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Transportation Research Procedia 00 (2023) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2023 Montreal 17-21 July 2023

Optimizing demand-responsive IoT-based waste collection services: a two-step clustering technique

Sofia Giasoumi[a]*, Goncalo Homem de Almeida Correia[b], Michiel de Bok[a,b]
Lóránt Tavasszy[b,c]

[a]*Significance, Grote Marktstraat 47, Den Haag, 2511 BH, the Netherlands*
[b]*Department of Transport & Planning, Delft University of Technology, Stevinweg1, Delft, 2628 CN, the Netherlands*
[c] *Department of Engineering Systems and Services, Delft University of Technology, Jaffalaan 5 Delft, 2628 BC, the Netherlands*

Abstract

The use of the Internet of Things (IoT) brings radical advancements in the domain of waste collection as it enables the organization of demand-responsive schedules, which allows a step change in the efficiency of operations. One major drawback of demand-responsive schedules is that they bring about uncertainty in the planning of resources and strong variability in their deployment, as it follows daily demand. This is undesirable in real-life operations as it makes it difficult to reserve resources, secure commitment from suppliers, and ensure the stability of operational processes. The challenge, therefore, is to create scheduling approaches for waste collection that are not only efficiency-driven but also both demand responsive and supply-friendly. In this paper, we present a solution approach for the waste collection vehicle routing problem in an IoT context (IoT-WCVRP) that focuses on these requirements and demonstrate its applicability through a case study of Rotterdam in The Netherlands. In this case, our approach increases vehicle utilization rates by 5% and reduces emissions and travelled kilometres by 6% and 8% respectively.

Keywords: IoT, WCVRP, Demand-responsive, Clustering methods, Urban waste collection

* Corresponding author. Tel.: +31 644 202 799.
E-mail address: giasoumi@significance.nl

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Peer-review under responsibility of the scientific committee of the World Conference on Transport Research – WCTR 2023.

1. Introduction

The Internet of Things (IoT) is the core technology of digital transformation - it is the key to turning products, machines, facilities, and other physical things into digital assets. Its integration into the waste collection domain allows for the creation of cyber-physical systems, which integrate 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 wireless sensors monitor at regular intervals each container's waste fill level and transmit the data to the cloud of the waste management operator. Such a system holds the potential of reshaping waste collection services toward more demand-responsive, efficient, and dynamic operations (Pardini et al., 2019). With access to real-time information on the status of each container, 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 important indicators of inefficient waste collection management as the former poses an array of hazards to human health and deteriorates citizen satisfaction, whilst the latter incurs higher operational costs and strains unnecessarily the environment with avoidable pollution emissions. The importance of IoT in waste collection is additionally highlighted by the fact that the constant waste generation data stream transmitted by the installed sensors can aid in the identification of seasonal trends or events, and therefore it supports an appropriately adapted waste collection service.

Domain experts attest to the financial and environmental gains that can be achieved by operating a demand-responsive waste collection service. They also stress, however, that such a service is associated with strong variability in the deployment of resources to an extent that is undesirable in real-life operations. As the waste collection service responds to the daily waste generation, it can be understood that the daily constructed truck routes are completely variable in terms of the number and location of stops, duration of the route, and number and weight of containers. Without the planners' manual (and potentially partial) intervention, this can lead to an array of problems, starting with the loss of administrative control. As the drivers are not traditionally assigned to designated areas, it becomes difficult for administrators to efficiently control and organize their operations, as well as allocate responsibilities to the vehicle crew. The drivers, on the other hand, are no longer familiar with a pre-assigned territory and its relative characteristics (e.g. traffic and parking patterns), but they are in addition unaware of site-specific problems that could be encountered on previous days by other drivers (e.g. road works, blocked containers). This can lead to slower and more inefficient reactions from the drivers' side when unpredicted issues arise, but also to the need for enhanced internal communication between all drivers and planners.

A variety of models have been proposed for the IoT- waste collection vehicle routing problem (IoT-WCVRP), which uses the containers' real-time fill levels as a means to reduce waste demand uncertainty. However, the literature still lacks techniques specifically devoted to the previously explained IoT-derived planning issue. The present work introduces a smart solution approach for the IoT-WCVRP, which has as an overarching objective to balance the trade-off between demand-responsive and supply-friendly operations. This practically means maintaining the highest degree possible flexibility in vehicle dispatching, while also maintaining a certain level of consistency when demand varies from day to day. The proposed approach makes use of a two-step clustering technique that consecutively assigns waste containers to two-level clusters and subsequently solves a multi-trip VRP with intermediate facilities with the help of the repeated nearest neighbor algorithm and the application of a modified 2-Opt local improvement algorithm. To demonstrate the feasibility of the proposed solution three dynamic scheduling strategies are examined using real household waste data from the Municipality of Rotterdam in the Netherlands.

The remainder of the paper is organized as follows. Section 0 provides a literature review of the various models focused on the IoT-WCVRP, and discusses the most highlighted dynamic scheduling strategies applied to waste collection. Section 3 formulates the WCVRP while section 4 gives an outline of the proposed solution approach. Section 5 describes the real case study and Section 6 shows the results of the application of the model. Section 7 discusses and interprets the findings of the research, and outlines the limitations of the model. Lastly, Section 8 concludes the paper and presents some suggestions for model improvement and further research.

2. Literature Review

To construct optimal waste collection routes that pass by a selected set of containers can be referred to as the waste collection vehicle routing problem (WCVRP). An extensive set of solution approaches have been developed and applied to solve various components of the WCVRP which 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-hard combinatorial optimization problem which means that as its instances grow in size the time to solve the problem grows exponentially.

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 (Omara et al., 2018). The second addresses heuristic and metaheuristic methodologies which do not guarantee optimality but yield good results in a shorter execution time. This category is widespread among researchers as heuristics and meta-heuristics are often simple to describe and implement, which leads to their easy adaptability.

