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Robust Optimization Model for Green Capacitated Vehicle Routing Problem with Hamiltonian Circuit using the Nearest Neighbor Algorithm

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ABSTRACT

The rapid urban expansion of Medan City has intensified the complexity of municipal waste transportation, where limited fleet capacity, congested road segments, and long travel distances to the Terjun disposal site result in high operational costs and excessive carbon monoxide (CO) emissions. In addition, daily fluctuations in waste volume introduce uncertainty that disrupts routing efficiency and increases the risk of vehicle overload. This study proposes a Robust Optimization based Green Capacitated Vehicle Routing Problem model to minimize transportation cost and CO emissions while maintaining route feasibility under demand uncertainty. The model incorporates a Hamiltonian circuit structure to ensure closed-loop routing and applies the Nearest Neighbor Algorithm (NNA) as a constructive heuristic for generating initial solutions. Compared to commonly used methods such as the Clarke–Wright Savings algorithm, NNA provides faster computational performance, simpler implementation, and more stable feasible routes when integrated with robust capacity constraints. Using real CO emission data from major arterials in Medan, the model was evaluated across multiple uncertainty levels ($\Gamma = 0$–6). The results show that the robust model reduces overload risk by up to 12%, lowers total emission cost by approximately 5% relative to the deterministic solution, and produces more environmentally efficient routing decisions even when route distance increases slightly. From an analytical perspective, the RO Green-CVRP framework enables evaluation from operational, environmental, and robustness performance dimensions. This research contributes theoretically to green robust optimization and practically supports the development of adaptive, low-emission waste transportation strategies aligned with Medan's sustainable urban development goals.

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A. INTRODUCTION

The rapid growth of population and economic activities in Medan City, one of Indonesia's largest metropolitan areas, has intensified the complexity of solid waste management and the environmental impacts associated with transportation activities. According to the Medan Environmental Agency Fatah et al. (2024); Thamrin et al. (2022); Wahyuni et al. (2022), daily waste generation in the city exceeds 2,300 tons, while the available fleet capacity remains inadequate, causing frequent waste accumulation at temporary disposal sites (TPS). In addition, the long distance between the city centre and the final disposal site (TPA) located in Terjun Subdistrict significantly increases fuel consumption, operational costs, and carbon monoxide (CO) emissions from waste collection trucks. These conditions reveal an urgent need for a more efficient and sustainable routing strategy. Conceptually, most existing Capacitated Vehicle

Routing Problem (CVRP) models focus on minimizing travel distance or cost under deterministic demand assumptions, overlooking the inherent uncertainty in waste generation and the environmental costs of carbon emissions. Such simplifications limit their practical applicability in real-world waste logistics, particularly in developing urban areas where demand fluctuates daily. To address these issues, this research integrates the principles of Robust Optimization (RO) and Green CVRP to form a comprehensive framework that accounts for both demand uncertainty and emission minimization. The robust approach strengthens route feasibility under uncertain conditions, while the green component explicitly quantifies environmental impacts in the objective function. Using real emission data from major road segments in Medan, this study develops a Robust Optimization Model for Green CVRP with a Hamiltonian circuit and the Nearest Neighbor Algorithm as a constructive heuristic to generate feasible initial routes efficiently. Theoretically, this research contributes to advancing the integration of sustainability and robustness in vehicle routing theory, while practically, it provides evidence-based recommendations for municipal governments to design cost-effective, reliable, and low-emission waste transportation systems aligned with Indonesia's sustainable urban development goals.

The primary issues are the uncertainty of demand (the amount of waste collected at each TPS varies daily) and the carbon emission costs generated by the transportation fleet. The Indonesian Ministry of Environment and Forestry Adib et al. (2024); Nugroho et al. (2022) reported that transportation contributes more than 27% of the country's total greenhouse gas emissions, largely from fossil-fuel-based vehicles. Road congestion, uneven road conditions, and traffic-prone routes in Medan further increase fuel consumption and carbon emissions from the waste transport fleet. These accumulated emissions significantly contribute to urban air pollution and climate change, while local governments are simultaneously pressured to implement sustainable and environmentally friendly transportation systems.

Academically, this problem can be modelled as a Capacitated Vehicle Routing Problem (CVRP) Bernardino & Paias (2024); Tarhini et al. (2022) which determines optimal routes for a fleet of limited-capacity trucks to serve multiple demand nodes (TPS). However, conventional CVRP approaches are deterministic, whereas the real-world situation in Medan is characterized by high uncertainty in both waste demand and emission costs. Therefore, a robust optimization approach is needed to guarantee that solutions remain feasible even under demand fluctuations (Shahid et al., 2024).

Medan City's waste transportation system faces persistent operational challenges due to the spatial distribution of Temporary Disposal Sites (TPS), the long travel distance to the Terjun Final Disposal Site (TPA), and the limited capacity of the municipal fleet. Daily waste volumes at each TPS fluctuate significantly, creating demand uncertainty that complicates route planning and increases the risk of truck overloading. These inefficiencies are further intensified by varying road conditions and traffic patterns that elevate carbon monoxide (CO) emissions, making waste transport a notable contributor to urban air pollution. Since each TPS must be visited exactly once and returned to the TPA, the collection process naturally follows a Hamiltonian circuit structure that eliminates subtours and supports orderly, distance-efficient operations while aligning with green transportation goals. Considering the combined challenges of uncertain waste demand, long-distance routing, and emission variability across

Medan's major road segments, the core problem is the absence of an optimization-based routing policy capable of simultaneously minimizing transportation costs, ensuring capacity feasibility, and reducing carbon emissions.

