formula presented in equation (20).

$$distance(P_0, P_1, (x, y)) = \frac{|(y_1 - y_0)x - (x_1 - x_0)y + x_1 y_0 - y_1 x_0|}{\sqrt{(y_1 - y_0)^2 + (x_1 - x_0)^2}} \quad (20)$$

As per the suggestion of domain experts, when deciding the range of number of clusters the size of the fleet which is going to serve them should be taken into consideration and be set as a reference point. In addition, it should be considered that too few or too many clusters are undesirable as they can negatively affect the dispatch consistency and flexibility. Too few clusters will force disjoint groups of containers together, which consequently affects the performance of the routes, as well as the dispatch consistency as the routes are assigned to very large areas with no specific focus. Too many clusters can affect the dispatch flexibility and performance as artificial boundaries are created within groups of containers which consequently restrict the route construction. Lastly, the size of the range should be taken into consideration for practical reasons, that is to ensure that the Elbow method will correctly assess the differences between the clusters and find the optimal number.

Once the optimal number of clusters 'K' is determined, the K-means algorithm proceeds with the following steps. A schematic representation of the steps is depicted in Figure 3.4.

1. Initialize 'K' centroids' locations
2. Calculate the distance between each point and every centroid and assign them to their closest centroid.
3. Update centroid locations based on the locations of the assigned points
4. Repeat steps 2 and 3 until no improvements are possible, and no point switching is occurring from one cluster to another

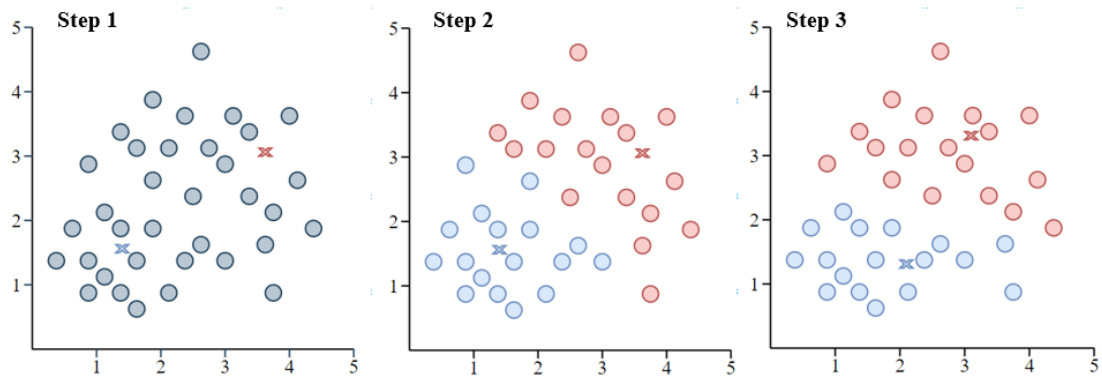


Figure 3.4 Schematic representation of each stage of the K-means clustering process

To initialize the cluster centroids' locations the 'k-means++' algorithm is utilized which is fed an arbitrary seed to achieve a deterministic behavior and eliminate randomness. This algorithm focuses on methodologically spreading the initial cluster centroids, in contrast to a random initialization, such that the solution is guaranteed to be $O(\log k)$ competitive to the optimal k-means solution. Although the implementation of this seeding algorithm takes extra time, the k-means part itself converges much quicker, therefore it additionally contributes to a lower computation time.

3.2.1.2 Operational-level clustering

A dynamic scheduling strategy determines daily which containers should be scheduled for collection, which constitutes the basis of the operational-level clustering. Three scheduling strategies with different characteristics and objectives are examined in the proposed model, see Figure 3.5. Each of the examined strategies makes use of the classification scheme presented in Table 3-3 to classify the containers according to their priority of collection. This scheme uses as criteria the waste accumulation period and the real-time fill level of the containers to classify them into a 'high', 'medium', and 'low' collection priority.

Table 3-3 Collection priority classification scheme

High priority	Medium priority	Low priority
Fill level >= 75% **OR** Accumulation period >=15 days	50% <= Fill level < 75%.	Fill level < 50%

The priority classification scheme is inspired by the work of Christodoulou et al. (2016) in which a priority level is assigned to each waste container, calculated based on the number of days passed since the last collection and a fill-level forecast. In their studies, the authors defined a maximum period that a container can remain uncollected, depending on the seasonal period and the region type a container is in (e.g city, village), ranging between 2 to 7 days.

In contrast to the work of Christodoulou et al.(2016), the time component considered in this research does not endeavor to control when each container should be collected but rather aims in responding to practical issues that may arise. For example, there could be a possibility that the sensor installed on a container is malfunctioning, signaling a lower fill level than what it actually is. No possible way exists to identify this issue rather than traveling to the spot, which makes the time component inclusion very critical. On the other hand, even if a sensor is transmitting all the correct measurements but the period of waste accumulation is extended odors can arise. Even though the containers considered in the network are situated underground, the smell can travel every time the lid opens for a new deposit, causing unpleasantness to the user.

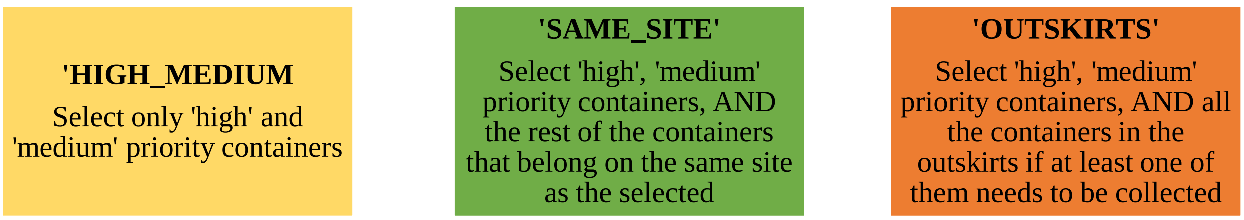


Figure 3.5 Scheduling strategies implemented in the proposed model

The first scheduling strategy is ‘HIGH_MEDIUM’ and regards the collection of only the ‘high’ and ‘medium’ priority containers. It can be often encountered in the literature, for example in the work of Johansson (2006) which creates routes not exclusively to full containers, but also to nearby containers which have an estimated fill level greater than a set threshold. The second scheduling strategy is ‘SAME_SITE’ and regards the collection of all containers located at the same site as containers classified as ‘high’ and ‘medium’ priority. A similar strategy to this is examined in the approach of Omara et al. (2018) in which the visited containers are not only the ones that require collection but also the ones that are on the assigned routes but their collection is not urgent. The third scheduling strategy is ‘OUTSKIRTS’ and regards the collection of all ‘high’ and ‘medium’ priority containers in addition to all the containers located on the outskirts of a city if that is deemed necessary. This strategy is similar to a proposition in the work of Christodoulou et al. (2016) which states that it is more economically viable to collect all containers in a remote area than to return the following day to partially collect them. To indicate which exact containers are on the outskirts of the city, manual labeling was performed as guided by the instructions of the domain experts.

It is acknowledged that a multitude of scheduling strategies have been proposed in the literature for the waste collection problem. These specific scheduling strategies were selected for examination as they are simple and can be applied to real-life operations without bringing added complexity to the system or additional investment expenses. Common between these strategies is the fact that they are focused on selecting which containers are most appropriate for collection. Other scheduling strategies could have been selected that are focused, for example, on choosing the most appropriate time to collect the containers or examining the sequence with which the containers should be collected depending on their urgency, etc.

K-Nearest neighbors algorithm (KNN)

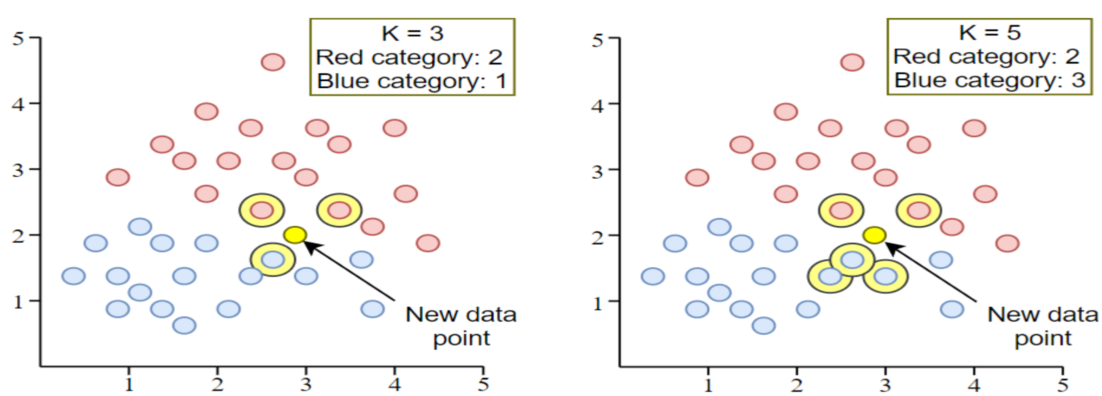
At the operational level clustering, the model identifies which containers that are already assigned in the static clusters are not scheduled for collection and removes them from the clusters. The remaining assigned containers are used as an input dataset to train and evaluate the KNN algorithm, which is finally used to assign the rest of the scheduled containers to the clusters.

The KNN algorithm is a supervised classification algorithm based on the notion that the features of a data point can be predicted based on the features of the majority of its neighbors. The algorithm takes as input the known classification of a dataset (training data) and uses it to learn how to classify other out-of-sample data points (new data). Like the K-means algorithm, the data used in the KNN algorithm needs to be standardized before making any actual predictions to ensure that the variables are uniformly evaluated. The exact steps of the KNN algorithm are enlisted below:

1. Determine the K value (number of neighbors)
2. Fit the KNN classifier to the training data
3. Make predictions for the new data
   3.1. Compute the distances between the new data and all the training data with the Euclidean distance
   3.2. Sort the distances in ascending order and use the first K elements to identify the K nearest neighbors
   3.3. Classify the new data based on the class of the majority of their K nearest neighbors

Regarding step 3.3, the class of the majority of the k nearest neighbors is expressed by the modal value of the classes of all the k nearest neighbors. To avoid the appearance of multiple modes, the number of neighbors examined in this study is always odd. Figure 3.6 displays a schematic representation of the algorithm classification capabilities under two different numbers of neighbors. When the number of neighbors is 3, the new data point is assigned to the red category, while when the number of neighbors is 5, the new data point is assigned to the blue category.

Figure 3.6 KNN algorithm classification under two different numbers of neighbors



In general, the lesser the number of neighbors the more poorly the algorithm generalizes to new data, as the risk of being overfitted on the training data increases. The larger the number of neighbors is, on the other hand, the more suppressed the effects of noise are. Nevertheless, if too many neighbors are used, the risk of underfitting arises, meaning the model loses its sensitivity. If for example all the neighbors are used, every prediction would be the same.

To find the optimal number of neighbors the tool GridSearchCV is used which is available in scikit-learn, a machine learning library for Python. To avoid the risk of overfitting and evaluate the results of the GridSearchCV tool, the input dataset is split into two parts. The *training* part, which is used to fit the model, and the test part, which is used to evaluate it as the classification is already known. The test size used in the model is 0.2, indicating that the test data is 20% of the input data, while 80% is the training data. To be able to reproduce the same data split and eliminate randomness, an arbitrary seed is set. It is acknowledged that the transformation to a deterministic behavior has its limitations as with the selection of a specific seed the outcomes are related only to a sample of the original data population. Ideally, instead of a random train-test split, cross-validation should be performed to obtain a confidence interval on the outcomes of the algorithm.

To use the GridSearchCV tool, a grid is first created with the possible number of neighbors that are wished to be examined. The GridSearchCV performs k-fold cross validation which separates the training data into k parts. The KNN classifier is then repeatedly fitted on each of the selected folds, and its performance is evaluated based on the remaining folds, for each examined number of neighbors on the grid. The optimal number of neighbors is the one that achieves the highest average performance across the k-folds. The tuned model resulting from the GridSearchCV is evaluated on the test data to understand its prediction accuracy and finally used to classify the unassigned containers to the clusters.

3.2.2 Routing model

To solve vehicle routing problems of large sizes researchers are usually opting for heuristic methodologies that can generate suitable high-quality solutions within a rational computational time. While optimality may be reached with mathematical programming, this approach is overly sensitive to growing problem dimensions and complexities as it requires an exponentially increased computation time.

This study follows a cluster-first route-second approach as explained in previous chapters, which divides the problem into n VRPs, with n representing the number of identified clusters. It could be argued that since the problem size is reduced to cluster level, mathematical programming could be used to solve the problem to optimality. On the other hand, as the real directed road network is considered, which is highly affected by the urban morphology, the problem's complexities increase. Due to the stated reasons and backed by the fact that the WCVRP is harder to solve than a regular VRP due to the added constraints and characteristics, heuristics are employed in the routing model to solve the WCVRP.

The routing model uses as input the travel time and distance between any two stops, obtained by applying Dijkstra's shortest path algorithm to GIS street network data, and the operational level clusters to construct for each as many routes as required to serve the daily demand. The model focuses on a two-step approach to construct a route. It starts by gradually generating an initial feasible routing solution with the use of the nearest neighbors algorithm, which later on optimizes with a modified 2-Opt algorithm.

Initial routing solution

A routing solution is considered feasible if it satisfies the time constraints related to shift duration and if the weight capacity of the vehicle is not violated at any point in the route. In the proposed approach such a solution is constructed gradually with the help of the nearest neighbors algorithm. In general, this algorithm starts the route from a random site, and visits consecutively the closest unassigned point, until all sites are visited or until all the constraints are met. Its random start and greedy nature are its downsides as it opts for the best option available at the moment, i.e. the closest point to the current location, and not the option which can lead to a globally optimal result. To increase the chance of finding local and global optima, the algorithm is set to no longer start from a random point, but to iterate over all unassigned sites as starting points and apply on each resulting route the 2-opt optimization algorithm. The fact that the problem size is reduced to the cluster level makes this technique feasible and tractable.

Modified 2-Opt algorithm

The classic 2-Opt algorithm does not take into consideration any intermediate facilities that should be inserted in a route at specific positions. As it is mandatory in the examined problem for the vehicle to visit the disposal facility to regain its capacity, the classic 2-Opt algorithm had to be modified. The 2-Opt algorithm uses the initial solution without disposal facility visits as a starting point and iteratively looks for improvement opportunities in the neighborhoods of that solution.

For each neighborhood of the route, it uses a swapping mechanism to replace two edges of the route with two other edges and then calculates the new travel distance. If the swapping leads to a shorter travel distance, the algorithm proceeds in inserting the disposal facility visits at the correct positions in the route and recalculates the new travel distance. If the resulting route's distance is shorter than the travel distance of the initial solution with disposal facility visits, then the current route is updated. The algorithm continues building on the improved route by repeating the procedure until no more improvements can be found.

Figure 3.7 shows an example of a 2-Opt swapping mechanism between nodes *c* and *d* of a route. The 2-Opt algorithm will examine all possible swapping combinations of the route, for example between nodes *d* and *e*, between nodes *b* and *d*, etc., but will only retain the most optimal combination for further improvement as described before.

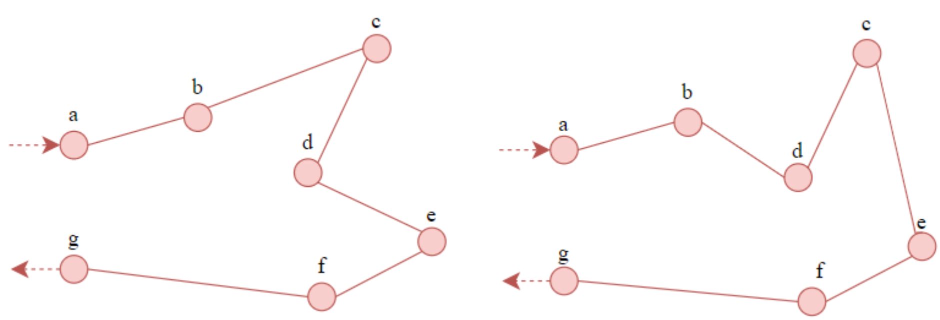


Figure 3.7 Schematic representation of a 2-opt swap move

The pseudocode describing the modified 2-Opt algorithm is presented in Table 3-4.

Table 3-4 Pseudocode of the modified 2-Opt algorithm

Algorithm: 2-Opt Algorithm	
Input: Initial solution without Disposal facility visits, Total travel distance of initial routing, link-level travel times and distances, collection sites data (coordinates, waste weight, service time), disposal facility coordinates, vehicle weight capacity	
Output: Optimized route	
Notations: Route = Initial solution without Disposal facility visits Route distance = Total travel distance of initial routing solution (with disposal facility visits) Points: collection sites (mini clusters of containers located at the same spot) n = number of Points in Route	
1	Declare Route as Best route
2	Declare Route distance as Best route distance
3	**FOR** i = 1: n-2
4	**FOR** j = i+2, n
5	Calculate the distance difference when the target Points are swapped
6	**IF** Distance difference < 0
7	Copy Best route as a Current route
8	Swap indices of target Points in Current route
9	Calculate the cumulative weight of the Current route
10	Find when to visit the Disposal facility by using the cumulative weight and the vehicle weight capacity
11	Insert in Current route the visits to the Disposal facility
12	Calculate the Current route distance
13	**IF** Current route distance < Best route distance
14	Declare Current route as Best final route
15	Declare Current route distance as Best route distance
16	Remove the Disposal Facility visits from the Best final route
17	Declare Best final route as Best route
18	**ELSE do nothing**
19	**ELSE do nothing**
20	Return Best route distance, Best final route

The pseudocode describing the steps of the proposed routing algorithm is presented in Table 3-5 and explained further below.

Table 3-5 Pseudocode of the proposed routing algorithm

Algorithm: Iterative nearest neighbors constructive heuristic with 2-Opt	
Input: Clusters of collection sites constructed at the operational level, link-level travel times and distances, collection sites data (coordinates, waste weight, service time), depot and disposal facility coordinates and service times, maximum shift duration, and vehicle weight capacity	
Output: Cluster-based constructed routes	
Notations: Points: collection sites (mini clusters of containers located at the same spot)	
1	**FOR** each cluster

```
Set all Points status as a Nan value
Assign all Points to the 'Available' set
Set the number of routes equal to one
WHILE the status of any Point is Nan
    FOR each Point in 'Available' set
        Set the status of all Points whose status is not equal to one, a Nan value
        Create an empty route
        Set Capacity equal to the vehicle weight capacity
        Set Shift Duration equal to the Maximum Shift Duration
        Set as Origin the Depot
        Set as Destination the Point
        WHILE the number of Points with status equal to Nan is not one AND the shift
        duration is sufficient
            IF Capacity AND Shift duration is sufficient
                Add the Origin-Destination trip to the route and calculate the
                remaining shift duration
                Calculate remaining capacity
                Set the status of the Destination Point as zero
            ELSE IF Capacity is not sufficient AND Shift duration is sufficient AND
            the total weight of Points with status equal to Nan is greater than 1000
                Set as Destination the Disposal facility
                Add the Origin-Destination trip to the route and calculate the
                remaining shift duration
                Calculate remaining capacity
            ELSE
                Set the remaining shift duration as equal to zero
            Set as Origin the Destination
            Calculate the distances between Origin and all Points whose status is equal
            to Nan
            Set as Destination the Point with shortest distance from the Origin
            IF Capacity is sufficient AND Shift duration is not sufficient AND the total
            weight of Points with status equal to Nan is lesser than or equal to 1000
                Increase the Shift duration by 0.25
            ELSE IF Capacity is not sufficient AND Shift duration is sufficient AND
            the total weight of Points with status equal to Nan is lesser than or equal to
            1000
                Increase the Capacity by 1000
        ELSE
            IF the destination of the last trip of the Route is Disposal facility
                Add the Origin-Destination trip to the route
            ELSE
                Set as Origin the destination of the last trip of the Route
                Calculate the distances between Origin and all Points whose status is
                equal to Nan
                Set as Destination the Point with shortest distance from the Origin
                Set the status of the Destination Point as zero
```

```
                Add the Origin-Destination trip to the route
                Set as Origin the Destination
                Set as Destination the Disposal facility
                Add the Origin-Destination trip to the route
                Set as Origin the Destination
                Set as Destination the Depot
                Add the Origin-Destination trip to the route
                Calculate the route's total travel distance and total collected weight
        Remove the Disposal Facility entries from the route and apply the 2-Opt
        algorithm
        Return the optimized route and its total collected weight and total travel distance
        Count the number of unassigned Points with status is still Nan
    IF any route has zero unassigned Points
        The best route has zero unassigned Points and the minimum travel distance
    ELSE
        The best route has the maximum total collected weight over travel distance ratio
    Set the status of all Points whose status is not equal to one, a Nan value
    Assign to the Points belonging in the best route a status value of zero
    Identify the order number of the best route's visits to the disposal facility
    Calculate the cumulative sum of the weight of waste of the best route
    IF the number of visits at the disposal facility is one
        DO nothing
    ELSE IF any Points with status equal to Nan remain unassigned
        IF the sum of the weight of the remaining Points and the weight collected
        between the two last visits at the disposal facility is lesser than the Vehicle
        weight capacity
            Remove the last visit and the Points assigned between the second to last
            and the last visit from Best route
    ELSE IF all Points are assigned AND the weight collected between the second and the
    last visit at the disposal facility is less than or equal to 1000kg
        Remove the second to last disposal facility visit from Best route
    Else do nothing
    DELETE from the 'Available' set the Points belonging in the best route
    Set the status of all Points whose status is not equal to one, a Nan value
    Assign to the Points belonging in the best route a status value of one
    IF the status of any Point is Nan
        Increase the number of routes by one
    ELSE
        BREAK
```

The pseudocode is built on blocks. The outer block regards the cluster level, the aim of which is to construct as many routes as required such that no scheduled collection site is left unattended. Zooming in and focusing on a cluster, the aim is to examine all available collection sites as starting points to increase the possibility of reaching a global optimum solution and not getting trapped on a local optimum solution.

