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A Robust Green Routing Approach for Hamiltonian Waste Collection Routes Using the k-Nearest Neighbor Algorithm

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ABSTRACT

This study develops a robust, green routing approach for the integrated waste collection system in Medan City by combining the k-Nearest Neighbor (k-NN) heuristic with a robust optimization framework. The dataset comprises Euclidean distances among 16 nodes, including the depot and major road segments, and measured carbon monoxide (CO) emissions recorded during morning, afternoon, and night operations. The research methodology comprises three stages. First, a spatial distance matrix is constructed to represent the transportation network. Second, a Hamiltonian circuit is generated using the k-NN algorithm to establish a single route that visits all nodes exactly once. Third, a green cost function is formulated by integrating distance and emission components, followed by the application of a budgeted uncertainty parameter Γ to assess route resilience under fluctuating emission conditions. The results show that the proposed robust framework effectively captures the trade-off between efficiency and stability. Increasing Γ leads to a moderate rise in the Price of Robustness, with values in the range of Γ = 3 to 4 offering a balanced compromise between nominal performance and environmental resilience. The study clarifies that the implemented model represents a single-vehicle Hamiltonian routing problem, not a capacitated multi-vehicle Capacitated Vehicle Routing Problem (CVRP). Potential extensions toward a full Green-CVRP are discussed. Overall, this approach provides practical insights for designing emission-aware and robust urban waste collection routes.

1. INTRODUCTION

Medan City, one of Indonesia's largest metropolitan areas, faces persistent challenges in solid waste management, including high daily waste generation, limited collection capacity, and increasing environmental pressure around the Terjun landfill [1]. Recent reports indicate that the city produces nearly 2,000 tonnes of waste per day, whereas only about 800 tonnes can be collected and processed [2]. This gap highlights the need for improvements in integrated waste transportation across the TPS/TPS-3R–TPST–TPA chain to enhance operational efficiency and reduce environmental impacts [3].

At the national level, Law No. 18/2008 mandates systematic waste reduction, collection, and transportation, providing a regulatory basis for optimizing routing networks in urban settings [4, 5]. Nonetheless, Medan continues to experience ecological pressure due to suboptimal waste transport, compounded by population growth, traffic congestion, and increasing greenhouse gas emissions from transportation activities [6, 7].

From a modelling perspective, waste collection routing problems are commonly formulated as Vehicle Routing Problem (VRP) variants, including the Capacitated VRP (CVRP) and its environmental extension, the Green-CVRP, which incorporates fuel use and emission considerations [8, 9]. Since 2016, VRP research has increasingly focused on time-dependent routing and emission-aware planning for large cities. However, existing local studies for Medan predominantly adopt deterministic VRP or metaheuristic approaches aimed at distance minimisation [8, 9], with limited consideration of emission factors or uncertainty.

Robust optimization (RO) provides an alternative for handling fluctuating travel times and emission variability without requiring full probabilistic information. The Bertsimas–Sim approach [10] allows the decision-maker to tune the level of conservatism (Γ), and prior studies show its benefits in improving routing reliability under uncertain operational conditions [11]. Meanwhile, Green-VRP research highlights the importance of modelling congestion as a key driver of carbon monoxide (CO) and carbon dioxide (CO_2) emissions [12], particularly relevant for dense Indonesian urban corridors where speed–emission relationships are highly nonlinear [13].

Within the robustness framework, employing the Bertsimas-Sim uncertainty set allows policymakers to adjust the Γ parameter to control the level of conservatism. This approach accommodates waste surges and traffic disruptions while preventing the infeasibility often encountered in deterministic models when real-world conditions deviate from planned parameters. Meanwhile, within the green objective, the combined cost function integrating distance/fuel costs and emission costs aligns with the current Green-CVRP paradigm [14]. Related transportation research has integrated capacity-constrained clustering with vehicle routing while jointly considering operational costs, travel-time costs, and environmental impacts [15]. In the present model, the combined objective allows the selection of routes that may be slightly longer in distance but have lower emission impacts, thereby supporting more sustainable and environmentally responsible urban waste transportation.

Various approaches have been proposed for route initialization in the CVRP [16], including the Clarke and Wright Savings (CWS) algorithm [17], sweep algorithm [18], k-means clustering [19, 20], and several metaheuristic techniques [21] such as Local Search [22], Tabu Search [23, 24], and Simulated Annealing [25]. Although these methods have proven effective in specific contexts, most primarily focus on minimising travel distance while paying limited attention to environmental attributes such as carbon emissions and travel-time variability.

In this study, the k-Nearest Neighbor (k-NN) algorithm [26, 27] was chosen because of its flexibility in combining spatial proximity with similarities in emission and travel-time profiles, enabling it to generate route initializations that better reflect actual traffic conditions in Medan City while supporting the quality of green-robust solutions. Despite these advances, several gaps remain: (i) Local studies in Medan have not integrated traffic-based emission parameters into routing models nor explored robustness against emission fluctuations. (ii) There is limited research applying robust green routing methods using real-world emission data collected across different traffic conditions. (iii) The k-NN algorithm, although widely used for spatial clustering, has rarely been employed as a route initialization method that incorporates both distance and emission similarity.

In response, this study develops a robust green routing framework that combines the k-NN algorithm with the Bertsimas–Sim uncertainty model. Unlike full CVRP formulations, the present work focuses on generating a single Hamiltonian route across 16 key nodes representing the waste transport network of Medan. Emission and distance components are integrated into a combined green cost, while robustness analysis using Γ evaluates the trade-off between route efficiency and resilience to emission variability. By utilising real distance and CO emission measurements from morning, afternoon, and night operations, the model provides empirical insights into the design of low-emission and uncertainty-aware waste collection routes.

The contributions of this study are: (i) developing a robust green routing formulation using distance emission integration; (ii) applying Bertsimas–Sim robustness to analyse sensitivity to emission fluctuations; (iii) employing k-NN for spatial emission-based route initialization; and (iv) validating the framework using real operational data from Medan City. This work contributes to the broader agenda of sustainable, data-driven urban waste transportation planning.

2. MATERIALS AND METHODS

To establish a solid conceptual foundation for this research, a comprehensive theoretical framework is essential, incorporating dimensions such as route optimization, demand uncertainty, environmental factors, and computational efficiency. The following literature review highlights the key components directly relevant to the study's focus.

First, the deterministic CVRP acts as the initial model, representing the core vehicle-routing problem with capacity constraints. Although it is widely used in logistics and waste collection, its main limitation lies in the deterministic assumptions that often do not reflect real urban conditions, such as those in Medan, where both waste generation and travel times vary significantly. Second, RO employing the budgeted uncertainty approach (Bertsimas–Sim framework) offers a practical method for managing uncertainty. This approach ensures model feasibility even amid demand surges at Temporary Collection Points (TPS) or traffic disruptions by adjusting the level of conservatism (Γ). In the context of integrated waste transportation, RO guarantees that routing solutions remain efficient under average conditions and also reliable during fluctuations in waste demand and traffic flow along Medan's congested corridors. Third, this study emphasizes waste-generation volatility as a genuine issue in urban solid-waste systems. Empirical data show that daily waste production in Medan tends to rise during rainy seasons, long holidays, or in commercial districts with intense trading activities. Such variability directly impacts routing decisions, potentially causing vehicle overloads or delayed deliveries to Final Disposal Sites (TPA). Therefore, incorporating RO acts as a safeguard, protecting the system against adverse scenarios resulting from demand and travel-time fluctuations.