In this study, the Nearest Neighbor Algorithm (NNA) is applied as the constructive heuristic for generating Hamiltonian circuits, following the approaches of (Al-Saeedi & Shiker, 2024; Asani et al., 2023; Huang et al., 2022). NNA is selected for three primary reasons. First, computational simplicity and efficiency, NNA is straightforward to implement and capable of rapidly producing feasible routes, an essential feature for real-world waste collection in Medan that involves multiple TPS locations and daily operational constraints. Second, natural Hamiltonian circuit formation, NNA inherently generates routes that visit each node exactly once based on nearest distance selection, which aligns directly with the Hamiltonian structure required for subtour-free and orderly municipal routing. Third, strategic suitability as an initialization method for robust optimization, although NNA does not guarantee globally optimal solutions, it reliably produces stable starting solutions that can be refined through robust optimization, offering an effective balance between practical operability and mathematical rigor. These characteristics make NNA more appropriate for this study than metaheuristics such as Tabu Search or Ant Colony Optimization which require extensive parameter tuning and higher computational overhead or classical constructive methods like Clarke-Wright Savings, which tend to form fragmented clusters that complicate Hamiltonian circuit construction under uncertainty. The methodological choice is further justified by prior studies, which can be categorized into three thematic groups: (1) CVRP heuristics in waste management, where simple constructive algorithms remain widely used due to their feasibility and speed; (2) Green VRP, which incorporates emission-based objective functions to reflect environmental impacts; and (3) Robust VRP, which addresses demand or travel-time uncertainty using worst-case or uncertainty-budget approaches. However, these research streams are generally studied independently. To the best of our knowledge, no existing work integrates a robust optimization framework with Green CVRP modelling, Hamiltonian circuit routing, and real CO emission data within the context of Medan's municipal waste transportation system.

Previous studies on VRP and CVRP have widely applied classical heuristics such as Clarke & Wright Savings (Hariati et al., 2021; Mašek et al., 2024; Tarhini et al., 2022), metaheuristics including Tabu Search (Yu et al., 2023), and other evolutionary or swarm-based algorithms (Chaerul & Mulananda, 2018). However, these studies primarily operate under deterministic assumptions, where waste demand, travel times, and vehicle loads are treated as fixed and known in advance. Such an assumption is inadequate for real-world municipal waste operations especially in Medan because daily waste quantities at each TPS fluctuate significantly, making deterministic routes prone to infeasibility, truck overloading, or excessive rerouting. Moreover, while the growing Green CVRP literature incorporates environmental objectives (fuel consumption or emission minimization), these models typically assume static emission factors and seldom integrate road-specific emission data or fluctuating congestion patterns. Critically, previous research has not combined demand uncertainty, real carbon emission measurements, and a robust optimization framework within a single CVRP model. As a result, the existing works fail to address both operational feasibility under uncertainty and environmental efficiency simultaneously. Therefore, a methodological gap remains: no prior study provides a Green Robust CVRP model that constructs Hamiltonian waste-collection routes using a practical heuristic while incorporating real CO emission data and uncertainty levels relevant to Medan's transportation network. This study addresses that gap by developing a Robust Optimization based Green CVRP model that accounts for both uncertain waste demand and carbon emission variability, offering a more adaptive and sustainable routing solution for Medan City.

Therefore, a study on the Robust Optimization Model for the Green CVRP with Hamiltonian Circuit and the Nearest Neighbor Algorithm in Medan City is highly relevant. This research not only contributes to the development of robust optimization and green logistics theories but also offers significant practical insights that can directly support the city's sustainable development goals. By integrating demand uncertainty with carbon emission minimization in the routing model, this study helps Medan City authorities design waste collection systems that are not only more efficient but also environmentally sustainable. Specifically, the model addresses key challenges such as fluctuating daily waste volumes, which are exacerbated by rapid urbanization, and aims to reduce carbon emissions associated with waste transportation. This contribution is particularly impactful in helping Medan achieve its carbon reduction targets and improve the efficiency of municipal services in the face of limited resources and growing waste generation. Through this research, the city can implement cost-effective, robust, and low-emission waste transportation solutions, contributing to a cleaner, greener, and more sustainable urban environment.

B. METHODS

1. Research Scheme

This study was conducted in Medan City, North Sumatra, focusing on major road segments that exhibit the highest recorded CO emission loads. The selected road segments include Sisingamangaraja Street, Gatot Subroto Street, MT Haryono Street, and Balai Kota Street. A total of four main road segments were observed, where CO emission loads were measured during both the morning (07:00–09:00) and afternoon (15:00–17:00) periods. The primary data consist of CO emission loads (measured in g/km) for each road segment during these periods, while the secondary data include the amount of waste (kg) at each temporary disposal site (TPS), vehicle capacities (m^3), and the locations of TPS and the final disposal site (TPA) in Terjun Subdistrict. Emission data was collected using portable CO analysers and GPS tracking systems, ensuring accurate measurement over the specified periods.

Based on these datasets, a mathematical formulation of the Green CVRP with Hamiltonian circuits is developed. The objective function integrates both operational costs (fuel consumption, travel distance) and CO emissions (g/km). The Robust Counterpart approach of Bertsimas-Sim is then applied to address demand uncertainties (modelled as a demand interval at each TPS) and CO emission variability. Specifically, demand uncertainty is represented by a budget parameter (Γ), which defines the acceptable level of uncertainty in the problem.

