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Research Paper

A Simulation Based Metaheuristics for Capacitated Vehicle Routing Problem

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Abstract

Waste collection and transportation are essential elements of effective waste management. However, despite their importance, previous studies have highlighted several challenges, such as routing inefficiencies and environmental concerns. This study seeks to develop an optimized approach for waste collection and transportation under conditions of demand uncertainty, capacity limitations, and traffic constraints, through the application of a simheuristics-based method. The methodology utilizes a simheuristics approach, integrating a Genetic Algorithm (GA) to determine optimal routing solutions, while employing Discrete Event Simulation (DES) to incorporate key economic, environmental, and social variables. Data were obtained from field experiments and Google Maps, and assumptions regarding capacity requirements, distances and collection points, transportation cost components, and road conditions were established to ensure the reliability of the simulation results. The application of the simheuristics approach effectively reduces total transportation costs by approximately 51%, while also significantly minimizing environmental impacts. This research contributes to the academic literature by presenting an innovative method that strengthens existing waste collection strategies with an emphasis on sustainability. Additionally, it offers valuable insights for waste management policy, enabling the optimization of waste collection without exceeding capacity limits.

Keywords: Waste collection and transportation; CVRP; Simheuristics

1. Introduction

The rapid and continuous growth of urban populations has significantly contributed to the escalating problem of municipal solid waste generation [1], [2], [3], [4],[5]. Municipal solid waste is characterized as a complex and multifaceted waste stream generated primarily from two societal sectors: the household and residential sector, which contributes approximately 55–65% of the total volume, and the commercial or industrial sector, which accounts for around 35–45% [6], [7]. In recent decades, the environmental impacts associated with municipal solid waste have garnered increasing global attention [8]. Moreover, solid waste is a critical issue in the context of sustainable development, as it is closely linked to the three pillars of sustainability: economic, environmental, and social dimensions [6].

The challenge of achieving sustainable solid waste management has become a global concern. If not addressed effectively, it can pose serious risks to both public health and the environment [2]. To improving sustainability in solid waste management requires effective strategies in waste management that consider economic, eco-friendly, and social acceptability [2], [6], [9]. The effective and efficient design of municipal solid waste management networks can significantly

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reduce investment, infrastructure, operational, and recycling costs, while also enhancing overall sustainability [10].

Municipal solid waste management comprises a series of activities, including waste generation, separation, storage, collection, transportation, treatment, recycling, and final disposal, carried out with careful consideration for public health, economic efficiency, environmental conservation, and responsiveness to community needs [1], [11], [12], [13], [14]. Within the solid waste management process, waste collection and transportation are among the most critical, complex, and challenging operational activities. Transportation, in particular, plays a vital role in these stages and is estimated to account for 50–80% of the total cost of solid waste management [8], [15], [16], [17], [18].

The collection, transportation, and disposal of solid waste constitute a crucial component of sustainable solid waste management strategies in many municipalities. Despite involving significant expenditures, these activities often receive insufficient attention [4], [19]. Collection activities encompass not only the gathering of recyclable solid waste but also its transportation to designated locations where the collection vehicles are subsequently emptied [20], [21].

The environmental consequences of inadequate waste management, encompassing air and water pollution as well as greenhouse gas emissions, are significant. With the rapid pace of urbanization, communities are increasingly challenged to achieve sustainability objectives that integrate economic, environmental, and social dimensions [3], [22]. Although waste management practices have advanced, several enduring challenges persist. Inefficient routing contributes to elevated operational costs and increased carbon emissions, while fluctuations in waste generation complicate collection scheduling and the efficient allocation of resources [4]. To tackle these pressing challenges, optimizing waste collection and transportation systems has become a critical priority [2]. Implementing efficient routing strategies can significantly reduce operational costs and environmental impact, while simultaneously enhancing the quality of service provided to communities [1].

As environmental regulations become increasingly stringent, municipalities are required to address compliance with sustainability standards, necessitating strategic waste management approaches that integrate sustainable practices. In numerous research studies, the waste collection problem within a given area is modeled as a Vehicle Routing Problem (VRP) to develop efficient and effective collection routes [23]. The VRP iss classified as an NP-hard combinatorial optimization problem, making it inherently difficult and complex to solve using exact methods. Consequently, heuristic and metaheuristic approaches are commonly employed to obtain near-optimal solutions efficiently [24].

Several studies have addressed the VRP in waste collection while considering sustainability aspects. For example, Akhtar et al. [15] developed a Backtracking Search Algorithm utilizing smart bins. Their research incorporated economic sustainability by seeking optimal routing solutions, improving fuel efficiency, and reducing fuel costs. Environmental sustainability was addressed by minimizing CO_2 emissions generated during the waste collection process. Qiao et al. [3] incorporated the triple bottom line aspects of sustainability—economic, environmental, and social by combining two metaheuristic methods: Particle Swarm Optimization (PSO) and Tabu Search (TS). The study aimed to minimize the total cost of waste collection, reduce CO_2 emissions, and lower penalty costs.

In certain cases, the Vehicle Routing Problem (VRP), aimed at optimizing vehicle routes, must account for uncertainties such as fluctuating demand and travel time, which may vary over time. As a result, the VRP can be characterized as stochastic or even dynamic in nature [25], [26], [27]. To deal whit this, simheuristics approaches have become popular in academia [28]. In the context of waste collection, the application of simheuristics remains highly limited. Although considerable efforts have been made to optimize waste collection and transportation using VRP and metaheuristic techniques, most existing studies primarily emphasize economic factors. Few have incorporated sustainability considerations, especially in addressing demand uncertainty within waste collection systems. To bridge this gap, the present study proposes a simulation-based metaheuristic approach GA-

DES that integrates economic, environmental, and social dimensions while accounting for capacity constraints. GA will obtain route optimization results based on the distance from point i-j, and vehicle capacity.

2. Literature Review

This section explores the application of simheuristics in optimization problems, with a particular focus on the Capacitated Vehicle Routing Problem (CVRP). The aim of this review is to examine prior research, identify existing gaps, and provide a foundation for the methodological development of this study. Simheuristics, which integrate simulation with metaheuristic approaches such as GA, have proven effective in managing uncertainties in waste collection and transportation contexts.

Research indicates that traditional deterministic methods often fall short in adapting to the dynamic nature of waste collection logistics, highlighting the necessity of a more flexible approach. For instance, research by Gruler et al. [25] has demonstrated the integration of environmental and economic objectives in waste management; however, these studies primarily emphasize single-objective functions. In contrast, this review highlights the need for a multidimensional framework that incorporates economic, environmental, and social dimensions—commonly known as the Triple Bottom Line (TBL) in the context of sustainability.

By addressing these gaps, this review lays the groundwork for exploring how simheuristics can improve efficiency and promote sustainability in waste collection. Moreover, foundational theories such as Combinatorial Optimization help elucidate the complex interdependencies inherent in vehicle routing and resource allocation, underscoring the relevance of this study's approach to contemporary waste management challenges.