Insertion heuristics are often preferred by researchers due to their simplistic nature. The most common criterion used to insert containers in a route is the shortest distance or time, meaning that the nearest neighbor containers are iteratively prolonging a constructed route (Faccio, 2011; Heijnen, 2019; Neffati, 2021; Vonolfen et al., 2011). Less used criteria in insertion algorithms include the farthest insertion (Abbatecola et al., 2016; Neffati, 2021), the quantity of waste the containers hold (Expósito-Márquez et al., 2019), and ratios of various quantities, for example between the "urgency of collection" and the cost of insertion (Teixeira et al., 2004). In the latest years, the focus is on metaheuristics which include ant colony optimization (Karadimas et al., 2005), genetic algorithms (Amal et al., 2018; Strand et al., 2020), particle swarm optimization (Hannan et al., 2018; Wu et al., 2020), simulated annealing (Babaee Tirkolaee et al., 2019; Buhrkal et al., 2012), tabu search (Arribas et al., 2010; McLeod et al., 2013; Zsigraiova et al., 2013) and neighborhood algorithms (Markov et al., 2016; Nuortio et al., 2006).

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, based on an array of rules, which are solved separately into complete routes. 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 authors use the real-time fill levels of the containers to allocate them to clusters which are formed before every collection using a predefined threshold level (Akhtar et al., 2017; Hannan et al., 2018; Ramos et al., 2018). Some researchers aggregate 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). Other researchers aim at the construction of clusters that are subject to constraints such as vehicle capacity (Abbatecola et al., 2016), shift duration (Kim et al., 2006), traffic temporal conditions (Arribas et al., 2010), or a balanced number of containers.

Many variations of the WCVRP exist, depending on the problem characteristics, the network size, and the often conflicting objectives and constraints (Dotoli & Epicoco, 2017). The minimization of distance and time are among the most popular objectives examined by researchers (Abdallah et al., 2019; Amal et al., 2018; Hannan et al., 2018; Neffati, 2021). Cost minimization is another important objective that can be rather ambiguous, as researchers often consider different types of costs in their studies. The main advantage of minimizing costs, nevertheless, is that different types of goals can all be expressed in terms of the same monetary unit (Markov et al., 2016; Mes et al., 2014; Omara et al., 2018; Ramos et al., 2018). The minimization of environmental effects is rarely studied, but certain related aspects that have been examined in the literature include the minimization of CO_2 emissions (Strand et al., 2020), the service of high-priority areas to reduce social and environmental fire hazards (Anagnostopoulos et al., 2015) and the minimization of energy consumption (Expósito-Márquez et al., 2019).

Depending on the level of realism that is to be adopted, the number of imposed constraints grows linearly. At the outset, the vehicles are typically subject to constrained capacities, meaning that the accumulated amount of waste of any route must not exceed the vehicle's capacity. 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 into a multi-trip VRP. This corresponds to more realistic operations as the vehicle can visit the disposal facility multiple times to unload its accumulated waste and regain its capacity, before returning to its 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). In specific cases, the number of stops allowed in a route is bounded to a maximum threshold so that a workload balance can be achieved (Kim et al., 2006; Buhrkal et al., 2012). For the same reason, added constraints have been imposed on the number of times a waste collection vehicle is allowed to visit a disposal facility (Son, 2014; Abbatecola et al., 2016).

The models specifically devoted to the use of IoT technology cover various components of the traditional waste collection problem but also use dynamic scheduling strategies. With the adoption of dynamic scheduling strategies, the question as to which containers should be collected and at what moment in time (usually which day) becomes an option. 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 and in real time. This is possible as real-time access to the actual amounts generated in the network is enabled, which reduces the related randomness and uncertainty of this otherwise stochastic variable. In the latter, schedules made for a rolling horizon are revised in response to real-time events (Ouelhadj & Petrovic, 2009).

With each approach, various trigger rules and ranking methods are examined to define the containers' eligibility for (possible) collection. Some authors following the predictive-reactive scheduling approach developed scheduling strategies in which containers are daily scheduled for collection based on their “attractiveness” in the whole system. Ramos et al. (2018), for example, developed a scheduling strategy that aims at waste quantity maximization throughout a rolling horizon, while Abdallah et al. (2019), Heijnen (2019), and Vonolfen et al. (2011) base the container selection on future container overflow predictions. Common among researchers who follow the completely reactive scheduling approach is the use of a predefined minimum fill level to select the containers to be collected each day (Zsigraiova et al., 2013; Anagnostopoulos et al., 2015; Ramos et al., 2018; Ferrer & Alba, 2019). Some researchers demonstrate, under a variety of scenarios, that the best collection results can be achieved with a static 70-75% minimum fill level (Faccio, 2011; Akhtar et al., 2017; Hannan et al., 2018). Other studies adopting the simplified approach, also select containers that 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 in a short time (Johansson, 2006; Mes et al., 2014; Christodoulou et al., 2016; Omara et al., 2018).

To better define the containers' eligibility for collection, researchers classify them based on a variety of ranking rules. Most common is the usage of different priority levels (e.g. “must-go”, a “may-go” or a “no-go”), by establishing certain threshold fill levels and special rules such as the day of the week, the type of location the container is located in, its interaction with the containers on the same collection site, etc. (Johansson, 2006; McLeod et al., 2013; Ferrer & Alba, 2019). Vonolfen et al. (2011), Anagnostopoulos et al. (2015) and Wu et al. (2020) 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 high priority, irrespective of their accumulated amount of waste. The work of Christodoulou et al. (2016) makes use of a hybrid classification method that regards not only the estimated container fill levels but also the waste accumulation period. Similarly, Mes et al. (2014) consider the expected number of days till the containers become full to schedule them for collection.

The review of the literature can be summarized as follows. Much of the effort in the literature on the IoT-WCVRP has been spent on examining various scheduling strategies and constructing the best routes throughout a given planning horizon with a given set of containers. Moreover, sophisticated algorithms have been developed that work towards multiple objectives and constraints. However, less attention has been paid to the complete variability which is associated with dynamic waste collection operations, which as described in the previous section poses a significant issue for such services. For a similar issue on local package delivery, but with a deeper focus on driver familiarity, Zhong et al. (2007) created a two-stage vehicle routing model based on a strategic core area design and operational cell routing. This work inspired the solution approach introduced in this paper, which aims in balancing the trade-off between dispatch consistency and flexibility by creating static and demand-responsive clusters of containers consecutively, and subsequently solving a multi-trip VRP with intermediate facilities. Our contribution is the new formulation of the WCVRP-IoT that includes this trade-off.