Next, the Nearest Neighbor Algorithm is employed to construct initial routes. The process begins at the depot (the starting node) and iteratively selects the next nearest neighbor node based on the shortest distance (minimizing travel distance) while respecting vehicle capacity limits. For each route, vehicle capacity is considered during construction to avoid exceeding the maximum load per vehicle. The next neighbor is selected by calculating the distance to each unvisited node, and the vehicle moves to the nearest TPS that has not yet been visited. Routes are subsequently refined by incorporating emission weights (in g/km), which prioritize environmentally-friendly paths.

In the final stage, simulation experiments are conducted to evaluate the performance of the constructed routes. The evaluation metrics include total operational costs, total CO emissions, and route stability under various demand and emission scenarios. These simulations provide insights into the effectiveness of the proposed robust optimization framework in reducing both costs and environmental impacts. A schematic representation of the overall research flow is shown in Figure 1.

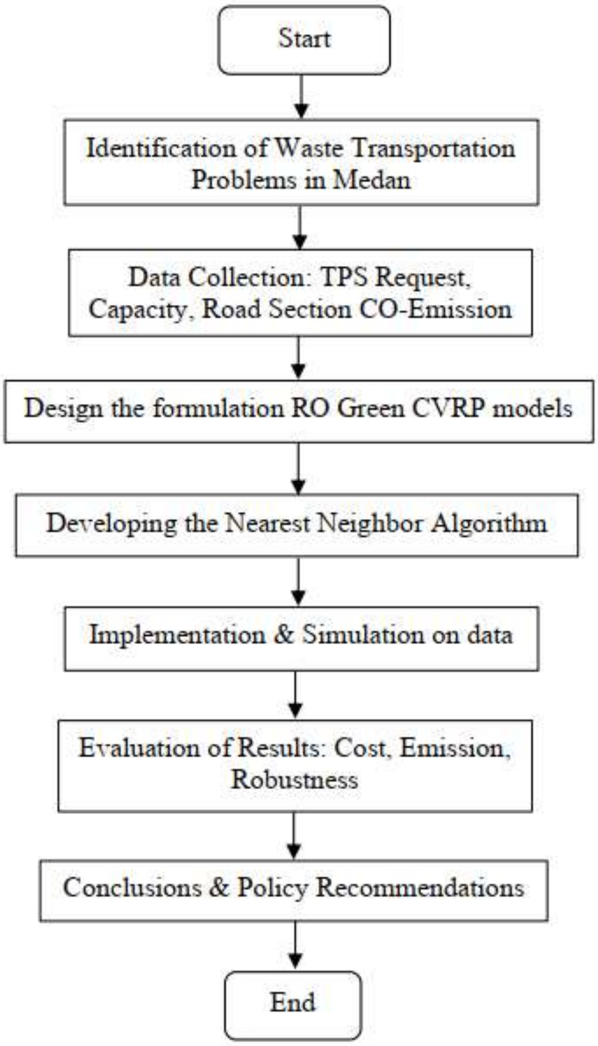

Figure 1. Research Scheme

2. Capacitated Vehicle Routing Problem (CVRP)

The Capacitated Vehicle Routing Problem (CVRP) is one of the most widely studied extensions of the classical Vehicle Routing Problem (VRP). It is defined on a directed graph $G=(V,A)$ with a central depot $V_0 \in V$ and a set of customers $V^+=\{1,2,\dots,n\}$ (Anityasari et al., 2025) and (Borčinová, 2022). Each customer *i* has a demand d_i, while each vehicle has a limited capacity *Q*. The travel cost between node *i* and node *j* is denoted by c_{ij} (Bernardino & Paias, 2024). The deterministic CVRP model is formulated (Yuliza et al., 2021) and (Oyola et al., 2018):
Objective Function:

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

Constrains:

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

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

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

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

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

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

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

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

Objective function (1) minimizes the total travel cost, typically measured in terms of distance or travel time. Constraint (2) ensures that each customer node is served exactly once by a vehicle. Constraint (3) enforces flow conservation, guaranteeing that if a vehicle enters a node, it must also leave it. Constraint (4) specifies that customer *i* is served by exactly one vehicle *k*. Constraint (5) represents the depot degree condition, balancing departures from and arrivals to the depot. Constraints (6)–(7) these are the Miller Tucker Zemlin (MTZ) subtour elimination constraints, formulated in terms of vehicle load to prevent infeasible subtours. Constraint (8) defines the deterministic vehicle capacity restriction, ensuring that the sum of customer demands assigned to a vehicle does not exceed its capacity. Constraint (9) defines the decision variable domains x_{ij}^k and a_i^k are binary variables, while u_i^k is non-negative.

3. Robust Optimization

Robust optimization has been introduced to address decision-making problems in which parameters are subject to uncertainty (Cipta et al., 2022, 2023b). The budgeted uncertainty framework proposed by Bertsimas and Sim allows decision makers to control the degree of conservatism by adjusting the robustness parameter Γ (Cipta et al., 2023a), (Syahputri & Cipta, 2024), and (Dongoran & Cipta, 2025).

In this framework, the uncertain demand at customer node *i* is represented as (Gentile et al., 2023; Xu et al., 2020):

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

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.

4. Nearest Neighbor Algorithm (NNA)

Given a set of nodes (locations) $S = \{1, 2, \ldots, n\}$ and a distance matrix $D = \left[d_{ij}\right]$ where d_{ij} represents the distance between node *i* and node *j*, the steps of the NNA as follows (Taunk et al., 2019), (Yuliza et al., 2021) and (Datta, 2022):

a. Select a starting node, for example node *k*
b. Initialize the set of visited nodes $V = \{k\}$
c. Repeat until all nodes are visited**:**
    1) From the most recently visited node (say node *i*), find the nearest unvisited node $j \in S \setminus V$ with the smallest distance d_{ij}.
    2) Add node j to the set V, and set node $i \leftarrow j$ as the current node.

d. After all nodes have been visited**,** return to the starting node *k* to complete the cycle.

