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

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A B S T R A C T

The Internet of Things (IoT) can bring radical advancements in the domain of waste collection, as it enables the organization of demand-responsive schedules which leads to higher efficiency operations. One major challenge in the deployment of demand-responsive schedules, nevertheless, is the uncertainty they bring in the planning of resources as they follow the daily waste demand. This is undesirable in real-life operations as it makes it difficult to reserve resources and ensure the stability of operational processes. Therefore, waste collection scheduling approaches need to be devised that are not only demand-responsive but also 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. We demonstrate its applicability through a case study of Rotterdam in The Netherlands, where real-life household waste data are used and the observed waste collection operations in the city are compared against the optimized outcomes of the model. The application results show that our IoT-WCVRP approach achieves the stated demand and supply trade-off, increases the vehicle utilization rates by 5%, and reduces emissions and travelled kilometres by 6% and 8% respectively.

1. Introduction

The Internet of Things (IoT) is a cornerstone of digital transformation, enabling the conversion of physical assets into digital resources. In the waste collection domain, IoT facilitates the development of cyber-physical systems, equipping waste containers with wireless sensors that provide sensing and networking capabilities. These sensors connect containers to the Internet and each other, monitoring their fill levels at regular intervals and transmitting the data to the waste management operator's cloud platform. Such a system holds the potential to reshape waste collection services towards more demand-responsive and efficient operations (Pardini et al., 2019).

The continuous data stream from the sensors supports the identification of seasonal trends and demand patterns, enabling an adaptive approach to waste collection. Real-time information on container status allows for dynamic organization, ensuring containers are collected only when necessary. This approach improves container capacity utilization, reduces overfilled containers, and addresses two key inefficiencies in traditional waste management: excessive operational costs and environmental strain. Collecting partially full containers results in higher costs, unnecessary pollution, and increased urban traffic. Conversely, overfilled containers deteriorate citizen satisfaction and pose an array of hazards to human health.

Experts highlight the financial and environmental benefits of demand-responsive waste collection systems (D. v/d Elzen, personal communication, Jan 2022). However, they also caution about the operational uncertainties these systems introduce, particularly in resource deployment. Unlike traditional static systems with fixed routes and stops, IoT-enabled services must accommodate more dynamic and variable routes, including changes in the number and location of stops, route duration, and the volume of containers serviced. Allocating drivers to specific areas becomes challenging, which can result in a loss of administrative control, making it difficult to efficiently manage operations and assign responsibilities to the vehicle crews. Additionally, as drivers are no longer assigned to specific areas, they lack familiarity with local traffic and parking patterns and may be unaware of site-

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specific issues encountered by drivers on previous days, such as roadworks or blocked containers. Consequently, there is a need for improved internal communication between drivers and planners, as well as a scheduling approach that accounts for these uncertainties.

A variety of models have been proposed for the IoT-waste collection vehicle routing problem (IoT-WCVRP) which use the containers' real-time fill levels as a means to reduce waste demand uncertainty, for example in the work of Ramos et al. (2018), Zsigraiova et al. (2013), Anagnostopoulos et al. (2015), Ferrer and Alba (2019). However, the literature still lacks studies that utilize real-life data for their applications as well as 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 maintain the highest possible degree of flexibility in vehicle dispatching, while also maintaining a certain level of route consistency when demand varies from day to day.

The proposed methodology first utilizes a two-step clustering approach to systematically allocate waste containers into clusters. In the first step of the approach, containers characterized by high and medium collection frequencies are identified and grouped into first-level clusters using the K-means clustering algorithm. This step segments containers into geographically fixed areas, establishing a stable foundation for consistent route planning. Following step is to identify which containers should be collected on a given day. This involves classifying all containers according to their collection priority, and subsequently selecting a scheduling strategy that utilizes the containers collection priorities to determine which specific ones to be collected. Three different scheduling strategies can be examined in the proposed approach, allowing to select the one that best aligns with the objectives set forward, such as prioritizing the collection of all high and medium-priority containers.

In the second step of the approach, the clustering process is finalized by employing the K-nearest neighbours (KNN) algorithm. Specifically, the KNN model is first trained on the containers within the first-level clusters that have been selected for collection. Subsequently, the trained model assigns the remaining selected containers to the cluster of their nearest neighbour within the trained dataset. The resulting second-level clusters only comprise the containers selected for collection, thus adapting to the daily waste demand, while their foundation in the first-level clusters ensures the advantages of route consistency are preserved.