3. Problem description

This section focuses on the formulation of the waste collection problem, where containers are selected for collection based on a scheduling strategy and are assigned to routes in such a way that the total travelled kilometres are minimized and the total collected waste is maximized. The problem can be defined as a multi-trip VRP with intermediate facilities, represented by waste disposal facilities, which are visited either once the effective weight payload of the vehicles is reached, or just before a vehicle shift is over. The vehicles are allowed to visit the 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 $V^m = \{2, \dots, 2+m\}$, and the set of arcs is $A = \{(i, j, r) \mid i, j \in V, i \neq j, r \in R\}$, where r denotes the road type with $R = \{Urban, Highway\}$. Let t_{ijr} and d_{ijr} be the travel time and travel distance associated with arc (i, j, r), and $K = \{1, \dots, k\}$ be the given set of homogeneous vehicles with maximum weight capacity VC and maximum shift duration T. $H_{i,k,\mathrm{n}}$ is a continuous variable indicating the driving duration of vehicle k when it passes from node i at moment n. 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 is served by vehicle k and 0 otherwise. Moreover, let $n_{ijr,k}$ be the number of times arc (i, j, r) is traversed by vehicle k, and ndf_k be the number of times vehicle k visits the disposal facility for unloading.

Each collection site $s \in \mathrm{S}$, where $\mathrm{S} \subseteq V^m$, and represents a set of nc containers that are situated at the same spot and are scheduled for collection on the same day, denoted by $s = \{1, \dots, \mathrm{nc}\}$. The service time st_s of each collection site is calculated with equation (1) where lt is the vehicle leveling time, and mt is the vehicle hook moving time. Leveling comprises the time needed to stabilize the vehicle for 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. The total weight of waste at each collection site is calculated with equation (2) where the associated fill level $f_{s,c}$ of each container $c \in \mathrm{s}$ is multiplied by its maximum volume capacity $vc_{s,c}$ and a volume to weight conversion rate denoted by β.

$$st_s = lt + nc \cdot mt \tag{1}$$

$$w_s = \beta \sum_{c \in s} f_{sc} \cdot vc_{s,c} \tag{2}$$

The model's objective is to successively determine the membership of waste containers to two-level clusters, such that the total travelled kilometres of the routes constructed to serve the second-level clusters are minimized. Equation (3) is used to calculate the total travelled kilometres where $n_{ijr,k}$ is the number of times arc (*i*,*j*,*r*) is traversed.

$$min \sum_{r \in R} \sum_{k \in K} \sum_{(i,j,r) \in A} d_{ijr} \cdot x_{ijr,k} \cdot n_{ijr,k} \tag{3}$$

The first clustering phase constructs geographically fixed clusters of containers that represent independent waste collection areas. The second clustering phase uses the first-level clusters as geographical cores and constructs flexible clusters that respond to the daily demand. The successive assignment of containers to the two-level clusters aims in balancing the trade-off between dispatch consistency and dispatch flexibility. With the first-level clusters, the daily constructed routes can be focused on specific areas, which can reduce the current route-associated variability and overlapping. This can help in maintaining dispatch consistency, which can consequentially lead to increased driver familiarity and better administration control, as the assignment of drivers to waste collection areas becomes possible. With the daily re-assignment of containers to the two-level clusters dispatch flexibility can be maintained, as the geographical areas' boundaries are flexible to accommodate the daily demand. The trade-off occurs as the fixed geographical cores of the clusters, which ensure vehicle dispatch consistency to a certain degree, limit the benefits that could be obtained by a fully flexible vehicle dispatch.

Except from the total travelled kilometres, the total CO_2 emissions produced is another important key performance indicator (KPI) that is considered in this study. More specifically, the total CO_2 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. To calculate the total amount of CO_2 emissions produced while driving, equation (4) is used, which references back to the work of Bala et al. (2021). The amount of CO_2 emissions produced on an arc (i, j, r) is the product of its length l, and an emission production factor $EP_{r,k,n}$. This factor depends on the arc's respective road type r, and the cumulative weight of waste $Q_{ij,k,n}$ the vehicle k carries at the start of the arc at node i each time n it traverses it. The emission production factor is given per road type for an empty and a full vehicle, therefore to translate it according to the cumulative weight of waste equation (5) is applied. 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.

$$ECO2_{driving} = \sum_{k\in K} \sum_{n=0}^{n_{ijr,k}} \sum_{r\in R} \sum_{(i,j,r)\in A} d_{ijr} \cdot x_{ijr,k} \cdot EP_{r,k,n} \tag{4}$$

$$EP_{r,k,n} = EP_{r,empty} + \frac{\left(EP_{r,full} - EP_{r,empty}\right) * Q_{ij,k,n}}{VC} \tag{5}$$

The total CO_2 emissions produced while vehicle k serves a collection site s is expressed by equation (6), where C_{idling} is an emission production factor expressed in CO_2 gr /min.

$$E_{CO2_{loading}} = EP_{idling} * \left(\sum_{k\in K} \sum_{s\in S} st_s \cdot y_{s,k}\right) \tag{6}$$

The total CO_2 emissions produced while vehicle k unloads its waste at the disposal V^f is expressed by (7), where ut is the fixed unloading time at a disposal facility.

$$E_{CO2_{unloading}} = EP_{idling} * \left(\sum_{k\in K} ut \cdot ndf_k\right) \tag{7}$$