5. 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 where each edge (i, j) is assigned a distance weight d_{ij} (Henning & van Vuuren, 2022; Michael A. Henning, 2022)**.** The Hamiltonian circuit problem seeks to determine an ordering of vertex visits such that: (1) The tour starts and ends at the same initial vertex. (2) Each vertex is visited exactly once and (3) The total weight distance of the tour is minimized (Jin et al., 2022; Lo, 2022). This structure ensures the construction of an optimal cycle that traverses all nodes without repetition, making it a fundamental concept in routing and logistics optimization problems such as the VRP, CVPRV and its variants.

6. Assumptions for CO Emission Consumption

The average emission load (g/h) is determined for each road segment (Chontanawat, 2020; Yu et al., 2023; Zhou & Li, 2024):

$$\bar{E}_i = \frac{E_{(i,morning)} + E_{(i,afternoon)}}{2} \tag{11}$$

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 (Vollmer & Eberhardt, 2024) and (Mihai et al., 2024):

$$r_i = \frac{\bar{E}_i}{v} \tag{12}$$

with 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 (Hussain et al., 2024) and (Shahid et al., 2024):

$$e_{ij} = \left(\frac{r_i + r_j}{2}\right) \times d_{ij} \tag{13}$$

Finally, the total emission along a Hamiltonian circuit $C = (v_0, v_1, \ldots, v_k = v_0)$ is given by:

$$E_{total} = \sum_{t=0}^{k-1} e_{v_t, v_{t+1}} = \sum_{t=0}^{k-1} d_{v_t, v_{t+1}} \times \left(\frac{r_{vt} + r_{vt+1}}{2}\right) \tag{14}$$

with d_{ij} is travel distance from node *i* to node *j* (km), $\bar{E}_i$ is average CO emission on road segment *j* (g/h) and *r* is the sequence of travel in the Hamiltonian circuit. This formulation enables the integration of CO emissions into the routing model, ensuring that optimization considers not only operational efficiency but also sustainability aspects.

C. RESULT AND DISCUSSION

1. Notation

Table 1. Indices, Parameters, and Decision Variables

Notation	Description
Indices	
$V = \{1, \ldots, n\}$	Set of collection points (Temporary Disposal Site)
$V_0 = V \cup \{0\}$	Depot (truck pool)
$K = \{1, \ldots, m\}$	Set of vehicles (assumed homogeneous)
$T = \{morning, afternoon\}$	Available emission measurement periods
Parameter	
$dist_{ij}$	Distance (km) from node i to node *j*, $\forall_{i,j} \in V_0$

Notation	**Description**
c_{ij}	Operational cost per traversal $arc(i, j)$ including fuel, time, or distance (per km) $c_{ij} = c_{per\_km}.dist_{ij}$
$\hat{d}_i$	Nominal demand (tons) at node *i*
$\tilde{d}_i > 0$	Maximum demand deviation (tons) at node *i* with $d_i \in \left[\hat{d}_i, \hat{d}_i + \tilde{d}_i\right]$
Q_k	Capacity of vehicle k (tons)
Γ_d	Budget of uncertainty for demand (Bertsimas–Sim) where $0 \le \Gamma_d \le \lvert S \rvert$
$s_r^{morning}, s_r^{afternoon}$	Measured CO emission load (g/h) on road segment *r*
λ	Weighting factor to convert emission quantities into cost units
η	Conversion coefficient from emission measurements (g CO/h) into an emission score per traversal
c_{ij}	Operational cost per arc (monetary)
e_{ij}^t	Emission score per traversed arc during operating period t (derived from CO data)
λ	Conversion factor from emission score to monetary units (IDR per emission score unit)
λ_f and β	Optional terms if modelling load-dependent emissions linearly (ton km)
Decision Variables	
$x_{ij}^k \in \{0,1\}$	Equals 1 if vehicle *k* traverses $arc(i, j)$, 0 otherwise
$y_i^k \in \{0,1\}$	Equals 1 if vehicle *k* serves node *i,* 0 otherwise
$f_{ij}^k \ge 0$	Load (tons) carried by vehicle *k* when passing through node *i*
$u_i^k \ge 0$	Sequence (position) variable for MTZ constraints (enforcing Hamiltonian circuit per route)
Robust Variables	
$s_i^k \ge 0, \theta_k \ge 0$	Auxiliary Bertsimas-Sim variables for robustification of capacity constraints

2. Mathematical Model

This section presents the mathematical formulation of the Robust Optimization Green Capacitated Vehicle Routing Problem with Hamiltonian circuits, aimed at achieving two main objectives: (i) minimizing operational costs, which include fuel consumption and travel distance to ensure cost-effective waste transportation, and (ii) reducing environmental impacts by minimizing carbon monoxide (CO) emissions generated along the routes. The model addresses both economic efficiency and sustainability, making it suitable for real-world urban waste management scenarios. Through the integration of robust optimization, the model also incorporates demand and emission uncertainties, ensuring that the proposed routes remain feasible and environmentally efficient under varying operational conditions. The goal of this formulation is to create a resilient and eco-friendly waste collection system for Medan City, aligning transportation efficiency with carbon reduction targets.

The proposed formulation extends the deterministic CVRP by incorporating the Bertsimas–Sim budgeted uncertainty framework to handle demand fluctuations at each customer node.