VRP is defined as the task of determining optimal routes for a fleet of vehicles to deliver goods to multiple locations, with the objective of minimizing transportation costs while adhering to constraints such as vehicle capacity and delivery time windows [29]. The CVRP, a specific variant of the VRP, further constrains vehicles to a limited capacity [1], [2], [15], [30]. This study focuses on the CVRP, addressing the complexities associated with wood waste transportation under capacity constraints. A simheuristics-based optimization algorithm is employed as the independent variable, with its impact on waste collection performance evaluated through total cost, carbon emissions, and overall operational efficiency—collectively serving as the dependent variables.

Simheuristic algorithms are specialized simulation-optimization approaches aimed to efficiently handle optimization problems with uncertainty [30]. Simheuristics play a significant role due to their simplicity and relatively low computational overhead compared to conventional metaheuristics, making them an attractive approach for solving stochastic combinatorial optimization problems [31]. They are widely applied in addressing routing and scheduling challenges. The following outlines the application of simheuristics across various categories of studied objects.

2.1. *Simheuristics in Home Healthcare*

Clapper et al. [32] applied simheuristics by integrating evolutionary algorithms with dynamic simulation-based optimization methods to address the routing and scheduling of Home Health Care (HHC) services in the Netherlands. HHC is a widely adopted service in Western countries. The time window constraint was a critical consideration, as it directly relates to the timely delivery of services as requested by clients. The author in his research, developed an Optimal Computing Budget Allocation (OCBA)-guided simheuristics model adopted from Chen & Lee [33]. In contrast to Clapper et al., [32], with the same object of HHC, Chen & Lee [33] used migrating birds optimization and stochastic simulation to perform HHC routing and scheduling problem (HHCRSP). While [34] focused on a single objective function—minimizing travel time, shift duration, and waiting time. Chen and Lee [33] aimed to reduce both travel and service costs. In addressing the social objective, they also incorporated penalty costs for violations of specified time windows. The constraints considered in their study included time windows, skill requirements, and working hours. Simheuristics have also been applied to parallel machine scheduling problems [31], where iterated greedy algorithms were used for optimization and Monte Carlo simulation for evaluating uncertainty. This approach effectively enhanced the objective of minimizing total processing time.

2.2. Simheuristics in Omnichannel Ritel and Electric Vehicel VRP

Bayliss et al. [35] addressed the Capacitated Vehicle Routing Problem (CVRP) in the context of omnichannel retail by employing Local Search Neighborhoods (LSN) for optimization and DES for system simulation. Their study focused on a single-objective function, emphasizing the economic aspect, specifically minimizing total travel distance and cost. Additionally, Keskin et al. [36] applied simulation-based heuristics to solve the Electric Vehicle Routing Problem (EVRP) with time windows, incorporating stochastic waiting times at recharging stations.

2.3. Simheuristics in Waste Collection

The primary constraint considered is vehicle capacity. Simheuristics have also been applied to the VRP within the context of waste collection processes [25], [37], [38]. Gruler et al. [25] employed a biased randomized optimization model combined with Monte Carlo simulation, incorporating a triple bottom line objective function—minimizing total costs and carbon emissions, maximizing customer satisfaction, and reducing work overload. In contrast, Tirkolaee et al. [37] utilized an ant colony optimization algorithm alongside Monte Carlo simulation to minimize total operating costs, including transportation expenses. Yazdani et al. [38] applied a GA integrated with stochastic simulation to address the collection of construction and demolition waste. Further details are presented in **Table 1** below.

Based on the literature review, studies that incorporate the triple bottom line framework remain limited. Specifically, in the context of municipal waste, only one study has been identified that applies a simheuristics approach while considering the triple bottom line dimensions [25]. Simheuristics are well-suited for addressing uncertainty and stochastic elements in both objective functions and constraints, which are common in real-world problems. This approach facilitates the development of more realistic and adaptive solutions to dynamic changes [28]. Furthermore, Gruler et al. [25] employed biased randomization techniques to enhance optimization, demonstrating that this method can yield rapid solutions with reasonably high quality. However, there remains a research gap in integrating the triple bottom line perspective with the application of simheuristics to waste-related problems. To address this, the present study advances simheuristics by integrating GA with DES.

Compared to the biased randomized method [25], GA are capable of producing more optimal solutions for complex VRP. Moreover, biased randomized approaches often yield highly variable solutions, whereas GA offers greater stability. In comparison to Monte Carlo methods [25], DES is more appropriate for transportation networks due to its alignment with discrete event dynamics [39]. The integration of GA and DES is well-suited for addressing the CVRP, as capacity constraints can be effectively incorporated during the crossover process to generate new populations. Additionally, GA is widely recognized for its effectiveness in solving complex optimization problems [38].

3. Problem Description

Indonesia ranks among the world's leading furniture-exporting countries, with an export value of USD 1.9 billion that increased by 33% to USD 2.5 billion in 2021. Wood waste represents the third-largest contributor to this sector. At the end of its lifecycle, wood waste is regarded as a valuable resource due to its potential for recycling and energy recovery [36]. Wood waste encompasses a range of materials, including forestry residues, sawdust, wood chips, and urban wood waste originating from construction and demolition activities [40], [41] (**Figure 1a**). To achieve optimal waste collection and transportation points, it is essential to establish integration between waste generators and end-users or processing facilities.

The primary issue in the collection and transportation (C&T) of wood waste is the occurrence of Over Dimension and Over Loading (ODOL) conditions during these processes (**Figure 1b**). This situation renders the waste collection unsustainable, particularly in relation to the environmental objective function, as it increases fuel consumption and emissions. Additionally,

Table 1. Literature review

No	Name	Year	Problem			Object	Approach				Optimization	Simulation	Objective function		
			VRP	S	R&S		E	H	M	S			Eco	Env	Soc
1	Clapper et al	2024			√	Home healthcare				√	Evolutionary algorithm	Simulation dynamically	√		
2	Fu et al	2024			√	Home healthcare				√	Migrating birds optimization	Stochastic simulation	√		
3	Nessari	2024		√		Job shop				√	Equilibrium optimizer	Monte Carlo	√		
4	Wang et al	2024	√			Urban logistics		√			Adaptive Large Neighborhood Search	-	√		
5	Abu-Marrul	2023		√		Machine				√	Iterated greedy	Monte Carlo	√		
6	Tirkolaee et al	2023	√			Medical waste			√		Simulated annealing	-	√		
7	Yousefloo et al	2023	√			Municipal waste	√				Mixed Integer Linear Programming	-	√	√	√
8	Bazirha et al	2022			√	Home healthcare				√	Genetic algorithm	Monte Carlo	√		
9	Bayliss et al	2022	√			Omnichannel retail				√	Local search neighborhood's	Discrete event simulation	√		
10	Bossa et al	2021	√			Dairy supply chain		√			Travelling salesman problem	-	√		
11	Keenan et al	2021	√			-				√	Saving algorithm	Monte Carlo	√		
12	Keskin et al	2021	√			EV recharging station				√	Adaptive Large Neighborhood Search	Discrete event simulation	√		
13	Yazdani et al	2021	√			Municipal waste				√	Genetic algorithm	Stochastic simulation	√		
14	Mojtahedi et al	2021	√			Municipal waste			√		Adaptive Memory Social Engineering Optimizer	-	√	√	√
15	Tirkolaee et al	2020	√			Solid waste				√	Ant colony	Monte Carlo	√		
16	Gruler et al	2020	√			Municipal waste				√	Biased randomized	Monte Carlo	√	√	√
17	Qiao et al	2020	√			Municipal waste			√		Particle Swarm Optimization (PSO)- Tabu Search (TS)	-	√	√	√
18	Wu et al	2020	√			Municipal waste			√		Particle Swarm Optimization (PSO)- Simulated Annealing (SA)	-	√	√	
19	Hannan et al	2018	√			Municipal waste			√		Particle Swarm Optimization (PSO)	-	√		
20	**This Study**	**2024**	**√**			**Wood waste**				**√**	**Genetic algorithm**	**Discrete event simulation**	**√**	**√**	**√**