The formulated problem is subject to:

$$\sum_{k\in K} \sum_{j\in V} x_{0jr,k} = 1 \qquad \forall r \in R \tag{8}$$

$$\sum_{k\in K} \sum_{i\in V} x_{i0r,k} = 1 \qquad \forall r \in R \tag{9}$$

$$\sum_{s\in S} y_{s,k} = 1 \qquad \forall k \in K \tag{10}$$

$$\sum_{i\in V} x_{ijr,k} = \sum_{i\in V} x_{jir,k} \qquad \forall r \in R, j \in V, k \in K \tag{11}$$

$$\sum_{n=0}^{n_{ijr,k}} \sum_{i\in V^d \cup V^f} Q_{ij,k,n} = 0 \qquad \forall k \in K, j \in V \tag{12}$$

$$Q_{ij,k,n} + w_j \le Q_{ji,k,n} + (1 - x_{jir,k})M \qquad \forall j \in \mathrm{S}, i \in V, r \in R, k \in K, n = \{0, \dots, n_{ijr,k}\} \tag{13}$$

$$Q_{ij,k,n} \leq VC \qquad \forall i \in V, r \in R, k \in K, n = \{0, \dots, n_{ijr,k}\} \tag{14}$$

$$H_{i,k,\mathrm{n}} \leq T \qquad \forall i \in V, k \in K, n = \{0, \dots, n_{ijr,k}\} \tag{15}$$

$$H_{i,k,\mathrm{n}} + st_j + t_{ij} \leq H_{j,k,n} + (1 - x_{ijr,k})M \qquad \forall (i,j) \in V, r \in R, k \in K, n = \{0, \dots, n_{ijr,k}\} \tag{16}$$

$$x_{ijr,k} \in \{0,1\} \qquad \forall (i,j) \in V, k \in K, r \in R \tag{17}$$

$$y_{s,k} \in \{0,1\} \qquad \forall s \in V^c, k \in K \tag{18}$$

$$Q_{i,k,t} \geq 0 \qquad \forall i \in V, k \in K, t \in T \tag{19}$$

$$H_{i,k,t} \geq 0 \qquad \forall i \in V, k \in K, t \in T \tag{20}$$

Constraints (8) and (9) impose that all k vehicles must start and finish their routes at the depot. Constraint (10) ensures that all collection sites are serviced exactly once, while constraint (11) ensures that the inflows and outflows of all nodes in the graph are equal. Constraint (12) 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 (13) 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 effective weight payload of the vehicles indicates the moment of visit to the disposal facility for unloading and is set by constraint (14). The effective weight payload is used instead of the maximum as it is assumed that the vehicles reach their maximum volume capacity before their maximum weight capacity. It must be noted, nevertheless, that a buffer volume capacity is usually reserved by the drivers to accommodate unexpected waste laid next to the containers which is incorporated in the effective vehicle capacity. The allowed shift duration is maintained by constraint (15) but it must be noted that only the effective time for collection is considered as the preparation and break time are ignored. Constraint (16) ensures that the cumulative time spent driving to and servicing each collection site of a planned route follows a logical progression. Finally, constraints (17), (18), (19), and (20) impose the binary and non-negative variables.

4. Solution approach

This solution approach follows a cluster-first route-second approach which divides the problem into a number of VRPs, each one corresponding to one of the 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 to solve the IoT-WCVRP. The flowchart presented in Fig. 1 depicts the sequential order of the steps of the proposed solution approach, as well as the algorithms that are employed at each step.

During the first clustering phase, all the containers are classified as per their historical monthly frequency of collection using the classification scheme presented in Table 1. The containers' monthly fill rate can be used instead of the monthly frequency of collection, and also be preferable, depending on data availability. Following the classification, the capacitated K-means algorithm is used to assign only the containers with high- or medium-frequency of collection into clusters (see Fig. 2a). The algorithm is fed an arbitrary seed to eliminate randomness and to identify the optimal number of clusters the Elbow method is employed.

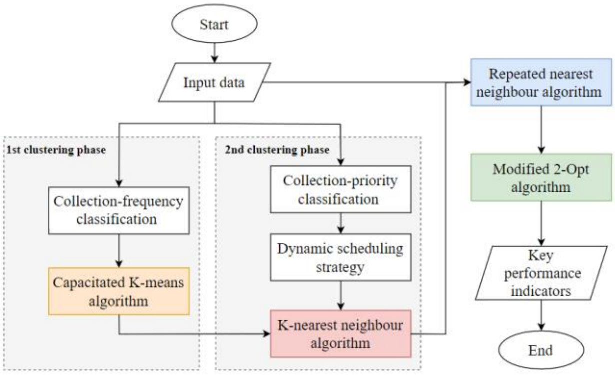

Fig. 1. Flowchart of the proposed solution approach

Table 1. Collection frequency classification scheme

Classification	Classification rule
High frequency	Frequency >= 15 times per month
Medium frequency	4 times per month < Frequency < 15 times per month
Low frequency	Frequency <= 4 times per month

The second clustering phase starts by classifying all the containers as per their priority of collection using the classification scheme presented in Table 2. Then, a dynamic scheduling strategy is selected, which uses the containers' priority classification to schedule only the most appropriate for collection. The three strategies considered are:

- 'High_Medium' strategy: selects for collection all high- and medium-priority containers;
- 'Same_Site' strategy: selects for collection all high- and medium-priority containers but also all containers that belong on the same site as those;
- 'Outskirts' strategy: selects for collection all high- and medium-priority containers but also all the containers located on the outskirts of a city if at least one of them needs to be collected

Table 2. Collection priority classification scheme

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

The K-nearest neighbor algorithm is finally employed to construct the daily container circuits. To find the optimal number of neighbors the tool GridSearchCV is used which is available in scikit-learn, a machine learning library for Python, with a test size of 0.2. This indicates 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 also set. From the containers scheduled for collection, the ones already assigned to the first-level clusters constitute the training dataset of the algorithm (see Fig. 2b), while the rest of the containers constitute the new data that needs to be assigned. Once the training is over, the algorithm assigns each new container to the cluster in which the majority of its already assigned neighbor containers belong (see Fig. 2c). Fig. 2d presents the daily container circuits for collection, which is important to notice follow the cores of the first-level clusters, but maintain flexible boundaries to accommodate the daily demand. As not all the containers are used to construct the first-level clusters, dispatch consistency can be maintained while dispatch flexibility is not hindered.

To construct the waste collection routes for each second-level cluster, initial feasible routing solutions are generated with the use of the repeated nearest neighbor algorithm and are later optimized with a modified 2-Opt algorithm. 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. Among the constructed routes, certain criteria are used to determine which one is the best. If more containers are unassigned in a cluster, then the whole procedure is repeated.