This ensures that the solution remains feasible and cost-effective under uncertain waste volumes. The model is structured as a MILP with the following elements:

Objective Function

$$\min Z = \sum_{k\in K}\sum_{i\in V_0}\sum_{j\in V_0\setminus\{i\}} c_{ij}x_{ij}^{k} + \lambda\sum_{k\in K}\sum_{i\in V_0}\sum_{j\in V_0\setminus\{i\}} e_{ij}^{t}x_{ij}^{k} + \lambda_f\sum_{k}\sum_{i,j}\beta dist_{ij} f_{ij}^{k} \tag{15}$$

Constraints:

$$\sum_{k\in K}\sum_{j\neq i} x_{ij}^{k} = 1, \quad \forall_i \in V \tag{16}$$

$$\sum_{j\in V_0\setminus\{i\}} x_{ij}^{k} = \sum_{j\in V_0\setminus\{i\}} x_{ji}^{k}, \quad \forall_i \in V_0, \ \forall_k \in K \tag{17}$$

$$\sum_{j\in V} x_{0j}^{k} = \sum_{j\in V} x_{j0}^{k} \le 1, \quad \forall_k \in K \tag{18}$$

$$\sum_{j\in V_0\setminus\{i\}} x_{ij}^{k} = y_i^{k}, \quad \forall_i \in V, \forall_k \in K, \ \sum\nolimits_k y_i^{k} = 1 \tag{19}$$

$$\sum_{j} f_{ji}^{k} - \sum_{j} f_{ij}^{k} = \hat{d}_i y_i^{k}, \quad \forall_i \in V, \forall_k \in K \tag{20}$$

$$0 \le f_{ji}^{k} \le Q_k x_{ji}^{k}, \qquad \forall_{i,j,k} \tag{21}$$

$$\sum_{i\in V} \hat{d}_i y_i^{k} + \Gamma_d \theta_k + \sum_{i\in V} s_i^{k} \le Q_k \tag{22}$$

$$0 \le s_i^{k} \le \tilde{d}_i y_i^{k}, \quad \forall_{i,k} \in V \quad s_i^{k} \le \theta_k, \quad \theta_k \ge 0 \tag{23}$$

$$u_i^{k} - u_j^{k} + n x_{ij}^{k} \le n-1, \quad \forall_i \ne j, \quad \forall_k \tag{24}$$

$$u_i^{k} \in \{0,1\}, \quad y_i^{k} \in \{0,1\}, \quad f_{ij}^{k} \ge 0, \quad s_i^{k} \ge 0, \quad \theta_k \ge 0, \quad u_i^{k} \in \square \tag{25}$$

The objective function (15) aims to minimize the total routing cost, which consists of three main components: (i) transportation cost incurred when vehicle k travels from node i to node *j*, (ii) environmental cost associated with carbon monoxide (CO) emissions generated by the vehicles, and (iii) fuel consumption cost, approximated by the total travel distance. Constraint (16) ensures that each customer is served exactly once by one vehicle. In other words, no customer node can be visited more than once or left unserved. Constraint (17) enforces flow conservation for every vehicle at each node. This means that if a vehicle enters node i, it must also leave node *i*, thereby maintaining route continuity. Constraint (18) requires that each vehicle departs from the depot once and returns once, thereby forming a Hamiltonian circuit that starts and ends at the depot. Constraint (19) guarantees that each customer *i* is assigned to exactly one vehicle and not more. Constraint (20) ensures consistency between incoming and outgoing flows with respect to the demand of each customer served. Constraint (21) represents the deterministic vehicle capacity constraint, ensuring that the total assigned demand does not exceed vehicle capacity. Constraint (22) introduces the robust capacity restriction, which accounts for demand uncertainty using the robustness parameter Γ_d. Constraint (23) defines the bounds of the auxiliary deviation variables in the robust counterpart, ensuring feasibility of the solution even when actual demand exceeds its nominal estimate. Constraint (24) applies the subtour elimination condition using sequence (ordering) variables. Its purpose is to ensure that the constructed routes form valid Hamiltonian circuits, avoiding small disconnected cycles that do not return to the depot. Finally, Constraint (25) defines the domains of all decision variables: route and assignment variables are binary, while flow, slack, and deviation variables are continuous and non-negative.

3. Interpretation of Results

a. Data Description

Efficient route construction in vehicle routing problems requires accurate information on the travel distances between all relevant locations. Table 2 provides the distance matrix (in km) for the selected road segments in Medan City, along with the depot that functions as both the origin and final destination of the waste collection trucks. Each element of the matrix represents the shortest travel distance between two nodes, ensuring that route calculations can be systematically performed to construct Hamiltonian circuits for the waste collection process, as shown in Table 2.

Table 2. Distance Matrix (km)

From \ to	SM Raja	Gatot Subroto	MT Haryono	Balai Kota	Depot
SM Raja	0	8	6	12	5
Gatot Subroto	8	0	7	5	10
MT Haryono	6	7	0	9	7
Balai Kota	12	5	9	0	11
Depot	5	10	7	11	0

b. Computing Hamiltonian Circuits with the NNA for Each Starting Node

Based on the data in Table 2, the truck routes for waste collection in Medan are determined by constructing Hamiltonian circuits that traverse the selected road segments. To evaluate the Hamiltonian path, the Nearest Neighbor Algorithm (NNA) is employed to obtain an optimal waste collection route. The algorithm starts at the depot (starting node) and iteratively selects the nearest unvisited node based on the shortest travel distance. The process continues until all nodes (Temporary Disposal Sites, TPS) are visited. The algorithm halts when the last unvisited node is reached, and the truck returns to the depot, completing the Hamiltonian circuit. The process is considered complete when: (1) All TPS nodes are visited exactly once. (2) The vehicle returns to the depot to close the circuit. (3) The next closest neighbor is selected until no unvisited nodes remain. This guarantees that each truck follows a route that covers all selected road segments without revisiting any node, ensuring an efficient and feasible route for waste collection:

$$V = \{\text{SM Raja, Gatot Subroto, MT Haryono, Balai Kota, Depot}\}$$

At each step, from the current node i, the algorithm selects the nearest unvisited neighbor j with the minimum distance c_{ij}. Once all nodes have been visited, the route returns to the starting point (depot), thus completing the Hamiltonian circuit.