With the use of the nearest neighbor heuristic, feasible routes that respect the constraints imposed by the optimization problem are constructed. Only in specific instances where the weight of waste of the yet to be assigned collection sites is lesser than or equal to 1000kg, the constraints are relaxed. The reason behind this choice is to achieve higher levels of efficiency. To be more precise, it would be more economical to extend the duration of a route that already operates in an assigned area, to accommodate 3-5 containers, which is what on average 1000kg roughly translates to, rather than dispatching a completely new route only for them. Regarding the vehicle weight capacity, not the maximum payload capacity is considered but 90% of it to offer some buffer in case of unpredicted waste disposal next to the containers. This specification allows for the vehicle weight capacity constraint relaxation if and when required.

Diving deeper, the next block regards the optimization of each of the generated initial routes with the 2-Opt algorithm, and their subsequent comparison to identify which one performs the best. Two criteria are used to define which route is the best, the total amount of weight and the total number of travel kilometers. Preference is given to routes that manage to visit all collection sites in the clusters. Between routes that manage to visit all collection sites, the best is the one with the least travel distance. In the case that collection sites remain unassigned, the best route is considered the one with the highest weight over travel distance ratio, selected among routes that visit the disposal facility the least number of times.

The last block aims to further optimize the best route. To do so it considers the number of visits to the disposal facility as well as the collection sites of the cluster that are not yet assigned. Based on the assumptions made for this model, if only one visit to the disposal facility is planned, it indicates that no further improvement can be achieved on the route. If no more collection sites are left to be assigned but the amount of waste collected during the last tour of the route is less than or equal to 1000kg, the model removes the second to last visit to the disposal facility from the route, thus relaxing the vehicle capacity constraint. On the other hand, if there are still unassigned collection sites while the last tour of the route is partially full, it is worth examining if combining those collection sites can lead to higher efficiency solutions. The requirement for this proposition is that the total weight of the unassigned collection sites plus the weight collected during the last tour of the route is lower than the vehicle capacity constraint. This proposition is implemented by removing from the route all the collection sites assigned during its last tour and inserting them into the same route as the unassigned collection sites to reduce the construction of partially full routes.

3.3 Discussion

This chapter formulated the WCVRP problem as a mathematical model and described the solution approach proposed to solve it, thereby addressing research sub-question 5. The model's objective is to successively determine the membership of waste containers in clusters, created both on a tactical and operational planning level, and create efficient routes such that the total kilometers traveled, and total CO_2 emissions produced to service the containers are minimized. The main constraints of the problem regard the vehicle's effective weight capacity, which indicates the moment of the visit to the disposal facility for unloading, and the vehicle's maximum allowed working duration. Among other logical constraints, such as the node inflow-outflow equality and the logical progression of weight accumulation and working duration, each vehicle is required to start and finish its route at the depot empty and visit each container site exactly once.

Derived from the requirements stated in Section 1.2, the overarching objective of the approach is to solve the problem in such a way that dispatch consistency is ensured without hindering dispatch flexibility. The proposed solution approach follows a cluster-first route-second approach as it makes use of a two-phase clustering technique to efficiently assign collection sites to clusters, and subsequently uses a routing model to construct as many routes as required for each cluster. The first clustering phase employs the K-means algorithm to assign specifically selected containers into static clusters, which is fed an arbitrary seed to ensure the reproducibility of the results. The second clustering phase uses the first-phase clustering outcomes and a scheduling strategy to create daily container circuits for collection by employing the K-nearest neighbor algorithm (KNN). The routing model uses the travel time and distance matrices between all nodes of the network and the operational level clusters, which indicate which collection sites must be collected on the same route, to construct the waste collection routes. The model initially uses the nearest neighbors algorithm to gradually construct routes starting from every unassigned collection site, and subsequently applies on each resulting route the modified 2-Opt algorithm. Once all the routes are constructed and optimized, the model determines which is the best performing route based on certain criteria, which later improves based on certain imposed rules as explained in 3.2.2.

It is expected that the first-phase clustering will lead to the construction of geographically fixed clusters of containers that will resemble independent waste collection areas. It is presumed that the route-associated variability and overlapping will be reduced if the routes are focused on each independent waste collection area. This tactic will enable maintaining dispatch consistency through the drivers' assignment to each of the waste collection areas, which will consequentially lead to increased familiarity and better administration control. The second clustering phase aims in maintaining dispatch consistency while simultaneously achieving dispatch flexibility. It achieves this by using the tactical level clusters as cores for the daily constructed clusters, hence achieving flexible boundaries to respond to the daily demands. Regarding the proposed routing model, it is speculated that the chosen criteria to select the best route, and subsequently improve it with certain imposed rules, will lead to the reduction of partially full routes and therefore to improved performance.

Nevertheless, for the implementation of the proposed solution approach, necessary assumptions had to be made which are expected to lead to suboptimal solutions. Assumptions were made at each phase and stage of the approach, for example, the selection of the arbitrary seed fed to the K-means algorithm for the results reproducibility, the rules imposed to classify the containers according to their frequency and priority of collection, the criteria, and rules used in the routing model, etc. To evaluate the developed model and demonstrate its applicability, a case study was selected which is introduced in Chapter 4. In the same chapter, the results of the model application are presented and interpreted, while Chapter 5 discusses how the necessary assumptions and limitations of the approach affect the model's outcomes.

Chapter 4 Model performance evaluation

The solid waste collection service of the Municipality of Rotterdam, in the Netherlands, is used as a case study for this research to demonstrate the applicability of the proposed solution approach presented in the previous chapter. This chapter starts by describing the waste collection system of Rotterdam and the methodologies currently employed in its planning system in Sections 4.1 and 4.2 respectively. Subsequently the requirements and objectives the service articulates for its future operations as an IoT-based waste collection service are presented in Section 4.3, addressing thereby in detail sub-question 1. Following is Section 4.4 which tests the developed model on the selected case study, and Section 4.5 which performs a sensitivity analysis to understand the model's sensitivity to certain parameters. Together, Section 4.4 and Section 4.5 address research sub-question 6. Section 4.6 investigates the application of each of the three dynamic scheduling strategies introduced in sub-section 3.2.1.2, and finally, Section 4.7 closes the chapter with a short discussion about the main findings.

4.1 The waste collection system of Rotterdam

The municipality of Rotterdam expands into an area of 325.8 km^2, of which approximately 106.6 km^2 constitute a body of water, and displays a population of 651,631 citizens as of 2021 (*Rotterdam: Total Population 2021 | Statista*). The municipality covers the city of Rotterdam in which most of the inhabitants live, but also several small villages on the outskirts. Rotterdam is divided by the river Nieuwe Maas into a northern and a southern part, each served by its own waste collection system.

Each waste collection system is comprised of one depot, one disposal facility, an allocated fleet, and a network of underground containers, as depicted in Figure 4.1. Generally, Rotterdam distinguishes five different waste fractions collected by the underground waste containers, but the focus of this research explicitly falls on solid household waste. Therefore, the containers and disposal facilities presented only relate to this waste fraction.

The depots constitute the starting and ending point of the operations as they function as the parking lots of the collection vehicles. The operations are split into two consecutive shifts, one in the morning starting at 6:30 AM till 2:00 PM, and one in the evening starting at 2:00 PM and ending at 10:00 PM. The effective time for waste collection is around 6.5 hours when the time for preparation and breaks is excluded. By the end of the first shift, the vehicles must return to the depot, usually empty, so that the second shift can begin. By the end of the second shift, it is a requirement due to fire hazards that the vehicles first visit a disposal facility to unload and then return to the depot empty.

The disposal facilities are located next to the river so that the collection vehicles directly unload their content in specially designed waste-carrying vessels. When those vessels become full, they travel to incinerator facilities to dispose of the waste for further processing. It is a requirement, again due to fire hazards, that the vessels are docked outside the disposal facilities overnight. Important to note here is the fact that the disposal facilities are open for use not only for the municipal waste collection service but also for private waste collection companies. This means that the arrival rates at the facility are completely random and uncontrolled, hence the disposal trips cannot be easily planned to minimize queuing time.

The northern waste collection system has a network of 3168 solid waste containers, while the southern system has a network of 1785 solid waste containers. These containers are strategically located in the city and are always accessible to residents as they serve as small temporary underground waste storage facilities until collection. A site where multiple containers are located is referred to as a collection site, see Figure 4.2. All waste containers are equipped with wireless sensors monitoring and transmitting their waste fill levels, giving indications about their capacity utilization state. This IoT enablement allows the waste collection systems to be intelligently managed through dynamic operations responding to the real demand levels.

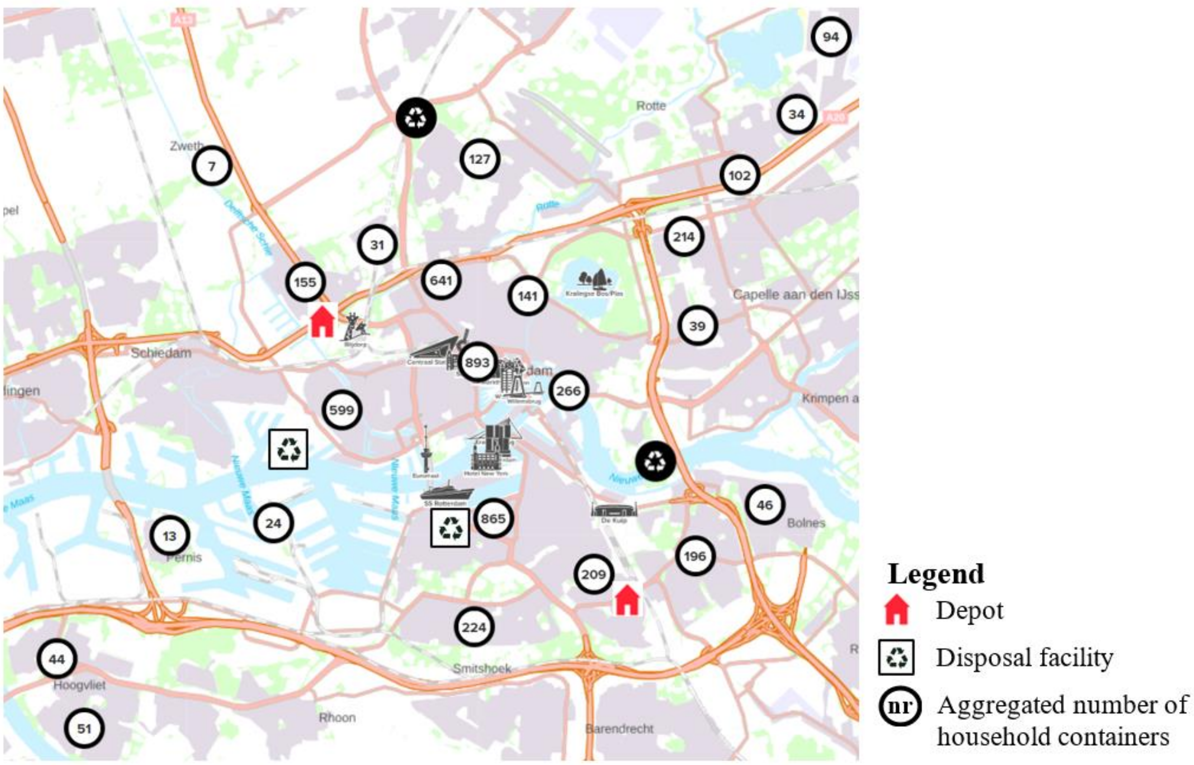


Figure 4.1 Waste collection system of Rotterdam
From Rotterdam Container Map, (https://kaartlaag.rotterdam.nl/containers)

Both waste collection systems employ a homogeneous vehicle fleet, constituted by a compactor truck with an installed crane to lift the underground containers, and outriggers used to level and stabilize the vehicle while it is idling. These vehicles have a maximum payload capacity of 10500kg, but only around 9000kg is effectively used because the vehicle gets full (volume) before reaching its full weight capacity. Currently, the northern waste collection system employs 13 vehicles, while the southern system employs 10 vehicles.

Figure 4.2 Collection site of multiple waste fractions containers

Figure 4.3 depicts the waste collection process of the Municipality of Rotterdam as performed on an average collection day. At the start of each shift, each waste collection route starts from its designated depot and travels to the first container on schedule. After the container is served, it is examined if the available vehicle volume capacity is sufficient to continue with the collection as per the schedule, or if the vehicle should visit its assigned disposal facility to unload the collected waste. After the vehicle has unloaded its contents, it is checked if there are still uncollected containers in its schedule. If there are no uncollected containers, the vehicle returns to its assigned depot and its shift is over. Otherwise, the route is reconstructed to visit in an optimized way the remaining containers, as drivers may opt for a different sequence of stops than what is originally planned. Several working tactics are adopted during real operations which are explained in sub-section 4.2.2.

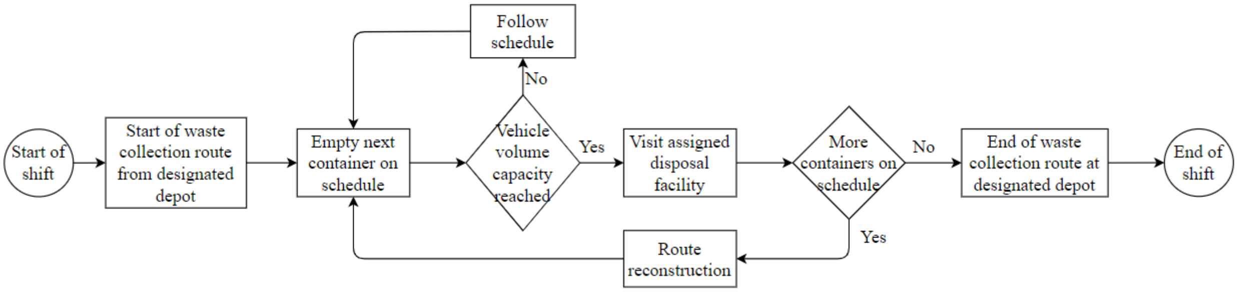


Figure 4.3 Current waste collection process of the municipality of Rotterdam

4.2 Current planning system

The current planning system of the waste collection department of Rotterdam operates on a feedback loop. The planners use methodologies devised from their knowledge and experience, and certain rules imposed by the department, to construct the daily waste collection routes. The drivers on their end, follow their assigned route and report at the end of their shift any issues they might have encountered, or suggestions for long-term planning improvements.

Some of the issues drivers may encounter along their routes are unexpected road works, blocked containers, etc. These situations make the containers' collection impossible as the vehicle must park directly next to them to be able to lift them with caution and not cause any damage to adjoining properties or cars. By sharing this information with the planners, reacting measures can be taken for the next shift such as rescheduling containers, avoiding specific roads when creating new routes, etc. closing in this way the feedback loop. For these reasons and many more described in 4.2.2, drivers have the freedom to change the sequence of orders in their schedule as well as to decide when to visit the disposal facility. The following sub-sections present the planning methodologies used by the planners, as well as valuable inputs provided by a driver who is the main operator of the planning system.

4.2.1 Planning methodologies

The current planning system considers the average waste fill level per collection site to consider them for collection. More specifically, it uses a predefined threshold fill level of 70% to include collection sites in the schedule. This specific threshold was proven to be the most beneficial in terms of minimum overflown containers as observed through a series of real-life experimentations.

A simple routing algorithm is currently used to construct the waste collection routes, which are thereafter manually edited and enriched by the planners using their knowledge and experience, as well as the feedback provided by the drivers. Among the points planners take into consideration when planning the routes are the physical boundaries of the city such as canals, parks, highways, etc., to ensure that the routes don't cross them. Furthermore, they consider the traffic conditions and activities that take place in specific areas of the city to avoid delays and disturbances. These considerations raise preferences regarding the time of the day each area should be serviced. For example, containers located in the city center are forced to be collected before the morning peak, or containers located next to schools outside peak hours.

Next to the above, a day-specific rule is imposed on the current planning system which states that all the collection sites that have not reached the predefined threshold, but are expected to during the weekend, should be included in the collection schedule on Fridays to minimize overflows. In addition, the planners must always be informed about the disposal facilities' opening and closing times and days, to plan the routes accordingly. The waste collection service currently takes place from Monday to Saturday, and sometimes on Sunday if enough drivers volunteer. As mentioned before, the disposal facilities are not publicly owned, therefore they operate on their own opening times. In particular, the disposal facility located in the northern city part (Keilehaven) is only open for operation during the weekdays, therefore the northern waste collection service is forced to use the other available disposal facility in the southern part (Brielselaan) during the weekend.

4.2.2 Driver inputs

To get a better understanding of the processes taking place during waste collection, a field trip was arranged with one of the drivers. Throughout the journey, the driver was interviewed to gain inputs from his point of view as he is the main operator of the system. The driver shared some important working tactics followed among drivers, which mainly regard the moment they decide to visit the disposal facility or return to the depot, the way they consider the parking occupancy patterns, and the way they use the road network for their operations.

Usually, drivers visit the disposal facility from 1 to 3 times per route. This depends on the number of containers assigned to a route and the distance of the furthest assigned container from the depot. The first visit to the disposal facility usually occurs when the vehicle volume capacity is reached. Nevertheless, that is not always the case. Based on their experience, some drivers decide to visit the disposal facility before the vehicle capacity is reached to avoid the long queuing time. Some others also visit the facility earlier if they are close to it but the remaining containers in their route are far away from their current location. It is also common for this reason for drivers to completely cancel the far away containers so that they can return to the depot and finish their shift on time. Of course, the canceled containers are planned with high priority for the next shift. Other times, drivers working the morning shift skip the last visit to the disposal facility entirely and return to the depot directly with waste in their vehicles. This may occur because the quantity collected is insignificant, or the remaining shift duration is not sufficient to perform that extra trip.

The parking occupancy of certain roads may sometimes force the drivers to change the sequence of orders in their routes. Due to the size of the vehicles, it is usually hard to navigate through narrow streets, either in the city center or in small cyclic neighborhoods. The hardship is aggravated when the collection time coincides with a high parking occupancy, which is usually during and after the evening peak time when most people return home from work. To avoid this situation drivers change the sequence of the orders in their route and serve the containers located in such areas at an earlier time. Lastly, the collection vehicles have special permission to drive in both directions of low hierarchy roads. These are local streets and roads which have the lowest speed limit and carry low volumes of traffic. As they are given this permission, drivers change the sequence of the orders in their schedule to optimize their routes and avoid visiting the same street twice to serve containers located on both sides.

4.3 Desired requirements and objectives

The municipality of Rotterdam adopted a holistic perspective in its approach toward a more efficient waste collection service which implies that all actors involved should be considered and seen as a whole. The four main actors in this regard are, the waste collection service providers, the waste collection system operators (drivers), the waste collection system users (citizens using the containers to dispose of their waste), and finally the citizens affected by the service operations (citizens living close to the containers).

Each of the actors has their own requirements if they are being observed at the individual level. The service providers' main goals are to achieve an economically and environmentally enhanced waste collection service and gain better administrative control. For the former, they are aiming for better utilization of the capacities of both containers and collection vehicles, which will result in a reduced number of vehicle movements, and consequently reduced fuel consumption and emission production. To gain better administrative control, they are interested in geographically partitioning the city into non-overlapping waste collection areas which will reduce the complete variability the collection crews are currently facing with their assigned routes. In this way, they state that a certain level of dispatch consistency can be maintained, but it should not be at the expense of dispatch flexibility, which is the key characteristic of a demand-responsive waste collection service.

The drivers as the system operators also present the need for a geographically partitioned city as they wish to maintain familiarity in a pre-assigned territory. This requirement is derived from the current practice in which the daily routes and schedules are completely variable. In addition, as already mentioned in 4.2.2, drivers tend to change the sequence of the orders in their schedule due to various reasons, especially when unpredicted issues arise. The drivers state that if they are familiar with the area they are working on, they can react faster and more efficiently.

The citizens, both users of the containers and the ones living near them, wish that the number of overflown containers be reduced as it causes an eyesore and inconvenience when visiting for disposal. Moreover, they report that the waste collection vehicles due to their size and their specific loading operations hinder the traffic flow, causing congestion in the streets. Derived from this reason is their requirement to reduce the number of times a collection vehicle visits the same street in a day. They suggest that containers belonging in the same street should be sequentially served by the same vehicle. This requirement coincides with the service providers' requirement of reducing the number of unnecessary vehicle movements, which would lead to reduced annoyance, fuel consumption, and emissions production.

The holistic approach the municipality decided to adopt is very significant as each actor plays a vital role in the whole system. Most of the actors' requirements, even though different, are interrelated, meaning they can be accomplished to an extent by the same approach. This case study is proven to be ideal for this research as the requirements stated above match closely the objectives of the research. More specifically, the main and shared goal is the partitioning of the city into independent collection areas to maintain a balanced trade-off between dispatch consistency and flexibility, which is aimed at the proposed solution approach via the two-phase clustering technique. In addition, the focus of both is on attaining an economically and environmentally enhanced waste collection performance, translating to a lesser number of travel kilometers, and a reduced CO_2 emissions production.

4.4 Computational results

In this section, the proposed solution approach is tested on the presented case study to evaluate its performance. As already mentioned, the city of Rotterdam is divided into a northern and a southern side, each with its own waste collection system. Both systems formulate the same WCVRP as they are identical in terms of the number of depots and disposal facilities, type of fleet (homogeneous), and working requirements. For simplification reasons, the northern side was chosen for analysis as its network of underground containers is larger and denser. For comparison reasons, the 17 routes realized by the waste collection service of Rotterdam for the northern side for one specific day (15/09/2021) were obtained as a sample and used hereafter to represent the current case. Unfortunately, due to data unavailability, only one day's realized routes were used for the comparison.

A preprocessing step had to be performed before testing the developed model. During this step, the provided data was prepared, the network of the city was set up, and the paths of each executed route of the current case were constructed, as only the sequence of collection sites was provided but not the actual traversed paths. More specifically, upon examination of the data, it was realized that the depot-related entries were not registered for any of the routes, while for some specific routes even the disposal facility entries were missing. To tackle the missing entries problem, the intermediate visits to the disposal facility were inserted in the route where the cumulative weight of waste carried was 9000kg. To calculate the weight of waste at each collection site the steps described in A.2 were followed. The final visits to the disposal facility were simply inserted at the end of the routes, and the depot entries were inserted at the start and very end of the routes.