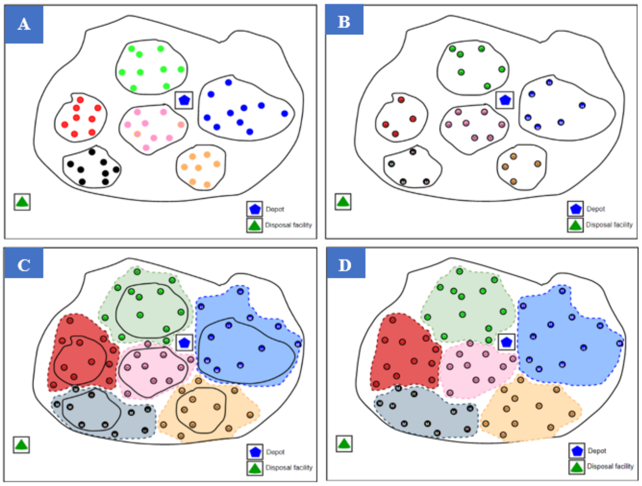

Fig. 2. (a) High- and medium-frequency containers assigned to first-level clusters; (b) Containers from the first-level clusters that are scheduled for collection are used as training input for the KNN algorithm; (c) The rest of the containers schedule

The repeated nearest neighbor algorithm constructs as many routes as the number of containers in a cluster as it uses each as a starting point (see Fig. 3), and visits consecutively the closest unassigned point, until all sites are visited or until all the constraints are met.

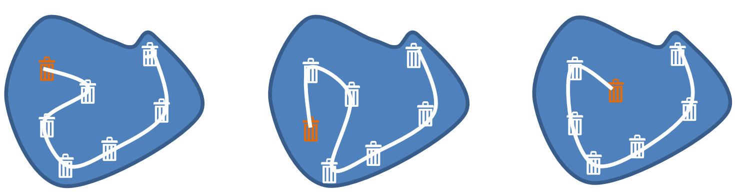

Fig. 3. Example of the repeated nearest neighbor algorithm

The classic 2-Opt algorithm is a simple local search algorithm that examines all possible swapping combinations of a route, but only retains the most optimal combination for further improvement. Although it can optimize an initial feasible solution, it 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 algorithm uses as a starting point the routing solution without disposal facility visits 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.

To identify which resulting route performs the best, two criteria are examined: the total weight of waste collected and the total number of kilometres travelled. Preference is given to routes that visit all scheduled containers in the clusters. Between routes that manage to visit all containers, the best is considered the one with the least travelled kilometres. Between routes that leave containers 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. The best route can further be optimized under certain conditions. If no more containers are left to be assigned but the amount of waste collected during the last tour of a route is less than or equal to 1000kg, the vehicle capacity constraint is relaxed and the second to last visit to the disposal facility is omitted. If there are still unassigned containers in the cluster while the last tour of a route is partially full (imposed by the time duration of a route), under the condition that their total combined weight is lower than or equal to the effective payload capacity, one fuller route is created to replace the two-partially full ones.

5. Model application

The solid waste collection service of the Municipality of Rotterdam in the Netherlands is used as a case study to demonstrate the applicability of the proposed solution approach. The municipality of Rotterdam expands into an area of 325.8 km2, of which approximately 106.6 km2 constitutes a body of water, and has a population of 651,631 citizens as of 2021 (*Rotterdam*, 2022). The municipality covers the city of Rotterdam 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 waste collection system. Each waste collection system is comprised of one depot, one disposal facility, an allocated fleet, and a network of underground containers (see Fig. 4). Generally, Rotterdam distinguishes five different waste fractions collected by underground waste containers, but the focus of this research explicitly falls on solid household waste.

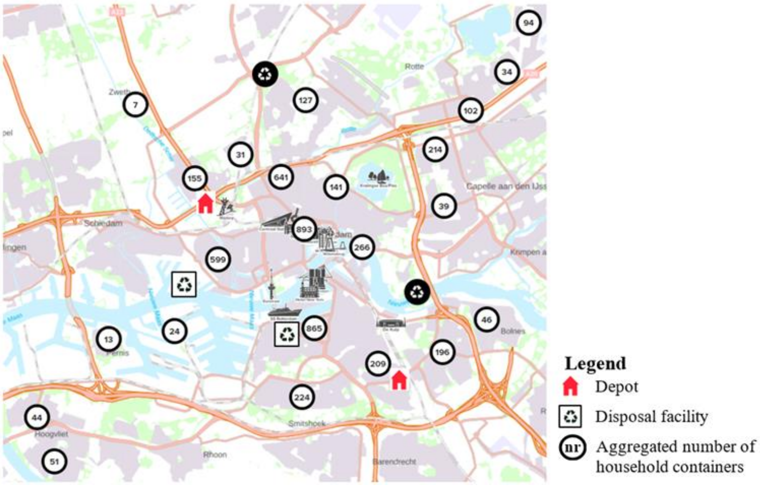

Fig. 4. Waste collection system of Rotterdam (From Rotterdam Container Map)

The depots constitute the starting and ending point of the operations as they function as the parking lots of the collection vehicles. The effective time for waste collection is around 6.5 hours as the time for preparation and breaks is excluded. By the end of the shift, the vehicles must return to the depot empty, so it is a requirement that the vehicles visit a disposal facility to unload before their return to the depot. The disposal facilities are located next to the river so that the vehicles directly unload their content in specially designed waste-carrying vessels. 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. Both waste collection systems employ a homogeneous vehicle fleet with a maximum payload capacity of 10500kg, but only around 9000kg is effectively used because usually, 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. 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. All waste containers are equipped with wireless sensors monitoring and transmitting their daily waste fill levels.