The last step of the proposed methodology involves solving each second-level cluster as a multi-trip Vehicle Routing Problem with Intermediate Facilities (VRP-IF) using the repeated nearest neighbour algorithm. The resulting routes are then optimized through a modified 2-Opt local improvement algorithm.

For the application of the model, real-life data provided by the municipality of Rotterdam in the Netherlands is used. This dataset includes information on the location and capacity of the waste containers within the network, as well as the type and capacity of the vehicles employed. Additionally, it contains waste demand data for a single day, such as the fill levels of the containers and the number of days since their last collection. A sample of seventeen routes completed by Rotterdam's waste collection service on the same day is used as the observed case for comparison with the model's outcomes.

The remainder of the paper is organized as follows. Section 2 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 case study of Rotterdam 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

Constructing 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 satisfactory results in a shorter execution time. This category is widespread among researchers as heuristics and metaheuristics 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 neighbour 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 neighbourhood 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 and 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 and 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 (Abbatecola et al., 2016; Arribas et al., 2010; Faccio, 2011; Kim et al., 2006; Zsigraiova et al., 2013), the drivers' break (Buhrkal et al., 2012; Kim et al., 2006), or the time windows in which containers can be collected throughout the day (Kim et al., 2006; McLeod et al., 2013; Nuortio et al., 2006). 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 (Buhrkal et al., 2012; Kim et al., 2006). 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 and 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 (Anagnostopoulos et al., 2015; Ferrer and Alba, 2019; Ramos et al., 2018; Zsigraiova et al., 2013). Some researchers demonstrate, under a variety of scenarios, that the best collection results can be achieved with a static 70–75% minimum fill level (Akhtar et al., 2017; Faccio, 2011; 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 (Christodoulou et al., 2016; Johansson, 2006; Mes et al., 2014; 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. (Ferrer and Alba, 2019; Johansson, 2006; McLeod et al., 2013). Vonolfen et al. (2011), Anagnostopoulos et al. (2015) and Wu et al. (2020) classify the containers as 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, 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.

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 two-step clustering technique proposed in this paper that aims to balance the trade-off between dispatch consistency and flexibility. 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 predefined scheduling strategy and are assigned to routes in such a way that the total travelled kilometres are minimized, and the vehicle capacity utilization is maximized. The problem can be defined as a multi-trip VRP with intermediate facilities, which are represented by waste disposal facilities, 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 $A = \{(i,j,r) | \, i,j \in V, i \neq j, r \in R\}$, 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 $s \in S$, where $S \subseteq V^m$, represents a set of c containers that are situated at the same spot, denoted by $s = \{1, \dots, c\}$. The service time st_s of each collection site is calculated with Eq. (1) where lt is the vehicle levelling time, and mt is the vehicle hook moving time. Levelling 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 Eq. (2) where the associated fill level $f_{s,c}$ of each container $c \in s$ is multiplied by its maximum volume capacity $vc_{s,c}$ and a volume to weight conversion rate denoted by β.

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

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

The proposed two-step clustering technique provides a way to balance the trade-off between dispatch consistency and flexibility. The model's objective is to assign waste containers to the two level clusters in such a way, that the total travelled kilometres of the routes constructed to serve the second-level clusters are minimized. Eq. (3) is used to calculate the total travelled kilometres, where $n_{ijr,k}$ is the number of times arc (i,j,r) is traversed.

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

In addition to the total kilometres travelled, the total CO2 emissions represent a critical key performance indicator considered in this study. The analysis accounts for multiple stages in the waste collection process where CO2 emissions are produced, including vehicle k driving, servicing a collection site s, and unloading waste at the disposal facility V^f. To calculate the total amount of CO_2 emissions produced while driving Eq. (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, Eq. (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.

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

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

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

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

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

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

The formulated problem is subject to:

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

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

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

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

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

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

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

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

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

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

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

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

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

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. Nevertheless, a buffer volume capacity is usually reserved by the drivers to accommodate unexpected waste laid next to the containers. The allowed shift duration is maintained by constraint (15) but only the effective time for collection is considered as preparation and break time are ignored. Constraint (16) ensures that the cumulative time spent driving to and servicing each collection site of a route follows a logical progression. Finally, constraints (17), (18), (19), and (20) impose the binary and non-negative variables.