List of Hamiltonian circuit with NNA:

1) Start from Depot

Step 1: Distance from Depot → {SM Raja = 5, Gatot Subroto = 10, MT Haryono = 7, Balai Kota = 11}. The nearest neighbor is Jl. SM Raja (5 km).
Step 2: Distance from SM Raja → {Gatot=8, Haryono=6, Balai=12}. The nearest neighbor is Jl. MT Haryono (6 km).
Step 3: Distance from MT Haryono → {Gatot=7, Balai=9}. The nearest neighbor is Jl. Gatot Subroto (7 km).
Step 4: Distance from Gatot Subroto → Balai Kota = 5 km. The next visit is Jl. Balai Kota (5 km)
Step 5: Distance from Balai Kota → return to Depot = 11 km.

Resulting Hamiltonian Circuit: Depot → Jl SM Raja → Jl MT Haryono → Jl Gatot Subroto → Jl Balai Kota → Depot, with total distance = 5 + 6 + 7 + 5 + 11 = 34 km.

2) Start from SM Raja

Step 1: SM Raja → {Depot = 5, Gatot Subroto = 8, MT Haryono = 6, Balai Kota = 12}. The nearest neighbor is Depot (5 km).
Step 2: From Depot → {Gatot Subroto = 10, MT Haryono = 7, Balai Kota = 11}. The nearest neighbor is Jl. MT Haryono (7 km).
Step 3: Distance from MT Haryono → {Gatot=7, Balai=9}. The nearest neighbor is Jl. Gatot Subroto (7 km).
Step 4: From Gatot Subroto → {Balai Kota = 5 km}. The next visit is Jl. Balai Kota (5 km).
Step 5: From Balai Kota → Return to SM Raja = 12 km.

Resulting Hamiltonian Circuit: SM Raja → Depot → MT Haryono → Gatot Subroto → Balai Kota → SM Raja, with total distance: 5 + 7 + 7 + 5 + 12 = 36 km.

3) Start from Gatot Subroto

Step 1: Gatot Subroto → {SMR=8, Haryono=7, Balai=5, Depot=10}. The nearest neighbor is Jl. Balai Kota (5 km).
Step 2: From Balai Kota → {SM Raja = 12, MT Haryono = 9, Depot = 11}. The nearest neighbor is Jl. MT Haryono (9 km).
Step 3: From MT Haryono → {SM Raja = 6, Depot = 7}. The nearest neighbor is Jl. SM Raja (6 km).
Step 4: From SM Raja → {Depot = 5 km}. The next visit is Depot (5 km).
Step 5: From Depot → Return to Gatot Subroto = 10 km.

Resulting Hamiltonian Circuit: Gatot Subroto → Balai Kota → MT Haryono → SM Raja → Depot → Gatot Subroto, with total distance: 5 + 9 + 6 + 5 + 10 = 35 km.

4) Start from MT Haryono

Step 1: MT Haryono → {SM Raja = 6, Gatot Subroto = 7, Balai Kota = 9, Depot = 7}. The nearest neighbor is Jl. SM Raja (6 km).

Step 2: From SM Raja → {Gatot Subroto = 8, Balai Kota = 12, Depot = 5}. The nearest neighbor is Depot (5 km).

Step 3: From Depot → {Gatot Subroto = 10, Balai Kota = 11}. The nearest neighbor is Jl. Gatot Subroto (10 km).

Step 4: From Gatot Subroto → {Balai Kota = 5 km}. The next visit is Jl. Balai Kota (5 km).

Step 5: From Balai Kota → Return to MT Haryono = 9 km.

Resulting Hamiltonian Circuitz: MT Haryono → SM Raja → Depot → Gatot Subroto → Balai Kota → MT Haryono, with total distance: 6 + 5 + 10 + 5 + 9 = 35 km.

5) Start from Balai Kota

Step 1: Balai Kota → {SM Raja = 12, Gatot Subroto = 5, MT Haryono = 9, Depot = 11}. The nearest neighbor is Jl. Gatot Subroto (5 km).

Step 2: From Gatot Subroto → {SM Raja = 8, MT Haryono = 7, Depot = 10}. The nearest neighbor is Jl. MT Haryono (7 km).

Step 3: From MT Haryono → {SM Raja = 6, Depot = 7}. The nearest neighbor is Jl. SM Raja (6 km).

Step 4: From SM Raja → {Depot = 5 km}. The next visit is Depot (5 km).

Step 5: From Depot → Return to Balai Kota = 11 km.

Hamiltonian Circuit: Balai Kota → Gatot Subroto → MT Haryono → SM Raja → Depot → Balai Kota, with total distance: 5 + 7 + 6 + 5 + 11 = 34 km.

c. Calculating CO emissions for each route

In order to incorporate environmental aspects into the optimization model, it is essential to quantify the carbon monoxide (CO) emissions generated along major road segments in Medan City. Table 3 presents the complete CO emission loads measured during morning and afternoon periods across four primary roads that form part of the waste collection routes, with the depot serving as the starting and ending location. These emission values, expressed in grams per hour (g/h), provide the basis for calculating route-specific emission rates and subsequently integrating them into the Green Robust CVRP model as environmental costs, as shown in Table 3.