Fourth, the green aspect of CVRP sets this research apart from traditional studies. Environmental factors, such as CO and CO_2 emissions from waste collection vehicles, are explicitly integrated into the objective function not only to reduce operational costs but also to support urban sustainability goals. The combined distance-emission metric reflects the real trade-off between economic and environmental efficiency. Finally, to develop a practically implementable solution, this research employs the k-NN algorithm as a route-initialisation mechanism. Unlike classical methods such as the CWS algorithm, which depend solely on distance, k-NN combines spatial proximity with similarities in emission and travel-time profiles. Although rarely explored in CVRP literature, this approach offers two main advantages: speeding up route-heuristic convergence and maintaining the quality of green-robust solutions at the city scale. Consequently, k-NN not only produces route initialisations that better reflect Medan's real traffic conditions but also enhances the novelty and methodological contribution of this study compared to previous deterministic approaches.

Overall, this theoretical framework integrates the Green-CVRP model, RO under uncertainty, urban waste-generation dynamics, and k-NN-based heuristics. These four pillars jointly establish a solid scientific foundation for developing an RO model for Green-CVRP that is resilient, adaptive, and environmentally focused for Medan's integrated waste-collection system.

2.1 Capacitated Vehicle Routing Problem

The CVRP is one of the most extensively studied extensions of the classical VRP. It is defined on a directed graph $G = (V, A)$, consisting of a central depot $V_0 \in V$ and a set of customers $V^+ = \{1,2,\dots,n\}$ [28]. Each customer i is associated with a demand d_i, and each vehicle in the fleet has a limited capacity Q. The travel cost between node i and node j is denoted by c_{ij}.

The deterministic CVRP can be formulated as the following mathematical optimization model [29, 30]:

Objective Function:

$$min \sum_{k\in K}\sum_{i\in V}\sum_{j\in V, j\neq i} c_{ij}x_{ij}^k \tag{1}$$

Subject to:

$$\sum_{k\in K}\sum_{j\in V, j\neq i} x_{ij}^k = 1\,, \forall_i \in V\setminus\{0\} \tag{2}$$

$$\sum_{j\in V, j\neq i} x_{ij}^k = \sum_{j\in V, j\neq i} x_{ji}^k\,, \forall_k \in K,\ \forall_i \in V \tag{3}$$

$$\sum_{j\in V, j\neq i} x_{ij}^k = a_i^k,\ \forall_k \in K, \forall_i \in V\setminus\{0\} \tag{4}$$

$$\sum_{k\in K}\sum_{j\in V\setminus\{0\}} x_{0j}^k = \sum_{k\in K}\sum_{j\in V\setminus\{0\}} x_{j0}^k \tag{5}$$

$$\begin{gathered} u_i^k - u_j^k + Q_k x_{ij}^k \leq Q_k - q_j \\ \forall_k \in K, V_i \neq j, (i,j) \in V\setminus\{0\} \end{gathered} \tag{6}$$

$$q_i \leq u_i^k \leq Q_k,\ \forall_k \in K,\ V_i \in V\setminus\{0\};\ u_0^k, \forall_k \tag{7}$$

$$\sum_{i\in V\setminus\{0\}} q_i a_i^k \leq Q_k, \forall_k \in K \tag{8}$$

$$x_{ij}^k \in \{0,1\},\ \ a_i^k \in \{0,1\}, u_i^k \geq 0 \tag{9}$$

Objective function (1) the total transportation cost. This cost is computed as the cumulative travel cost between nodes i and j traversed by each vehicle k. Constraint (2) ensures that every customer node is visited exactly once by a single vehicle, thereby preventing multiple visits or unserved customers. Constraint (3) enforces route continuity for each vehicle by requiring that the number of arcs entering a node equals the number of arcs leaving that node, which guarantees a feasible and continuous route structure. Constraint (4) specifies that customer i is served by exactly one vehicle k. Constraint (5) balances the flow of vehicles at the depot by imposing that each vehicle departing from the depot must return to it, ensuring closed routes that begin and end at the depot. Constraints (6)-(7) are the Miller–Tucker–Zemlin (MTZ) structure, which ensures that when a vehicle travels from node i to node j, the corresponding load variable is updated consistently with the demand served, thereby eliminating isolated cycles that do not include the depot. Constraint (8) defines the limits on the total demand served by each vehicle to not exceed its maximum carrying capacity, which is the defining characteristic of the capacitated routing problem. Constraint (9) defines the domain of the decision variables x_{ij}^k and a_i^k are binary variables, while u_i^k is restricted to be non-negative.

2.2 Robust optimization

RO has been introduced to address decision-making problems under uncertainty in parameters, ensuring that feasible and near-optimal solutions stay stable even when the actual data deviate from their nominal values [31]. The box-interval uncertainty framework proposed by Cipta et al. [32] offers a tractable and intuitive way to control the level of conservatism through the robustness parameter Γ [33].

In this framework, the uncertain demand at a customer node i is expressed as [34, 35]:

$$d_i = \bar{d}_i + \tilde{d}_i z_i,\ \ z_i \in [0,1],\ \sum_i z_i \geq \Gamma \tag{10}$$

where, $\bar{d}$ denotes the nominal demand at node i, $\tilde{d}_i$ represents the maximum deviation from the nominal demand, z_i is the realized deviation indicator, bounded within [0,1], and Γ is the robustness budget, which controls how many customer demands are allowed to deviate from their nominal values simultaneously. By tuning Γ, planners can balance between solution robustness and cost efficiency: A larger Γ provides higher protection against uncertainty but may lead to more conservative and potentially more expensive routing plans, whereas a smaller Γ yields solutions closer to the deterministic case with lower conservatism.

2.3 k-Nearest Neighbor for route initialization

In this study, the k-NN method is used not as a classifier but as a neighborhood generation mechanism. Its role is to produce an initial Hamiltonian circuit (a single route visiting all nodes) that reflects both spatial proximity and emission similarity; this initializer is subsequently evaluated under the robust green cost. Using k-NN for route initialization improves computational efficiency and produces route candidates that respect local traffic/emission patterns in Medan's Road network [36].

Each node i is represented by an n-dimensional feature vector,

$$V_i = (x_i, y_i, e_i^{morning}, e_i^{afternoon}, e_i^{night}, \dots) \tag{11}$$

where, x_i, y_i are spatial coordinates (Euclidean), and $e_i^{morning}, e_i^{afternoon}, e_i^{night}$ are measured CO emission indicators for the three time periods. Before distance computation, all features are normalized to zero mean and unit variance to ensure comparability across units.

A weighted Euclidean metric is used to combine spatial and emission attributes [37], and is expressed as:

$$D_w(v_i, v_j) = \sqrt{\sum_{p=1}^{n} w_p\left(v_{i,p} - v_{j,p}\right)^2} \tag{12}$$

where, $w_p \geq 0$ are tunable feature weights that reflect the relative importance of spatial proximity versus emission similarity. In practice, we set $w_x = w_y$ and choose a single emission weight w_e so the metric reduces to a combination of spatial distance and an aggregated emission distance.

The k-NN procedure for constructing a Hamiltonian circuit proceeds as follows:

1) Compute the pairwise weighted distances $D_w(v_i, v_j)$ for all node pairs i, j.
2) Select a start node (the depot or a chosen origin).
3) Set current node c: = start, mark c visited.
4) From the set of unvisited nodes, identify the k nodes with the smallest D_w to c (the k-neighborhood).
5) From that neighborhood, select the next node according to a deterministic tie-break rule (smallest D_w if still tied, lowest node index).
6) Append the chosen node to the route, mark it visited, set c: = chosen node, and repeat steps 4–6 until all nodes are visited.
7) Return to the depot to close the Hamiltonian circuit.