4. Solution approach

The proposed 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 constructed 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 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 and the algorithms that are employed at each step. Fig. 2 demonstrates in a visual form every phase of the two-step clustering technique.

During the first-level clustering, all the containers are classified as per their historical monthly frequency of collection using the

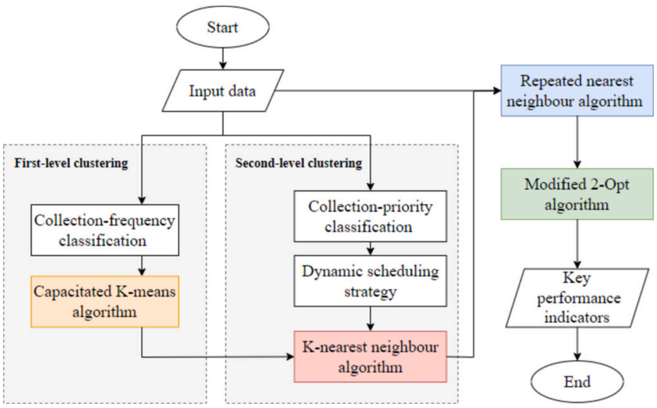

Fig. 1. Flowchart of the proposed solution approach.

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 and medium collection frequencies into geographically fixed areas (see Fig. 2a). The Elbow method is employed to identify the optimal number of clusters to be constructed, and the algorithm is fed an arbitrary seed to eliminate randomness. With these first-level clusters, the daily constructed routes can be focused on specific areas, which can reduce the route-associated variability and overlapping. This can help in maintaining dispatch consistency, which can lead to increased driver familiarity and better administration control, as the assignment of drivers to areas becomes possible.

Following step is to identify which containers require collection. This involves classifying all containers according to their collection priority, as detailed in Table 2. Subsequently, selecting a scheduling strategy from the three options presented in Table 3, that utilizes the containers collection priorities to determine which specific ones to be collected (see grey containers in Fig. 2b). This allows to select the scheduling strategy that best aligns with objectives set forward. The clustering process is finalized by employing the K-nearest neighbour (KNN) algorithm. To find the optimal number of neighbours for the KNN algorithm, 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 80% of the input data is training data, while 20% is test data. To be able to reproduce the same data split, an arbitrary seed is set. The KNN model is trained and tested on the containers within the first-level clusters that have been selected for collection (see coloured containers in Fig. 2c). The trained model then assigns the remaining selected containers (see grey containers in Fig. 2d) to the cluster of their nearest neighbour within the trained dataset. The second-level clusters presented in Fig. 2e maintain flexible boundaries that adjust to include all containers selected for collection, adapting to daily waste demand. Their foundation in the first-level clusters ensures the advantages of route consistency are also preserved.

Table 1
Collection frequency classification scheme.

Classification	Classification rule
High frequency	Frequency $\geq$ 15 times per month
Medium frequency	4 times per month $<$ Frequency $<$ 15 times per month
Low frequency	Frequency $\leq$ 4 times per month

Table 2
Collection priority classification scheme.

Classification	Classification rule
High priority	Fill level $\geq$ 75% OR Accumulation period $\geq$ 15 days
Medium priority	50% $<$ Fill level $<$ 75%
Low priority	Fill level $<$ 50%