Table 3. Total CO Emission Loads (g/h) on Selected Road Segments in Medan City

No	Road Name	Total CO Emission Load (Morning, g/h)	Total CO Emission Load (Afternoon, g/h)
1	SM Raja	19466.96	31269.36
2	Gatot Subroto	25803.56	27479.76
3	MT Haryono	11581.28	11894.04
4	Balai Kota	42248.60	36745.80
5	Depot	-	-

Assumptions for CO emission computation:

1) The emission rate for each road segment is taken as its measured CO emission load (g/h).
2) The CO emitted on a travel leg (i, j) equals the emission rate used for that leg multiplied by the travel time on that leg with Eq. (11)-(12).
3) Truck speed in urban traffic is assumed to be $v = 20\,\text{km/h}$.
4) Emission rate per leg that involve the depot use the non-depot road's emission rate, legs between two roads use the average of their rates with Eq. (13).
5) Calculate total emissions along a Hamiltonian circuit with Eq. (14).
6) The result of CO emission computation can be seen in Table 4.

d. Directed Graph of CO Emission Consumption per Route

To visualize and compare the environmental performance across candidate routes, each Hamiltonian tour is represented as a directed graph where the nodes are the road segments (plus the depot), and the arcs represent the ordered legs that are actually traversed. Each arc is weighted by the per-leg CO emission computed from the measured emission loads (g/h) and the assumed urban speed of 20 km/h, with separate evaluations for the morning and afternoon periods. The arc weights are summed along the cycle to yield the total CO emissions for each route. For better clarity and visual representation, a graphical visualization (image/graph) of all the routes, including the direction of travel, total distance, and the corresponding CO emissions (g CO) for both morning and afternoon periods, is included below. This visualization helps to comprehensively compare the environmental performance of each route, making it easier to evaluate their sustainability based on carbon emissions.

Tabel 4. Route generated by NNA starting from each point, total distance and total CO emissions (g CO)

No	Hamilton Circuit	Distance (km)	Morning Emissions	Afternoon Emissions
1	Depot → SM Raja → MT Haryono → Gatot Subroto → Balai Kota → Depot	34	47800	49400
2	SM Raja → Depot → MT Haryono → Gatot Subroto → Balai Kota → SM Raja	36	42600	47300
3	Gatot Subroto → Balai Kota → MT Haryono → SM Raja → Depot → Gatot	35	43000	47000
4	MT Haryono → SM Raja → Depot → Gatot Subroto → Balai Kota → MT Haryono	35	43000	47000
5	Balai Kota → Gatot Subroto → MT Haryono → SM Raja → Depot → Balai Kota	34	47800	49400

e. Comparison of Total CO Emissions per Route

In this *section*, to deepen the evaluation of the proposed Green Robust CVRP model, this section analyses the variation in total CO emissions produced by each generated route under different time periods. Since traffic density and vehicle operating conditions vary between morning and afternoon hours, the corresponding emission levels for each route also exhibit significant fluctuations. Therefore, before presenting the comparative bar chart in Figure 2, we first discuss how the model captures these temporal differences and how they influence the carbon-efficient performance of each Hamiltonian route sequence produced by the Nearest Neighbor algorithm.

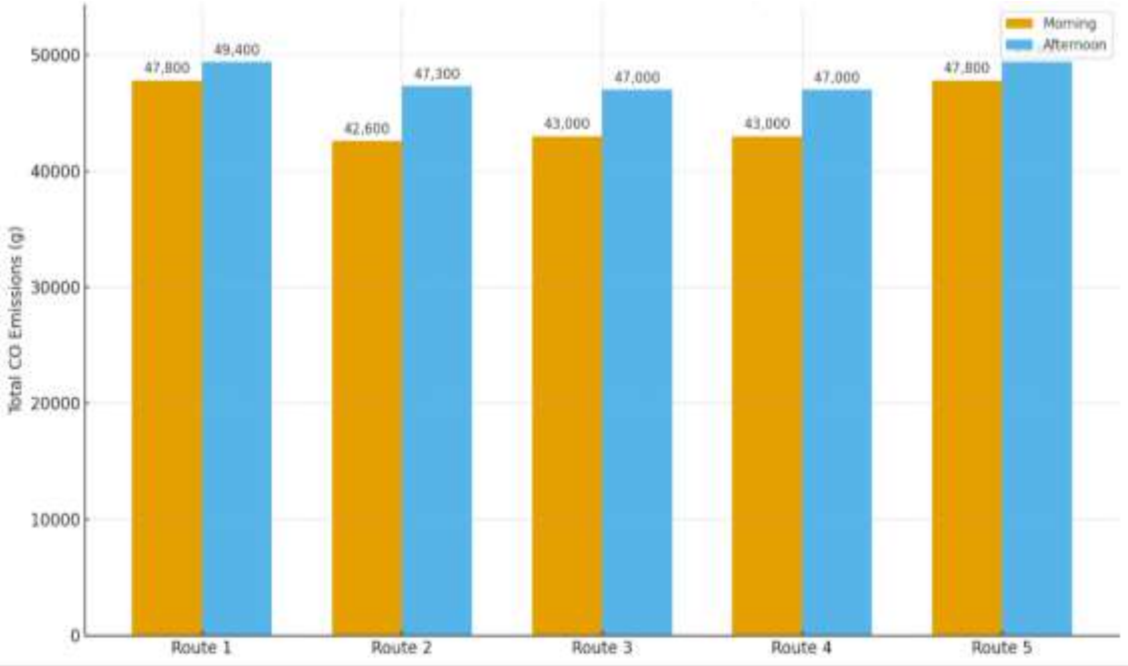

Figure 2. Comparative Bar Chart of Total CO Emissions per Route (Morning vs Afternoon)