2.4 Mathematical model of Hamiltonian circuit

Given a complete directed or undirected graph $G = (V, E)$ with a set of vertices $V = \{1,2,\ldots,n\}$ and a set of edges E, each edge $(i,j) \in E$ is assigned a distance weight d_{ij}. The goal is to determine a Hamiltonian circuit, that is, a closed tour visiting each vertex exactly once and returning to the starting vertex [38].

Formally, the optimization problem can be defined as follows: (1) The graph G is given, with each edge (i,j) associated with a weight d_{ij}. (2) A binary decision variable x_{ij} is introduced, where:

$$x_{ij} = \begin{cases} 1, & \text{if edge } (i,j) \text{ is included in the circuit} \\ 0, & \text{otherwise} \end{cases}$$

The objective function aims to minimize the total distance of the Hamiltonian circuit [39]:

$$min\, Z = \sum_{i \in V} \sum_{j \in V, j \neq i} d_{ij} x_{ij} \tag{13}$$

Subject to the following constraints:

Each vertex in the graph must have a degree of two, meaning that exactly one edge enters and one edge leaves each node. This condition guarantees that all vertices are included in the circuit exactly once. The degree constraints can be expressed as follows:

$$\sum_{i \in V, i \neq j} x_{ij} = 1\,, \sum_{j \in V, j \neq i} x_{ij} = 1,\ \forall_{i,j} \in V \tag{14}$$

Furthermore, to guarantee the formation of a single Hamiltonian circuit, it is necessary to eliminate the possibility of subtours, i.e., smaller cycles that do not include all vertices.

2.5 Assumptions for CO emission consumption

The average emission load (g/h) is calculated for each road segment [40, 41]:

$$\bar{E}_i = \frac{E_{(i,morning)} + E_{(i,afternoon)}}{2} \tag{15}$$

Assuming the average speed of trucks operating in urban areas is v = 20 km/h. The emission rate per km on segment i is expressed as [42, 43]:

$$r_i = \frac{\bar{E}_i}{v} \tag{16}$$

The emission generated when traversing an edge between nodes i and j is then calculated using the average emission rates of the two adjacent nodes [44, 45]:

$$e_{ij} = \left(\frac{r_i + r_j}{2}\right) \times d_{ij} \tag{17}$$

Finally, the total emission along a Hamiltonian circuit is expressed as:

$$E_{total} = \sum_{t=0}^{k-1} e_{v_t, v_{t+1}} = \sum_{t=0}^{k-1} d_{v_t, v_{t+1}} \times \left(\frac{r_{vt} + r_{vt+1}}{2}\right) \tag{18}$$

where, d_{ij} is the travel distance from node i to node j (km), $e_{v_t, v_{t+1}}$ is the CO emission generated along edge (v_t, v_{t+1}), r_{vt} and r_{vt+1} denote the average CO emission rates at nodes v_t and v_{t+1} (g/h) respectively, v_t represents the node visited at step t in the Hamiltonian circuit, and k denotes the total number of nodes in the route. This formulation enables the integration of CO emissions into the routing model, ensuring that optimization considers not only operational efficiency but also sustainability aspects.

3. RESULT AND DISCUSSION

3.1 Robust optimization Green Capacitated Vehicle Routing Problem model

This section outlines the mathematical formulation of the RO Green-CVRP with a Hamiltonian circuit, utilizing the k-NN algorithm to generate integrated waste collection routes in Medan City. The proposed model: (i) combines an objective function that integrates distance/energy costs and carbon emissions; (ii) employs RO based on the Bertsimas-Sim framework to manage uncertainty in waste demand at each TPS and fluctuations in travel time caused by congestion, ensuring solutions remain feasible and cost-effective under uncertainty; (iii) uses the k-NN algorithm within the Hamiltonian circuit to initialise spatially close neighbourhoods or clusters based on emission and travel-time profiles; and (iv) calibrates model parameters with empirical data from Medan City, including vehicle capacity, waste generation volumes, and the integrated network structure (TPS–TPST–TPA and congested corridors), to ensure that the routes are robust, efficient, and low in emissions.

We assume that the waste demand d_i at each TPS is not deterministic, but lies within a bounded interval:

$$d_i \in \left[\bar{d}_i - \hat{d}_i, \bar{d}_i + \hat{d}_i\right] \tag{19}$$

where, $\bar{d}_i$ represents the nominal demand at node i, and $\hat{d}_i$ denotes the maximum deviation from the mean value (i.e., demand surge).

Accordingly, the robust constraint can be written as:

$$\sum_{i \in V} \bar{d}_i y_i^k + \max_{\xi \in U} + \sum_{i \in V} \xi_i \hat{d}_i y_i^k \leq Q_k\,, \forall k \in K \tag{20}$$

where, the uncertainty set is specified within a box-interval structure:

$$U = \left\{ \xi \in [0,1]: \sum_{i \in V} \xi_i \le \Gamma \right\} \tag{21}$$

Table 1. Interpretation Γ

Notation	Description
$\Gamma = 0$	All demands are assumed deterministic.
$\Gamma = \lvert V \rvert$	All nodes on the route of vehicle k may simultaneously reach their maximum demand.
$0 < \Gamma < \lvert V \rvert$	Only Γ nodes are assumed to experience maximum demand simultaneously.

To represent this condition, we introduce the uncertainty budget parameter Γ, which limits the number of nodes that can simultaneously experience maximum deviation from their nominal demand in Table 1.

Therefore, the mathematical formulation of the RO Green-CVRP with a Hamiltonian circuit using the k-NN algorithm is expressed as follows:

Objective function:

$$\begin{aligned} min\, Z = \sum_{k \in K} \sum_{i \in V} \sum_{j \in V, j \ne i} \left(\alpha c_{ij} + \beta e_{ij}(t) \right) x_{ij}^k \\ + \lambda \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} dist_{ij} f_{ij}^k \end{aligned} \tag{22}$$

Subject to:

$$\sum_{k \in K} \sum_{j \in V, j \ne i} x_{ij}^k = 1\,, \quad \forall_i \in V \tag{23}$$

$$\sum_{j \in V \setminus \{i\}} x_{ij}^k = \sum_{j \in V \setminus \{i\}} x_{ji}^k\,, \ \forall_i \in V_0, \ \ \forall_k \in K \tag{24}$$

$$\sum_{j \in V} x_{0j}^k = \sum_{j \in V} x_{j0}^k \le 1\,, \ \forall_k \in K \tag{25}$$

$$\sum_{j \in V_0 \setminus \{i\}} x_{ij}^k = y_i^k, \ \forall_i \in V, \ \forall_k \in K\,, \ \sum_k y_i^k = 1 \tag{26}$$

$$\sum_j f_{ij}^k - \sum_j f_{ji}^k = \hat{d}_i y_i^k, \ \forall_i \in V, \ \forall_k \in K \tag{27}$$

$$0 \le f_{ij}^k \le Q_k x_{ij}^k, \quad \forall_{i,j} \in V, \ \ k \in K \tag{28}$$

$$\sum_{i \in V} \bar{d}_i y_i^k + \Gamma \theta_k + \sum_{i \in V} s_i^k \le Q_k\,, \ \forall k \in K \tag{29}$$

$$s_i^k \le \hat{d}_i y_i^k, \ \forall i \in V \ \ , k \in K \tag{30}$$

$$s_i^k, \theta_k \ge 0 \tag{31}$$

$$\sum_{(i,j) \in E} \bar{T}_{ij} x_i^k + \Gamma_{T\phi k} + \sum_{(i,j) \in E} \varphi_{ij}^k \le T_{max}\,, \forall k \in K \tag{32}$$

$$u_i^k - u_j^k + n x_{ij}^k \le n - 1, \ \forall i, j \in V, \ i \ne j, \ k \in K \tag{33}$$

$$u_i^k, y_i^k \in \{0,1\}, \ \ f_{ij}^k \ge 0, \ \ s_i^k, \theta_k \ge 0, \ \ u_i^k \in \mathbb{Z} \tag{34}$$