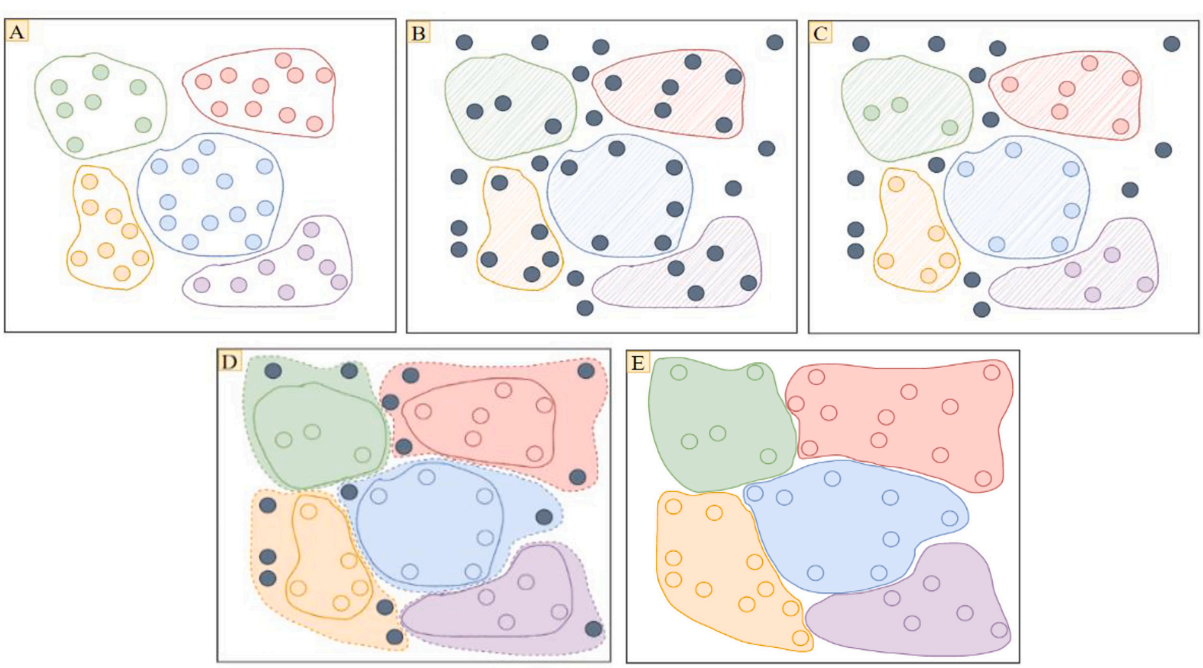

Fig. 2. (a) Containers with high and medium collection frequencies are allocated to first-level clusters with the capacitated K-means algorithm; (b) A dynamic scheduling strategy is applied to determine which containers need immediate collection. The selected containers are grey in colour; (c) Of the selected containers (from step B), the coloured containers are used as a training dataset for the KNN algorithm as they retain their first-level cluster assignments; (d) Containers that were not initially assigned to clusters (grey containers) are now allocated to the nearest cluster based on the trained KNN model. This expands the clusters to include additional containers; (e) The resulting second-level clusters include all containers selected for collection while maintaining flexible boundaries and their foundation in the first-level clusters.

Table 3
Dynamic scheduling strategies.

Scheduling strategy	Description
'High_Medium' strategy	Selects for collection all high- and medium-priority containers
'Same_Site' strategy	Same as 'High_Medium' strategy and all containers that belong on the same site as those
'Outskirts' strategy	Same as 'High_Medium' strategy and all the containers located on the outskirts of a city if at least one of them requires collection. The outskirts refer to the small villages around the city, and the containers located in the outskirts are pinpointed by the waste collection service

To construct the waste collection routes for each second-level cluster, initial feasible routing solutions are generated with the repeated nearest neighbour 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. The repeated nearest neighbour algorithm constructs as many routes as the number of containers in a cluster is, as it uses each as a starting point (see Fig. 3). It then visits consecutively the closest unassigned point until all sites are visited or until all the constraints are met.

The classic 2-Opt algorithm is a simple local search method that evaluates all possible swapping combinations of a route, retaining only the most optimal for further improvement. While effective in optimizing an initial feasible solution, it does not account for intermediate facilities that need to be inserted at specific positions in the route. Since the vehicle must visit a disposal facility to regain capacity, the classic 2-Opt algorithm requires modification.

The modified algorithm begins with a routing solution that excludes disposal facility visits and iteratively searches for improvement opportunities in the solution's neighbourhoods. For each neighbourhood, a swapping mechanism replaces two route edges with two others and calculates the new travel distance. If the swap results in a shorter distance, the algorithm proceeds by inserting disposal facility visits at the correct positions and recalculates the new travel distance. If the updated route is shorter than the initial solution with facility visits, it is updated. This process continues, with the algorithm refining the route by repeating the procedure until no further improvements can be found.

To determine the best-performing route, the following criteria are considered. First, preference is given to routes that visit all containers within the clusters, with the optimal route being the one that covers the least distance. For routes that leave containers unassigned, the preference shifts to those that visit the disposal facility the fewest times, with the best route among them being the one that has the highest weight-to-distance ratio.

Further optimization of the best route is possible under certain conditions. If no containers remain to be assigned but the waste collected during the last leg of the route is less than or equal to 1000 kg, the vehicle's capacity constraint is relaxed, and the second-to-last disposal facility visit is omitted. If there are still unassigned containers in a cluster while the last leg of a route is partially full (due to time constraints), and their combined weight is within the vehicle's effective payload capacity, a single, fuller route is created to replace the two partially full routes. If containers remain unassigned within the cluster, the entire procedure is repeated.