For simplification reasons, the northern side is chosen for analysis as its network of underground containers is larger and denser. To compute the distance and time matrices between all relevant locations, Dijkstra's algorithm was employed, which uses the city's road network with road-associated average speeds. The current case is considered a sample of 17 routes as realized in one day by the waste collection service of Rotterdam for the northern side. To compute the collection frequency of the containers, a log of their service frequency for the month of April (2020) is used. To compute the containers' priority of collection on the examined day as well as the weight of waste they carry, their dimensions, last-registered fill levels, and waste accumulation period until that day is used. To construct the paths and timelines of the sample routes important assumptions had to be made as only the visiting sequence of the waste containers has been provided. The time spent to service each container, the time spent at the disposal facility for unloading, and the moment the drivers visit the disposal facility had to be assumed based on empirical knowledge obtained when discussing with the company. These parameters' values can be found in Table 7, as well as the emission production factor and the volume-to-weight conversion rate β that are used to calculate the CO_2 production.

6. Results

In this section, the proposed solution approach is tested on the presented case study to evaluate its performance. The configuration used to compare the model's outputs with the current case is referred to as the base case. Out of the total 3165 containers 2389 were selected to construct the first-level clusters, the optimal number of which is 12 (see Fig. 5a) as derived from the Elbow method when examining the range 13 ± 4. Thirteen constitutes the size of the fleet of the northern waste collection system while 4 is an arbitrary number to create some slack. To ensure a fair comparison between the base case and the current case, the same 1279 containers collected by the sample routes were selected to populate the second-level clusters (see Fig. 5b), meaning no specific scheduling strategy was applied. The GridSearch CV algorithm indicated that 23 neighbor containers should be used in the KNN algorithm.

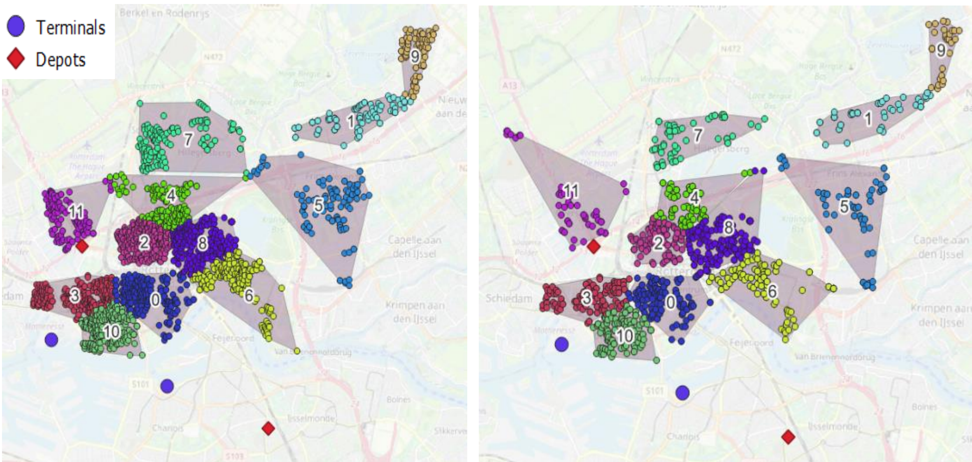

Fig. 5. a) First-level clusters b) Second-level clusters

From Fig. 5a, which presents the first-level level clusters, it can be observed that most of the containers are assigned to appropriate clusters, but that is not the case for containers located farther away from dense agglomerations, 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 could potentially be different.

Looking at Fig. 5b, which presents the second-level level clusters, we can see that some containers are not assigned optimally, for example at the boundaries of clusters 4 and 8, and that can be attributed to two reasons. The first reason regards the first-level clusters formation, 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 second-level clusters, as observed. The second reason can probably be attributed to the fact that a uniform distance weight was considered in the GridSearchCV tool. If a weighted approach was followed instead, meaning that the nearby containers of an unassigned container have more weight than the containers farther away, the containers' assignment could have possibly been better.

Table 3. Current case vs Base case under a variety of KPIs

Scenarios	Number of routes	Average vehicle utilization	Total kilometres	Average duration	CO2 (kg)	Weight/ Total kilometres
Current Case	17	75%	826	5.5	1433	286
Base Case	19	80%	761	4.7	1351	311

The performance of the routes constructed for the current case and the base case is compared in Table 3 under a variety of key performance indicators (KPIs). First, it can be seen that the base case achieves an almost 8% reduction in the total travelled kilometres when compared to the current case, though it is important to remind here that the routes of the current case had to be solved 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. Moreover, Table 3 shows that even though two additional routes are constructed for the base case, a shorter average route duration is achieved, as well as a higher average vehicle capacity utilization and a lower CO_2 production. More specifically, the base case achieved a 5% increase in the average vehicle capacity utilization and a 5.7% decrease in CO_2 production, which proves that by reducing the construction of partially-full routes, higher efficiency levels can be achieved. Lastly, it can be observed that the weight over total kilometres ratio of the base case is 8.8% higher than the current case as the total collected waste remains the same but the total kilometres are comparatively lesser. In conclusion, the approach provides a significant improvement in all KPI's.

6.1. Sensitivity analysis

To evaluate the robustness of the model's solution, several configurations of different tunable parameters used at the first-level clustering are examined. In Table 8 in the appendix, the indicative parameter values taken into consideration in this analysis are presented. The parameters examined are the range of the 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. It must be stated that the scenarios examined are not exhaustive of all the different combinations that could have been checked. Table 8 also presents for each scenario the KPIs used to evaluate the model's performance and the percentage difference between them and the base case (scenario 1). By comparing all the KPIs we can see that the best-performing scenarios 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. The range in which the percentage difference of all scenarios fluctuates within, which is derived from the extreme values of the best and worst scenarios, is presented in Table 4. The fact that the fluctuation range for each of the examined KPIs is roughly ±4% of the base case proves that the model results are robust and the examined parameters play a trivial role in the overall performance of the model.

Table 4: Percentage difference ranges for each KPI

	Total kilometres	Total CO2 (kg)	Total fuel (ltr)	Weight/ Total kilometres
Max	3.9%	2.9%	3.0%	3.2%
Min	-3.1%	-1.5%	-1.6%	-3.7%

6.2. Scheduling strategies evaluation

This section demonstrates how the developed model can be used to investigate and evaluate different scheduling strategies. More specifically, the dynamic scheduling strategies introduced in section 4 are investigated to understand how the different ways of selecting the containers can affect the efficiency of the operations. The base case is used as a reference to compare the performance of each scheduling strategy, therefore the model is tuned to the parameters of scenario 1 (see Table 8 in the appendix). It must be reminded that for the base case no scheduling strategy is applied, only the containers collected on the examined day are scheduled for collection in the model.