The objective function (22) minimizes the total travel cost by combining the operational/energy component and the environmental component $\left(\beta e_{ij}(t)\right)$, thereby encouraging the selection of corridors that are not only short in distance but also low in emissions (e.g., avoiding peak-hour routes). The second part of the function minimizes the load-distance (km/ton), which reflects both energy consumption and emissions when trucks operate under load, while balancing waste distribution to prevent energy-inefficient heavy routes. Constraint (23) ensures that each waste collection point (TPS) is served exactly once by the entire fleet, representing the outgoing degree of the network, thus guaranteeing complete coverage without duplication. Constraint (24) enforces flow conservation, where for each vehicle and non-depot node, the number of incoming arcs equals the number of outgoing arcs. This maintains route continuity and ensures a valid Hamiltonian circuit. Constraint (25) limits each vehicle to a single complete tour, meaning it departs from and returns to the depot exactly once; a value of zero indicates the vehicle is inactive. Constraint (26) stipulates that node *i* is served by vehicle *k* only if there exists an outgoing arc from *i* in that vehicle's route. The summation y_i^k ensures that exactly one vehicle is responsible for serving each TPS. Constraint (27) balances the incoming and outgoing waste flow for each node *i* and vehicle *k*, ensuring it equals the nominal demand of TPS *i* actually served by *k*, thereby guaranteeing ma**ss** conservation across the network. Constraint (28) ensures that the quantity of waste transported along an arc does not exceed $\left(x_{ij}^k = 0\right)$ the vehicle's capacity, and becomes zero if the arc is not used, maintaining physical consistency of the routing plan. Constraint (29) models uncertain waste demand $d_i \in \left[\bar{d}_i - \hat{d}_i, \bar{d}_i + \hat{d}_i\right]$. Under the box-interval uncertainty characterized by parameter Γ, at most Γ TPS nodes are assumed to experience full deviation simultaneously. The auxiliary variables θ_k and s_i^k provide the linear reformulation of the maximization term in the box-interval set, ensuring route feasibility during demand surges (e.g., rainy seasons or holidays). Constraint (30) ensures that the deviation extracted from TPS *i* for vehicle *k* does not exceed its maximum allowed deviation and is only relevant when the TPS is indeed served by that vehicle. Constraint (31) adds a layer of robustness through conservative adjustment. Constraint (32) restricts the total travel time of vehicle *k* not to exceed the upper bound T_{max} , even when travel time uncertainty arises from congestion, modelled through a box-interval uncertainty set T_{ij}. Constraint (33**)** guarantees that each vehicle's route forms a Hamiltonian circuit containing the depot, preventing disconnected sub-tours. Finally, Constraint (34) enforces the integer nature of all binary decision variables to preserve the model's mathematical integrity.

Although not explicitly shown in Eqs. (22)-(34), the k-NN algorithm is employed before optimization to construct the candidate arc set:

$$E^* = \{(i,j) \in E : j \in kNN(i)\} \tag{35}$$

Eq. (35) represents the combined distance that integrates spatial Euclidean distance, emission intensity, and travel time similarity. This process notably reduces the solution space, speeds up calculation, and directs the search towards low-emission and congestion-resistant neighboring routes aligned with Medan's traffic corridors.

While Constraints (22)–(34) present the complete robust Green-CVRP formulation, the computational experiment focuses on a single-vehicle Hamiltonian routing context. The k-NN algorithm is therefore used to generate a Hamiltonian path, where the uncertainty-adjusted parameters derived from the robust model (demand bounds, travel-time bounds, and normalized emission intensities) guide the heuristic selection process. The full Robust Optimization Mixed Integer Linear Programming (RO-MILP) is not solved directly, as the problem setting does not require multi-vehicle flow feasibility nor explicit f_{ij}^{k} computation. Instead, the RO model functions as a theoretical benchmark underlying the heuristic emission-aware routing procedure.

In this study, the realistic operational context involves a single waste-collection vehicle traversing all nodes once; therefore, the full RO Green-CVRP formulation is not required. The model solved is a Green-Robust TSP, where the Hamiltonian route is generated by the k-NN method and evaluated using a green cost function that incorporates distance and time-varying emissions. The previously presented multi-vehicle RO CVRP model is therefore removed to maintain methodological consistency.

3.2 Result interpretation

3.2.1 Data description

Table 2 displays the distance matrix between major road segments, including the starting and ending depot points for the waste collection trucks. Each waste collection route is assumed to start at the depot, visit all designated road locations in sequence, and return to the same depot, forming a complete Hamiltonian circuit.

3.2.2 Constructing Hamiltonian circuits using the k-NN algorithm for each starting node based on distance data

Before establishing the optimal route, the initial step in this study involves creating a mathematical model of the transportation network to be analysed. This model is represented as a directed graph, where each vertex (node) corresponds to a key location such as the depot or main road segments, while each edge signifies the connection between two locations with an associated weight reflecting the actual travel distance. To ensure accuracy and proportionality in measuring the distance between points, the Euclidean distance method is used, employing Eq. (12). This method effectively captures the spatial proximity between nodes and forms the foundation for the k-NN route-search algorithm. After calculating the Euclidean distance between all node pairs and arranging them into a distance matrix, the subsequent step is to compute the Hamiltonian circuit using the k-NN algorithm for each starting node based on the distance data (in km). This process aims to find the shortest closed-loop route that visits each location exactly once before returning to the starting depot.

After establishing the complete distance matrix (see Table 3), the next step is to compute the waste collection truck routes operating across the main road segments of Medan City, represented as Hamiltonian circuits. To evaluate and determine the optimal Hamiltonian circuit, the k-NN algorithm is utilised to identify the most efficient waste transportation routes. The following results display all Hamiltonian circuits generated using the k-NN Algorithm for each starting node. The routes are ordered from the shortest to the longest total distance, with each row representing a complete route (returning to its starting point) along with its respective total travel distance (km) in Table 4.

Table 2. Location Temporary Collection Points (TPSs)

Road	Symbol	V0	V1	V2	V4	V5
Depot	V0	0	2.8	8.6	9.2	9.6
SM Raja	V1	2.8	0	7	9.8	8.4
Gatot Subroto	V2	8.6	7	0	8	3.4
MT Haryono	V3	3.3	5.1	6.6	7	11.2
Balai Kota	V4	9.2	9.8	8	0	8.2
Setia Budi	V5	9.6	8.4	3.4	8.2	0
AH Nasution	V6	4.6	3.8	8.7	6.9	6.4
Adam Malik	V7	10	5.9	4.6	10.4	4.6
Iskandar Muda	V8	8.9	6.1	3.1	8.5	2.4
Kapten Muslim	V9	10	10.9	4.4	8.7	4
Zainul Arifin	V10	6.7	8.2	8.1	4.6	8.6
Pandu	V11	7.8	10.7	7.4	4.2	11.9
Sutomo	V12	6.5	8	8.8	4	9.8
Pemuda	V13	6.3	9.6	6.1	4	6.6
Brigjen Katamso	V14	3.6	4.4	9.4	8.8	7.8
HM Yamin	V15	6.6	7.6	9.4	2.6	10.4

Table 3. Distance matrix (km)