Apart from the above, the coordinates of the containers had to be identified from a description file by using their address and ID. When trying to associate one with the other, multiple inconsistencies were identified between the registered addresses and the container IDs. For example, some containers either didn’t exist in the description file, or they existed under different IDs and/or addresses. Where no correlation could be found, Google Maps and Route Vision (waste collection planning server) were used to find the correct coordinates. Furthermore, the geospatial data of the road network of the city was retrieved by the OpenStreetMap Foundation. To be suitable for use, this data was manipulated in the geographic information system QGIS (v3.22.0) following the steps described in A.4. Finally, to construct the current case’s routes paths Dijkstra’s algorithm was employed, and both distance and time were used as costs to construct the shortest paths. The assignment module of the Tactical Freight Simulator (TFS) (de Bok et al., 2021) was employed for this task, which required some modifications to be suitable for the waste collection context.

The configuration built to test the model’s outputs with the current case is referred to as the base case. Out of the total 3165 containers, 2389 were used to construct the tactical level clusters, which were selected based on their historical monthly frequency of collection. To ensure a fair comparison between the base case and the current case, the same 1279 containers collected on the examined day were used to populate the operational level clusters, meaning no specific scheduling strategy was applied. Regarding the parameters selection, no capacity constraints were considered for the tactical level clusters formation, and the range used to find the optimal number of tactical level clusters was set to 13 ± 4 [9 - 17], as per the explanation given in 3.2.1.1. Thirteen constitutes the size of the fleet of the northern waste collection system as stated in Section 4.1.

The mathematical method indicated that the optimal number of clusters K is 12. Figure 4.4 shows the inertia for all cluster solutions of the examined range and proves that an elbow appears when the number of clusters is 12. The identified K was used in the K-means algorithm to construct the tactical level clusters which are presented in Figure 4.5. It can be observed that most of the containers appear to be assigned to the appropriate clusters, but not the ones located further away from dense masses, for example at the boundaries of clusters 4,7, and 5. This can be attributed to the fact that the algorithm was fed an arbitrary seed to ensure that the results are reproducible and deterministic. If a different seed was selected, the initial starting conditions would have been different, and the resulting clusters potentially better. Ideally, the algorithm should be run for several iterations with the goal of improving the resulting clusters' inertia, and then select the solution with the least inertia for the subsequent model steps.

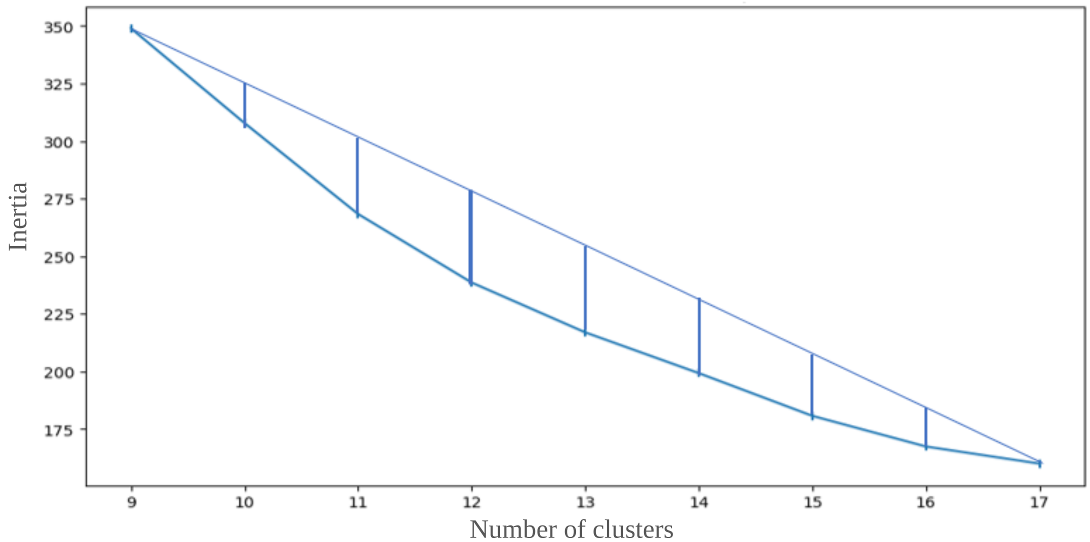


Figure 4.4 Inertia (WSS) for all cluster solutions

The GridSearch CV algorithm showed that 23 neighbor containers should be used in the KNN algorithm to assign the containers in the clusters with an accuracy of 99%. The dense network of containers, as well as their large number, forces such a large number of neighbors to be used for the assignment. These many neighbors are especially beneficial where the boundaries of the clusters are adjacent (see boundaries of clusters 3, 0, and 10) as the algorithm expands its solution space to make the assignment as accurate as possible as presented in Figure 4.6.

Looking at Figure 4.6, we can see that some collection sites are not assigned optimally, for example at the boundaries of clusters 4 and 8, which can be attributed to two reasons. The first reason regards the tactical level clusters formation, as it was already mentioned that the collection sites at the boundaries of clusters 4, 7, and 5 were not appropriately assigned. Because a collection site located near those boundaries was scheduled for collection on that specific day, meaning it was included in the training dataset of the KNN algorithm, it conveyed the problem to the construction of the operational level clusters, as observed. The second reason can be probably attributed to the fact that a uniform distance weight was assigned to all the assigned collection sites when the GridSearchCV tool was used. If a weighted approach was followed instead, meaning that the nearby collection sites of an unassigned collection site have more weight than the collection sites which are farther away, the containers' assignment could have possibly been better. It was decided to follow the uniform distance weight in the developed model for simplicity reasons, but it is recommended that the weighted approach is examined in future research to determine its effect on the containers' assignment.

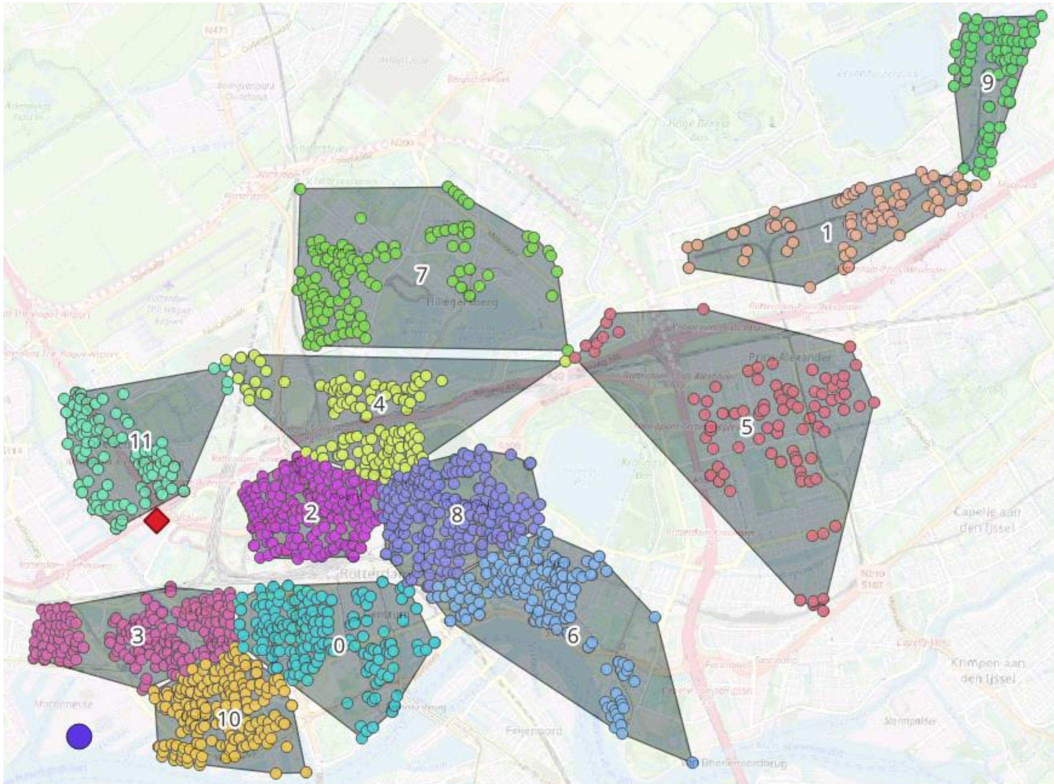


Figure 4.5 Tactical level clusters

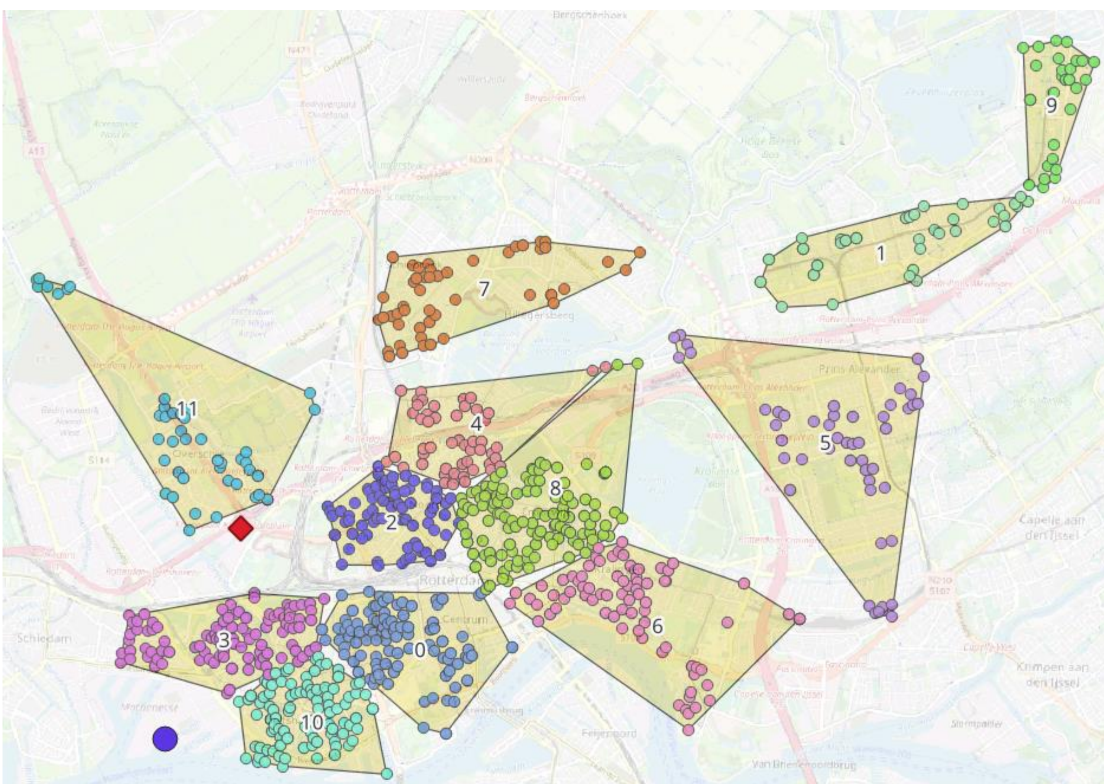


Figure 4.6 Operational level clusters

The routes of the current case and the base case were constructed by solving towards both distance and time. Figure 4.7-A shows the total travel kilometers per configuration, with a distinction between kilometers traveled on city roads and highway roads. As expected, the configurations solved towards distance result in a lower number of total travel kilometers, in comparison to their respective configurations solved towards time. On the other hand, the configurations solved towards time present an increased usage of highway roads and a decreased usage of city roads, in comparison to the configurations solved towards distance which are mostly using city roads. This can be attributed to the higher speeds achieved on the highway roads which result in shorter travel times. With a shift towards highway roads, social benefits can be achieved as the city traffic is reduced, and the emissions produced by the waste collection vehicles change concentration areas.

Overall, the base case performs better than the current case, with an 8.5% and 7.9% reduction of the total travel kilometers when solved towards time and distance respectively. It is important to note that the current case configurations presented here are an optimized version of the routes executed in real life as their paths were constructed under the consideration of the shortest path. Due to this reason, it can be said, without certainty, that the improvement threshold could have been larger. Figure 4.7-B shows the total time spent for each configuration, with a distinction between the driving time and the idling time, as well as the average duration of the routes. Similarly to Figure 4.7-A, the configurations solved towards time result in a lower total time spent, which is attributed majorly to the reduced driving time as the idling time remains almost the same.

Looking at Figure 4.7-B and Figure 4.7-C, it is interesting to see that even if two additional routes were constructed in the base case configurations, it was still managed to achieve a shorter average route duration and simultaneously a higher average vehicle capacity utilization. More specifically, the base case configurations achieved a 6% increase in the average vehicle capacity utilization, which proves that by reducing the construction of partially-full routes, higher efficiency levels can be achieved. It should be stated that the average vehicle capacity utilization for both configurations of the current case is the same as the order of the stops is the same, as well as the amount of collected waste and the number of executed routes. For the same reasons, except for the order of the stops, the average vehicle capacity utilization of the base case configurations is also the same. To get a clearer idea of the vehicle capacity utilization when the problem is solved towards distance and time, the median value is examined. The base case configurations achieved a 94.4% and 92.9% median vehicle capacity utilization when solved towards distance and time respectively, in comparison to the 81.4% achieved in the current case which proves the validity of the results.

The total amount of emissions produced and fuel consumed for every configuration are presented in Figure 4.7-D. The configurations solved towards time result in a lower by 1.5% amount of emissions and fuel, in comparison to their respective configurations solved towards distance, which is an almost negligible amount. The differences can be explained, nevertheless, by the fact that the fuel and emission factors used to calculate these indicators have larger values for the city roads due to the constant stop-and-go movements of the vehicles. As mentioned earlier, the configurations solved towards distance present a greater usage of the city roads than the ones solved towards time, which can explain the difference between the two.

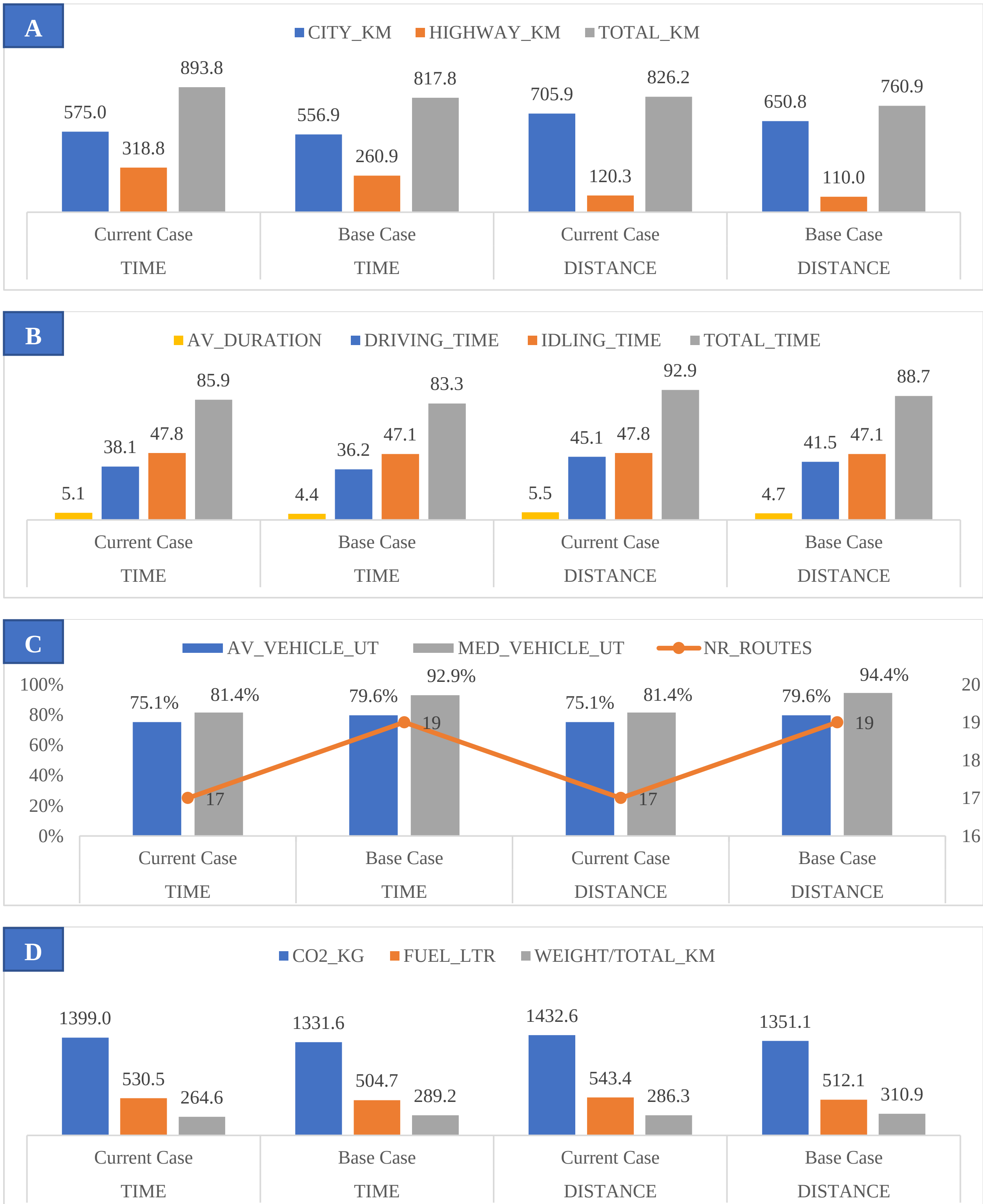


Figure 4.7 Current case vs Base case under a variety of KPIs

Figure 4.7-D displayed also the ratio of weight over travel kilometers for every examined configuration. This indicator proves to be of significance for the waste collection service as it gives a collective indication of the efficiency of the service. In general, the configurations solved towards distance result in a higher weight over travel kilometers ratio as the total collected waste remains the same but the total travel kilometers are comparatively lesser. More specifically, the base case configurations achieved an 8.9% and 8.2% increase in comparison to the current case configurations when solved towards time and distance respectively. Nevertheless, when comparing the base case configurations to each other, we see that the one solved towards distance achieved a 7% higher weight over travel kilometers ratio in comparison to the one solved towards time.

An example of a route solved by the model towards distance is presented in Figure 4.8. It is evident that the route mainly traverses through secondary roads, rather than highway roads, due to the shorter distances. By zooming in on the waste collection area part of the route, we can observe certain inefficiencies which can be attributed to poor network data, hindrances posited by the actual road network design, or a known limitation of the model. The network data was retrieved by an open-source and during the model application, multiple network problems were identified which had to be fixed. An example of such a network problem is presented in A.4, along with the steps followed to solve it. Other instances where the links' directions were not matching the actual roads' directions were ignored, as it was not in the scope of this study to improve the open-source network of the studied area. These known problems contribute to the routes' inefficiencies.

Next to the above, the real network design can posit hindrances in the construction of efficient routes. Containers in hard-to-reach locations such as one-way streets, dead ends, or with poor connection to the rest of the network, force a route to a seemingly illogical sequence of stops. In such routes, collection sites geographically close to each other, see nodes 2 and 7, may not be collected in close sequence as it is difficult to be reached through the real network. Even though the route path constructed based on such a sequence looks irregular, it proves to be the most efficient.

Lastly, it is an acknowledged limitation of the model that it restricts the choice of the collection site to be visited after returning from the disposal facility to the one closest to the collection site last served. Ideally, every unassigned collection site should be considered as a starting point after returning from the disposal facility, as is the case when a new route is constructed. This imposition reduces the chance of creating the optimal route.

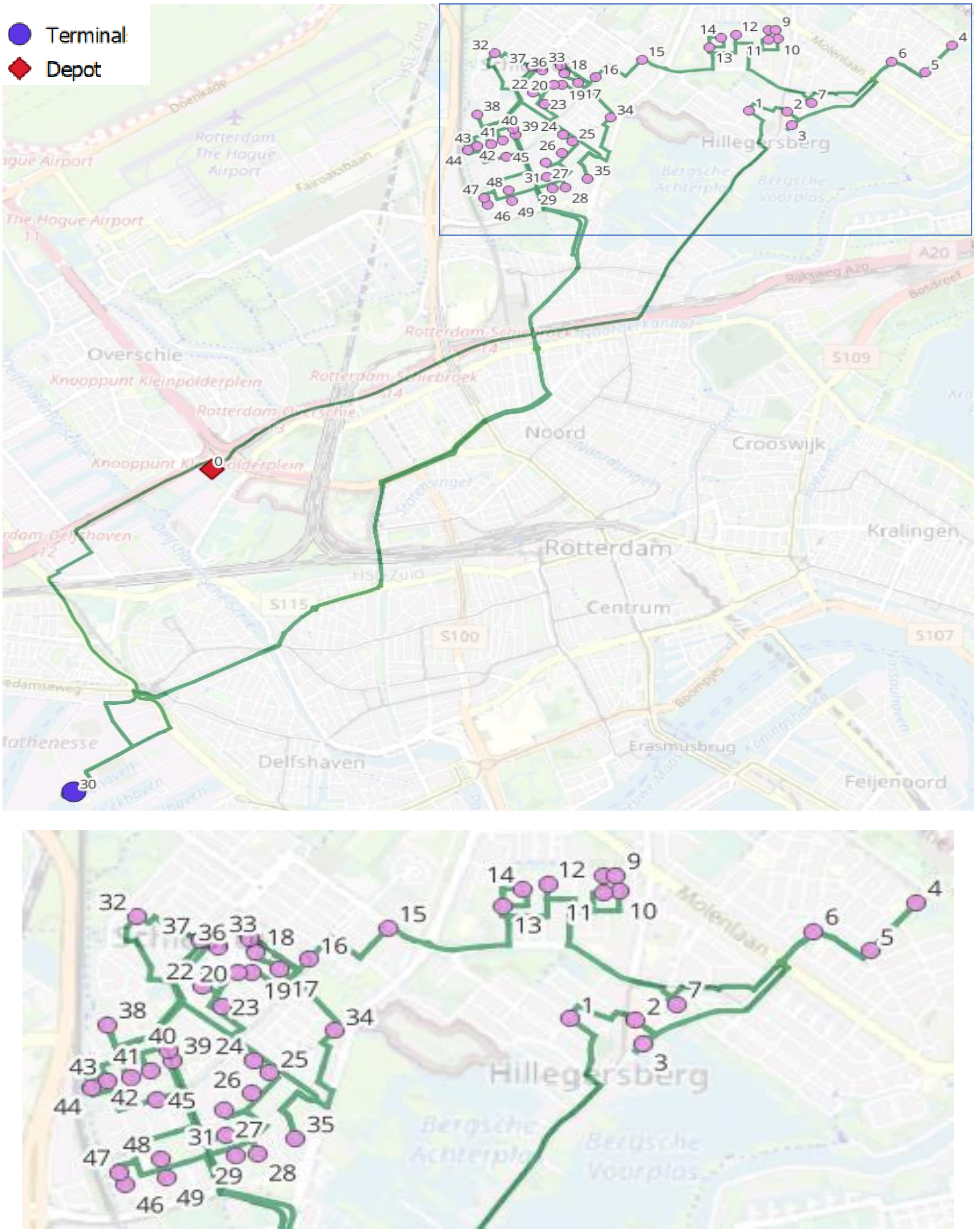


Figure 4.8 Example of a route solved towards distance

4.5 Sensitivity analysis

To evaluate the robustness of the model's solution, several configurations of different tunable parameters used at the tactical level clustering were examined. The reason behind this choice is to understand how changes at the initial stage of the solution affect the final results. In Table 4-1, the indicative parameter values examined in this analysis are presented. The parameters examined were the range of number of clusters used in the Elbow method to find the optimal number of clusters and a variety of combinations of different minimum and maximum capacity constraints. Configuration 9 represents the base case used to test the model and compare it with the current case, which is also used as a reference point for the comparison of the examined configurations. It is important to note that the purpose of the sensitivity analysis is not to identify the best performing combination of parameters, but rather to test some indicative values to understand how sensitive the model is. For this reason, the configurations examined are not exhaustive of all the different combinations that could have been examined.