5. Model application

The 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 Nieuw Maas into a northern and a southern part, each served by its dedicated 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.

The depots serve as the starting and ending points for the operations, functioning as parking areas for the collection vehicles. The effective waste collection time is approximately 6.5 h, excluding time for preparation and breaks. By the end of the shift, vehicles must return to the depot empty, requiring a visit to a disposal facility to unload before heading back. It is important to note that the disposal facilities are accessible not only to the municipal waste collection service but also to private waste collection companies. As a result, the arrival rates at these facilities are random and uncontrolled, making it difficult to plan disposal trips in a way that minimizes queuing times.

Both waste collection systems operate a homogeneous fleet of vehicles with a maximum payload capacity of 10,500 kg, though the effective payload is typically around 9000 kg, as the vehicle tends to reach its volume capacity before its weight capacity. The northern system employs 13 vehicles and manages a network of 3168 solid waste containers. The southern system employs 10 vehicles and manages a network of 1785 solid waste containers. All containers are equipped with wireless sensors that monitor and transmit 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. For the observed case we consider 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 the waste they carry, we used their dimensions, last-registered fill levels, and waste accumulation period until that day. To construct the paths and timelines of the sample routes important assumptions were made as only the visiting sequence of the waste containers was provided.

The vehicle levelling and hook moving time, the time spent at the

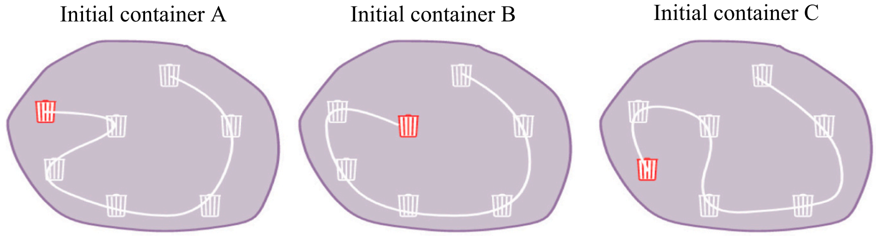

Fig. 3. Example of the repeated nearest neighbour algorithm where each container is used as a starting point.

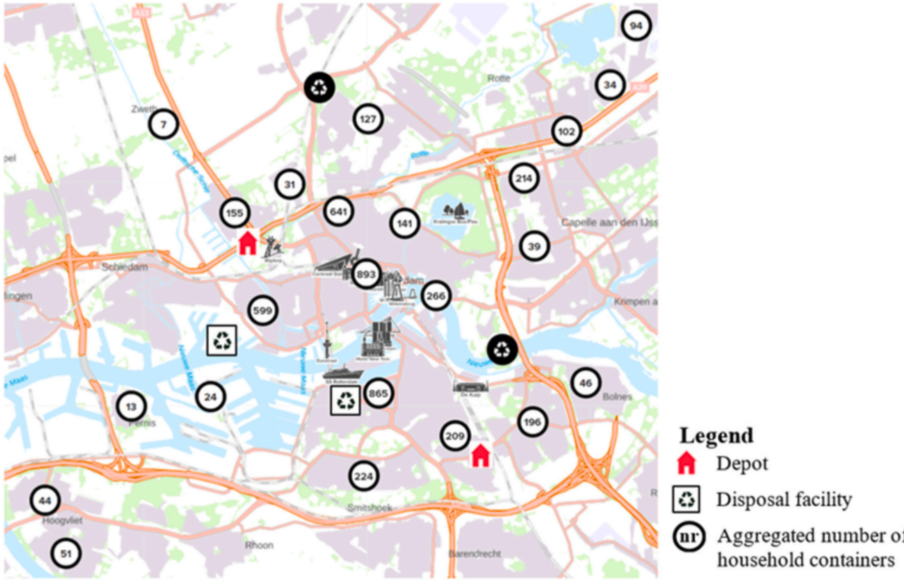

Fig. 4. Waste collection system of Rotterdam (From Rotterdam Container Map).

disposal facility for unloading, and the moment the drivers visit the disposal facility had to be assumed based on empirical knowledge obtained by the experts of the waste collection department of Rotterdam. These parameters' values can be found in Table 4, along with the emission production factor and the volume-to-weight conversion rate β that are used to calculate the CO_2 production. The emission production factors used for the idling state of the vehicle were retrieved by the study of Lim (2003). The factors used for the driving state were calculated using information retrieved by Volvo (Mårtensson & Trucks, 2022).