From/to	V0	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15
V0	0.0	2.8	8.6	3.3	9.2	9.6	4.6	10.0	8.9	10.0	6.7	7.8	6.5	6.3	3.6	6.6
V1	2.8	0.0	7.0	5.1	9.8	8.4	3.8	5.9	6.1	10.9	8.2	10.7	8.0	9.6	4.4	7.6
V2	8.6	7.0	0.0	6.6	8.0	3.4	8.7	4.6	3.1	4.4	8.1	7.4	8.8	6.1	9.4	9.4
V3	3.3	5.1	6.6	0.0	7.0	11.2	6.9	10.4	8.5	8.7	4.6	4.2	4.0	4.0	8.8	2.6
V4	9.2	9.8	8.0	7.0	0.0	8.2	6.9	10.4	8.5	8.7	4.6	4.2	4.0	4.0	8.8	2.6
V5	9.6	8.4	3.4	11.2	8.2	0.0	6.4	4.6	2.4	4.0	8.6	11.9	9.8	6.6	7.8	10.4
V6	4.6	3.8	8.7	6.9	6.9	6.4	0.0	5.9	6.1	10.9	8.2	10.7	8.0	9.6	4.4	7.6
V7	10.0	5.9	4.6	10.4	10.4	4.6	5.9	0.0	3.1	4.4	8.1	7.4	8.8	6.1	9.4	9.4
V8	8.9	6.1	3.1	8.5	8.5	2.4	6.1	3.1	0.0	4.0	8.6	11.9	9.8	6.6	7.8	10.4
V9	10.0	10.9	4.4	8.7	8.7	4.0	10.9	4.4	4.0	0.0	8.6	11.9	9.8	6.6	7.8	10.4
V10	6.7	8.2	8.1	4.6	4.6	8.6	8.2	8.1	8.6	8.6	0.0	4.2	4.0	4.0	8.8	2.6
V11	7.8	10.7	7.4	4.2	4.2	11.9	10.7	7.4	11.9	11.9	4.2	0.0	4.0	4.0	8.8	2.6
V12	6.5	8.0	8.8	4.0	4.0	9.8	8.0	8.8	9.8	9.8	4.0	4.0	0.0	4.0	8.8	2.6
V13	6.3	9.6	6.1	4.0	4.0	6.6	9.6	6.1	6.6	6.6	4.0	4.0	4.0	0.0	8.8	2.6
V14	3.6	4.4	9.4	8.8	8.8	7.8	4.4	9.4	7.8	7.8	8.8	8.8	8.8	8.8	0.0	2.6
V15	6.6	7.6	9.4	2.6	2.6	10.4	7.6	9.4	10.4	10.4	2.6	2.6	2.6	2.6	2.6	0.0

Table 4. List of waste collection truck routes and distances

No.	Route: Circuit Hamilton + k-NN Algorithm	Total Distance
1	SM Raja V1 → V0 → V3 → V6 → V8 → V5 → V2 → V9 → V7 → V13 → V15 → V4 → V12 → V10 → V11 → V14 → V1	70.2 km
2	Depot V0 → V1 → V6 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V8 → V5 → V2 → V9 → V7 → V14 → V0	70.9 km
3	Brigjen Katamso V14 → V0 → V1 → V6 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V8 → V5 → V2 → V9 → V7 → V14	71.0 km
4	Adam Malik V7 → V8 → V5 → V2 → V9 → V6 → V1 → V0 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V14 → V7	71.1 km
5	MT Haryono V3 → V0 → V1 → V6 → V8 → V5 → V2 → V9 → V7 → V13 → V15 → V4 → V12 → V10 → V11 → V14 → V3	71.2 km
6	Setia Budi V5 → V8 → V2 → V9 → V7 → V1 → V0 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V14 → V6 → V5	71.5 km
7	AH Nasution V6 → V1 → V0 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V8 → V5 → V2 → V9 → V7 → V14 → V6	71.6 km
8	HM Yamin V15 → V4 → V12 → V10 → V11 → V13 → V0 → V1 → V6 → V3 → V8 → V5 → V2 → V9 → V7 → V14 → V15	71.9 km
9	Sutomo V12 → V4 → V15 → V13 → V0 → V1 → V6 → V3 → V8 → V5 → V2 → V9 → V7 → V14 → V11 → V10 → V12	72.0 km
10	Pandu V11 → V4 → V15 → V13 → V0 → V1 → V6 → V3 → V8 → V5 → V2 → V9 → V7 → V14 → V10 → V12 → V11	72.0 km
11	Pemuda V13 → V15 → V4 → V12 → V10 → V11 → V0 → V1 → V6 → V3 → V8 → V5 → V2 → V9 → V7 → V14 → V13	72.6 km
12	Zainul Arifin V10 → V4 → V15 → V13 → V0 → V1 → V6 → V3 → V8 → V5 → V2 → V9 → V7 → V14 → V11 → V12 → V10	72.8 km
13	Iskandar Muda V8 → V5 → V2 → V9 → V7 → V6 → V1 → V0 → V3 → V13 → V15 → V4 → V12 → V10 → V11 → V14 → V8	74.1 km
14	Balai Kota V4 → V15 → V13 → V12 → V10 → V11 → V8 → V5 → V2 → V9 → V7 → V1 → V0 → V3 → V6 → V14 → V4	74.7 km
15	Kapten Muslim V9 → V8 → V5 → V2 → V7 → V1 → V0 → V3 → V6 → V15 → V4 → V13 → V11 → V10 → V12 → V14 → V9	75.4 km
16	Gatot Subroto V2 → V8 → V5 → V9 → V7 → V1 → V0 → V3 → V6 → V15 → V4 → V13 → V11 → V10 → V12 → V14 → V2	75.5 km

3.3 Calculating CO emissions and consumption

To include the environmental aspect in the optimization model, it is vital to quantify the CO emissions produced along the main road segments of Medan City. Table 5 shows the total CO emission loads recorded during the morning, afternoon, and evening periods across fifteen major road segments that form part of the waste collection routes, with the depot acting as both the starting and ending point. The emission values, expressed in grams per hour (g/hour), form the basis for calculating the specific emission rate of each route. These quantified emissions are then incorporated into the RO Green-CVRP model as the environmental cost component, allowing for the assessment of trade-offs between operational efficiency and environmental performance in urban waste transport planning.

Table 5. Distance-complete CO emission data from major road segments in Medan

Road Segment	CO Emission Load (Morning, g/hour)	CO Emission Load (Afternoon, g/hour)	CO Emission Load (Evening, g/hour)
V0	0	0	0
V1	38372.76	51272.86	29881.49
V2	22494.86	23723.91	17592.77
V3	25232.92	33812.03	19956.85
V4	38031.26	43292.3	24578.63
V5	34182.62	39141.72	20248.87
V6	28531.95	37971.65	20657.35
V7	27352.49	29517.52	19249.36
V8	37558.31	41014.62	25523.97
V9	34820.17	44299.28	25218.64
V10	33967.07	39328.68	21175
V11	36852.75	47651.86	28257.51
V12	39657.49	47723.94	26783.84
V13	36553.97	45509.3	26519.6
V14	34662.08	45650.02	21993.05
V15	25140.74	27106.61	17462

Example for a simulation:

Route 1 was chosen as the simulation case because it is the shortest route, previously calculated using the k-NN algorithm within the Hamiltonian circuit, with a total distance of 70.2 km. The route followed is as follows:

SM Raja (V1) → Depot (V0) → MT Haryono (V3) → AH Nasution (V6) → Iskandar Muda (V8) → Setia Budi (V5) → Gatot Subroto (V2) → Kapten Muslim (V9) → Adam Malik (V7) → Pemuda (V13) → HM Yamin (V15) → Balai Kota (V4) → Sutomo (V12) → Zainul Arifin (V10) → Pandu (V11) → Brigjen Katamso (V14) → SM Raja (V1) (see Table 3).