Table 4-1 Sensitivity analysis examined configurations

Configurations	Range	Min. Capacity	Max.Capacity	Nr of clusters	Inertia	Nr of neighbors
1	13±3	None	None	12	238.62	23
2	13±3	105	None	12	262.89	3
3	13±3	100	None	12	253.70	13
4	13±3	95	None	12	248.97	25
5	13±3	None	200	13	272.73	23
6	13±3	105	200	13	273.09	9
7	13±3	100	200	13	272.97	7
8	13±3	95	200	13	272.95	15
9	**13±4**	**None**	**None**	**12**	**238.62**	**23**
10	13±4	105	None	12	262.89	3
11	13±4	100	None	12	253.70	13
12	13±4	95	None	12	248.97	25
13	13±4	None	200	14	215.07	15
14	13±4	105	200	13	273.09	9
15	13±4	100	200	13	272.97	7
16	13±4	95	200	14	225.23	15
17	13±5	None	None	12	238.62	23
18	13±5	105	None	12	262.89	3
19	13±5	100	None	12	253.70	13
20	13±5	95	None	12	248.97	25
21	13±5	None	200	14	215.07	15
22	13±5	105	200	13	273.09	9
23	13±5	100	200	14	229.80	5
24	13±5	95	200	14	225.23	15

Looking at Table 4-1 we can see that for every examined range, the respective configurations solved without a maximum capacity constraint perform the same, as proven by the inertia value of the constructed clusters and the optimal number of neighbors identified by the GridSearchCV tool. This can be attributed to the fact that every number of clusters included in each of the examined ranges was able to give a solution to the problem as it was not too restrictive, and that the K-means algorithm was fed a specific seed to keep the initial starting points constant. With this observation, it can be inferred that, on the condition that all the selected number of clusters examined in the Elbow method can solve the problem at hand, the size of the range used is trivial.

Differences arise between the respective configurations of every examined range when they are solved with a maximum capacity constraint. For the algorithm to satisfy this constraint a larger number of smaller clusters needs to be created. As the smaller number of clusters examined are unable to give a solution to the problem under these constraints, they are removed from the range used in the Elbow graph. As can be seen in Table A- 1, Table A- 2, and Table A- 3, which present the respective elbow graphs for each configuration and examined range, a solution to the problem with maximum capacity constraints can be found by using a minimum of twelve clusters. This leads to the reduction of the range 13±3 to [12-16], of the range 13±4 to [12-17], and of the range 13±5 to [12-18]. This range reduction leads the Elbow method to identify a different optimal number of clusters, as if we look at Configurations 5, 13, and 21, for example, which are solved under the same capacity constraints, we can see that the optimal number of clusters identified is 13, 14, and 14 respectively. This indicates that the choice of an optimal number of clusters is sensitive to the range examined, if not all the initially selected number of clusters can solve the problem at hand as the range is no longer symmetrical.

Table 4-2 exhibits for each examined configuration the KPIs used to evaluate the model's performance and the percentage difference between them and the base case (configuration 9). In regards to all the examined KPIs, the best performing configurations are 2, 10, and 18 which are solved under the same combination of capacity constraints, while the worst performing configurations are 6, 14, and 22. Table 4-3 shows for each KPI the range in which the percentage difference to the base case of all configurations fluctuates within, which is derived from the extreme values of the best and worst configurations. The results of the sensitivity analysis first proved that the results of the model are robust as the KPIs values of every examined configuration were fluctuating within just a range of ±4% when compared to the base case configuration. As the fluctuation range between the three examined ranges is small, the tactical-level and operational-level clusters created for the 13±4 range are displayed in Section A.7 to show how the capacity constraints are affecting the clusters formation.

Table 4-2 KPIs of configurations 1s-24

Configurations	Range	TOTAL_KM		CO2_KG		FUEL_LTR		WEIGHT/ TOTAL_KM	
1	13±3	760.86	0.0%	1351.08	0.0%	512.12	0.0%	310.86	0.0%
2	13±3	736.96	-3.1%	1330.22	-1.5%	504.14	-1.6%	320.95	3.2%
3	13±3	759.25	-0.2%	1353.97	0.2%	513.23	0.2%	311.53	0.2%
4	13±3	765.43	0.6%	1364.03	1.0%	517.08	1.0%	309.01	-0.6%
5	13±3	787.62	3.5%	1390.87	2.9%	527.36	3.0%	300.30	-3.4%
6	13±3	790.31	3.9%	1388.12	2.7%	526.28	2.8%	299.28	-3.7%
7	13±3	767.94	0.9%	1364.73	1.0%	517.36	1.0%	308.00	-0.9%
8	13±3	771.59	1.4%	1366.25	1.1%	517.95	1.1%	306.54	-1.4%
9	**13±4**	**760.86**	**0.0%**	**1351.08**	**0.0%**	**512.12**	**0.0%**	**310.86**	**0.0%**
10	13±4	736.96	-3.1%	1330.22	-1.5%	504.14	-1.6%	320.95	3.2%
11	13±4	759.25	-0.2%	1353.97	0.2%	513.23	0.2%	311.53	0.2%
12	13±4	765.43	0.6%	1364.03	1.0%	517.08	1.0%	309.01	-0.6%
13	13±4	778.13	2.3%	1378.46	2.0%	522.60	2.0%	303.97	-2.2%
14	13±4	790.31	3.9%	1388.12	2.7%	526.28	2.8%	299.28	-3.7%
15	13±4	767.94	0.9%	1364.73	1.0%	517.36	1.0%	308.00	-0.9%
16	13±4	779.36	2.4%	1385.60	2.6%	525.32	2.6%	303.48	-2.4%
17	13±5	760.86	0.0%	1351.08	0.0%	512.12	0.0%	310.86	0.0%
18	13±5	736.96	-3.1%	1330.22	-1.5%	504.14	-1.6%	320.95	3.2%
19	13±5	759.25	-0.2%	1353.97	0.2%	513.23	0.2%	311.53	0.2%
20	13±5	765.43	0.6%	1364.03	1.0%	517.08	1.0%	309.01	-0.6%
21	13±5	778.13	2.3%	1378.46	2.0%	522.60	2.0%	303.97	-2.2%
22	13±5	790.31	3.9%	1388.12	2.7%	526.28	2.8%	299.28	-3.7%
23	13±5	753.71	-0.9%	1351.77	0.1%	512.36	0.0%	313.81	0.9%
24	13±5	779.36	2.4%	1385.60	2.6%	525.32	2.6%	303.48	-2.4%

Table 4-3 Percentage difference ranges for each KPI

	TOTAL_KM	CO2_KG	FUEL_LTR	WEIGHT/ TOTAL_KM
Max	3.9%	2.9%	3.0%	3.2%
Min	-3.1%	-1.5%	-1.6%	-3.7%

4.6 Scheduling strategies evaluation

This section demonstrates how can the developed model be used to investigate and evaluate different scheduling strategies. More specifically, the dynamic scheduling strategies introduced in 3.2.1.2 were investigated to understand how the different selection of collection sites can affect the efficiency of the operations. The base case was used as a reference to compare the performance of each scheduling strategy, therefore the model was tuned to the parameters of configuration 9.

Figure 4.9-A depicts for each examined scheduling strategy and the base case, the total number of containers selected for collection, as well as their collection priority classification and average capacity utilization. The priority classification follows the rules presented in Table 3-3 which was introduced in 3.2.1.2. The 'HIGH_MEDIUM' strategy selected the least number of containers for collection among the other strategies, and in contrast presented the highest average container capacity utilization at 72%. The 'OUTSKIRTS' AND 'SAME_SITE' strategies selected the same number of high and medium priority containers as the 'HIGH_MEDIUM' strategy, and also an additional number of 315 and 262 low priority containers respectively. The extra total weight of waste collected for both the 'OUTSKIRTS' AND 'SAME_SITE' strategies, in comparison to the 'HIGH_MEDIUM' is around 20 tons (see Figure 4.9-B) which explains the construction of 3 additional routes (see Figure 4.9-C). For the base case, it is evident that not all high and medium priority containers were collected, as per their classification on the studied day. Instead, 35% of all collected containers were of low priority, meaning they were carrying less than 50% of their capacity. This explains why its average container capacity utilization is the lowest among the studied strategies at 58%.

Figure 4.9-B presents for each examined strategy the total collected weight, the total number of travel kilometers, and the ratio of the two which as mentioned before constitutes a significant efficiency indicator. By comparing the 'HIGH_MEDIUM' AND 'SAME_SITE' strategies, it can be observed that even though the latter collected 20 more tons of waste, which equals to almost 3 additional routes, the additionally driven kilometers were just 40. This can be attributed to the zero kilometers driven when collecting containers located at the same site, and the necessary trips to the disposal facility for unloading. This also explains why the weight over kilometers ratio of the 'SAME_SITE' strategy is larger than that of the 'HIGH_MEDIUM's strategy. The 'OUTSKIRTS' strategy even though collecting almost the same amount of waste as the 'SAME_SITE' strategy, travels 50 more kilometers which leads to reduced weight over traveled kilometers ratio, specifically to 296.4 in comparison to the 313.3 of the 'SAME_SITE' strategy. Simultaneously, the 'OUTSKIRTS' strategy presents an increase in the average vehicle capacity utilization despite the additional number of constructed routes.

Lastly, Table 4-4 shows the total CO2 emissions produced and total fuel consumed for each of the examined strategies, with a distinction between the driving and idling states. As a reminder, the quantities produced/consumed while driving are affected by the travel kilometers, the type of the road, and the accumulated weight of waste that is being carried by the vehicle. The total idling quantities are a summation of the quantities produced/consumed while idling at the disposal facility and those when idling at the collection sites to serve each container.

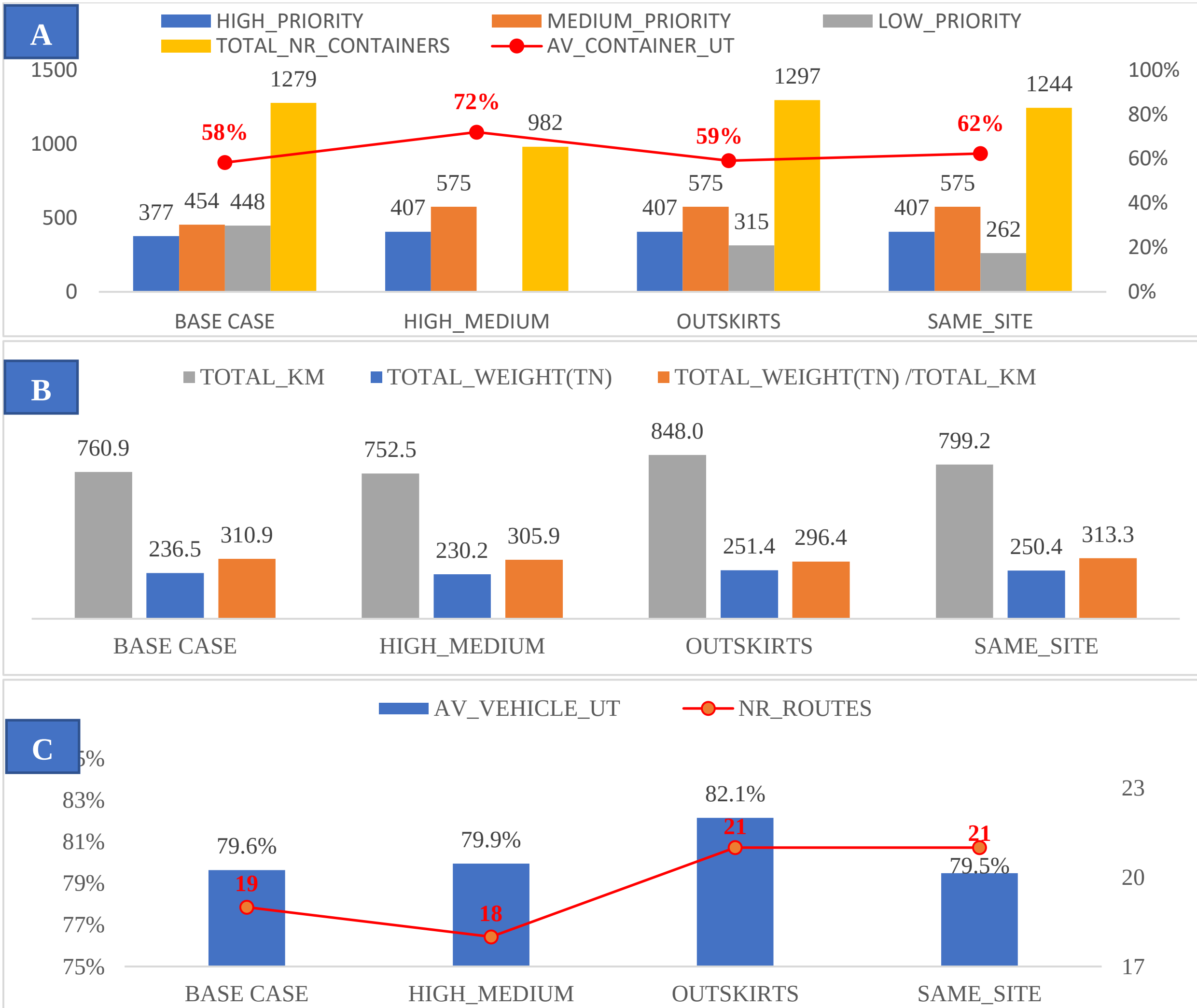


Figure 4.9 Dynamic scheduling strategies under a variety of KPIs

Table 4-4 CO2 emissions produced and fuel consumed per dynamic scheduling strategy

INDICATOR	STATE	LOCATION	BASE CASE	HIGH_MEDIUM	OUTSKIRTS	SAME_SITE
CO2(KG)	DRIVING	ALL	952.4	942.6	1055.3	994.3
CO2(KG)	IDLING	DISPOSAL FACILITY	93.1	90.3	95.9	98.7
CO2(KG)	IDLING	COLLECTION SITES	305.6	269.5	346.0	297.3
CO2(KG)		**TOTAL**	**1351.1**	**1302.4**	**1497.1**	**1390.4**
FUEL(LTR)	DRIVING	ALL	366.1	362.4	405.7	382.2
FUEL(LTR)	IDLING	DISPOSAL FACILITY	34.1	33.1	35.1	36.2
FUEL(LTR)	IDLING	COLLECTION SITES	111.9	98.7	126.7	108.9
FUEL(LTR)		**TOTAL**	**512.1**	**494.1**	**567.4**	**527.3**

It can be observed that the total CO2 emissions produced, and total fuel consumed while driving, are relative to the kilometers traveled, for all examined scheduling strategies. This can be proved, for example, by the ‘HIGH_MEDIUM’ strategy for which the least number of kilometers are traveled, and the least quantities of CO2 emissions are produced.

The total CO2 emission production and fuel consumption at an idle state at the disposal facility are higher with a higher number of visits as a constant service time of 20 minutes is defined. The total CO2 emission production and fuel consumption when idling at the collection sites are affected by the time spent serving them. The time to serve each collection site depends on the number of containers located there that need collection, and the time needed to stabilize the vehicle, see 0. As the stabilizing part happens only once per collection site, time savings can be realized at collection sites with multiple containers for collection. These savings can be proven if we compare the ‘BASE CASE’, ‘SAME_SITE’, and ‘OUTSKIRTS’ strategies.

The former two follow a similar principle in selecting containers for collection. In the ‘BASE CASE’, the average fill level of a collection site is the criterion used to schedule all its containers for collection. In the ‘SAME_SITE’ strategy the fill level of each container is considered independently to be selected for collection, and containers are selected in addition that are not fit for collection but are located at a collection site which is scheduled for collection. The amount of CO2 produced while servicing the collection sites of the ‘BASE_CASE’ and ‘SAME_SITE’ strategies is 305.6 kg and 297.3 kg respectively, with the almost 8kg difference attributed to the 35 more containers that were collected in the former. By comparing the ‘OUTSKIRTS’ strategy to the ‘BASE_CASE’ strategy we see that even though 18 more containers are collected, almost half the difference between the ‘BASE_CASE’ and ‘SAME_SITE’ strategies, the difference in the amount of CO2 emissions produced is almost 40 kg, which is almost five times the difference observed between the ‘BASE_CASE’ and ‘SAME_SITE’ strategies. This observation proves the savings that can be achieved by collecting all the containers located at a collection site.

4.7 Conclusions

This chapter initially described the waste collection system of Rotterdam which was used as a case study to demonstrate the applicability of the proposed solution approach. Subsequently, it presented the requirements and objectives the waste collection service articulates for its future operations as an IoT-based waste collection service addressing thereby in detail sub-question 1. Following that, it addressed sub-research question 6 by testing the developed model on the presented case study and performing a sensitivity analysis to prove the robustness of the model’s solutions. Finally, it demonstrated how can the developed model be used to investigate the scheduling strategies introduced in sub-section 3.2.1.2. Even though the results obtained by the model are promising, it should be recognized how its limitations and the necessary assumptions that had to be made for its implementation affect its outcomes. The next chapter discusses how the necessary assumptions and limitations of the approach affect the model’s outcomes.

Chapter 5 Discussion

The primary aim of this research was to improve the performance of an IoT-based waste collection service by employing the knowledge of the domain. As stated by domain experts, dispatch consistency and flexibility are a requirement for waste collection services that employ IoT technology, besides the obvious need to operate as economically and environmentally friendly as possible. The results presented in the previous chapter proved that the developed model could achieve all the stated research objectives. However, it is important to recognize how the model's outcomes are affected by its limitations and the necessary assumptions that had to be made for its implementation. This chapter is focused on interpreting and analyzing the main findings of the research in relation to the aforementioned. It starts with Section 5.1 which discusses the findings of the model testing, followed by Section 5.2 which analyses the model's sensitivity, and closes with Section 5.3 which comments on the findings of the model's demonstration on the selected scheduling strategies.

5.1 Model testing

Testing the model on the selected case study firstly proved that the overarching objective of maintaining dispatch consistency without hindering dispatch flexibility can be achieved, which is an objective of great significance for an IoT-based waste collection service. That is because it allows for the reduction of complete variability which is associated with fully demand-responsive operations and can lead to better administrative control and driver familiarity with preassigned territories.

Furthermore, it was proven that the model can achieve an economically and environmentally enhanced waste collection performance as the routes it constructed were better performing than the routes realized by the waste collection service of Rotterdam. More specifically, it proved that with the construction of a larger number of shorter but fuller routes, the vehicle capacity utilization can be increased, and a lower number of travel kilometers, a higher weight over distance ratio, and a reduced CO2 emissions production and fuel consumption can be achieved. Lastly, it was demonstrated that by solving the examined problem using distance as a cost, the model produces higher performance routes in terms of all the examined KPIs. When solving towards time nevertheless, a shift towards higher usage of highway roads is observed. With this shift, social benefits can be achieved as the city traffic is reduced and the emissions produced by the waste collection vehicles change concentration areas.

To ensure a fair comparison between the model's outcomes and the routes realized in real life, the same containers collected on the examined day were also scheduled for collection in the model. However, important assumptions had to be made to construct the paths and timelines of the routes realized in real-life as only the sequence of collection sites was provided. More indicatively, the time spent to service the containers, the time spent at the disposal facility for unloading, but also the moment the drivers visit the disposal facility, for some specific routes, was unavailable.

To compute the time spent to service all the containers of a collection site, Equation (22) was used which assumes a static service time of 0.75 minutes per container, and 1.5 minutes to level the waste collection vehicle. In addition, a fixed duration of 20 minutes was assumed to be the time spent at the disposal facility, including waiting in the queue and unloading the vehicle. In real-life operations, the duration of a disposal facility visit is completely variable due to the facility being open for use not only for the municipal waste collection service but also for private waste collection companies. The moment drivers visit the disposal facility for unloading was assumed to be the moment the vehicle carries an accumulated weight of 9000kg of waste. The weight payload of the vehicle was used as a constraint and not its volume capacity as no information was provided regarding its compaction capabilities. In real-life operations, drivers visit the disposal facility not only when the vehicle is full, but also when the disposal facilities are less busy, which is something that was not considered in the model.