Figure 1. (a) Type of wood waste; (b) Overweight wood waste collection; (c) Damaged road

Table 2. Matrix origin – destination (OD) (km)

		Demand	Depo	1	2	3	4	5	6
0	Depo	0	0	4.4	4.1	3,8	1.6	1	5.4
1	A furniture	30	4.4	0	0.3	0.65	2.7	3.4	4.8
2	B furniture	25	4.1	0.3	0	0.55	2.4	3	5.2
3	C furniture	30	3.8	0.65	0.55	0	2.3	2.8	4.1
4	D furniture	20	1.6	2.7	2.4	2.3	0	1	5.7
5	E furniture	25	1	3.4	3	2.8	1	0	5.3
6	F furniture	40	5.4	4.8	5.2	4.1	5.7	5.3	0

ODOL trucks contribute to various problems, including road damage (**Figure 1c**) and traffic accidents. Therefore, it is essential for the government to enforce penalties in the form of fines for violations of regulations regarding the allowable load per vehicle. Currently, the vehicle used for transporting wood waste is a Colt Diesel Double (CDD), which has a standard capacity of 4 to 5 tons. Each sack of wood waste weighs approximately 4 to 5 kilograms. During the transportation process, a total of 170 sacks are carried (as shown in **Table 1**), resulting in an estimated total weight of around 7 tons. This indicates that the vehicle is operating under ODOL conditions, as illustrated in **Figure 1b**.

Therefore, this study aims to address the CVRP in the context of wood waste collection by incorporating the triple bottom line objectives: the economic aspect focuses on determining the optimal route to minimize transportation time and costs; the environmental aspect aims to reduce carbon emissions; and the social aspect seeks to minimize associated social costs. The following presents the origin-destination data matrix for the wood waste collection process in Mlonggo, Jepara, Central Java.

3.1. *Problem Assumptions and Formulation*

The assumptions used are as follows:

a. There is only 1 depot, as the initial point of departure and the final point of return.
b. The depot in this case also functions as a wood waste storage warehouse.
c. The vehicle departs empty, then the vehicle returns to the depot with wood waste.
d. Vehicles have the same capacity limit.
e. Each point can only be visited by 1 time by 1 vehicle.
f. Fuel consumption for overweight trucks is at a ratio of 1:4, meaning 1 liter of fuel is used for every 4 kilometers traveled, whereas for non-overweight trucks, the consumption ratio is 1:6, with 1 liter of fuel covering 6 kilometers.
g. The use of fuel oil is always added 5 liters for reserves.
h. Vehicles can travel more than once within the same area, but at different points.

The mathematical formulation is presented below. Then parameters and variable decisions are also presented (**Table 3**).

Objective Function

a. Transportation Cost

$$CT = C_f + C_v \sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv} \tag{1}$$

b. Fuel Consumption

$$F_c = \sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv}\frac{D_{ij}}{F_{c_{ijv}}} + 5 \tag{2}$$

c. Carbon Emission

$$E_{CO_2} = (\sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv}\, F_c) * F_e \tag{3}$$

d. Carbon Emission Tax

$$TC_x = E_{CO_2} * C_x \tag{4}$$

e. Penalty Cost

$$TC_p = (\sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv}K_{ijv}) * C_p \tag{5}$$

Objective Function

Minimize Z = (Eq. (6))

$$\sum_{v=1}^{C_f}\sum_{i=0}^{C_f}\sum_{j=0}^{C_f} X_{ijv} + \sum_{v=1}^{C_v}\sum_{i=0}^{C_v}\sum_{j=0}^{C_v} X_{ijv} + TC_x = E_{CO_2} * C_x + (\sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv}K_{ijv}) * C_p \tag{6}$$

Table 3. Parameters and decision variables

Parameters	Description	Unit
N	All nodes {i = 1,2,…,n}, 0 is the depot	-
V	All vehicle	-
K	Vehicle capacity	Sack
M	Amount of wood waste	Sack
D_{ij}	Distance from i to j	km
T	Number of trips	-
CT	Transportation cost	IDR
C_f	Fixed cost of transportation	IDR
C_v	Variable cost of transportation	IDR
F_c	Fuel consumption	Liter
E_{CO_2}	Emission carbon	Kg/CO_2
TC_x	Tax emission, then C_x is tax cost amount	IDR
TC_p	Penalty cost, then C_p is penalty cost amount	IDR
F_e	Emission factor	KgCO_2/kWh
Variable	**Explanations**	
X_{ijv}	1= if vehicle v visits from node i to j, 0 = otherwise	
Y_{iv}	1= if vehicle v visits from to node i, 0 = otherwise	
T_v	1= if vehicle v makes more than 1 trip, 0 = otherwise	
$F_{c_{ijv}}$	divided by 4 (liter) if vehicle v visits from node i to j is overweight, divided by 6 (liter) if vehicle v visits from node i to j is normal	
K_{ijv}	1= if vehicle v visits from node i to j over capacity, 0 = otherwise	

Subject to

$$\sum_{V=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv} = 1 \quad \forall i = 0,1,2,\dots\dots,0 \tag{7}$$

$$\sum_{V=1}^{V}\sum_{i=0}^{N} X_{iv}K = 0 \tag{8}$$

$$\sum_{V=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} M_{ijv} \leq K\,, \qquad \forall i = 0,1,2,\dots\dots,0 \tag{9}$$

$$\sum_{V=1}^{V}\sum_{i=1}^{N} Y_{iv} = 1, \qquad \forall i = 1,2,\dots\dots,N \tag{10}$$

$$\sum_{V=1}^{V}\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ijv}T_v \geq 1\,, \qquad \forall ij \neq before \tag{11}$$

Objective function model (1) represents the economic aspect, models (2) to (4) address environmental aspects, and model (5) reflects the social aspect. Model (6) integrates all objective functions into a single cost-based optimization formulation, where transportation costs represent the economic component, emission tax costs correspond to the environmental component, and penalty costs reflect the social component. Constraint (7) ensures that each vehicle departs from and returns to the depot. Constraint (8) specifies that vehicles must start their routes empty. Constraint (9) enforces that the waste transported does not exceed the vehicle's capacity. Constraint (10) ensures that each collection point is visited only once. Constraint (11) allows vehicles to make multiple trips, each visiting different points from previous trips.