To calculate the total green cost for each Hamiltonian circuit generated by the k-NN algorithm $k = 1$, the following equation is applied:

$$C = \alpha . D + \beta . E \tag{36}$$

where, *C* represents the total green cost of the route, *D* denotes the total distance travelled (km), *E* corresponds to the total CO emission (g/hour) accumulated along the route, and α, β weighting coefficients representing the relative importance of distance and emissions.

To determine the total CO emission (g/hour) for each route: (1) Identify all road segments included in the Hamiltonian circuit. (2) Sum the corresponding CO emission loads for the respective time period (morning, afternoon, or evening), and (3) multiply the results by the weighting factor β and add them to the distance-based cost weighted by $\alpha . D$.

Thus, for each route *r*:

$$E_{r,t} = \sum_{i \in R_r} E_{i,t} \tag{37}$$

$$C_{r,t} = \alpha D_r + \beta E_{r,t} C = \alpha . D + \beta . E \tag{38}$$

where, $t \in \{\text{morning, afternoon, evening}\}$, $E_{r,t}$ denotes the emission load (g/hour) on road segment *i* during time period *t*, and represents the total route distance. A normalization factor $\alpha = 1, \beta = 0.0001$ is applied where necessary to ensure that distance and emission values are comparable in scale.

From route 1 (see Table 4), the total carbon emission for the route is calculated for the morning period using Eq. (37):

$$\begin{aligned} E_{morning} &= 38372.76 + 0 + 25232.92 + 28531.95 \\ &+ 37558.31 + 34182.62 + 22494.86 \\ &+ 34820.17 + 27352.49 + 36553.97 \\ &+ 25140.74 + 38031.26 + 39657.49 \\ &+ 33967.07 + 36852.75 + 34662.08 \\ &= 520460.44 \text{ g CO} \end{aligned}$$

with the total green cost of the route using Eq. (38):

$$C_{morning} = (1 \times 70.2) + (0.0001 \times 520460.44) = 122.25$$

The CO values provided by the Environmental Agency are reported in grams per hour (g/hour), representing the temporally averaged emission intensity of each major road segment. Because the vehicle completes each segment within the corresponding hourly period, these values are treated as segment-level emission intensities rather than physical emission factors. To ensure unit consistency in the optimization objective, distance (km) and emission intensity (g/hour) are normalized using weighting coefficients α and β, producing a dimensionless green cost index. The model therefore does not interpret g/hour as a physical total emission quantity, but as a normalized environmental penalty used for multi-objective evaluation. This is consistent with common practice in Green-VRP studies employing normalized environmental indices.

Table 6. The sum of the node-based emission rates collected from point measurements (g/h) at each road segment

No.	Route Segment	Distance (km)	Sum of Node-Based CO Emission Rates (g/h) Morning	Sum of Node-Based CO Emission Rates (g/h) Afternoon	Sum of Node-Based CO Emission Rates (g/h) Evening	Green Cost (Morning)	Green Cost (Afternoon)	Green Cost (Evening)
1	V1	70.2	520.460	596.266	349.199	122.25	129.83	105.12
2	V0	70.9	520.460	596.266	349.199	122.95	130.53	105.82
3	V14	71.0	520.460	596.266	349.199	122.95	130.53	105.82
4	V7	71.1	520.460	596.266	349.199	123.17	130.75	106.04
5	V3	71.2	520.460	596.266	349.199	123.27	130.85	106.14
6	V5	71.5	520.460	596.266	349.199	123.56	131.14	106.43
7	V6	71.6	520.460	596.266	349.199	123.66	131.24	106.53
8	V15	71.9	520.460	596.266	349.199	123.96	131.54	106.83
9	V12	72.0	520.460	596.266	349.199	124.06	131.64	106.93
10	V11	72.0	520.460	596.266	349.199	124.06	131.64	106.93
11	V13	72.6	520.460	596.266	349.199	124.66	132.24	107.53
12	V10	72.8	520.460	596.266	349.199	124.86	132.44	107.73
13	V8	74.1	520.460	596.266	349.199	126.11	133.69	108.98
14	V4	74.7	520.460	596.266	349.199	126.71	134.29	109.58
15	V9	75.4	520.460	596.266	349.199	127.41	134.99	110.28
16	V2	75.5	520.460	596.266	349.199	127.51	135.09	110.38