The paths of the routes were constructed with the use of Dijkstra's algorithm which considers the least cost path creation. This fact, in combination with all the stated assumptions used to construct the routes' schedules, obviously led to the construction of routes that are different than the ones realized in the real-life operations. The stated assumptions were also carried in the model, first for comparison reasons, and second because the model is focused on a deterministic rather than stochastic behavior, which consequently presents implications for the accuracy of the solutions in realistic settings. Due to the explained reasons, it is easy to understand that the improvement threshold achieved by the model would have been different, perhaps even larger, if the paths and timelines of the routes realized in real-life were used for comparison instead of being resolved.

As already mentioned, the vehicle visits the disposal facility for unloading the moment it reaches an accumulated weight of 9000kg of collected waste. To calculate the weight of waste each container is carrying and decide if it should be included in a route or not, its fill level is multiplied by its maximum volume capacity and a fixed waste density of 75kg/m^3. With the stated simplifications, the model constructs efficient waste collection routes but with strict disposal facility visits. In real-life operations, such strict visits to the disposal facility would be hard to follow as the vehicle could get full earlier or later than planned. That is first due to waste density being a stochastic variable affected by the variety of disposable materials generated by households, and second due to the overflowing waste put next to the containers which is not easy to monitor or predict. To adapt to these unexpected issues, as well as accidents, road works, or road congestion, a flexible methodology that reconfigures routes in real-time is proposed that is unfortunately not considered in the developed model. The model, however, with the proposition of the tactical-level clusters enables the assignment of drivers to specific areas, hence enhancing their familiarity with them and allowing them to change their route in real-time by knowledge and experience.

To achieve a deterministic model behavior and ensure the model's results reproducibility, except for the assumed parameter values mentioned before, the algorithms employed in the model are set to be deterministic. More specifically, a seed was fed to the K-means algorithm to keep the starting points constant with every model run, while to ensure reproducibility of the train and test data used in the KNN algorithm an arbitrary seed with a specific split ratio (80% train data, 20% test data) was used. The GridSearchCV tool was used to find the optimal number of neighbors used in the KNN algorithm but it was restricted to a non-weighted approach, meaning nearby or far away containers are considered with the same significance.

Testing the model proved that restricting the starting points of the K-means algorithm can lead to a suboptimal clusters' formation, which can affect the final solution as the inefficiencies are conveyed by the model to the second clustering phase, and subsequently to the constructed routes. To be more precise, it has been observed that containers located further away from dense masses were not appropriately assigned to the tactical-level clusters, which led to the inappropriate assignment of nearby-located containers to different operational-level clusters. It is expected that if a different seed was selected for the K-means algorithm or several runs were performed to improve the resulting clusters' inertia, the model results would have been different and probably better.

Furthermore, if a weighted approach was followed instead in the GridSearchCV tool, the containers' assignment could have been possibly better and not have conveyed the tactical-clusters problem further in the final solution. Lastly, the model currently performs the containers' assignment to the clusters by using the euclidean distance. As it is logical, the euclidean distance cannot represent the actual road distance between the network's nodes, which proves to be problematic during clustering at locations where neighbor containers are bounded by physical boundaries such as highways, canals, parks, etc. It is recommended that the containers located close to physical boundaries are assigned to clusters by using the road distance instead of the euclidean in an effort to construct more compact and efficient clusters.

Certain limitations of the two-stage routing model affect the construction of the final cluster-based routes. Firstly, it is speculated that the better the initial routing solution is, the better results the optimization algorithm will produce. In the current routing model, the nearest neighbors algorithm is used (NN) which is completely greedy. It is expected that if the algorithm's greediness is tuned so that it chooses a random container among multiple to construct the route, the probability of finding the most efficient initial route will be increased.

Second, it is a known limitation of the routing model that it restricts the choice of the collection site to be visited after returning from the disposal facility to the one closest to the collection site last served. This imposition reduces the probability of finding the optimal route. It is suggested that every unassigned collection site is considered as the route's returning from the disposal facility starting point, as is the case when a completely new route is constructed. For the optimization of the initial routes, the 2-Opt algorithm is employed which performs the intra-route improvements. While this algorithm performed very well, it would be worthy to examine other local search algorithms to see if they can lead to even better-performing solutions. The developed model is currently missing an algorithm to perform inter-route swaps which could again possibly lead to a larger improvement threshold.

5.2 Model sensitivity

To evaluate the stability of the solution, several configurations of different parameters used at the tactical level clustering were examined. The parameters examined were the range of number of clusters used in the Elbow method to find the optimal number of clusters and combinations of different minimum and maximum capacity constraints. The results of the sensitivity analysis first proved that the results of the model are robust as the KPIs values of every examined configuration were fluctuating within just a range of ±4% when compared to the base case configuration.

Furthermore, it was proven that the size of the range used to find the optimal number of clusters is trivial when all the selected number of clusters examined in the Elbow method can solve the problem at hand. This was proved by all the configurations solved under no maximum capacity constraints, which were also the best-performing among the rest. On the contrary, the examination of configurations with a minimum and a maximum capacity constraint showed that not all the numbers of clusters selected in the Elbow method could provide a solution to the problem. This proved that the choice of optimal number of clusters is sensitive to the range examined if that is not symmetrical. Nevertheless, as it was pointed out already, the differences between all the examined configurations were small, regardless of the number of clusters constructed or the capacity constraints imposed.

As only one day's routes were used for this analysis, no hard conclusions can be drawn on the real effect of the two examined parameters on the model's sensitivity. That is because a scheduling strategy indicates daily which containers (already assigned in the tactical level clusters) should be used as a training input for the KNN algorithm to assign the rest of the scheduled unassigned containers to the operational level clusters. It is suggested that more days that present different characteristics should be examined, in addition to more configurations presenting various combinations of the examined parameters, to get a better idea of the fluctuation range of the KPIs values and thereby the model's sensitivity to the examined parameters.

5.3 Model demonstration

To select the containers to populate the tactical level clusters, a classification scheme with certain imposed rules was utilized which use as a criterion their historical monthly frequency of collection. The containers classified as having a high and medium frequency of collection were selected for the tactical level clustering to ensure that the high waste generation sources are the ones guiding the partition of the city into independent waste collection areas. In this way, even the monthly area partitioning becomes demand responsive.

It is acknowledged, nevertheless, that using the container's frequency of collection as a selection criterion introduces circularity in the system and does not accurately represent the waste generation patterns of the containers. This is because the frequency of collection is not only affected by the fill levels of the containers, but also by the way the waste collection service operates e.g. shift duration, no operations during the weekends, etc. If another criterion was used, like the waste fill rates of the containers, or different classification rules for that matter, is expected that the model outcomes would have been different and probably closer to the real optimum solution.

Each of the examined scheduling strategies makes use of a classification scheme with imposed rules to classify the containers according to their priority of collection. This scheme uses as criteria the waste accumulation period and the real-time fill level of the containers to classify them into a 'high', 'medium', and 'low' collection priority. The investigation of the three scheduling strategies proved that depending on the objectives put forward, certain strategies perform better than others.

The strategy which selects for collection only the high and medium priority containers, achieves a higher average container capacity utilization, travels the least number of kilometers, and carries the least amount of waste. The strategy which selects for collection not only high and medium priority containers but also the rest of the containers located at the sites scheduled for collection, achieves the highest weight over travel kilometers among the rest of the strategies. The strategy which selects not only the high and medium priority containers but also all the containers located in the outskirts if at least one needs servicing performs the worst among the rest of the strategies for almost every examined KPI. This strategy, however, achieves the highest average capacity utilization in comparison to the rest.

Overall, the strategies performed as expected, but it is acknowledged that a different set of priority classification rules would have led to completely different outcomes. Undeniably, to concretely conclude the behavior of each, they should be tested under various classification rules and on multiple days which present different waste generation patterns. Furthermore, to show their full potential they should be examined for several consecutive days as the fill level and accumulation period of each container, which is used for their priority classification, is affected by the previous day's executed schedule.

Chapter 6 Conclusions and recommendations

This final chapter formulates the main conclusions of the research in Section 6.1 and summarily addresses in Section 6.2 the research question and sub-questions leading this research. Finally, it provides recommendations for model improvements, future research, and a take-way message for the waste collection service of Rotterdam in Section 6.3.

6.1 Conclusions

This research proved that the functional requirement of an IoT-based waste collection service to maintain a trade-off between dispatch consistency and dispatch flexibility can be achieved through the proposed two-phase clustering technique. By achieving this trade-off, the unwanted complete variability which is currently associated with fully demand-responsive operations can be reduced, and efficiency gains can be simultaneously achieved, as demonstrated with the application of the model to the selected case study.

The model solved the formulated WCVRP towards the minimization of both distance and time to understand how different objectives affect its final solutions. Under both objectives and all examined KPIs, the model's solutions performed better than the current situation of the case study. Solving towards distance specifically, led to a lower number of travel kilometers and higher weight over travel kilometers ratio, which is a very important indicator in describing the efficiency of the whole waste collection system. On the other hand, solving towards time led to a lower travel time and to an increased usage of highway roads, and a decreased usage of city roads, which translates to reduced city traffic and a location shift of the produced emissions. Solving towards time also resulted in a lower amount of produced emissions in comparison to solving towards distance, but with an almost negligible difference of around 1.5%. For both studied objectives, all the above were achieved with the construction of a larger number of shorter but fuller routes, which simultaneously led to an increased average vehicle capacity utilization. Overall, solving towards both objectives led to satisfying results, but depending on the goals of a waste collection service, the most appropriate objective can be followed.

Depending on the objectives put forward, certain scheduling strategies perform better than others, as investigated by the developed model. For example, the strategy which selects for collection only the high and medium priority containers achieves a higher average container capacity utilization, travels the least number of kilometers but collects the least amount of waste. The strategy which selects for collection not only high and medium priority containers but also the rest of the containers located at the collection sites scheduled for collection, achieves the highest weight over travel kilometers among the rest of the strategies. The strategy which selects not only the high and medium priority containers, but also all the containers located in the outskirts if at least one needs servicing, performs the worst among the rest of the strategies for almost every examined KPI. This strategy, however, achieves the highest average capacity utilization in comparison to the rest.

6.2 Addressing research questions

1. *What are the functional requirements of an IoT-based waste collection service as derived from the knowledge of the domain?*

Domain experts attest to the considerable benefits IoT brought to waste collection operations. The access to real-time information brought using this technology enabled the dynamic organization of collection schedules and the creation of demand-responsive routes. As experienced by real-life operations, nevertheless, the complete variability associated with the creation of demand-responsive routes is undesirable due to administrative inconvenience, the need for enhanced internal communications, driver unfamiliarity with site-specific inconveniences, etc.

The requirements of the domain experts are therefore to maintain a certain level of consistency between the routes when the containers' location and demands vary from day to day, without hindering the dispatch flexibility, which is closely related to the demand-responsive routes. The overarching requirement is nevertheless to attain an economically and environmentally enhanced waste collection performance. As the dynamic scheduling strategies are responsible for choosing the most appropriate containers for collection, which directly affect the performance of the system and the efficiency of the routes, it is a requirement that a variety of them is evaluated to identify the most beneficial to the system.

2. *What scheduling strategies have been proposed to schedule containers for collection?*

IoT-based waste collection services follow a variety of dynamic scheduling strategies to guide the container scheduling process and ensure that a waste collection system's capacity is respected. Researchers have proposed a blend of dynamic scheduling strategies which utilize the enabled dynamicity brought by the IoT. Depending on the goals of the research, completely reactive scheduling or predictive-reactive scheduling approaches are proposed. In the former, no firm scheduling is generated in advance, and decisions are made locally in real-time, while in the latter schedules made for a rolling horizon are revised in response to real-time events. With each approach, various trigger rules and ranking methods exist to define the containers' eligibility for (possible) collection.

Most of the dynamic scheduling approaches proposed in the literature are focused on the individual container level. Some of the proposed strategies that follow a reactive-scheduling approach, assign priority levels to waste containers according to their real-time fill levels, or a prespecified waste accumulation period. Other strategies following a predictive-reactive scheduling approach predict the day at which it will be most beneficial to collect each container, in terms of the maximum amount of waste, minimum overflown containers, etc. Strategies adopted in real-life practice approach the matter in a more aggregated manner. When assigning containers in the collection schedule they focus on the collection site level and take into consideration the characteristics of the immediate collection area such as topology, population, waste generation patterns, etc. to make the assignment area and time-specific.

3. How has the waste collection problem been approached in literature?

The waste collection problem is generally approached as a vehicle routing problem, hence referred to as WCVRP, as it involves finding an optimal design of routes, traveled by a fleet of vehicles to serve a selected set of containers. Many variations and specializations of the WCVRP exist, depending on the problem characteristics and the often-conflicting goals and constraints. A vast number of solution approaches exist to solve the WCVRP, but the approaches which adopt clustering techniques to solve the IoT-based WCVRP most closely reach the predefined requirements of dispatch consistency and flexibility. The clustering techniques proposed in the literature follow an array of rules to perform the container assignment to the most beneficial cluster, which can either lead to the creation of completely static or variable clusters. If the rules dictate that the container assignment to clusters must be performed before any scheduling strategy is applied, meaning all the containers must be used, the clusters constructed are static, ensuring the operations dispatch consistency. At the same time, the rigid boundaries of the clusters may impose limitations on the routing efficiency and flexibility as the waste demands vary daily.

On the other hand, if only the containers scheduled for collection are assigned to clusters, as indicated by the rules of a scheduling strategy, the constructed clusters will vary daily to accommodate the uncertain demand. It can be understood that with this approach full dispatch flexibility can be achieved, which is nonetheless inconvenient due to practical reasons. Studies adopting this approach have been observed to also impose constraints on the cluster formation concerning vehicle capacity, shift duration, balanced size, time windows, etc. As in real-life operations, multiple constraints are considered at the same time, such as vehicle capacity and shift duration, it can be inferred that inefficient routes may be created with the imposition of the individual constraints. Overall, it can be concluded that no approach has been encountered in the literature to achieve the stated requirements set forth by the domain experts for the IoT-based WCVRP, and simultaneously achieve an economically and environmentally enhanced performance.

4. What solution approaches are employed in literature to solve the waste collection problem?

The solution approaches employed in literature to solve the WCVRP can be distinguished into two categories. The first employs mathematical programming techniques to solve small network instances to optimality, but at the expense of exponentially increasing computation time. The second addresses heuristic and metaheuristic methodologies which do not guarantee optimality but yield good results in a shorter execution time. This category also proves to be the most widespread among researchers as heuristics are often simple to describe and implement, which leads to their easy adaptability. It is common practice for the latter approach to create initial feasible routes with algorithms such as insertion heuristics, swarm intelligence, etc., and subsequently improve them with local improvement methods. The improvement methods encountered in the literature are neighborhood search algorithms and general heuristic methods, such as genetic algorithm, simulated annealing, and tabu search, which are usually combined with various local search enhancement methods. Irrespective of the choice of an exact or inexact solution approach, the WCVRP complexity can be reduced by reducing the problem size. This approach, usually referred to as a cluster-first route-second approach, partitions the containers set into individual smaller instances which are solved separately into complete routes. Clusters are generally created with rules imposed by the geography of the area, the characteristics of the containers themselves, and various objectives such as balanced travel time or a balanced number of containers in a cluster. Their size is usually restricted by the vehicle capacity or some time-imposed constraints.

5. *What solution approach is proposed to reach the stated functional requirements?*

The proposed solution approach has an overarching objective to construct routes in such a way that a trade-off between dispatch consistency and flexibility can be maintained. For this reason, the approach makes use of a two-phase clustering technique to efficiently assign collection sites to clusters, and subsequently constructs as many routes as required for each cluster to accommodate its demand. The first clustering phase employs the K-means algorithm to assign specifically selected containers into static clusters, which is fed an arbitrary seed to ensure the reproducibility of the results. The containers selected to populate the static clusters are classified according to their frequency of collection following the imposed rules of a classification scheme. Required input for the algorithm is the definition of the number of clusters to be constructed, which is determined by examining a range of number of clusters with the help of the elbow method combined with mathematics.

The second clustering phase aims at the creation of daily container circuits for collection with the employment of the K-nearest neighbor algorithm (KNN). A completely reactive scheduling approach is followed before this phase, realized through a selected scheduling strategy, to schedule the most appropriate containers for collection. The tactical level clusters created at the first clustering phase and the containers scheduled for collection through the scheduling strategy are used as input for this phase. The model identifies which containers already assigned in the tactical level clusters are not scheduled for collection and removes them from the set and uses the remaining assigned containers as an input dataset to train and evaluate the predictive performance of the KNN algorithm. Once the training is over, the algorithm assigns each unassigned container scheduled for collection to the cluster in which the majority of its already assigned neighbor containers belong. To find the optimal number of neighbors for the KNN algorithm, the GridSearch CV tool is used which is restricted to a non-weighted approach, meaning the same weight is assigned to all neighbor containers.

The routing model uses the travel time and distance matrices between all nodes of the network, and the operational level clusters which indicate which collection sites must be collected on the same route, to construct the waste collection routes. For every cluster, the model uses the nearest neighbors algorithm to gradually construct routes starting from every unassigned collection site and subsequently applies on each resulting route the modified 2-Opt algorithm. As the classic 2-Opt algorithm does not take into consideration any intermediate facilities that should be inserted in a route at specific positions, like the vehicles' visits at the disposal facility to regain their capacity, it had to be modified. Once all the routes are constructed and optimized, the model determines which is the best performing based on certain criteria, which further improves based on certain imposed rules as explained in full detail in sub-section 3.2.2.

6. *How does the developed model perform?*

To demonstrate the applicability of the proposed solution approach and evaluate the performance of the developed model a case study was selected. To test the model, its constructed routes were compared with the routes realized in real life for one specific day. The results proved the enhanced performance of the models' constructed routes, but also the fact that dispatch consistency can be maintained without hindering dispatch flexibility. More specifically, the routes constructed with the model presented a lower number of travel kilometers, a higher weight over distance ratio, and reduced $CO2$ emissions production and fuel consumption.

To evaluate the sensitivity of the solution, several configurations of different parameters used at the tactical level clustering were examined. The reason behind this choice is to understand how changes at the initial stage of the solution affect the final results. The parameters examined were the range of number of clusters used in the Elbow method to find the optimal number of clusters, and combinations of different minimum and maximum capacity constraints. The results of the sensitivity analysis proved that the solutions of the model are robust, with the values of the selected KPIs fluctuating within just a range of ±4% when compared to the initial solution.

Regardless of the model's stated limitations discussed in Chapter 5, both model testing and sensitivity analysis results proved that the model's performance is promising. Nevertheless, as the model was tested and analyzed on only one day's data, no hard conclusions can be drawn about its overall performance. Therefore, it is suggested that the model is tested on more days that present different characteristics, to get a better idea of the fluctuation range of the KPIs values and thereby the model's sensitivity to the examined parameters.

Main research question: ***"How can the knowledge of the domain be used to improve the performance of an IoT-based waste collection service?"***

Precise and accurate problem definition is critical for the success of any project. Domain knowledge can often help in reaching this precision and accuracy. Specifically for an IoT-based waste collection service, which is a relatively new concept in practice, using the knowledge of the domain is critical when endeavoring to improve its performance. Domain experts attest that operating a demand-responsive service brings financial and environmental gains to a waste collection service, but it simultaneously introduces complete variability in the system which is undesirable for various reasons. To solve this problem and consequently optimize the waste collection service's performance, the domain experts stress the need for a balanced trade-off between dispatch consistency and flexibility. This means, being able to exploit to the highest degree possible the benefits of demand-responsive operations, while also maintaining a certain level of dispatch consistency when demand varies daily.

Once the requirements articulated by the domain experts are known, the relative literature is studied to find if and how the specific problem has been approached. After establishing that no approach in literature has been reported to achieve the stated functional requirements, a solution approach was proposed to solve the WCVRP. This approach regards the use of a two-phase clustering technique to successively determine the membership of waste containers to clusters, created both on a tactical and operational planning level, in a way that dispatch consistency and flexibility can be maintained when the demand varies daily. Subsequently, to create for each resulting cluster as many routes as required, such that the total kilometers traveled, and total CO2 emissions produced to service the containers are minimized.

The solution approach's applicability has been demonstrated with a case study. The results of the model were promising as they achieved not only the functional requirements but also an economically and environmentally enhanced performance in comparison to the case study. In addition, the model's sensitivity was examined with different configurations of tunable parameters used in the first-clustering phase. The results of the sensitivity analysis proved that the solutions of the model are robust, with the values of the selected KPIs fluctuating within just a range of ±4% when compared to the initial solution. Conclusively, the model can be used by any waste collection service which presents the same characteristics and imposes the same constraints as the formulated WCVRP the model is intended to solve. The model is equipped with multiple tunable parameters and uses a variety of user-imposed rules to construct the final solution, which enables its generalizability and transferability to new data and situations. Nevertheless, it is important to recognize the model's limitations as it is focused on the attainment of specific requirements, and it does not aim to address everything that takes place during waste collection scheduling or routing.

6.3 Recommendations

6.3.1 Model improvements

The developed model was proven to achieve not only the stated functional requirements but also an economically and environmentally enhanced performance when compared to a case study. However, its limitations and simplifications are acknowledged, hence some recommendations are provided for its improvement.

- The containers used to populate the tactical level clusters have been selected based on their historical monthly frequency of collection, specifically the ones with a high and medium frequency of collection. To avoid circularity in the model and ensure that the fast-filling containers are used indeed to construct the clusters, it is suggested that the fill rate of the containers is used instead of their collection frequency. This also means that a different classification scheme should be devised as well to select the most eligible containers for assignment.
- To ensure the stability of the formation of the tactical level clusters, an arbitrary seed was fed to the K-means algorithm, which nevertheless restricts us from finding the optimal clustering solution. It is suggested that the K-means algorithm is run for several iterations with the goal of improving the resulting clusters' inertia, and then selecting the solution with the least inertia for the subsequent model steps.
- To ensure reproducibility of the train and test data used in the KNN algorithm, an arbitrary seed was used with a specific split ratio (80% train data, 20% test data). To avoid having to use a specific train/test split, k-fold cross-validation should be performed instead.
- Currently, the GridSearchCV tool, employed to find the optimal number of neighbors to be used in the KNN algorithm, is following a non-weighted approach. It is suggested that a weighted approach is examined to understand if attaching a larger weight on close-by containers and a smaller weight on far-away containers leads to better-performing solutions.