3.2. Simheuristics (GA-DES)

GA is recognized as one of the most powerful models in metaheuristics for solving complex problems [42]. While DES refers to modeling systems with random variables that change over time (dynamic systems), DES is widely used in manufacturing and supply chain systems [43]. In this study, simheuristics is performed by finding the optimal value of GA operations, then these optimization results are used to configure simulations, where simulations are used to evaluate the feasibility of solutions obtained from GA [44]. The steps of GA as follows **Table 4**.

Where n_c is number of customer, T_k is truk capacity, P_z is population size, C_r is crossover rate, G_n is number of generation, M_r is mutation rate. In contrast to Bazirha et al., [45], Rabe et al., [28] and Yazdani et al., [38] this study incorporates capacity constraints into the GA process, ensuring that during the crossover operation, the combination of two parent solutions—both of which represent valid routes adhering to capacity limits—produces offspring solutions that also comply with these constraints.

If any offspring solution exceeds the capacity ($\geq T_k$), strategies such as re-routing or load reassignment are used to correct this violation before further evaluation. Additionally, the mutation process includes a capacity verification step, ensuring that any modifications to the route or distribution remain within the defined capacity limits.; if the mutation results in an overload ($\geq T_k$), the solution is discarded or readjusted within acceptable limits. This iterative approach ensures that, through successive generations, the GA progressively evolves toward an optimal routing solution that enhances efficiency while satisfying cargo capacity constraints.

Therefore, based on the results of the algorithm, the optimal solution corresponds to the route with the shortest distance. This selected route is then used to calculate travel time, transportation costs, emissions produced, emission taxes, and penalty costs. This route will also be used as E_0 = entity in DES simulation. The procedure for DES is as follows (**Table 5**).

Simpy is basically the library or function used to perform DES simulation in Phyton. DES starts by inputting parameters including alternative solutions S_{alt} ($Mlonggo_1$, ... , $Mlonggo_{n)}$, that has been prepared, and the distance of route solutions generated by the GA, travel time T_{time} , transportation cost CT, carbon emission E_{Co2}, tax emission TC_x, penalty cost TC_p and total cost TC. Entities in this case are several simulations that will be run based on predefined parameters, for example ("Mlonggo 1", 19.25, 43, 556725, 23.35375, 700.61, 24000000, 500000, 25057425.61). Different from Bayliss et al., [35] and Keskin et al., [36], in this study, the DES accounts for varying road conditions through three simulation scenarios: under light traffic, vehicle speed increases by 20%; under normal traffic, speed remains unchanged; and under heavy traffic, speed decreases by 40%. The DES identifies the optimal solution among several alternatives based on the total cost defined in Eq. (6). **Figure 2** below, is a diagram of the GA-DES simheuristics model performed, where the orange box is the constraint used, the yellow box illustrates the uncertainty considered and the blue box is the result of the GA and DES analysis.

Table 4. GA procedures

Genetic Algorithm for CVRP Procedure
Step 1: Input initial data
1.1 Parameters ($n_c, T_k, P_z, C_r, G_n, M_r$)
1.2 Coordinates (x,y)
1.3 Distance matrix (d_{xy})
1.4 Amount of waste (m_0, ... m_n)
Step 2 : Generate random N solution in P_1
2.1 P(i) - Initial solution (P_z, n_c) with dtype : integer, will be used for next optimization step. Where d_{xy} = 0,1,2,…….,0
2.2 Ensure that customer in P_1 <= T_k
Step 3: Crossover or recombination
3.1 **Parent selection:** parent chromosome (P_c) − choose two parents x and y from P(i), based on fitness value
3.2 **Determine a crossover point:** randomly chosen by P_c, where genetic information exchange will occur. where m_n<= T_k, child1 = parent2
3.3 **Genetic recombination:** Genes between the crossover point and the chromosome ends are exchanged between the two parents with capacity constraint to produce new offspring (**Figure 3**)
3.4 **Offspring Evaluation**: After the offspring (I_c)are generated, their fitness values are calculated using a fitness function to determine how well they solve the given problem.
3.5 **Replacement**: The offspring generated can then be used to replace some individuals in the original population.
Step 4: Mutation: mutate each solution with I_c in population P(i). (**Figure 4**)
Step 5: Fitness assignment: evaluate and assign a fitness value of each solution in P(i) which has been mutated before. If $m_t > T_k$ will be penalized.
Step 6 : Selection: select N solutions from P(i), based on their fitness value with capacity constraint.
Step 7 : Stopping criteria when the result is satisfied, or return to step 3 if else.
Output : Best solution based on route (S_{route})

Table 5. DES procedures

Discrete Event Simulation with Initial Solution from GA
Use the SimPy
Step 1: Initial simulation environment
Parameters ($S_{alt}, D(s_{route}), T_{time}, CT, E_{Co2}, TC_x, TC_p, TC$)
Step 2: Define simulation process
env.process(truck.run_trip())
Step 3: Create simulation environment
Entity based on parameters
Traffic conditions simulation (light, normal, heavy)
Step 4: Run the simulation
Call env.run()
Output: Best solution (S_{best}) based on total cost