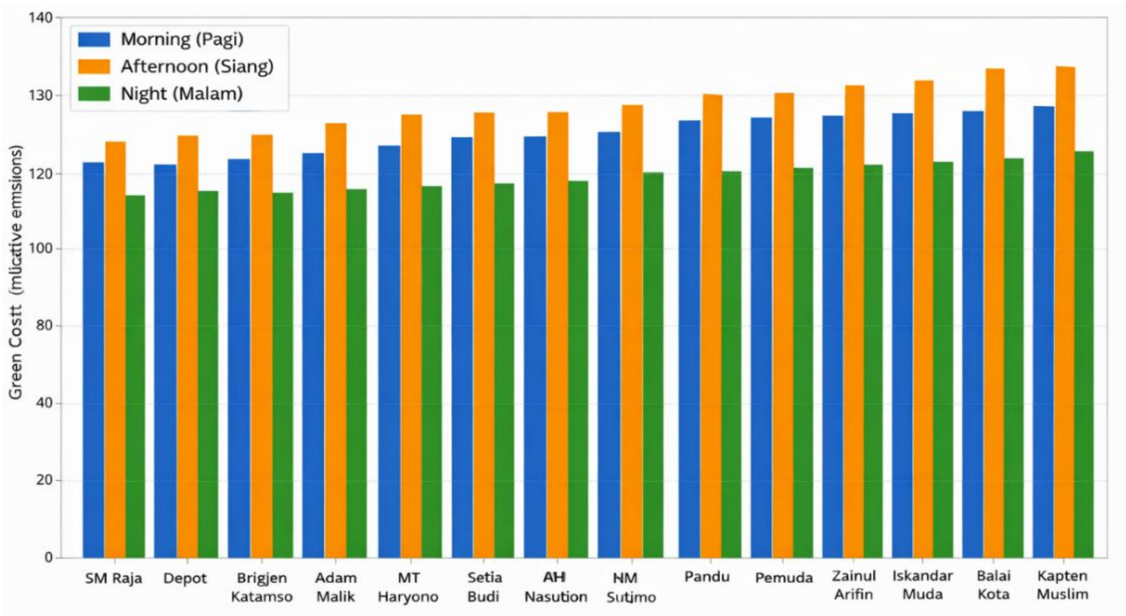

Figure 1. Comparison of green cost for each route

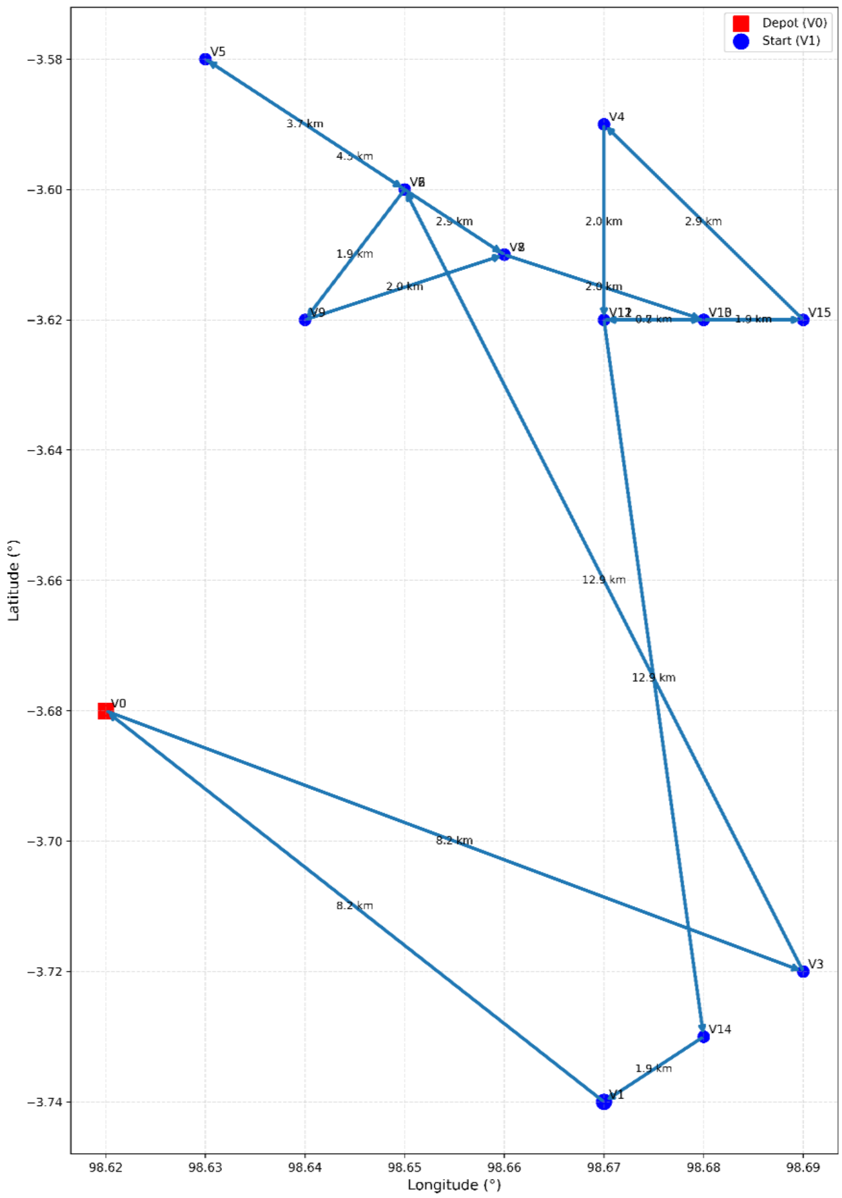

Figure 2. The directed graph generated from the Hamiltonian circuit with SM Raja (route 1)

Based on Table 6, the processed distance matrix and CO emission load data for the sixteen main road segments in Medan City, a total of sixteen Hamiltonian circuits were generated. Each circuit represents a possible waste collection truck route derived using the k-NN algorithm (k = 1). Every circuit begins at a specific road segment (for example, SM Raja, Depot, Adam Malik, etc.) and returns to the same starting point after visiting all other segments exactly once.

The emission values in Table 6 do not represent total emissions along each route. Instead, they are the aggregated CO emission rates (g/h) from all road segments included in each Hamiltonian circuit. These values reflect the relative emission intensity of different routes, not the actual grams emitted during traversal.

The calculation results in Figure 1 show that the total route distance varies from 70.2 km to 75.5 km. The overall emission load per route stays nearly the same because each route covers the same streets, only in a different visiting order. The average total emissions per route are about 520.460 g CO (morning), 596.266 g CO (afternoon), and 349.199 g CO (evening).

During the morning period, the average CO emission level remains moderate since traffic volume has not yet reached its peak. The total emission per route is around 520.460 g CO, while the morning green cost ranges from 122.25 (Route SM Raja) to 127.51 (Route Gatot Subroto). This shows that a mere 5 km increase in route length can raise the green cost by about 5 points, owing to the linear relationship between distance and total cost. The SM Raja route demonstrates the highest efficiency, with a total distance of 70.2 km and the lowest green cost of 122.25, making it the most suitable option for morning operations.

In the afternoon, CO emissions increase significantly due to heavier traffic congestion, higher air temperatures, and longer vehicle idle times. The total CO emission reaches 596.266 g per route, and the green cost rises by approximately 6–7 points compared to the morning. This increase emphasizes the substantial impact of the emission component ($\beta \cdot E$) on the overall green cost, despite the emission weighting coefficient β remaining relatively small (0.0001).

At night, traffic volume drops significantly, signal waiting times are shorter, and temperature conditions become more stable. As a result, the total CO emissions decrease to 349.199 g per route, and the green cost reduces substantially, ranging from 105.12 to 110.38. This decrease of approximately 15–20 points compared to daytime operations shows that nighttime routing is more environmentally friendly and energy-efficient. The SM Raja route again exhibits the best performance 105.12, followed by the Depot and Brigjen Katamso routes with nearly identical figures. Therefore, shifting operational hours from the afternoon to the evening could cut the total green cost by about 20%, without changing the route structure.

3.4 Directed graph illustration and carbon emission consumption

After determining the optimal routes using the k-NN method based on the Euclidean distance matrix, the next step is to visualize the results as a directed graph. This graph shows the movement of waste collection trucks from one point to another in sequence until they return to the depot, following the principles of a Hamiltonian circuit.

Besides illustrating the connections between route points, the directed graph also shows the CO emission loads for each road segment. Therefore, the illustration not only displays the waste collection network's structure but also indicates how emission intensity varies across different operational periods (morning, afternoon, and evening). This visualisation offers essential insight into the connection between route length, travel direction, and environmental impact. For clarity, a directed graph illustration is shown for route 1, depicting the most efficient route configuration.

Based on Figure 2, each node represents a major road segment in Medan City, while each directed edge indicates the sequential movement of the waste collection truck from one point to another until returning to the depot, thereby forming a closed Hamiltonian circuit. The graph is supplemented with quantitative data on both the inter-node distances (km) and the corresponding CO emission loads generated along the route. Based on the results, the total distance covered by the truck in this route is 70.2 km, with total CO emissions of 493.411 g (morning), 597.016 g (afternoon), and 345.098 g (evening).

Visually, the direction of the arrows in the graph indicates an efficient travel pattern, where road segments such as MT Haryono – Depot – AH Nasution – Brigjen Katamso serve as the main connectors to other critical locations such as Gatot Subroto, Setia Budi, and Pandu. This structure demonstrates that the SM Raja route exhibits a compact and stable network configuration, achieving high efficiency in terms of both travel distance and carbon emission consumption, thus representing the most optimal and robust route among all alternatives analyzed in this study.

3.5 Price of robustness based on green cost (morning–afternoon–evening)

Using the data from Table 6 (green cost per route), a robust cost simulation was conducted for the best-performing route (SM Raja). This route was chosen as the primary example, and the analysis was subsequently generalized to all other routes. For each Γ value:

$$Z_{robust}(\Gamma) = Z_{morning} + \frac{\Gamma}{6}\left(Z_{afternoon} - Z_{morning}\right) \tag{39}$$

Eq. (39) is a linear interpolation between two scenario costs (morning and afternoon). That treats robustness as moving the objective linearly toward the afternoon scenario, which is not what the Bertsimas–Sim budgeted uncertainty model does. Bertsimas–Sim assumes a set of independent uncertain parameters (here: per-segment emission deviations). For a fixed decision (one particular route), the robust counterpart evaluates the worst-case combination of up to Γ parameters deviating simultaneously to their worst-case values. This is combinatorial, not a simple interpolation between two scenario totals.