6. Results

This section evaluates the performance of the proposed solution approach by testing it on the observed case. The setup used to compare the model's simulated outputs with the observed case is termed the reference 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). This was derived from the Elbow method when examining the range 13 $\pm$ 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 reference case and the observed 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 GridSearchCV algorithm indicated that 23 neighbour containers should be used in the KNN algorithm.

Table 4
The parameters' values used in the proposed solution approach.

Symbol	Unit	Description	Value
ut	Minute	Unloading time at the disposal facility	20
lt	Minute	Vehicle levelling time	1.5
mt	Minute	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

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, as it was already mentioned that the collection sites at the boundaries of clusters 4, 7, and 5 were not appropriately assigned. Because a site located near those boundaries was selected 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 had been followed instead, meaning that the nearby neighbours of an unassigned container have more weight than the containers farther away, the containers' assignment could have possibly been better.

The performance of the routes constructed for the observed case and the reference case is compared in Table 5 under a variety of key performance indicators (KPIs). First, it can be seen that the reference case achieves an almost 8% reduction in the total travelled kilometres when compared to the observed case, though it is important to remind here that the routes of the observed 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 5 shows that even though two additional routes are constructed for the reference case, a shorter average route duration is achieved, in addition to a higher average vehicle capacity utilization and a lower CO_2 production. More specifically, the reference 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 reference case is 8.8% higher than the observed case as the total

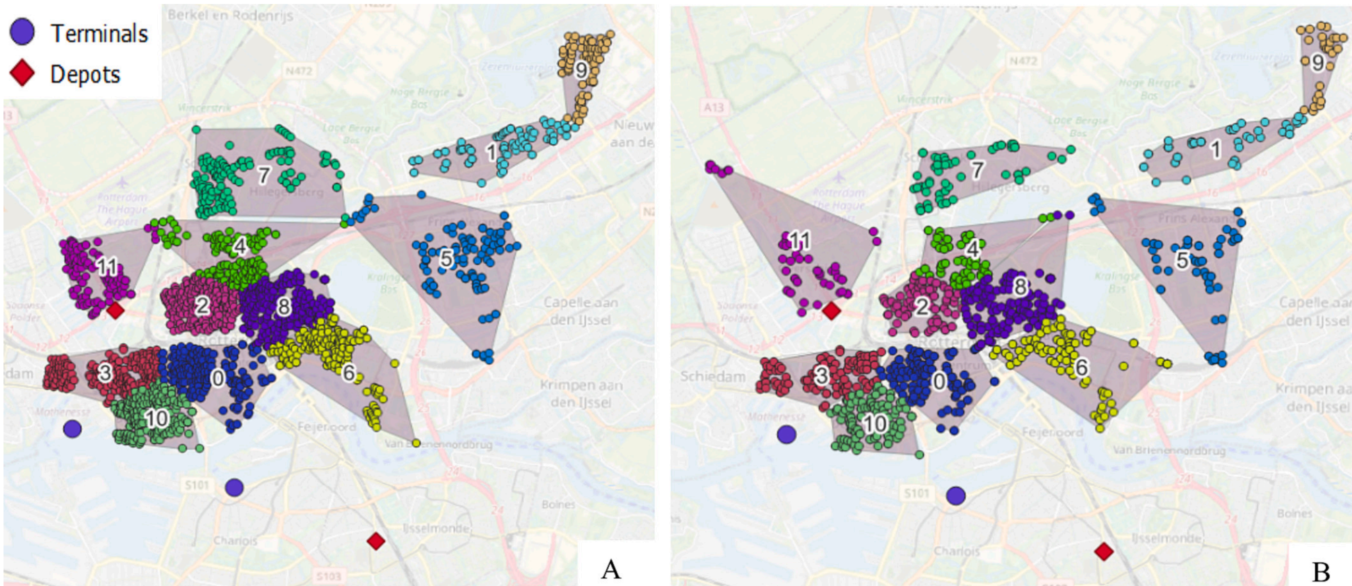

Fig. 5. (a) Geographically fixed first-level clusters (b) Flexible boundaries second-level clusters.