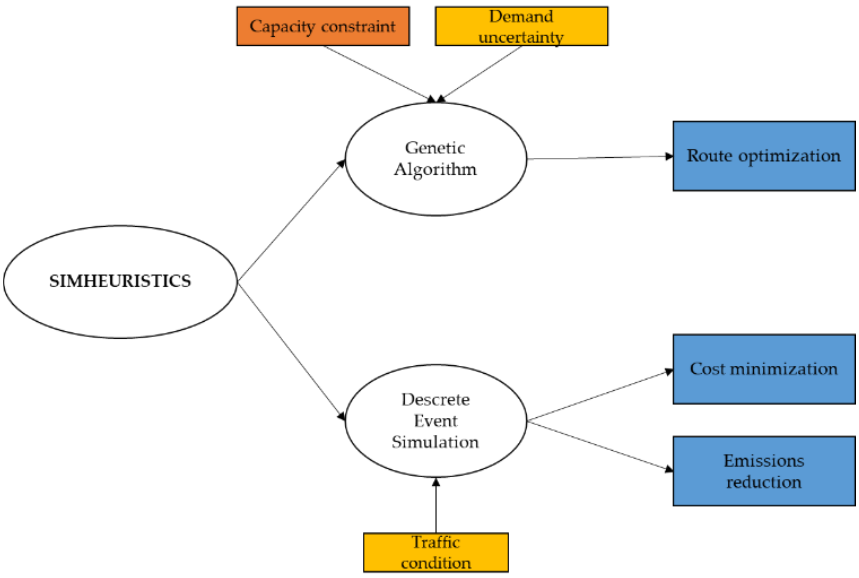

Figure 2. Simheuristics diagram

4. Results and Discussion

4.1. Simheuristics

This entire algorithm was done using Spyder (Phyton 3.12) running on a laptop with Intel® Core™ i5-7200U CPU @ 2.5Ghz. **Table 2** is an example of an OD matrix related to wood waste collection. Where existing route (T_0) is 0-1-2-3-4-5-6-0 with Dij_{total} = 19,25 km, CT= IDR 556,725, E_{CO_2} = 23,35375 Kg/CO_2. Because $T_0 > T_k$ then added TC_p in accordance with the applicable regulations in Indonesia according to Law Number 22 Year 2009 is IDR 500,000. So the total cost becomes IDR 1,057,425.61. After processing the data using GA, the initial population (P_i) was obtained, as follows **Table 6**.

After obtaining P_i with Dij_{total} from $P_{1,......,n}$ and fitness value f, in GA process, crossover process is performed with rate 0.75 [46]. This crossover process is done by crossing the genetic parents (mom and dad) to get a new child or offspring (**Figure 3**) with the starting and ending points xy = 0 namely depot, and ensuring that each child obtained does not exceed the predetermined T_k. Following the generation of a new offspring, a mutation process is performed to preserve population diversity and prevent convergence to local optima, as illustrated in **Figure 4**.

Mutation is done with a rate of 0.5, the results of individual permutations will be calculated Dij_{total} and the f value, and the last step is to choose the population that will be best solution, details are as follows **Table 7**.

Based on the mutation results in **Table 7**, Individual 1 achieves the shortest total distance, measuring 20.45 kilometers. The corresponding routes are illustrated in **Figure 5** and **Figure 6**. This selected route or trip will be used as an initial reference (T_1) for calculating transportation costs, emissions, emission taxes and ticket fees. $CT =$

$C_f + C_v$ (1), where C_f include the driver's salary (C_s) has been set by the company, then C_v consists of truck rental costs (C_{rt}), fuel cost (C_{fuel}) and driver's meals (C_{dr}). To calculate fuel oil consumption, for vehicles that do not exceed capacity, $F_c = (\frac{D_{ij}}{6}) + 5$, assuming fuel consumption ratio is 1 liter for 6 km, while for vehicles with overload capacity will be calculated by $F_c = (\frac{D_{ij}}{4}) + 5$, assuming 1 liter is used for 4 km, and an additional 5 liters as backup fuel for each vehicle.

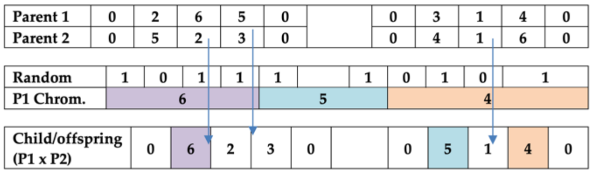

Figure 3. Crossover process

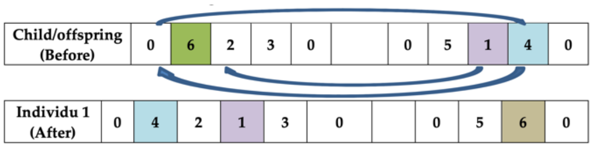

Figure 4. Mutation process for individual 1

Table 6. Initial population

Individual	Nodes	Distance (KM)	Fitness
1	[[0, 4, 5, 1, 0], [0, 3, 2, 6, 0]]	25.35	0.039448
2	[[0, 3, 6, 4, 0], [0, 1, 2, 5, 0]]	23.90	0.041841
3	[[0, 2, 4, 5, 0], [0, 3, 6, 1, 0]]	25.60	0.039062
4	[[0, 5, 3, 2, 0], [0, 1, 6, 4, 0]]	24.95	0.040080
5	[[0, 5, 3, 2, 0], [0, 6, 1, 4, 0]]	22.95	0.043573
6	[[0, 4, 2, 5, 0], [0, 6, 3, 1, 0]]	22.55	0.044346
7	[[0, 4, 6, 1, 0], [0, 3, 2, 5, 0]]	24.85	0.040241

Table 7. Solution after mutation

Population	Nodes	Distance (KM)	Fitness
Individual 1	**[[0, 4, 2, 1, 3, 0], [0, 5, 6, 0]]**	**20.45**	**0.048900**
Individual 2	[[0, 1, 3, 2, 4, 0], [0, 6, 5, 0]]	21.3	0.046948
Individual 3	[[0, 6, 5, 4, 0], [0, 1, 3, 2, 0]]	23	0.043478
Individual 4	[[0, 5, 4, 2, 0], [0, 6, 3, 1, 0]]	23.04	0.043384
Individual 5	[[0, 2, 6, 5, 0], [0, 3, 1, 4, 0]]	24.3	0.041068
Individual 6	[[0, 6, 5, 4, 0], [0, 1, 3, 2, 0]]	23	0.043478
Individual 7	[[0, 2, 3, 4, 1, 0], [0, 5, 6, 0]]	25.75	0.038835