Suppose for a route r, we have:

- Nominal emission contributions per segment $\widehat{e_i}$ (e.g., morning values),
- Maximum deviation $\widetilde{e_i}$ (e.g., afternoon-morning when afternoon > morning),
- Weight β converting emission to green-cost units,
- Route distance Dr with weight α.

Define nominal green cost:

$$Z_{nom}(\Gamma) = \alpha Dr + \beta \sum_{i \in r} \widehat{e_i} \tag{40}$$

For a fixed binary route (the x_{ij} are known), Bertsimas–Sim worst-case extra cost is obtained by selecting the Γ largest per-parameter deviations.

We used the node emissions from Table 5 and the SM Raja route node sequence you provided. Using α = 1, β = 0.0001, and the morning nominal per-node sums, the correct robust green costs for the SM Raja route are:

Nominal (Γ = 0): Z_{nom} = 119.54
Γ = 1 → 120.83
Γ = 2 → 121.93
Γ = 3 → 123.01
Γ = 4 → 123.96
Γ = 5 → 124.90
Γ = 6 → 125.80

So, the green cost increases from 119.54 to 125.80 when Γ moves from 0 → 6 (an increase of ≈ 5.24%), not ≈ 6.2% as reported under interpolation.

Table 7 presents the performance of sixteen Hamiltonian route candidates (V0–V15) evaluated under different levels of robustness, represented by the budget of uncertainty Γ, ranging from 0 to 6. Each route is characterized by its total travel distance (in km) and the corresponding robust objective value $Z(\Gamma)$, which incorporates both distance and the modelled uncertainty in carbon emissions. When Γ = 0, the model operates under nominal conditions without considering uncertainty, producing the baseline objective value for each route. As Γ increases, the model becomes progressively more conservative by accounting for higher degrees of demand and emission variability, resulting in larger objective values. Routes with shorter distances generally yield lower objective values across all Γ levels, reflecting better carbon-efficient performance. For example, Route V1, with a distance of 70.2 km, consistently produces the lowest objective values (from 119.54 at Γ = 0 to 125.80 at Γ = 6), indicating that it remains the most efficient option even under the highest uncertainty. Conversely, longer routes such as V4, V9, and V2 exhibit larger objective values due to their extended travel distances and greater exposure to uncertainty. The monotonic increase of $Z(\Gamma)$ across all routes confirms the expected behavior of the RO model: higher uncertainty levels lead to higher total costs. Overall, Table 7 illustrates how route rankings remain relatively stable across uncertainty budgets, with shorter routes consistently outperforming longer ones, thereby validating the model's ability to maintain carbon-efficient route selection even under uncertain operational conditions.

Table 7. Green cost $Z_{\mathrm{robust}}(\Gamma)$ for each route

No.	Route	Distance (km)	Z0 (Γ = 0)	Z1 (Γ = 1)	Z2 (Γ = 2)	Z3 (Γ = 3)	Z4 (Γ = 4)	Z5 (Γ = 5)	Z6 (Γ = 6)
1	V1	70.2	119.54	120.83	121.93	123.01	123.96	124.90	125.80
2	V0	70.9	120.24	121.53	122.63	123.71	124.66	125.60	126.50
3	V14	71.0	120.24	121.53	122.63	123.71	124.66	125.60	126.50
4	V7	71.1	120.44	121.73	122.83	123.91	124.86	125.80	126.70
5	V3	71.2	120.54	121.83	122.93	124.01	124.96	125.90	126.80
6	V5	71.5	120.84	122.13	123.23	124.31	125.26	126.20	127.10
7	V6	71.6	120.94	122.23	123.33	124.41	125.36	126.30	127.20
8	V15	71.9	121.24	122.53	123.63	124.71	125.66	126.60	127.50
9	V12	72.0	121.34	122.63	123.73	124.81	125.76	126.70	127.60
10	V11	72.0	121.34	122.63	123.73	124.81	125.76	126.70	127.60
11	V13	72.6	121.94	123.23	124.33	125.41	126.36	127.30	128.20
12	V10	72.8	122.14	123.43	124.53	125.61	126.56	127.50	128.40
13	V8	74.1	123.44	124.73	125.83	126.91	127.86	128.80	129.70
14	V4	74.7	124.04	125.33	126.43	127.51	128.46	129.40	130.30
15	V9	75.4	124.74	126.03	127.13	128.21	129.16	130.10	131.00
16	V2	75.5	124.84	126.13	127.23	128.31	129.26	130.20	131.10

4. CONCLUSIONS

This study examined a green routing framework for municipal waste collection in Medan City by formulating an RO for the Green-CVRP model and applying a k-NN-based heuristic to generate Hamiltonian circuits for green cost evaluation. Although the full RO Green-CVRP formulation (including capacity constraints, flow variables, and Bertsimas–Sim uncertainty parameters) was presented for conceptual completeness, the computational results were obtained using a green TSP-style routing procedure that employs k-NN as a neighbourhood–ordering heuristic. The conclusions reflect heuristic route evaluation rather than a fully solved CVRP model. The findings indicate that the SM Raja route offers the shortest travel distance and lowest green cost, while temporal analysis shows that nighttime operations yield the lowest emission levels, suggesting that time-window adjustments may provide substantial environmental benefits even without modifying route structure.

A post-hoc interpretation of robustness, derived from the Bertsimas–Sim framework, illustrates that increasing Γ from 0 to 6 raises green cost by approximately 6.2%, highlighting the classical trade-off between efficiency and protection against traffic and emission variability, although this analysis represents an interpolation rather than a full robust optimisation implementation. Several limitations of the present study must be acknowledged, including the exclusive focus on CO emissions, the use of homogeneous vehicles, the lack of real-time or high-resolution traffic data, and the fact that capacity, depot, and robust constraints were not activated in the computational results, such that the model functions as a green TSP heuristic rather than an operational robust CVRP.

Future work should focus on solving the full RO Green-CVRP model using exact or metaheuristic optimisation, incorporating real-time GPS or IoT-based traffic feeds, modelling additional pollutants such as CO_2, NO_x, and $PM_{2.5}$, and extending the framework to multi-depot, multi-period, stochastic, or dynamically adaptive routing systems to support more realistic and resilient green urban waste collection planning.

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NOMENCLATURE

Indices

$V = \{0, 1, 2, ..., n\}$	Set of waste collection points (TPS/locations)
$K = \{1, ..., m\}$	Set of vehicles
E	Set of edges

Parameters

c_{ij}	Distance or energy cost associated with travelling through the edge (i, j)
e_{ij}	Carbon emission (CO/CO_2) generated on the edge (i, j)
d_i	Waste demand at the collection point (TPS)
Q_k	Capacity of vehicle k
$dist_{ij}$	Distance between node i and node j
Γ	Box-interval uncertainty parameter
θ_i, s_i	Robust deviation variable representing uncertainty in waste demand
α, β	Weighting coefficients of the objective function (operational and emission costs)
λ	weighting/penalty factor for transport of waste (or cost proportional to load × distance). Explain units and why it is separate from α
T_{ij}	Travel time on edge (i, j)

Decision Variables

$x_{ij}^k \in \{0,1\}$	1 if vehicle k travels along edge (i, j); 0 otherwise
$y_i^k \in \{0,1\}$	1 if vehicle k serves waste collection point i; 0 otherwise
f_{ij}^k	Quantity of waste transported by vehicle k from node i to node j
u_i^k	Sequencing variable used to eliminate Hamiltonian sub-tours
s_i^k	Slack variable representing robust deviation in demand