Table 5
Observed case vs Reference case under a variety of KPIs.

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

collected waste remains the same but the total kilometres are comparatively lesser. In conclusion, the approach provides promising improvements, considering that also the main objective of balancing the trade-off between dispatch consistency and flexibility is achieved.

6.1. Sensitivity analysis

To assess the robustness of the model's solution, different scenarios involving the tunable parameters used in the first-level clustering are examined. Table 6 presents the parameters values considered in this analysis, including the range of cluster numbers assessed through the Elbow method to determine the optimal number of clusters, as well as various combinations of minimum and maximum capacity constraints. Additionally, Table 6 lists the KPIs used to assess the model's performance, along with the percentage differences of each scenario to the reference case (Scenario 1). The scenarios analysed are representative, though not exhaustive of all combinations that could be tested.

By comparing all the KPIs we can see that the best-performing

Table 6
Tuneable parameters considered in the model sensitivity analysis and the relevant key performance indicators.

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%

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, which is derived from the extreme values of the best and worst scenarios, is presented in Table 7. The fact that the fluctuation range for each of the examined KPIs is roughly $\pm 4\%$ of the reference case proves that the model results are robust and the examined parameters play a trivial role in the overall performance of the model.

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 Table 3 are investigated to understand how the different ways of selecting the containers can affect the efficiency of the operations. The reference case serves as a benchmark to compare the performance of each scheduling strategy. Therefore, the model is calibrated using the parameters from Scenario 1 (see Table 6). It is important to note that for the reference case, no scheduling strategy is applied. Instead, only the containers collected on the examined day are selected for collection in the model.

The performance of the evaluated strategies is presented in the following figures and tables. Fig. 6 depicts for each scheduling strategy and the reference case the total number of containers selected for collection, as well as their collection priority classification (refer to Table 2 for the rules). Table 8 presents the performance of each of the scheduling strategies and the reference case under a variety of indicators.Table 9 shows the total CO_2 emissions produced by each scheduling strategy while the vehicles are in both the driving and idling state.

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 constructs the least number of routes among the other strategies and produces the least CO_2 emissions both while driving and idling.

The 'Reference_Case' follows a similar container selection as the 'Same_Site' strategy as all the containers located in a collection site that is selected for collection are selected. Nevertheless, not all containers with high and medium priorities 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 reference case stands only at 58% which is the lowest among the other strategies. Even though the 'Same_Site' strategy collects thirty-five containers less than the 'Reference_Case' it still collects 13 more tons of waste.

The 'Outskirts' and 'Same_Site' strategies select the same number of containers with high and medium priorities as the 'High_Medium' strategy, but also an additional 315 and 262 containers of low priority, 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 km compared to the High_Medium strategy, while the 'Outskirts' strategy travels 95 km more. That is expected as the 'Outskirts' strategy selects for collection all the containers that are located on the outskirts of the city, if at least one of them requires it, which forces the vehicles to travel exceedingly long distances irrespective of the accumulated amount of waste.

Total idling CO_2 emissions include those generated while unloading at the disposal facility and those produced while idling at collection sites. The time to service each collection site depends on the number of containers located there that need collection, and the time required 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 are evident when comparing the 'Same_Site' and 'High_Medium' strategies as the former collects 262 additional containers but produces just 27 additional kg of CO_2 while idling at the collection sites.

Overall, the 'High_Medium' seems to be the best-performing strategy with the lowest travel distance and CO_2 emissions. This is particularly clear in driving emissions, as it involves the fewest containers and routes. Nevertheless, it 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 f46 additional km 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 levelling takes place only once per site. All these strategies highlight potential improvements over the observed waste collection approach in Rotterdam, as the 'Reference_Case' reveals that not all containers with high and medium priorities were collected.

Table 7
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%

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 is 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 that cannot easily respond to the requirements of a real-life service.

Furthermore, to achieve a deterministic model behaviour 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 an arbitrary seed with a specific split ratio (80% train data, 20% test data) was used to ensure the reproducibility of the train and test data used in the KNN algorithm. The GridSearchCV tool was used to find the optimal number of neighbours used in the KNN algorithm, but it was restricted to a non-weighted approach.

Evaluating 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-level clusters, and subsequently to the constructed routes. To ensure the stability of the formation of the first-level clusters, it is suggested that the K-means algorithm is run for several iterations to improve the resulting clusters' inertia, and then select 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.