- The possibility of imposing capacity or weight constraints on the operational level clusters should be examined to reduce partially-full routes and achieve higher efficiency gains
- The model currently performs the containers' assignment to the clusters by using the euclidean distance. As it is logical, the euclidean distance cannot represent the actual road distance between the network's nodes, which proves to be problematic during clustering at locations where neighbor containers are bounded by physical boundaries such as highways, canals, parks, etc. It is recommended that the containers located close to physical boundaries are assigned to clusters by using the road instead of the euclidean distance in an effort to construct more compact and efficient clusters.
- For the construction of the initial routes, the repeated nearest neighbor is employed. This algorithm creates as many routes as the points that need to be assigned in a cluster. That is because it uses each available point as a starting point of a route, which populates iteratively by assigning the closest neighbor container. This is performed to increase the chances of finding the optimal solution. It is suggested that the greediness of the algorithm is tuned so that it doesn't choose the immediately best container but a random one among multiple, e.g. 3. With the change in the greediness the algorithm would be transformed to the randomized nearest neighbors algorithm (RNN).
- The model restricts the choice of the collection site to be visited after returning from the disposal facility to the one closest to the collection site last served. This imposition reduces the chance of finding the optimal route. Instead, the routing model should be modified such that every unassigned collection site is considered as a starting point after returning from the disposal facility, as is the case when a new route is constructed.
- For the optimization of the initially constructed routes, the 2-Opt algorithm was employed in the model which performs intra-route improvements. Different local search algorithms can be used instead, like 3-Opt, relocate, and exchange which may perform better than the 2-Opt. It should be noted that the 2-Opt algorithm had to be modified to be applicable on a multi-trip WCVRP, as waste collection routes require intermediate disposal facility visits for unloading
- Once all the routes are constructed per cluster, the model is instructed to proceed to the next cluster, therefore it stops trying to find a better solution. It is suggested that local search heuristics are employed, like 2-Opt*, 3-Opt*, redistribute, chain, etc. which perform inter-route swaps to improve the final solution
- The developed model does not impose a constraint on the maximum number of routes that should be servicing each cluster. This can easily be implemented to ensure the cluster-driver assignment and consequently, the sought-after dispatch consistency. It should be noted that the cluster-specific maximum number of routes would be identified with multiple model executions to understand the average requirements of each. With this constraint nevertheless, the risk of leaving containers unattended is increased. Therefore, a scheme should also be in place to ensure that all the high-priority containers are assigned to a route, and the unattended containers are only of medium-priority.
- To be able to draw hard conclusions on the model's robustness more combinations of tunable parameters' values should be examined, on days with different waste generation patterns, and different case studies

6.3.2 Future research

Future works can focus on making the developed model more realistic so that it can be more representative of real-life operations and therefore increase its applicability.

- The developed model uses the capacity constraint of the vehicles to insert the disposal facility trips in the routes. Strategies that are followed in practice to achieve higher levels of efficiency should be examined in future works. Some examples are: 1. to visit the disposal facility if it is close to it even if it is not fully loaded, 2. to consider the peak hours of the disposal facility to avoid visiting when it is too busy, if possible, 3. to skip the last trip to the disposal facility before returning to the depot, only for vehicles working in the morning shift and are semi-full, 4. to visit the disposal facility when the vehicle volume capacity is reached, implying that the compaction capabilities of the vehicle must be considered as well, etc.
- Future work could focus on analyzing the visiting patterns at the disposal facility by considering its capacity, as well as the activities taking place therein. The outcomes of this work can be used as an input for the developed model to improve the moment a vehicle visits the disposal facility, but also to assign a more realistic service time at the disposal facility than just a fixed duration of 20 minutes which is currently used in the model.
- The model can be extended with the use of time windows. More specifically, time windows are suggested to be assigned to containers: 1. located in the vicinity of public transport stations and education buildings, 2. at locations with high traffic conditions, and 3. at locations with accessibility issues or restrictions.
- In real-life operations, drivers have special permission to drive on certain roads in reverse, such that the collection of certain containers is easier. This special permission could be investigated in future works to identify which links of a network are most appropriate to be transformed to a two-way flow (to replicate the reverse direction). Some requirements to be considered are 1. Low traffic conditions, 2. Wide enough roads 3. Low-hierarchy roads (with low speeds)
- To achieve more realistic travel times, it is suggested that in future works the speed associated with each link of the network is specific for different parts of the day, such that congestion effects are easier to take into consideration. This will be especially useful when time windows are examined. Furthermore, it would be an interesting option to explore the incorporation of planned roadworks in the model, such that links' unavailability will be considered in the route's path creation.
- In the model a homogeneous fleet was considered, which is not very realistic as usually, the fleet of a service is slowly expanding, acquiring throughout time vehicles with different capacities and related costs. It is suggested that in future research a heterogeneous fleet is considered, which would nevertheless increase the complexity of the problem as it would require an advanced container-vehicle assignment. In addition, the use of electric vehicles should be investigated in the future to understand the effects on the performance of the service, which would require the imposition of an additional constraint, that of the battery duration.
- Waste collection is a multifaceted problem as it regards the collection of solid and recyclable waste by both the public and private sectors. Nonetheless, this research was focused only on household solid waste collection for simplicity. For future research is suggested that waste collection is approached as one entity, with the objective of mapping, organizing, and assessing all the different services under one scope, which can eventually lead to holistically better performing operations.

- The issue of overflown containers was overlooked in this research, but in reality, it constitutes one of the biggest issues of IoT-based waste collection operations as there is no way to monitor or predict it. It is suggested that in future research various strategies are explored to approach this issue, for example, the use of a special vehicle focused on only collecting the overflown waste as identified by drivers passing by, or through orders received by citizens.
- In this research, to calculate the weight of solid waste each container carries, a fixed weight to volume conversion rate was used, while in reality waste density is stochastic. This simplification would lead to visits to the disposal facility earlier or later than planned. It is suggested that the model is modified to enable rerouting to flexibly adapt to unexpected demand.

6.3.3 Recommendations for the waste collection service of Rotterdam

Testing the developed model in the case study, demonstrated except from the accomplishment of the stated requirements, the efficiency gains that can be achieved for the waste collection service of Rotterdam. Dividing the city into smaller non-overlapping waste collection areas with flexible boundaries to accommodate the daily demand, can lead to the construction of efficient cluster-focused routes and better administrative control.

The investigation of three different dynamic scheduling strategies showed that depending on the objectives of a waste collection service, certain strategies perform better than others. The strategy which selects for collection only the high and medium priority containers (‘HIGH_MEDIUM’) achieves a higher average container capacity utilization, travels the least number of kilometers but collects the least amount of waste. This strategy is suggested to be followed in days that present relatively low waste generation. The strategy which selects for collection not only high and medium priority containers, but also the rest of the containers located at the collection sites scheduled for collection (‘SAME_SITE’), achieves the highest weight over travel kilometers among the rest of the strategies. This strategy is proposed to be followed on days with higher waste generation, but specifically on Mondays and Fridays to deal with the reduced operations of the weekend.

The strategy which selects not only the high and medium priority containers, but also all the containers located in the outskirts if at least one needs servicing (‘OUTSKIRTS’), achieves the highest average vehicle capacity utilization in comparison to the rest strategies but performs the worst for every other examined KPI. Despite not performing the best, this strategy still shows potential. It is recommended that a policy is examined in which the residents of the outskirts area are informed in advance about the arrival of the waste collection vehicle so that they can dispose of their waste on time. This will aid in collecting a higher amount of waste while traveling the same amount of kilometers, therefore to an even higher vehicle capacity utilization and weight over travel kilometers ratio.

To be able to determine when it is most beneficial to use each strategy, it is suggested that they are investigated on different days which present different waste generation patterns, and different working patterns (e.g. reduced or no waste collection operations during the weekend). Instead of only examining them for individual days, it is furthermore suggested that they are examined for consecutive days to understand their long-term potential or limitations. That is because the fill level and waste accumulation period of each container, which are the criteria used to assign them for collection, are affected by the previous day's executed schedule which is determined by a selected scheduling strategy.

Except for the investigation of the scheduling strategies, the model can further be used by the waste collection service to understand the transport mechanisms of waste and how the road network is utilized by the waste collection vehicles. Among others, important aspects to be considered should be the routes' compactness, which regards the overlapping of routes, and the identification of the most frequently used roads. With information on the network usage, a timely concept to be examined would be the calculation of CO2 emissions production per resulting waste collection area, to understand the impact of the waste collection routes.

Applying the model for a consecutive number of days can enable the identification of underused containers, as it requires as input the containers' daily waste fill levels, which can thereafter be moved to other locations in need of additional capacity. In continuation to the above, containers in hard-to-reach locations such as one-way streets, dead ends, or with poor connection to the rest of the network can also be identified, as they may cause the formation of inefficient waste collection routes. Analyzing the location and usage of such containers can enable their placement in more beneficial locations.

In regards to the application of the model, it is suggested that is tested under different combinations of tunable parameters to identify which combination is the most beneficial for the specific needs of the service. To analyze the southern side of the city, for example, the model has to be tailored to it as it has a different size and density network of containers than the northern side. Lastly, for an easier application of the model it is suggested that all the data files used are consistent with each other, in terms of locations and identifications of containers and their installed sensors, and most importantly there are all up to date.

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Annex

A.1 Parameter values

Table-A 1 The parameters' values used in the proposed solution approach

Symbol	Unit	Description	Value
$\boldsymbol{ut_{k,df}}$	min	Unloading time of vehicle k at disposal facility	20
l_t	min	Vehicle leveling time	1.5
m_t	min	Vehicle hook moving time	0.75
Con	kg/m^3	Volume to weight conversion rate	75
$\boldsymbol{F_{idling}}$	ltr/min	Fuel consumption factor of idling vehicle	0.052
$\boldsymbol{F_{city,empty}}$	ltr/km	Fuel consumption factor: empty vehicle & city road	0.53
$\boldsymbol{F_{city,full}}$	ltr/km	Fuel consumption factor: full vehicle & city road	0.83
$\boldsymbol{F_{highway,empty}}$	ltr/km	Fuel consumption factor: empty vehicle & highway road	0.25
$\boldsymbol{F_{highway,full}}$	ltr/km	Fuel consumption factor: full vehicle & highway road	0.30
$\boldsymbol{C_{idling}}$	CO2 gr/min	CO2 emission production factor of idling vehicle	137.05
$\boldsymbol{C_{city,empty}}$	CO2 gr/km	CO2 emission production factor: empty vehicle & city road	1387
$\boldsymbol{C_{city,full}}$	CO2 gr/km	CO2 emission production factor: full vehicle & city road	2153
$\boldsymbol{C_{highway,empty}}$	CO2 gr/km	CO2 emission production factor: empty vehicle & highway road	650
$\boldsymbol{C_{highway,full}}$	CO2 gr/km	CO2 emission production factor: full vehicle & highway road	780

Table-A 1 shows the parameters' values considered in the proposed solution approach. The unloading time at the disposal facility, the vehicle leveling and hook moving time, as well as the volume to weight conversion rate were provided by the experts of the waste collection department of Rotterdam. The emission production and fuel consumption factors used for the idling state of the vehicle were retrieved by the study of Lim (2003). The fuel consumption factors for the empty and full state of a vehicle on the highway were suggested by Volvo (Mårtensson & Trucks, n.d.), but the respective factors for the city were unavailable. According to Michael O'Connor (Autolist), most vehicles achieve at least five more miles per gallon (mpg) on the highway than in the city due to the constant stop-and-go movement of the vehicles. This information was translated to ltr/km and subsequently used to calculate the respective city-based fuel consumption factors. Volvo (Mårtensson & Trucks, n.d.) stated that 2.6kg of CO2 emissions are produced by one liter of standard diesel fuel, which was used to calculate all the driving emission production factors.

A.2 Collection site weight calculation

Equation (21) is used to calculate the total weight of waste at a collection site s, where Con is a volume to weight conversion rate, and $F_{s,c}$ and $C_{s,c}$ are the fill level and maximum volume capacity respectively of every container c located at collection site s.

$$W_s = Con \sum_{c \in s} F_{sc} * C_{s,c} \tag{21}$$

A.3 Collection site service time calculation

The service time of each collection site S_s is calculated with equation (22)(22), where l_t is the vehicle leveling time, m_t is the vehicle hook moving time, and n is the number of containers at a collection site. Leveling comprises the time needed to stabilize the vehicle for the loading, and the time needed to safely place the hook back in the vehicle. Moving time comprises the time needed to lift each container, unload its content, and safely place it back in its initial position.

$$S_s = l_t + n * m_t \tag{22}$$

A.4 Road network preprocessing

An example of network links' inconsistent directions is presented in Figure-A 1, where there is no way to reach the yellow node. To solve such issues, and only wherever necessary, the one-way links were transformed into two-way links. To make the characteristics of the road network more realistic, an average speed was assigned to each link which was retrieved by the road network of Rotterdam used in the Tactical Freight Simulation (TFS) model.

To make the road network suitable for use in the Dijkstra algorithm the following steps were followed:

1. Project all the collection sites to the closest points on the road network
2. Split the links where the projected collection sites are created
3. Create network nodes at the start and end of each link of the network to identify their coordinates

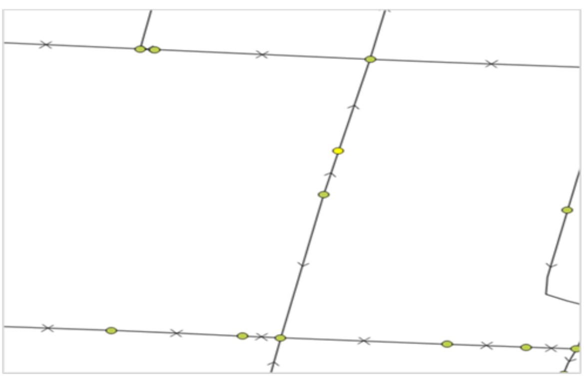


Figure-A 1 Inconsistencies between one-way links' direction

A.5 Practitioners' summary

Domain experts attest that operating a demand-responsive service brings financial and environmental gains to a waste collection service, but it simultaneously introduces complete variability in the system. Due to various reasons such as administrative inconvenience, the need for enhanced internal communications, and driver unfamiliarity with site-specific inconveniences, complete variability is undesirable in real-life operations. To solve this problem and consequently optimize the waste collection service's performance, the domain experts stress the need for a balanced trade-off between dispatch consistency and flexibility. This means, being able to exploit to the highest degree possible the benefits of demand-responsive operations, while also maintaining a certain level of dispatch consistency when demand varies daily.

To achieve the stated trade-off and a better organization of the waste collection service a smart solution approach is proposed, the objective of which is to construct routes in such a way that the total traveled kilometers, as well as the total CO_2 emissions produced, are minimized. The approach firstly uses a two-phase clustering technique to consecutively assign waste containers to two-level clusters. It subsequently uses a routing model to construct for each of the second-level clusters as many routes as required to accommodate its demand.

In the first clustering phase certain waste containers, selected based on their historical monthly frequency of collection, are assigned to geographically fixed clusters. These clusters resemble independent waste collection areas where drivers can be assigned, a fact which ensures that dispatch consistency can be maintained as the drivers' assigned routes will be always cluster-specific. A scheduling strategy then selects which containers should be scheduled for collection based on their priority, which depends on their waste fill level and the accumulation period the waste is in the container. The containers which are not scheduled for collection but are assigned in the fixed clusters are removed, while the rest of the containers remain in the clusters to be used as cluster cores for the second clustering phase.

In the second clustering phase, the containers which are scheduled for collection but don't belong in any cluster are finally assigned to the one where most of their neighbor containers belong. The second-level clusters prove that even if the cluster cores are stable, their boundaries are flexible to respond to the daily demands and consequently ensure dispatch flexibility. The routing model uses the second-level clusters, which indicate which collection sites must be collected on the same route, and the travel time and distance matrices between all nodes of the network, to construct the waste collection routes. The routing model constructs for every second-level cluster as many initial routes as required to accommodate its demand, which optimizes later with a variety of rules.

Testing the developed model on the solid waste collection service of Rotterdam, proved that not only the stated trade-off can be achieved but also significant efficiency gains. More specifically, the model demonstrated that collecting the same containers with a sample of routes executed in real-life can lead to a lower number of traveled kilometers, a higher weight over distance ratio, and reduced CO_2 emissions production and fuel consumption. All the stated gains were achieved with the construction of a larger number of shorter but fuller routes, which led to an also increased average vehicle capacity utilization.

Three dynamic scheduling strategies were selected for examination to demonstrate how can the developed model be used. Each of the examined strategies makes use of the priority classification of the containers to determine if they should be scheduled for collection. The 'HIGH_MEDIUM' strategy, which schedules for collection only the 'high' and 'medium' priority containers, achieves the highest average container capacity utilization, travels the least number of kilometers but also collects the least amount of waste. As the least number of containers is scheduled for collection with this strategy, it is suggested that is followed on days that present relatively low waste generation. The 'SAME_SITE' strategy, which schedules for collection all 'high' and 'medium' priority containers and additionally all the containers located at those collection sites, achieves the highest weight over travel kilometers among the rest of the strategies. This strategy proves that savings can be achieved by collecting all the containers located at a collection site, as no additional kilometers need to be traveled other than for the trips to and from the disposal facility for unloading. This strategy is proposed to be followed on days with higher waste generation, but specifically on Mondays and Fridays to deal with the reduced operations of the weekend.

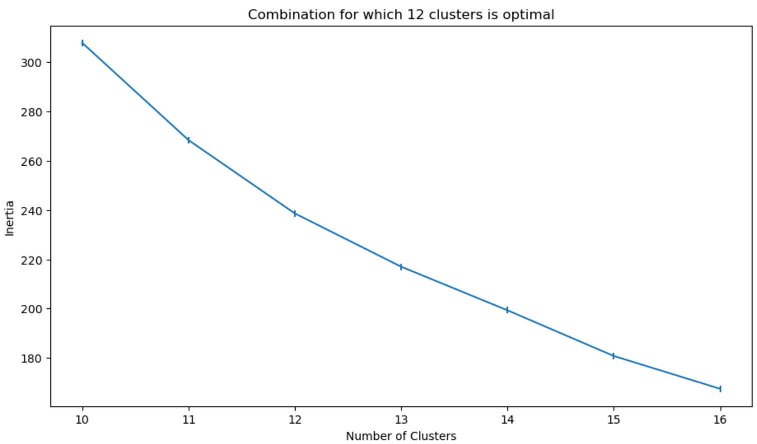
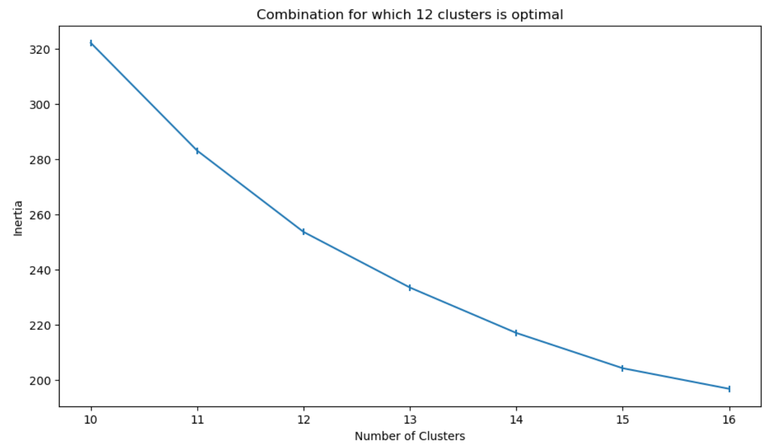
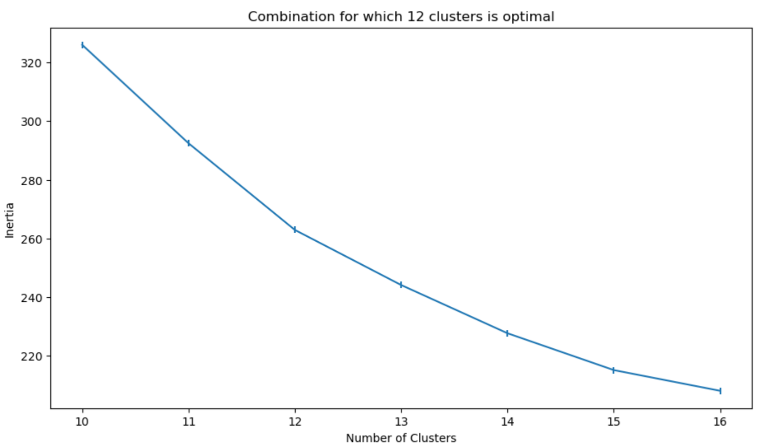
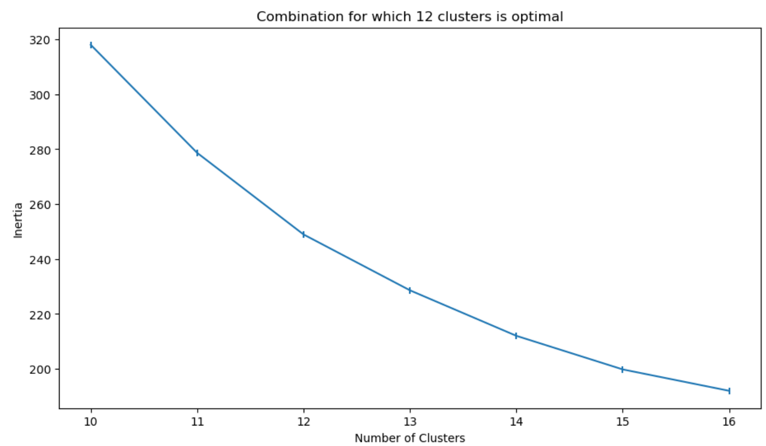
The 'OUTSKIRTS' strategy, which schedules for collection all 'high' and 'medium' priority containers, and all the containers located on the outskirts of a city if at least one of them needs servicing, achieves the highest average vehicle capacity utilization in comparison to the rest of the strategies, but performs the worst for almost every examined KPI. Despite not performing the best, this strategy still shows potential. It is recommended that a policy is examined in combination with the 'OUTSKIRTS' strategy, in which the residents of the outskirts are informed in advance about the arrival of the waste collection vehicle so that they can dispose of their waste on time. This will aid in collecting a higher amount of waste while traveling the same amount of kilometers, therefore to an even higher vehicle capacity utilization and weight over travel kilometers ratio.