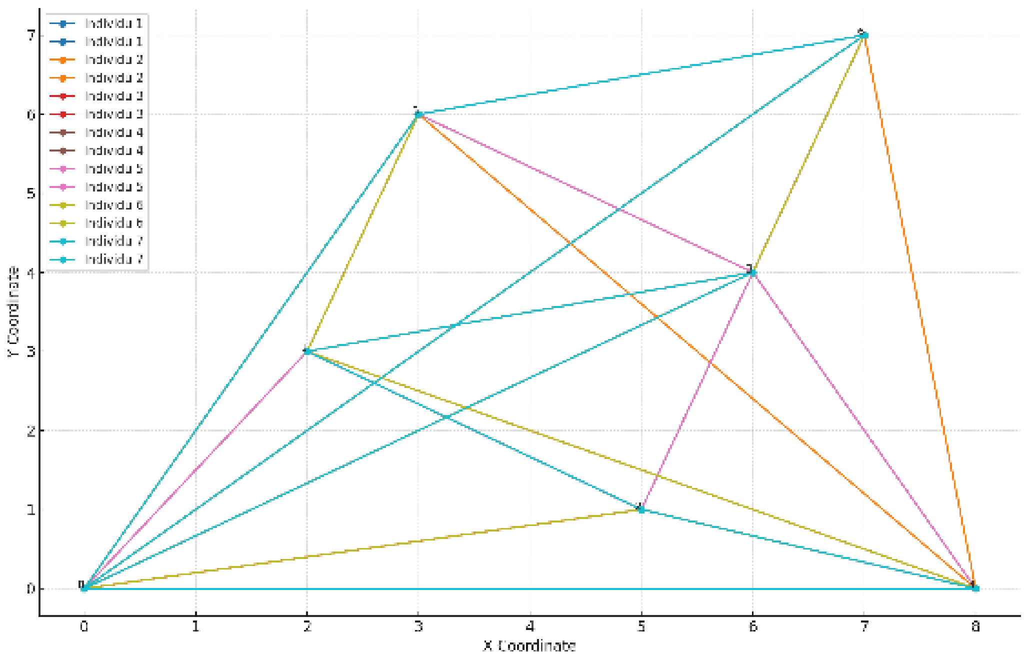

Figure 5. Visualitation of all individuals

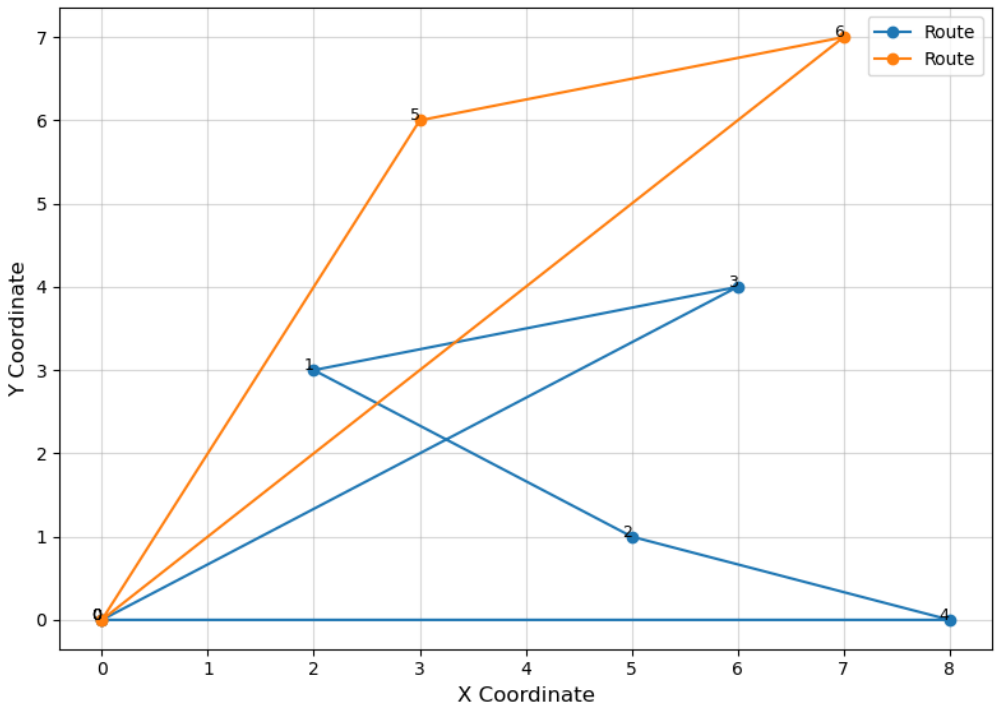

Figure 6. Visualitation of individual 1

If T_0 is 0-1-2-3-4-5-6-0, at T_1 it is known the trip is divided into 2 with newest route is 0, 4, 2, 1, 3, 0 and 0, 5, 6, 0. It is assumed that there will be 2 possible uses of the vehicle, i.e. using 1 vehicle (v_1) to serve 2 trips at once, or 2 vehicles (v_2)that will serve each trip. This basis will be taken into consideration for alternatives, followed by route alternatives T_0 and T_1. Overall, the alternative solutions are presented in **Table 8** below, along with their objective functions

E_{CO_2} was obtained from $F_c * F_e$, where F_e is 2,83. Thus TC_x obtained from E_{CO_2}* IDR 30,00, in accordance with regulations of Law no. 7 of 2021. While TC_p only applies to vehicles with overweight. Therefore, in the alternative solution, TC_p only applied for 2 simulations, namely OW-v_1 - T_1 and OW- v_1 - T_1. All these alternative solutions are used as entities in DES function. From DES results, obtained the best solution, namely Non-OW- v_1 - T_1, which is a condition where 1 vehicle serves 2 trips on a route that has been optimized using GA, where the result of transportation costs is IDR 547,176 with E_{CO_2} is 24,06775 Kg/CO_2, so it is necessary to pay TC_x IDR 722,03 without having to pay a penalty cost for not violating the determined vehicle capacity requirements. Based on **Table 9**, A-5 has the lowest total cost and carbon emissions. Some of the main outcomes of this research are:

a. The developed simheuristic model can be concurrently applied to CVRP while incorporating the sustainability dimensions of the triple bottom line.
b. A single vehicle making one overweight trip incurs higher costs compared to using two vehicles making separate trips within normal capacity limits.
c. The effectiveness of the proposed method is demonstrated by its alignment with the mathematical objective (6), which aims to minimize the total cost across all sustainability dimensions. Prior to the application of simheuristics, the total cost was IDR 1,057,425.61; following the implementation of the simheuristic approach, the total cost was reduced to IDR 549,625.47.

This study presents a novel application of simheuristics by integrating simulation with metaheuristics to manage uncertainty in waste collection routing, providing a more robust solution compared to the traditional deterministic approaches previously employed by Yousefloo et al. [45]. Unlike the previous study by Hannan et al. [15], Trikolaee et al. [37], [47] and Yazdani et al. [38], which only relied on a single objective function, i.e., economic, this study explicitly integrates economic, environmental, and social factors for a more sustainable waste management

Table 8. Alternative solution

Alternative	Nodes	D	T	CT	E_{CO_2}	TC_x	TC_p
OW-v_1-T_0 (A-1)	0-1-2-3-4-5-6-0	19,25	43	IDR 556.725	23,35375	IDR 700,61	IDR 500.000
Non-OW- v_1-T_0 (A-2)	(0-1-2-3-0), (0-4-5-6-0)	22,35	49	IDR 549.330	25,19825	IDR 755,95	-
Non-OW- v_2-T_0 (A-3)	(0-1-2-3-0), (0-4-5-6-0)	22,35	49	IDR 931.176	35,96775	IDR 1.079,03	-
OW-$v_1 - T_1$ (A-4)	0-4-2-1-3-5-6-0	14,05	40	IDR 547.885	20,25975	IDR 607,79	IDR 500.000
Non-OW- v_1-T_1 (A-5)	(0-4-2-1-3-0), (0-5-6-0)	20,45	44	IDR 547.176	24,06775	IDR 722,03	-
Non-OW- v_2-T_1 (A-6)	(0-4-2-1-3-0), (0-5-6-0)	20,45	44	IDR 932.876	36,86025	IDR 1.105,81	-

Where, OW (Overweight), Non-OW (Non-Overweight) D (Distance/km), T (Time/Minutes), Eco2 (Carbon Emission/KgCO$_2$), TCx (Tax Emission/IDR), TCp (Penalty Cost/IDR).