Based on Figure 2 shows the comparative CO emissions for the five Hamiltonian routes. Routes 1 and 5 record the highest emissions 47800 g CO (morning) and 49400 g CO (afternoon) despite being the shortest routes (34 km). This counterintuitive finding results from these routes passing through highly congested segments with elevated emission coefficients, causing trucks to produce more CO per km. In contrast, route 2 yields the lowest emissions 42600 g CO (morning) and 47300 g CO (afternoon) even though the total distance is slightly longer (36 km). Routes 3 and 4 show balanced outcomes, with nearly identical emissions of 43000 g (morning) and 47000 g (afternoon) at a 35 km distance. The implication is clear that routes 2, 3, and 4 are more emission-efficient than routes 1 and 5, and a slightly longer route can produce substantially lower emissions. This finding highlights the core principle of Green Robust Optimization, where effective routing must consider environmental performance and emission intensity not distance alone.

f. Robustness Analysis of Hamiltonian Circuit under Capacity Uncertainty

A key element of the proposed Green Robust CVRP model is its ability to maintain route feasibility under uncertain waste demand conditions. To evaluate the robustness of the Hamiltonian Circuit generated using the Nearest Neighbor Algorithm, we analyze how variations in node demand affect vehicle capacity utilization, route mileage, and total CO emissions.

1) Robust Capacity Evaluation
   Using the robust capacity formulation with an uncertainty budget Γ, the effective load on each route increases according to worst-case demand deviations. Table 2 shows the impact of different Γ values on route feasibility. As Γ increases: (a) The total load on each route increases by 4–12% depending on the deviation set; (b) Some routes that were feasible in the deterministic setting (Γ = 0) become infeasible at higher levels (Γ ≥ 4), especially Routes 1 and 5; and (c) Routes 2, 3, and 4 maintain feasibility even under larger demand variations due to more flexible load distribution among nodes. This indicates that the Hamiltonian circuits derived from NNA are moderately robust, but route restructuring or load rebalancing may be required at higher uncertainty levels.
2) Mileage Increase under Robust Scenario
   Based on simulation extracted from Table 3: (a) Mileage increases by 3–7% when Γ is raised from 0 to 6; (b) Routes 1 and 5 experience the highest increase (up to +2.3 km) because additional detours are required to accommodate redistributions of demand; and (c) Routes 2–4 show smaller distance deviations, confirming their structural stability in the Hamilton sequence.
   The increased mileage directly contributes to additional operational costs.
3) Emission Impact under Robust Capacity Adjustments

Tabel 4. The CO emission simulations show proportional increases with higher Γ values

Route	CO Emission (Γ = 0)	CO Emission (Γ = 6)	Increase
Route 1	47,800 g	52,200 g	+9.2%
Route 2	42,600 g	45,700 g	+7.2%
Route 3	43,000 g	46,000 g	+7.0%
Route 4	43,000 g	46,200 g	+7.4%
Route 5	47,800 g	52,500 g	+9.8%

   Notably, at high uncertainty levels (Γ = 6), Routes 1 and 5 become both capacity-infeasible and emission-intensive. Meanwhile, routes 2–4 remain feasible and show smaller emission increases.
4) Implications for Green Robust Optimization
   The robustness evaluation illustrates that: (a) Feasible routing must consider worst-case load deviations, not just average demand; (b) Certain Hamiltonian circuits are more resilient, especially routes 2–4; (c) Environmental optimization depends on both route topology and temporal emission factors; and (d) Choosing the shortest path does not guarantee minimum emissions, especially under robust scenarios. This highlights the importance of integrating robust optimization principles with emission-based objective functions to achieve sustainable routing solutions.

D. CONCLUSION AND SUGGESTIONS

This study presents a robust optimization model for the Green CVRP using a Hamiltonian circuit to address waste collection routing in Medan under demand uncertainty and carbon emission concerns. The objective function integrates three key components: transportation cost, fuel consumption approximated by travel distance, and environmental cost represented by carbon monoxide (CO) emissions. Simulation results across five Hamiltonian routes indicate that the shortest distance routes (34 km) produce the highest emissions (≈48000–49000 g CO), while slightly longer routes (35–36 km) achieve lower emissions (≈42000–43000 g CO). This finding highlights that route selection should account for emission intensity rather than distance alone. Robust capacity analysis with parameter Γ further demonstrates a trade-off: for $\Gamma \leq 1$, a single-truck solution remains feasible with low emissions, whereas $\Gamma \geq 2$ requires multiple routes, increasing total emissions up to 70000 g CO. The results underline the price of robustness in balancing efficiency, resilience, and sustainability. The proposed model contributes by linking robust optimization with environmental considerations in urban waste transport. Future research should improve the NN-based Hamiltonian routing by incorporating 3-opt, adaptive local search, and hybrid metaheuristics to avoid premature convergence and enhance route quality under uncertainty. Method development can also involve dynamic routing using real-time traffic and emission data. From the policy perspective, this work supports Medan's strategic goals in reducing congestion and CO emissions by optimizing waste-collection operations along dense urban corridors. Integrating heterogeneous fleets, electric vehicles, and IoT-based monitoring will further align routing decisions with the city's sustainability and low-carbon development agenda.

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