Overall, the strategies performed as expected, but it is acknowledged that a different set of priority classification rules would have led to different outcomes. To concretely conclude on the behavior of each, they should be tested under various classification rules and on multiple days which present different waste generation patterns. To show their full potential they should be examined for several consecutive days as the waste fill level and accumulation period of each container, which are used for their priority classification, are affected by the previous day's executed schedule.

The model is equipped with multiple tunable parameters and uses a variety of user-imposed rules to construct the final solution, a fact which enables its generalizability and transferability to new data and situations. It is important to recognize nevertheless the model's limitations, which are mainly derived from its deterministic behavior, as it is focused on the attainment of specific requirements, and it does not aim to address everything that takes place during waste collection scheduling or routing. The model can be used to investigate not only the three selected scheduling strategies but also the transport mechanisms of waste and how the road network is utilized by the waste collection vehicles. For example, with information on the network usage, the CO2 emissions production per resulting waste collection area can be calculated, which would aid in understanding the impact of the waste collection routes. Applying the model for a consecutive number of days can enable the identification of underused containers, or containers in hard-to-reach locations on the network which cause the formation of inefficient routes, which can thereafter be moved to more beneficial locations to better exploit them.

A.6 Sensitivity analysis results - elbow graphs

Table A- 1 Elbow graphs range 13±3

Config.	Elbow graph	Config.	
1		3	
2		4	

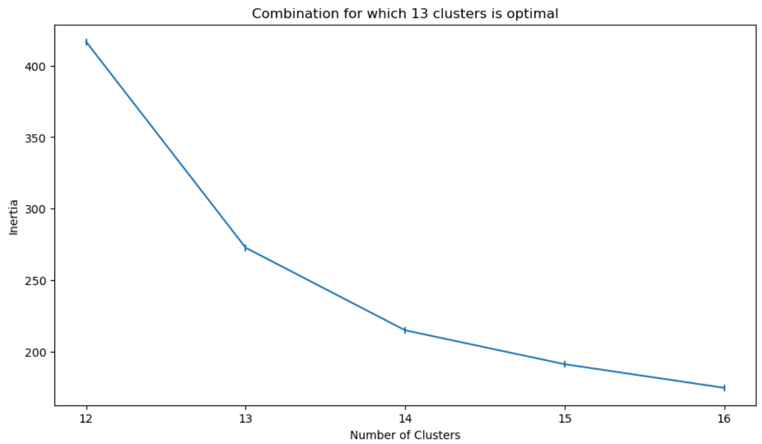
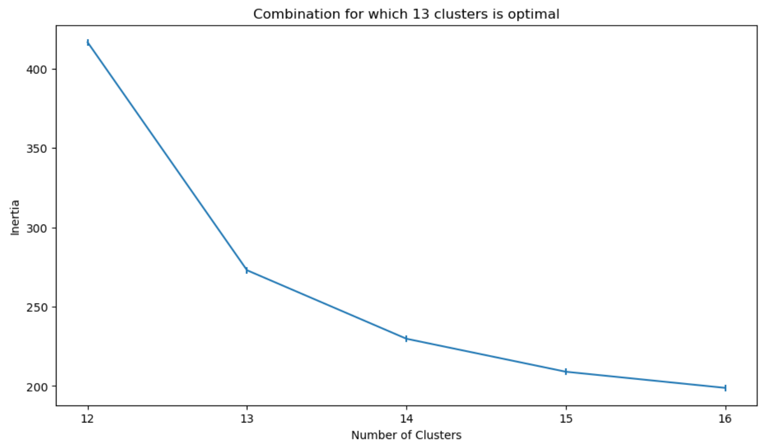
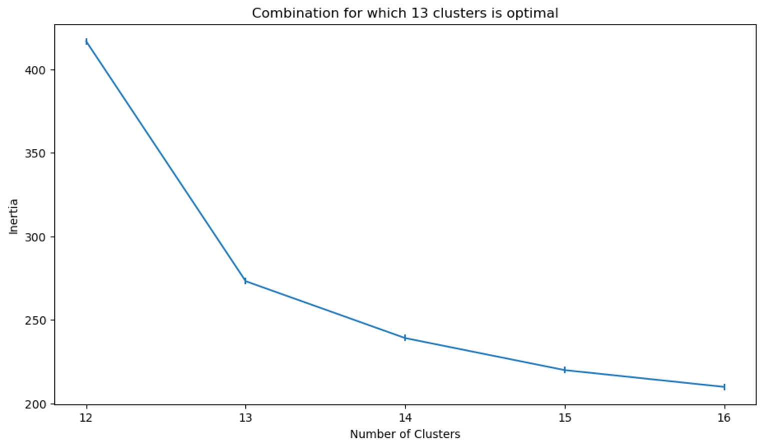
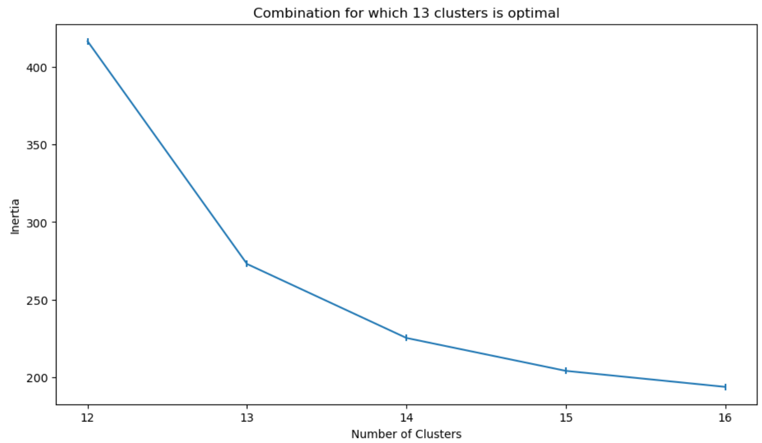
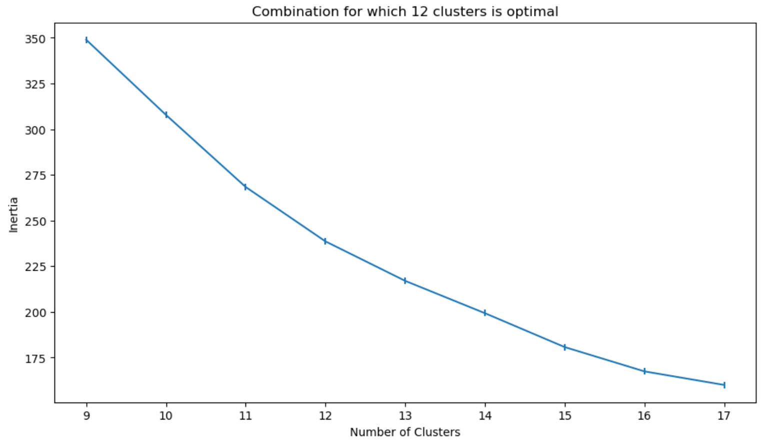
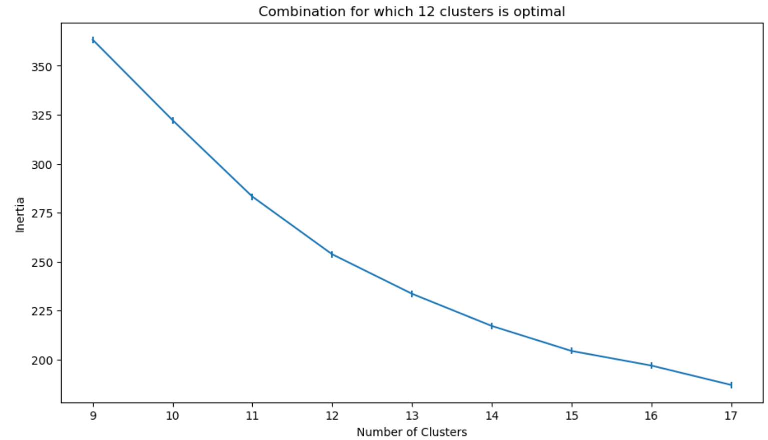
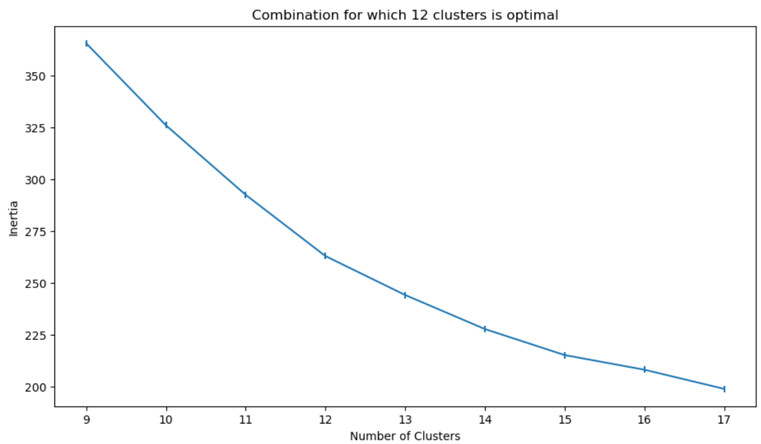
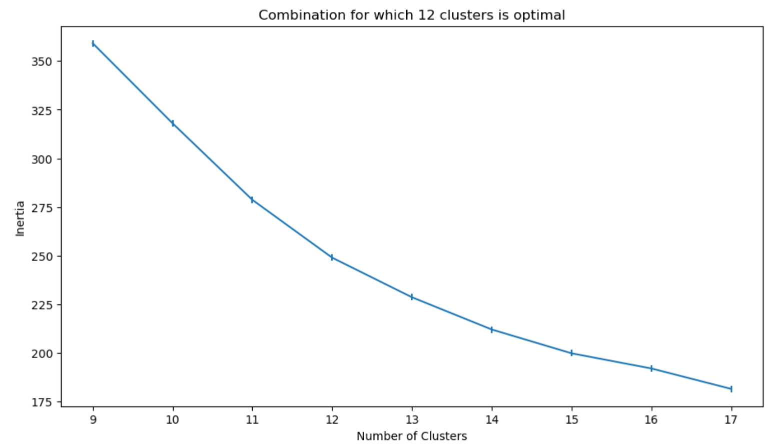
Config.	Elbow graph	Config.	
5		7	
6		8	

Table A- 2 Elbow graphs range 13±4

Config.	Elbow graph	Config.	
9		11	
10		12	

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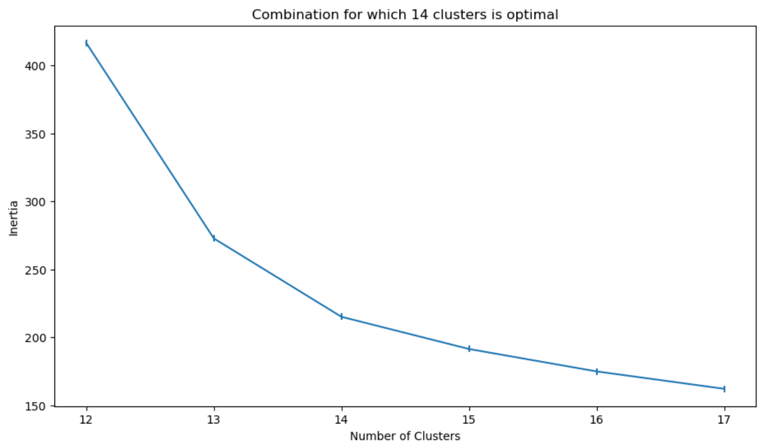
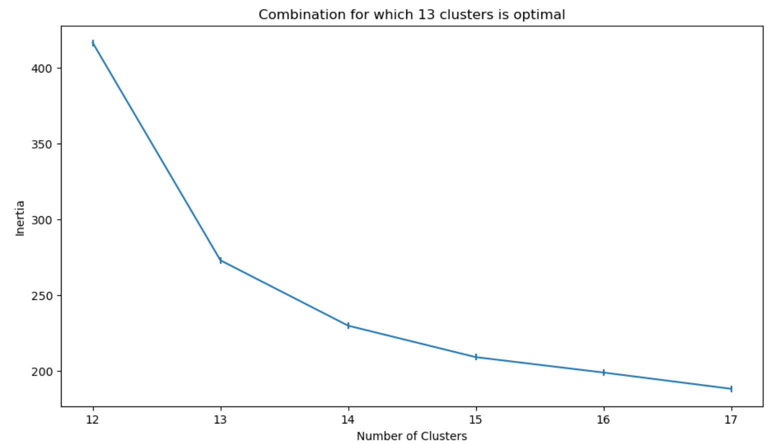
<tr><td>13</td><td>
</td><td>15</td><td>
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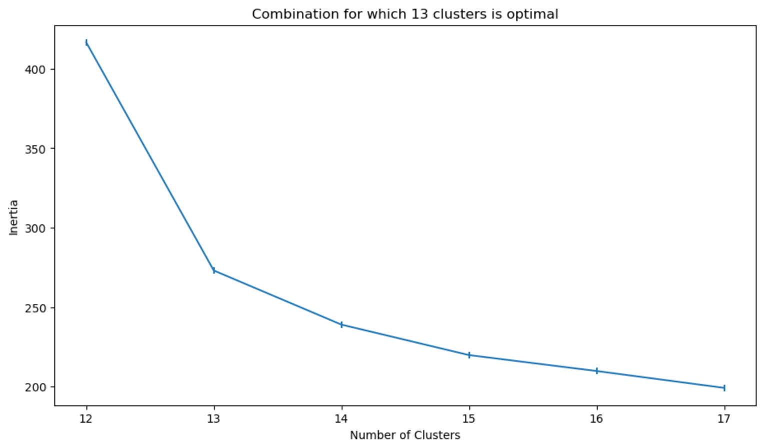
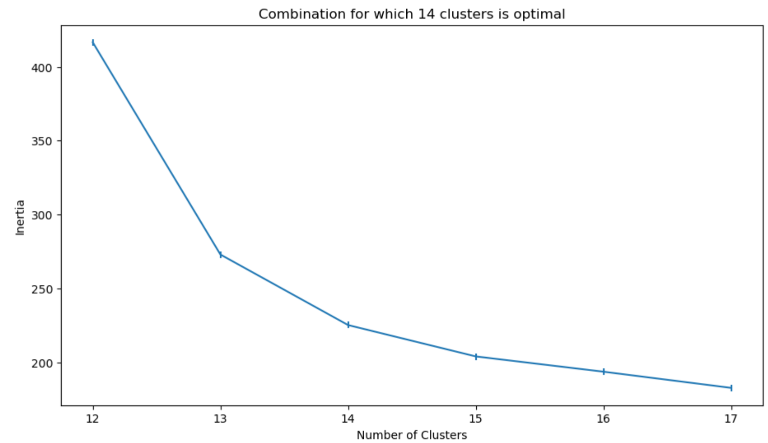
<tr><td>14</td><td>
</td><td>16</td><td>
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Table A- 3 Elbow graphs range 13±5

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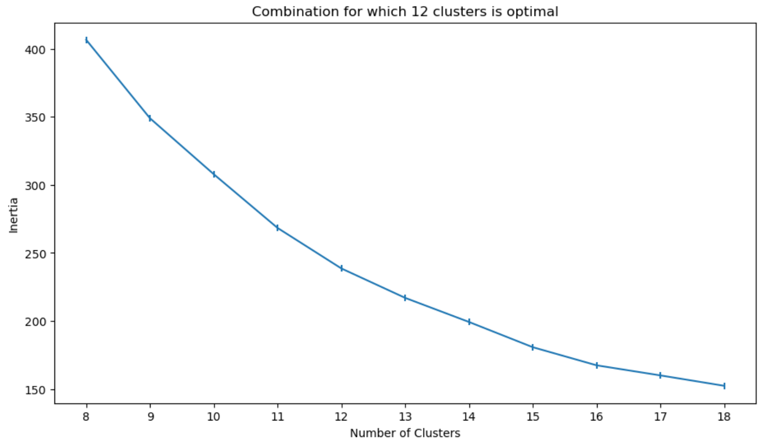
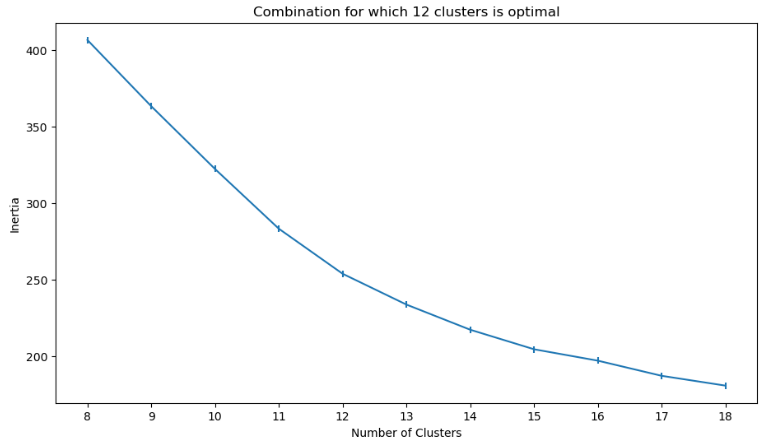
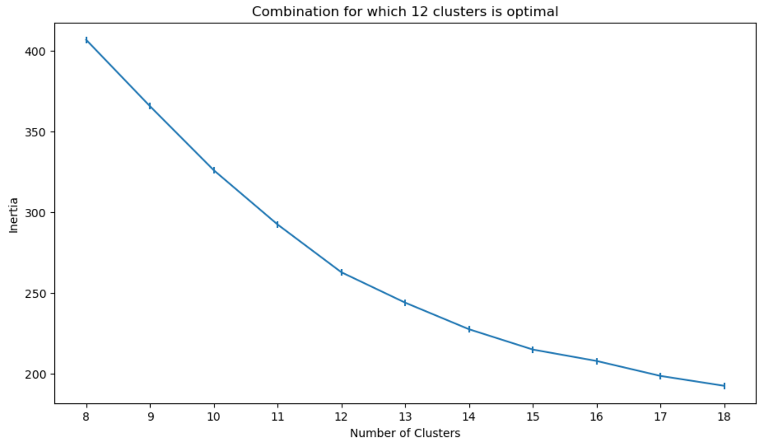
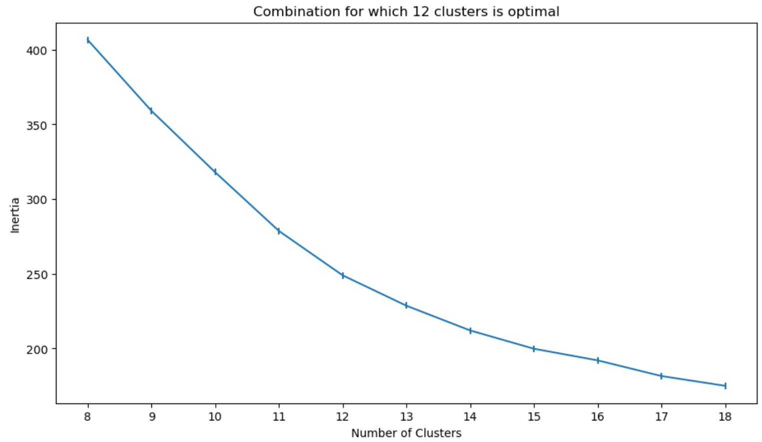
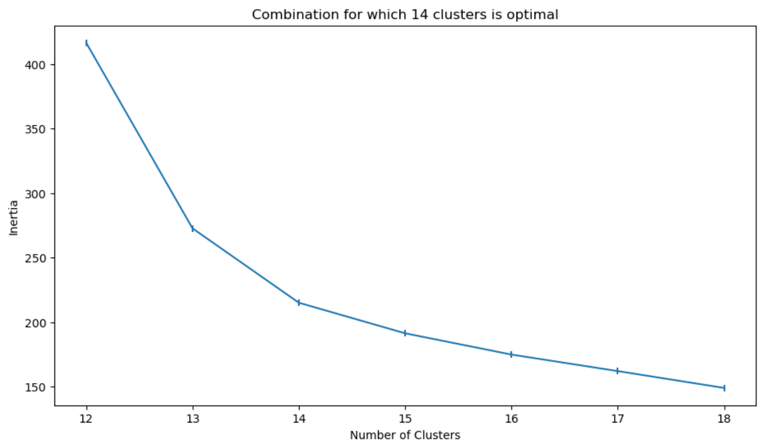
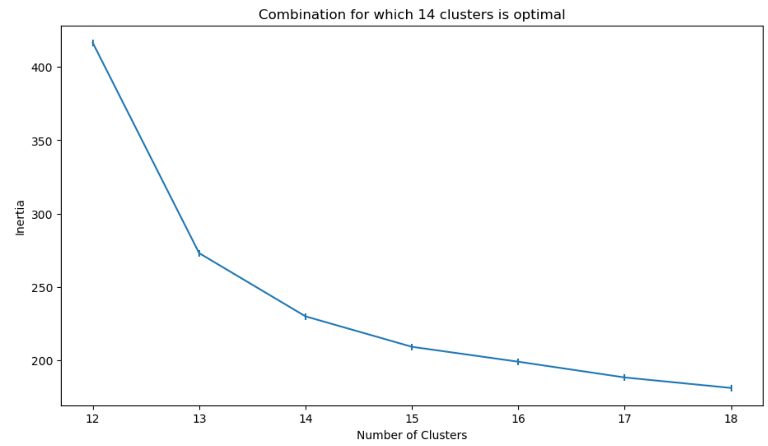
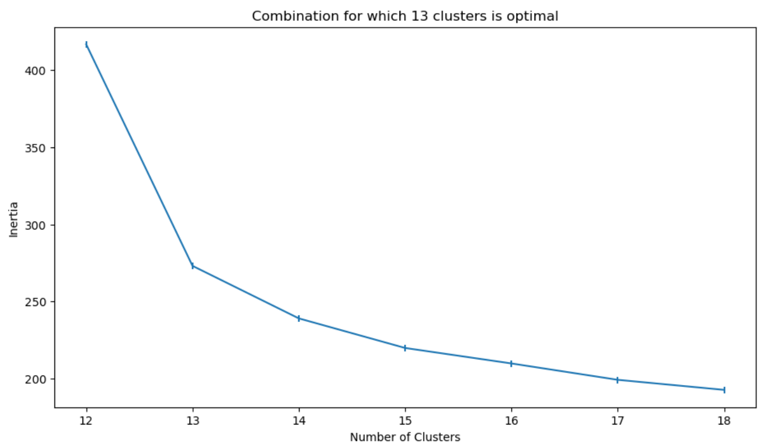
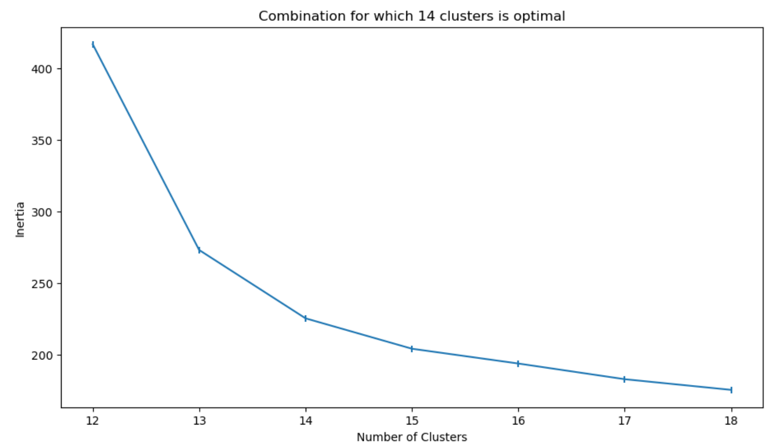
17		19	
18		20	