Table 9. DES result based on traffic condition

Traffic Condition	Shortest Travel Time	Highest Fuel Efficiency	Lowest Total Cost	Lowest Carbon Emissions
Light	A-6 (20.52 min)	A-2 (4.00 L)	A-5 (549,625.47)	A-5 (24.07 kg)
Normal	A-2 (24.32 min)	A-2 (4.00 L)	A-5 (549,625.47)	A-5 (24.07 kg)
Heavy	A-2 (38.83 min)	A-2 (4.00 L)	A-5 (549,625.47)	A-5 (24.07 kg)

strategy which is rarely researched [3]. In contrast to Qiao et al. [3], with similarities in focusing on the triple bottom line aspect, he combined two metaheuristics namely Partical Swarm Optimization (PSO) and Tabu Search (TS). Moreover, the simulation techniques employed in these prior studies have been largely confined to Monte Carlo methods [25], [26], [31], [37], [45], [48], which often fail to account for dynamic uncertainties in service demand. This limitation hinders the adaptability of routing strategies in real-world contexts, where waste generation is inherently non-uniform and subject to significant fluctuations over time. To address these limitations, this research proposes a simheuristic approach that integrates a GA with DES to enhance sustainability in waste collection under uncertainty. Beyond its significant contribution to the TBL dimensions, this study also brings attention to ODOL issues an often-overlooked aspect in vehicle routing which have critical implications for both operational efficiency and environmental sustainability.

Thus research is conducted on social aspects, namely penalty costs for vehicle overcapacity violations, in contrast to Qiao et al. [3] used penalty costs for overload assignment conditions, then Fu et al. [35] used for excess time. This study advances the genetic algorithm (GA) by incorporating vehicle capacity constraints, an aspect that has not been addressed in previous research [28], [38], [45]. Sensitivity analysis of GA parameters, conducted on mutation rate and number of generations, provides deeper insight into optimization stability, an aspect rarely explored in previous studies conducted by Yazdani et al. [38] and Bazirha et al. [45]. From an axiological perspective, this research offers valuable contributions to the waste transportation industry, logistics companies, and transportation policy makers by supporting the optimization of vehicle route management. It emphasizes the integration of sustainability considerations and the application of computer programming and simulation to address uncertainty.

4.2. Sensitivity Analysis

Sensitivity analysis of genetic algorithms is crucial, as it provides a deeper understanding of how the algorithm's performance responds to variations in key parameters [38], [49]. Sensitivity analysis enables the authors to identify which parameters have the greatest impact on the performance of the GA. Sensitivity tests are also essential for assessing the stability and convergence speed of the genetic algorithm in response to changes in parameter values. This evaluation is crucial to ensure that the algorithm consistently converges toward an optimal solution under varying conditions. In this study, the authors performed a sensitivity analysis on the mutation rate and the number of generations.

Figure 7 presents the results of the sensitivity analysis conducted at mutation rates of 0.05, 0.1, 0.2, and 0.5. The box plot illustrates the interquartile range (IQR), which spans from the first quartile (Q1, 25%) to the third quartile (Q3, 75%). The line within the box represents the median (Q2, 50%), indicating the central value of the dataset, while the whiskers (lines extending beyond the box) depict the data distribution excluding outliers M_r 0.05 has the lowest fitness value is 0.27, M_r 0.1 with fitness value 0.35, M_r 0.2 with fitness value 0.45, and M_r 0.5 with fitness value is 0.55. When viewed from the box size and whisker length, it tends to be small and stable for each M_r, its indicates that the data is quite consistent. To assess whether there is a significant difference, an ANOVA test was performed, yielding a sum of squares (sum_sq) value of 0.05. This value reflects the extent to which variations in average fitness can be attributed to differences in mutation levels. A larger sum of squares (sum_sq) value indicates that the differences between groups have a greater influence on the total variation of the data. Degree of freedom values (df) = 3, where each category on M_r is 3. F value = 25.42 > 0.05 indicates that a significant difference exists between at least one pair of mutation levels in affecting average fitness. A higher F value indicates a more significant difference between these groups. Since the P-value is 0.00001, which is less than 0.05, it can be concluded that the differences between mutation levels are not due to chance and significantly affect average fitness.

Furthermore, sensitivity analysis was conducted at G_n each 20, 50, 100 and 200. The results show that at G_n= 20 best distance of 20.65 KM is obtained, G_n= 50 with best distance 20.45 KM, G_n= 100 with distance of 20.45 KM, and G_n= 200 with distance of 20.85 KM (**Table 10**). The results of the ANOVA test indicate that the F-statistic value is 1.34, which is greater than 0.05, suggesting that there is variation or difference among the groups. However, the P-value is 0.28, which exceeds 0.05, indicating that there is insufficient evidence to reject the null hypothesis. This suggests that there is no significant difference in the distances traveled across different generations. In other words, the solutions identified by the genetic algorithm do not show substantial improvement from one generation to the next in terms of distance reduction.

Table 10. Solution of each generation

Num. of generation	Route	Distance	Fitness	Best Route
20	[[0, 3, 2, 1, 4, 0], [0, 6, 5, 0]]	**20.65 km**	0.0484	[[0, 3, 2, 1, 4, 0], [0, 6, 5, 0]]
	[[0, 6, 3, 4, 0], [0, 2, 1, 5, 0]]	22.20 km	0.045	
	[[0, 2, 6, 5, 0], [0, 1, 4, 3, 0]]	28.80 km	0.0347	
	[[0, 2, 1, 6, 0], [0, 5, 3, 4, 0]]	22.30 km	0.0448	
	[[0, 4, 1, 2, 5, 0], [0, 3, 6, 0]]	21.90 km	0.0456	
	[[0, 2, 4, 3, 0], [0, 6, 1, 5, 0]]	27.20 km	0.0367	
	[[0, 1, 5, 3, 0], [0, 4, 2, 6, 0]]	29.00 km	0.0344	
50	[[0, 2, 3, 6, 0], [0, 5, 4, 1, 0]]	23.25 km	0.043	[[0, 3, 1, 2, 4, 0], [0, 5, 6, 0]]
	[[0, 3, 1, 2, 4, 0], [0, 5, 6, 0]]	**20.45 km**	0.048	
	[[0, 3, 6, 4, 0], [0, 2, 1, 5, 0]]	24.00 km	0.416	
	[[0, 5, 6, 2, 0], [0, 1, 4, 3, 0]]	28.80 km	0.451	
	[[0, 1, 2, 3, 0], [0, 5, 4, 6, 0]]	22.15 km	0.034	
	[[0, 2, 5, 3, 0], [0, 4, 6, 1, 0]]	30.20 km	0.045	
	[[0, 6, 1, 3, 0], [0, 2, 5, 4, 0]]	24.35 km	0.033	
100	[[0, 4, 2, 1, 3, 0], [0, 5, 6, 0]]	**20.45 km**	0.048	[[0, 4, 2, 1, 3, 0], [0, 5, 6, 0]]
	[[0, 1, 3, 2, 4, 0], [0, 6, 5, 0]]	21.30 km	0.046	
	[[0, 6, 5, 4, 0], [0, 1, 3, 2, 0]]	23.00 km	0.043	
	[[0, 5, 4, 2, 0], [0, 6, 3, 1, 0]]	23.04 km	0.043	
	[[0, 2, 6, 5, 0], [0, 3, 1, 4, 0]]	24.30 km	0.041	
	[[0, 6, 5, 4, 0], [0, 1, 3, 2, 0]]	23.00 km	0.043	
	[[0, 2, 3, 4, 1, 0], [0, 5, 6, 0]]	25.75 km	0.038	
200	[[0, 6, 4, 2, 0], [0, 1, 3, 5, 0]]	26.45 km	0.037	[[0, 4, 3, 2, 1, 0], [0, 5, 6, 0]]
	[[0, 4, 5, 3, 0], [0, 6, 1, 2, 0]]	23.80 km	0.042	
	[[0, 2, 6, 5, 0], [0, 1, 4, 3, 0]]	28.80 km	0.347	
	[[0, 6, 3, 5, 0], [0, 2, 4, 1, 0]]	26.90 km	0.371	
	[[0, 1, 5, 2, 0], [0, 3, 4, 6, 0]]	32.10 km	0.311	
	[[0, 6, 5, 3, 0], [0, 4, 1, 2, 0]]	26.00 km	0.038	
	[[0, 4, 3, 2, 1, 0], [0, 5, 6, 0]]	**20.85 km**	0.047	