The performance of the examined strategies is presented in the following figures and tables. Fig. 6 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. The priority classification follows the rules presented in Table 2. Table 5 presents the performance of each of the examined strategies and the base case under a variety of indicators, while Table 6 shows the total CO_2 emissions produced by each strategy while the vehicles are in both the driving and idling state.

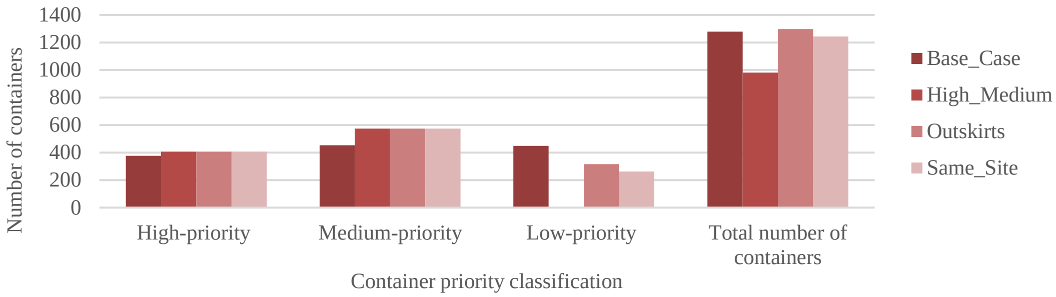

Fig. 6. Dynamic scheduling strategies under a variety of KPIs

Table 5: Performance of the examined dynamic scheduling strategies

Strategy	Total kilometres	Total weight (TN)	Average vehicle utilization	Average container utilization	Number of routes	Weight (kg)/ Total kilometres
Base_Case	761	237	80%	58%	19	311
High_Medium	753	230	80%	72%	18	306
Outskirts	848	251	82%	59%	21	296
Same_Site	799	250	80%	62%	21	313

Table 6. CO_2 emissions produced and fuel consumed per dynamic scheduling strategy

Indicator	State	Location	Base_Case	High_Medium	Outskirts	Same_Site
CO_2 (kg)	Driving	-	952	943	1055	994
CO_2 (kg)	Idling	Disposal facility	93	90	96	99
CO_2 (kg)	Idling	Collection sites	306	270	346	297

Firstly, we can see that the 'High_Medium' strategy selects the least number of containers for collection among the other strategies, and in contrast presents the highest average container capacity utilization at 72%. As an expected result, it produces the least number of routes among the other strategies and produces the least CO_2 emissions both while driving and idling. The 'Base_Case' follows a similar container selection as the 'Same_Site' strategy as all the containers located in a collection site which is scheduled for collection are collected. Nevertheless, 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. For this reason the average container utilization for the base case stands only at 58% which is the least among the other strategies. For this reason, even though the ‘Same_Site’ strategy collects 35 containers less than the ‘Base_Case’, it still collects 13 more tones of waste.

The ‘Outskirts’ and ‘Same_Site’ strategies select the same number of high- and medium-priority containers as the ‘High_Medium’ strategy, but also an additional 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 which explains the creation of 3 additional routes. Nevertheless, for the same amount of waste the ‘Same_Site’ strategy travels 46 additional kilometres compared to the High_Medium strategy while the ‘Outskirts’ strategy travels 95 kilometres more. That is expected as the ‘Outskirts’ strategy schedules for collection all the containers that are located in the outskirts of the city, if at least one of them requires it, which forces the vehicles to travel very long distances irrespective of the accumulated amount of waste.

As a reminder, the total idling quantities are a summation of the quantities produced while idling at the disposal facility and those when idling at the collection sites to serve each container. 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. As the stabilizing part happens only once per collection site, savings can be realized at collection sites with multiple containers for collection. These savings can be proved if we compare the ‘Same_Site’, and ‘High_Medium’ strategies as the former collects 262 additional containers but produces just 27 additional kg of CO_2 emissions while idling at the collection sites.

Overall, the ‘High_Medium’ seems to be the best-performing strategy with the lowest number of kilometres and lowest amount of produced CO_2 emissions. That is especially true in the driving state as it collects the least number of containers and creates the least number of routes. Nevertheless, is critical in such operations to collect as much waste as possible in a day, which is what the ‘Same_Site’ strategy smartly achieves with just 46 additional kilometres compared to the ‘High_Medium’ strategy. Similarly, the ‘Same_Site’ strategy shows a better performance in the production of CO_2 emissions while idling at the collection sites, as the vehicle leveling takes place only once per site. All these strategies clearly indicate the room for improvement for the current strategy of the waste collection service of Rotterdam as the ‘Base_Case’ which represents it did not collect all the high- and medium-priority containers, as per their classification on the examined day.

7. Discussion

The results presented in the previous section showed that the developed model can achieve all the stated research objectives. However, it is important to recognize that the model’s outcomes are affected by its limitations and the necessary assumptions that had to be made for its implementation.

In the model, the moment the vehicle reaches its effective payload capacity it makes a trip to the disposal facility for unloading. In real-life operations, experienced drivers visit the disposal facility not only when the vehicle becomes full, but also when the disposal facilities are less busy, which is something that was not considered in the model. Further to that, a vehicle may become full earlier or later than planned, due to waste density being a stochastic variable, and overflowing waste put next to the containers which are hard to monitor or predict. In the model, waste density is a fixed parameter and overflowing waste is not considered. With these simplifications, the model constructs routes with strict disposal facility visits which can’t easily respond to the requirements of a real-life service.

To achieve a deterministic model behavior and ensure the 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. 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. Testing the model showed 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 ensure the stability of the formation of the first-level clusters is suggested that the K-means algorithm is run for several iterations to improve the resulting clusters' inertia, and then selecting the solution with the least inertia for the subsequent model steps. Similarly, it is suggested that a weighted approach is followed in the GridSearchCV tool to understand if attaching a larger weight on close-by containers and a smaller weight on far-away containers leads to a better containers' assignment and restricts the problem of the first-level clusters being conveyed further in the final solution.