Config.	Elbow graph	Config.	
21		23	
22		24	

A.7 Sensitivity analysis: Tactical and operational level clusters – range (13±4)

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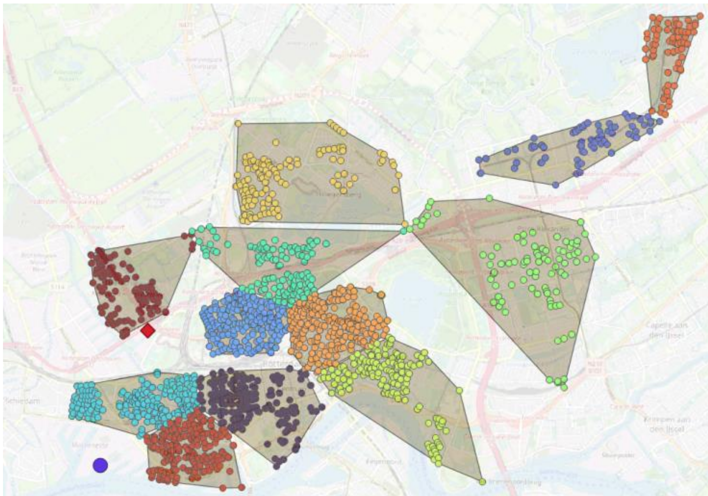
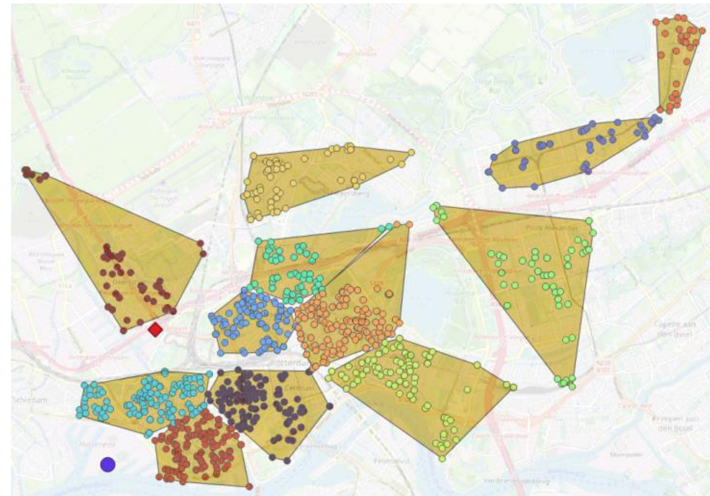
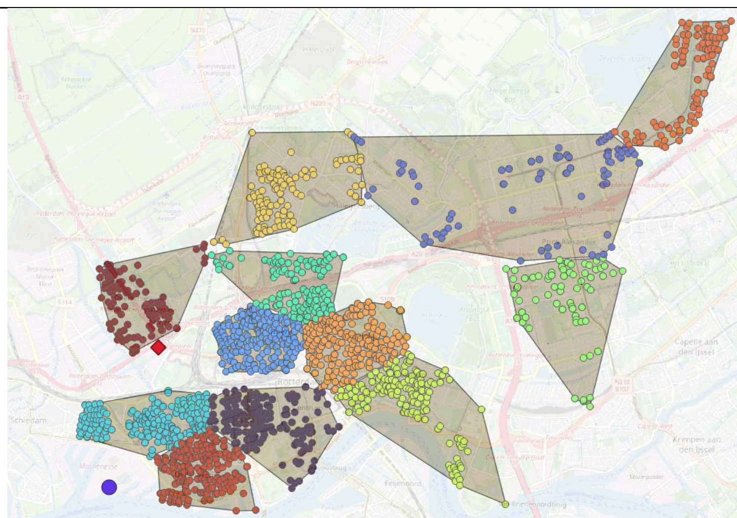
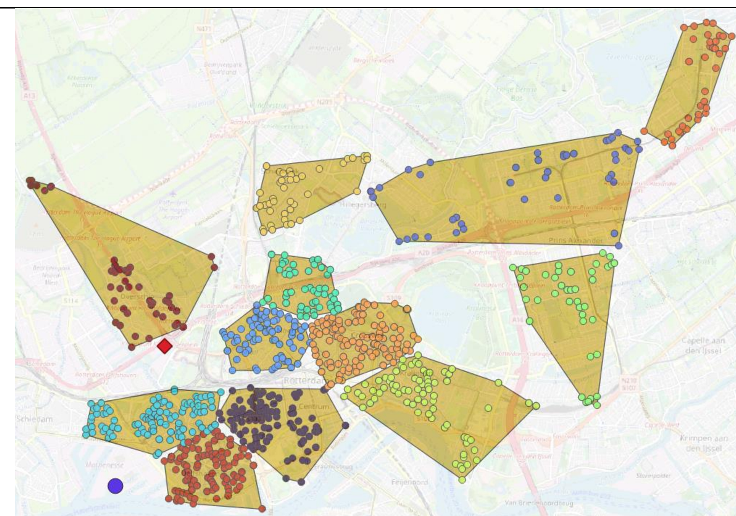
9		9	
10		10	

Table A- 4 Tactical and operional level clusters for Sensitivity analysis (Range 13±4)

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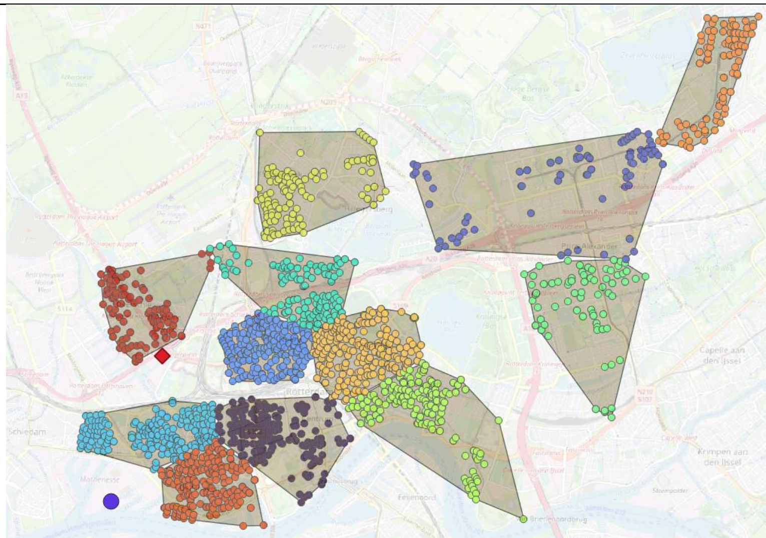
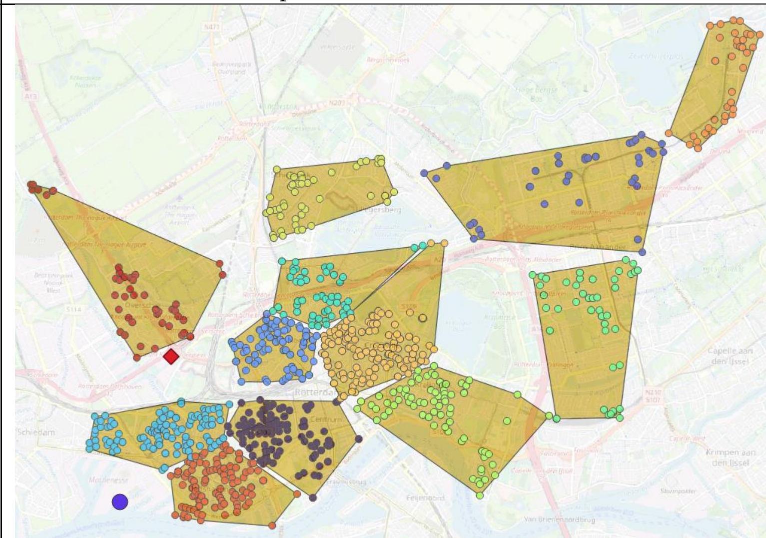
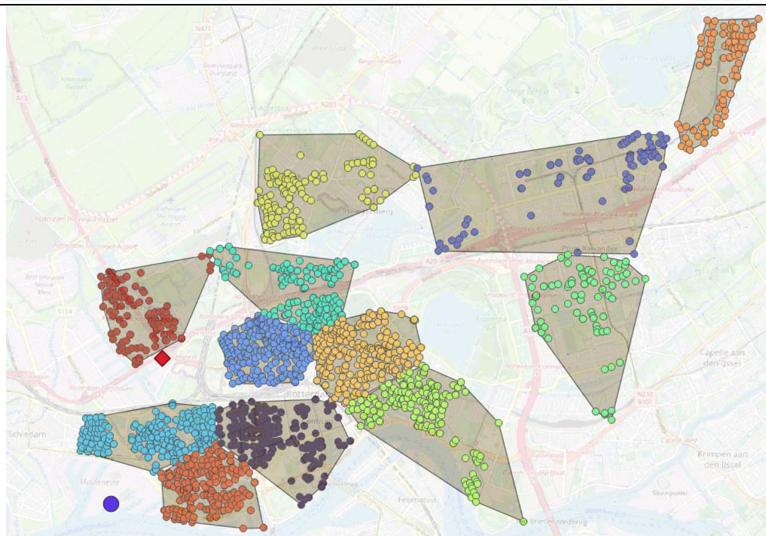
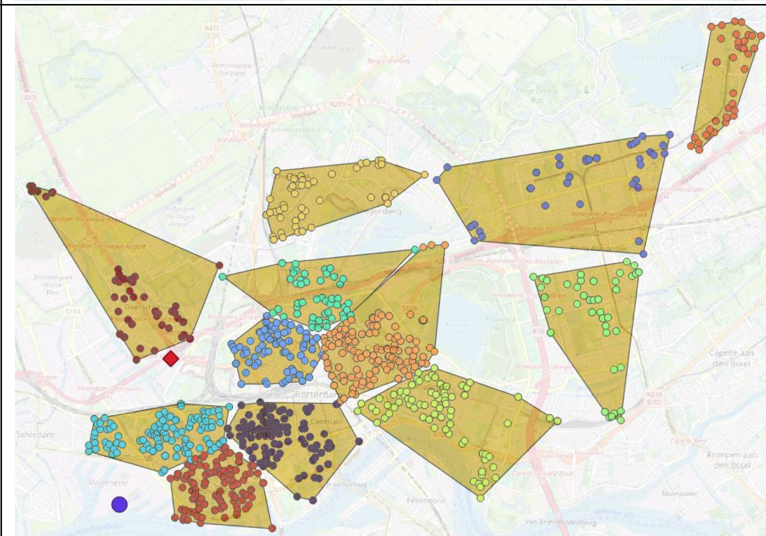
11		11	
12		12	

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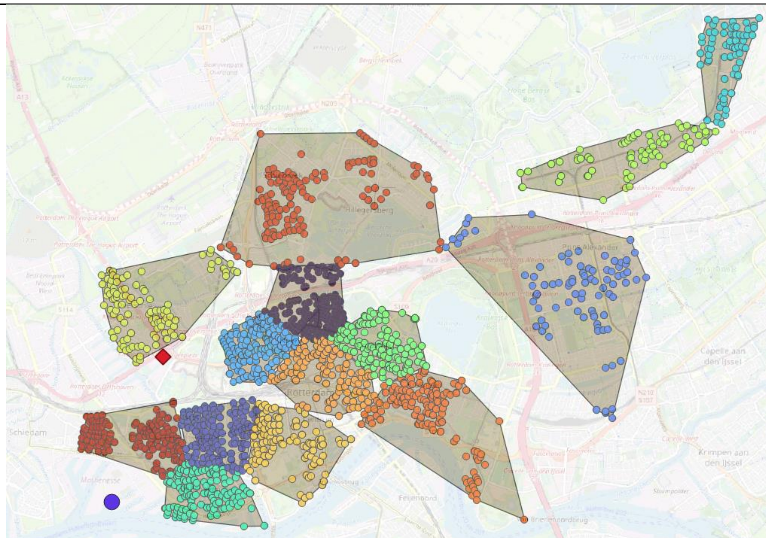
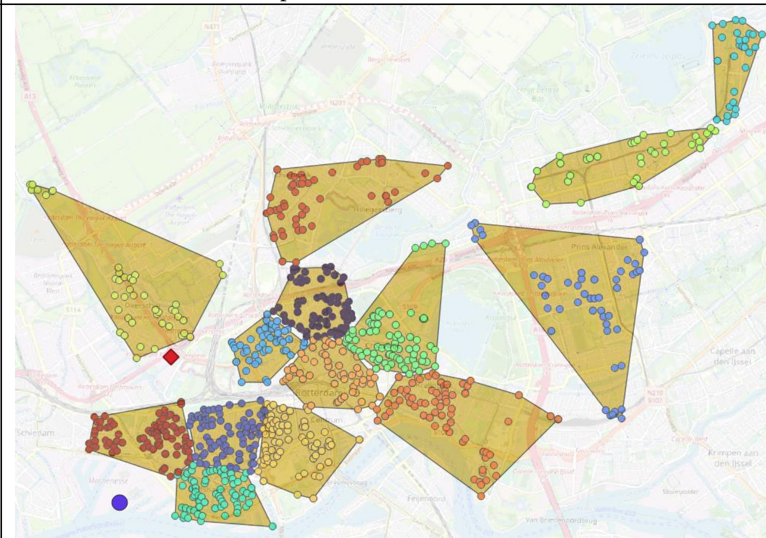
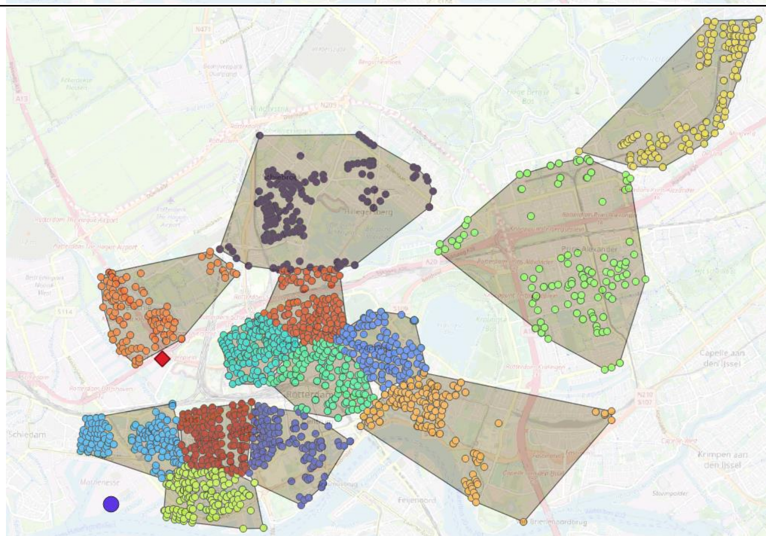
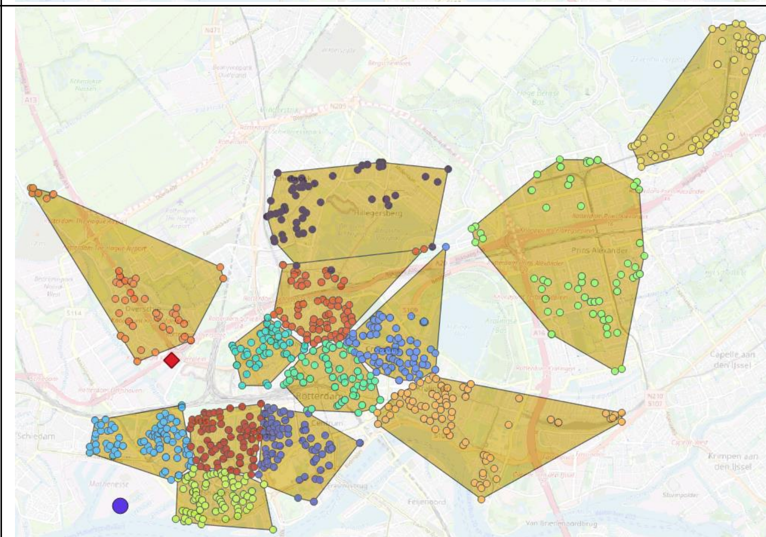
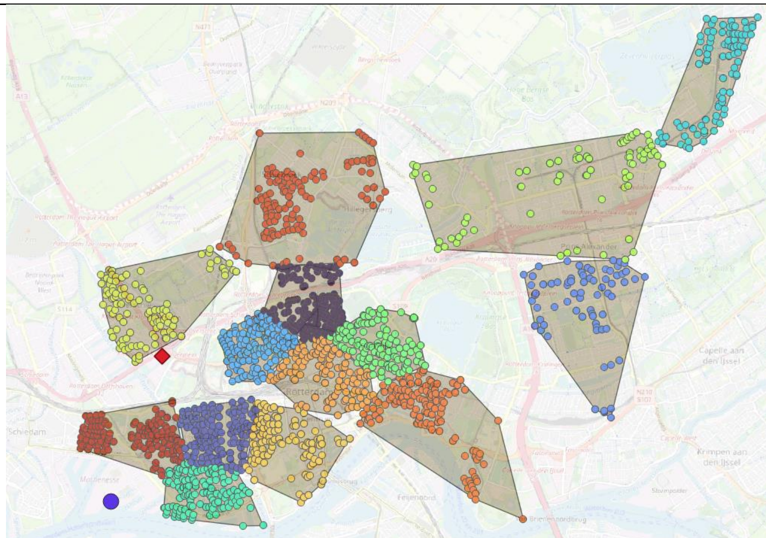
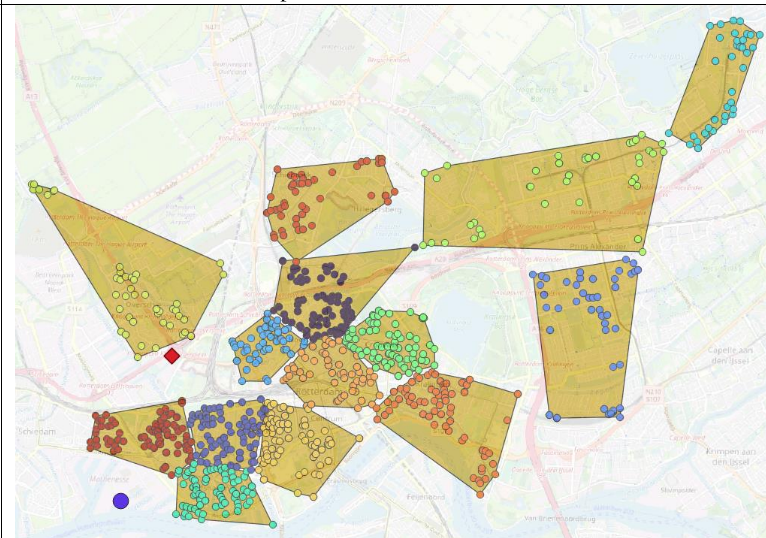
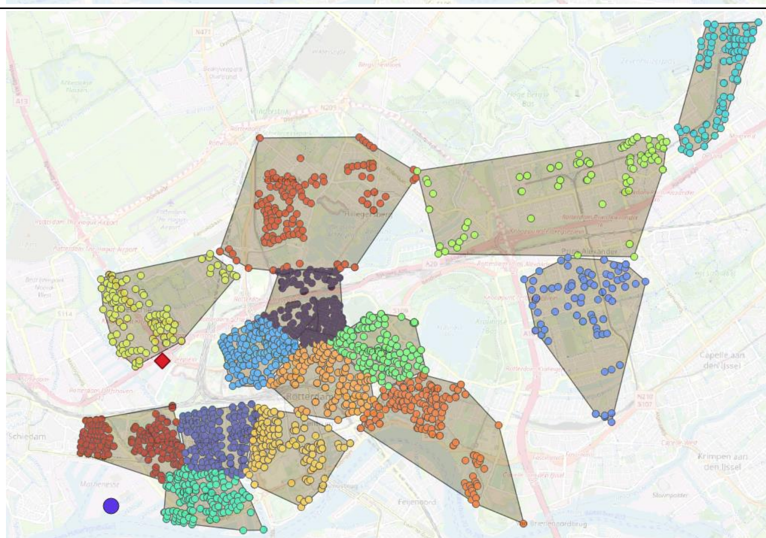
13		13	
14		14	

Config.	Tactical level clusters	Config.	Operational level clusters
15		15	
16		16