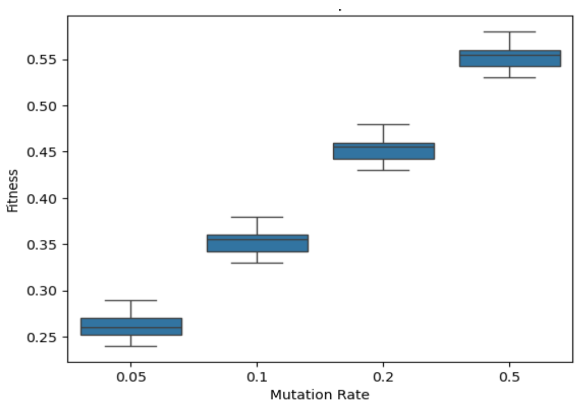

Figure 7. Sensitivity for mutation rate

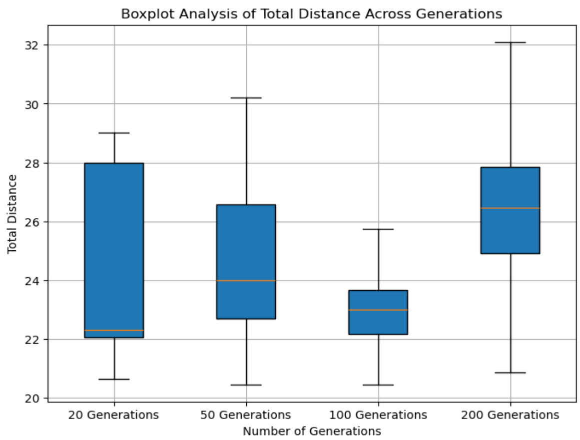

Figure 8. Boxplot of G_n sensitivity

Box plots (**Figure 8**) indicate that while the distributions are approximately normal at 20 generations, the ranges are considerable and exhibit high variability. At 50 generations, there are noticeable fluctuations in solution finding, with some values exceeding the median, indicating the presence of suboptimal solutions. At generation 100, the box plot is smaller, indicating reduced variation, which suggests that the solution is more stable. Additionally, the median is positioned centrally, signifying greater consistency compared to the 50-generation results. In contrast, at 200 generations, the variation is considerably larger, with a relatively wide range; furthermore, the median is higher than that at 100 generations, suggesting that there are more non-optimal solutions. Thus, in this scenario, overfitting is likely to occur, leading the algorithm to explore less efficient solutions.

5. Conclusion

Transportation waste is a crucial element of effective waste management, encompassing the logistics involved in collecting, transporting, and disposing of wood by-products generated from industries such as furniture manufacturing and construction. The Capacitated Vehicle Routing Problem (CVRP) provides an essential framework for optimizing waste collection routes, effectively addressing challenges associated with varying waste quantities and adhering to vehicle capacity regulations. To address these complexities, the research utilizes simheuristics—an integration of simulation and heuristic methods—alongside GA-DES to generate effective solutions amid uncertainty. This combined approach takes into account the economic, environmental, and social dimensions of sustainability. The outcome of the genetic algorithm is an optimal route that considers capacity, resulting in the deployment of two trucks with standard capacity to make multiple trips. DES facilitates the identification of optimal solutions among various alternatives by considering triple bottom line aspects across different scenarios of vehicle speed based on road conditions. The results from GA-DES were able to achieve a 51% reduction in transportation costs, utilizing a standard capacity of 5 tons and a maximum transport capability of 100 sacks.

This research makes a significant contribution to the literature on the Vehicle Routing Problem (VRP) by incorporating sustainability considerations. It expands upon the traditional VRP framework, which has primarily concentrated on optimizing distance and transportation costs. Additionally, simheuristics provide valuable insights into how uncertainty can be integrated into the optimization of vehicle routes. However, this study has certain limitations, including the use of small-scale sample data. Moreover, the simheuristic models employed assume a fixed demand distribution, whereas in real-world scenarios, demand fluctuations are often more dynamic and complex. Nonetheless, the global relevance of this research lies in its potential applicability across various waste management systems. With the continued growth of urban populations and the rising generation of waste, cities are encountering escalating challenges that require innovative approaches to achieve sustainable waste management. The proposed model enhances operational efficiency in waste logistics while also supporting global sustainability objectives, particularly those articulated in the Sustainable Development Goals (SDGs)—specifically Goal 11 (Sustainable Cities and Communities) and Goal 12 (Responsible Consumption and Production).

Several directions for future research include testing the application of this method on a larger business scale and incorporating the triple bottom line dimensions—particularly the social aspect—into studies of waste transportation vehicle routing problems (VRP). Additionally, simheuristic approaches can be employed to address more complex VRPs involving uncertainties in waste volume and limited collection time. Other uncertainty modeling techniques, such as stochastic programming, are also appropriate for problems with known probability distributions, as they enable scenario-based optimal solutions. Fuzzy theory is applicable in situations where uncertainty cannot be precisely defined, as it allows representation through fuzzy sets. Robust optimization, on the other hand, is well-suited for dynamic operational environments, as it provides optimal solutions even amid parameter fluctuations. Furthermore, advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) can support the development of more sophisticated methods for addressing complex routing problems.

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Author's Declaration

Authors' contributions and responsibilities

The authors made substantial contributions to the conception and design of the study. The authors took responsibility for data analysis, interpretation and discussion of results. The authors read and approved the final manuscript.

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Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interest.

Additional information

No additional information from the authors.

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