The inefficient assignment of closely-located containers to different clusters can also be attributed to the fact that the Euclidean distance is used instead of the actual road network distance to perform the containers' assignment to the clusters. Especially at locations where neighbor containers are bounded by physical boundaries such as highways, canals, and parks, it is recommended that they are assigned to clusters by using the road network instead of the euclidean distance to construct more compact and efficient clusters.

Certain limitations of the two-stage routing model also affect the performance of the final routes. It is a known limitation of the routing model that restricts the choice of the container 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 therefore it is suggested that every unassigned collection site is considered as the route's starting point when returning from the disposal facility, 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 worth examining other local search algorithms, including inter-route improvement algorithms, to see if they can lead to even better-performing solutions.

To select the containers to populate the first-level clusters, a classification scheme with certain imposed rules was utilized which uses 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 first-level clustering to ensure that the high waste generation sources are the ones guiding the partition of the city into independent waste collection areas. It is acknowledged, nevertheless, that using the container's frequency of collection (due to data unavailability) 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. If the waste fill rates of the containers were used, 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.

8. Conclusions and recommendations

Demand-responsive waste collection schedules bring about uncertainty in the planning of resources and strong variability in their deployment, as they follow the daily demand. The contribution of this paper to the literature is the new formulation of the IoT-WCVRP which includes the balanced trade-off between demand-responsive and supply-friendly operations. This practically means maintaining to the highest degree possible flexibility in vehicle dispatching, while also maintaining a certain level of consistency when demand varies from day to day.

The applicability of the proposed solution approach was demonstrated through a case study of Rotterdam in The Netherlands. The case showed that significant gains can be achieved by constructing shorter but fuller cluster-focused routes. More specifically, the approach increases vehicle utilization rates by 5% and reduces emissions and travelled kilometres by 6% and 8% respectively when compared to the current case.

With this approach, different scheduling strategies can be evaluated to investigate which are the most beneficial under the objectives put forward, as they take into account the priority classification of the containers. Moreover, it can be further used to understand the transport mechanisms of waste and how the road network is utilized by waste collection vehicles. Among others, the routes' compactness can be evaluated, which regards the overlapping of routes, the identification of the most frequently used roads, and the CO_2 emissions produced per waste collection area.

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 IoT-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.

Future research could focus on making the developed model more representative of real-life operations to further 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 could be examined as well, for example visiting the disposal facility if the vehicle is close to it even if it is not fully loaded, or to consider the peak hours of the disposal facility to avoid visiting when it is too busy. The model can be extended with the use of time windows assigned for example at containers located in the vicinity of public transport stations and education buildings, at locations with high traffic conditions, and at locations with accessibility issues or restrictions. Furthermore, the use of electric vehicles could be investigated in the future to understand the effects on the performance of the service, which would of course require the imposition of additional constraints such as the battery duration, or the number of containers that can be lifted by the vehicle. Lastly, the issue of overflown containers was ignored 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 various strategies are explored to approach this issue, for example, with 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.

Appendix A. Parameters values

Table 7. The parameters' values used in the proposed solution approach

Symbol	Unit	Description	Value
ut	min	Unloading time at disposal facility	20
lt	min	Vehicle levelling time	1.5
mt	min	Vehicle hook moving time	0.75
β	kg/m^3	Volume to weight conversion rate	75
EP_{idling}	CO_2 gr/min	CO2 emission production factor of idling vehicle	137
$EP_{city,empty}$	CO_2 gr/min	CO2 emission production factor: empty vehicle & city road	1387
$EP_{city,full}$	CO_2 gr/min	CO2 emission production factor: full vehicle & city road	2153
$EP_{highway,empty}$	CO_2 gr/min	CO2 emission production factor: empty vehicle & highway road	650
$EP_{highway,full}$	CO_2 gr/min	CO2 emission production factor: full vehicle & highway road	780

Table 7 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 factors used for the idling state of the vehicle were retrieved by the study of Lim (2003), while to calculate the factors used for the driving state information was retrieved by Volvo (Mårtensson & Trucks).

Appendix B. Model sensitivity analysis

Table 8: Model sensitivity analysis

Scenarios	Range	Min Capacity	Max Capacity	Total kilometres	Total CO2 (kg)	Total fuel (ltr)	Weight/ Total kilometres
1	13±4	None	None	0.0%	0.0%	0.0%	0.0%
2	13±4	105	None	-3.1%	-1.5%	-1.6%	3.2%
3	13±4	100	None	-0.2%	0.2%	0.2%	0.2%
4	13±4	95	None	0.6%	1.0%	1.0%	-0.6%
5	13±4	None	200	2.3%	2.0%	2.0%	-2.2%
6	13±4	105	200	3.9%	2.7%	2.8%	-3.7%
7	13±4	100	200	0.9%	1.0%	1.0%	-0.9%
8	13±4	95	200	2.4%	2.6%	2.6%	-2.4%
9	13±3	None	None	0.0%	0.0%	0.0%	0.0%
10	13±3	105	None	-3.1%	-1.5%	-1.6%	3.2%
11	13±3	100	None	-0.2%	0.2%	0.2%	0.2%
12	13±3	95	None	0.6%	1.0%	1.0%	-0.6%
13	13±3	None	200	3.5%	2.9%	3.0%	-3.4%
14	13±3	105	200	3.9%	2.7%	2.8%	-3.7%

15	13±3	100	200	0.9%	1.0%	1.0%	-0.9%
16	13±3	95	200	1.4%	1.1%	1.1%	-1.4%
17	13±5	None	None	0.0%	0.0%	0.0%	0.0%
18	13±5	105	None	-3.1%	-1.5%	-1.6%	3.2%
19	13±5	100	None	-0.2%	0.2%	0.2%	0.2%
20	13±5	95	None	0.6%	1.0%	1.0%	-0.6%
21	13±5	None	200	2.3%	2.0%	2.0%	-2.2%
22	13±5	105	200	3.9%	2.7%	2.8%	-3.7%
23	13±5	100	200	-0.9%	0.1%	0.0%	0.9%
24	13±5	95	200	2.4%	2.6%	2.6%	-2.4%

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