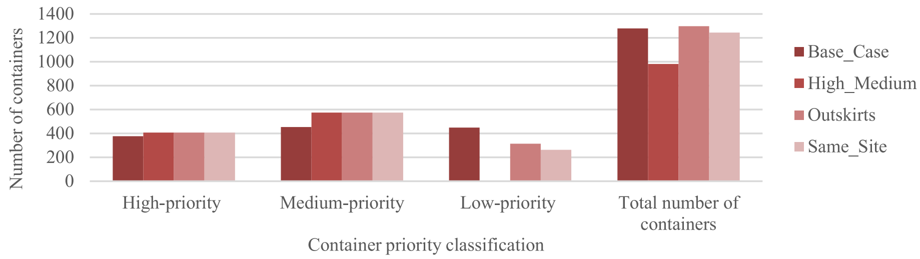

Fig. 6. Scheduling strategies under a variety of KPIs.

Table 8
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
Reference_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 9
CO_2 emissions produced and fuel consumed per dynamic scheduling strategy.

Indicator	State	Location	Reference_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

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. Especially at locations where neighbour 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 distance instead of the Euclidean distance to construct more compact and efficient clusters.

Certain limitations of the two-step routing model also impact the performance of the final routes. A known constraint of the model is that it restricts the selection of the next container to be visited, after returning from the disposal facility, to the one closest to the most recently serviced collection site. 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 with high and medium collection frequencies 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, operating or not 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 uncertainty in the planning of resources as they follow the daily demand. The contribution of this paper to the literature is the proposed solution approach for the IoT-WCVRP, which has as an overarching objective to maintain the highest possible degree of flexibility in vehicle dispatching, while also maintaining a certain level of route consistency when waste demand varies from day to day.

Real-life waste data provided by the municipality of Rotterdam in the Netherlands was used for the application of the model, which not only showed that gains can be achieved but further demonstrated its feasibility and applicability. The results showed that by constructing shorter but fuller cluster-focused routes, the model increases vehicle utilization rates by 5% and reduces emissions and travelled kilometres by 6% and 8% respectively when compared to the observed case. A reminder that the observed case considered in this research was solved with Dijkstra's algorithm under the consideration of the shortest path due to the unavailability of the traversed paths and timelines.

With the proposed model three different scheduling strategies can be examined, depending on the collection objectives set forward. Applying the model showed that there is room for improvement in the observed way the selection of containers for collection is performed, as under different scheduling strategies additional gains can be achieved. Among others, the model can be further used to understand the transport mechanisms of waste and how the road network is utilized by waste collection vehicles, to evaluate the routes' compactness which regards the overlapping of routes, and to calculate the CO_2 emissions produced per waste collection area.

In general, the developed model can be used by any waste collection service that has 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. Other 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 considering 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.

The findings offer valuable insights for both businesses and public authorities in waste management. The model enhances resource efficiency by improving vehicle utilization by 5%, reducing emissions by 6%, and cutting travel distances by 8%, benefiting both cost reduction and environmental sustainability efforts. Its flexibility in vehicle dispatching is particularly important for handling daily demand uncertainties, allowing businesses to optimize resources and public authorities to adjust collection schedules based on changing priorities, such as cost, sustainability, or service improvement. Additionally, the model optimizes route compactness and road network utilization, helping to reduce traffic congestion and improve overall operational efficiency.

Furthermore, the model aligns with public policy goals for sustainability, offering a practical approach to reducing waste collection's carbon footprint. Its scalability allows it to be applied across different waste management systems, making it a versatile tool for municipalities and service providers. Future research directions, such as exploring electric vehicle integration or managing overflowing containers, could further enhance its impact. Overall, the model strikes a balance between efficiency, flexibility, and sustainability, providing both businesses and public authorities with a robust tool to improve waste collection operations while meeting evolving priorities.

CRediT authorship contribution statement

Sofia Giasoumi: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Formal analysis, Data curation. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Supervision, Methodology. **Michiel de Bok:** Writing – review & editing, Supervision, Conceptualization. **Lóránt Tavasszy:** Writing – review & editing, Supervision, Project administration. **Jos Streng:** Writing – review & editing, Conceptualization. **Daan van den Elzen:** Writing – review & editing, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article. Any interpretation or opinion expressed in this paper are those of the authors and do not necessarily reflect the view of the Delft University of Technology, Significance or the Municipality of Rotterdam.

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