International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I9P136

Volume 72 Issue 9, 390-404, September 2024

Original Article

Vehicle Routing Optimization for Sustainable Last-Mile Delivery

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Received: 06 May 2024 Revised: 08 August 2024 Accepted: 17 August 2024 Published: 28 September 2024

Abstract - *Urban last-mile delivery is witnessing significant growth alongside the expansion of e-commerce; however, this surge poses sustainability challenges such as traffic congestion and increased emissions. Addressing this, the study introduces an advanced model, the Sustainable Heterogeneous Vehicle Routing Problem with Time Windows (SHFVRPTW), built upon the Vehicle Routing Problem with Time Windows (VRPTW). This mathematical model seeks to optimize last-mile vehicle routing, considering various constraints to enhance delivery efficiency, customer satisfaction, and sustainability. In this research, vehicles start from a depot with limited capacity, serving each customer within a specified time window and ensuring demand fulfillment before heading back to the depot. The problem is mathematically formulated and initially solved using the branch and bound method as an exact solution, implemented in LINGO. However, the computational time for solving large cases becomes excessively long. Therefore, a genetic algorithm is employed to expedite the solution process. Results indicate that the algorithm outperforms exact methods, providing solutions 57% faster than with an objective function gap closer to the exact solution at 34%.*

Keywords - *Vehicle routing problem, Last-mile delivery, Sustainability, Customer satisfaction, E-commerce.*

1. Introduction

The increasing popularity of e-commerce presents new difficulties for last-mile vehicle scheduling and routing services [1]. Many enterprises attempt to improve last-mile delivery efficiency. This last step of the delivery procedure is very important in order to guarantee customer satisfaction. Indeed, consumer expectations are increasingly high regarding delivery times, delivery timeslots, and the organization of shipments [2]. The last-mile delivery phase can present different challenges, such as traffic congestion, strict delivery timeframes, accuracy in addressing parcel security concerns, environmental impact reduction, cost optimization, efficient management of returns, and accommodating customer preferences [3]. In this context, striking a balance between improving customer satisfaction and optimizing route efficiency is a priority for logistics service providers. Vehicle routing optimization is paramount for logistics services, as optimized routes and timing significantly reduce operational costs while enhancing service quality [4]. Thus, the Vehicle Routing Problem (VRP) presents an essential optimization method. It comprises the optimization of many minimum-cost travel paths to provide different customers using a dynamic or fixed fleet [5]. Many different versions of (VRP) have been developed in response to real-world complexity scenarios. These include the Capacitated Vehicle Routing Problem (CVRP), Heterogeneous VRP (HVRP), Dynamic Vehicle Routing Problem (DVRP), Vehicle Routing Problem with Time Window (VRPTW), Open Vehicle Routing Problem (OVRP), etc [6]. However, there is a significant lack of research on the use of VRP and its variants to account for multiple constraints, including time windows, vehicle capacity, different vehicle types, and the environmental impact of last-mile delivery. Most existing studies isolate different aspects, such as customer satisfaction or sustainability impact, and are therefore limited in understanding the full range of issues faced by modern logistics service providers. Furthermore, environmental sustainability has become a very important factor in modern logistics and has not been considered by traditional VRP models despite its increasing importance in the modern business environment. Given the importance of this topic and the increasing complexity of distribution networks and environmental constraints. This research seeks to fill this gap by proposing an advanced form of the VRP model while considering these multiple dimensions (time windows, vehicle capacity, heterogeneous vehicles, and environmental considerations). Time windows impose strict temporal constraints on deliveries, necessitating precise planning to avoid delays and minimize operational costs. Concurrently, vehicle capacities introduce physical limits on the quantity of goods that can be transported, thereby adding additional complexity to routing planning. Furthermore, the growing awareness of environmental challenges pushes industries to rethink their logistical practices. Reducing greenhouse gas emissions, minimizing noise pollution, and limiting the ecological footprint of transportation operations have become essential objectives to guarantee the enduring sustainability of their operations. Our approach not only seeks solutions to operational problems but also considers sustainable environmental goals and offers a holistic solution to many issues associated with last-mile delivery. The structure of this paper is as follows: Section 2 gives an overview of past works done, and Section 3 describes the mathematical model formulation. Finally, the problem-solving methodologies are discussed in Section 4, followed by the computational results. In the final section, Section 5, the conclusion of this study and future perspectives are presented.

2. Literature Review

There are several variants for vehicle routing problems depending on constraint types and needs. Thus, this section reviews the various vehicle routing problem algorithms. The Vehicle Routing Problem (VRP) was originally formulated by Dantzig and Ramser [7], extending the Traveling Salesman Problem (TSP) introduced by Flood [8]. VRP is typically defined on a graph containing a set of nodes. Traditionally, the central node is designated as the depot, while the other nodes indicate customers (or demands) to be served. The objective of VRP is to determine a set of itineraries for a fleet of similar vehicles based at the depot, such that each node is visited exactly once while reducing the total routing cost [9]. Among the most prevalent variants of the Vehicle Routing Problem (VRP), challenges related to specific constraints or organizational methods are encountered. One of the fundamental constraints is capacity constraint (weight, volume, etc.), which constitutes the central issue of constrained vehicle routing. The objective is to reduce the overall cost, defined by either minimal distance or minimal travel time of routes while adhering to vehicle capacity [10]. Another significant constraint is that of time windows, where each customer specifies a time window in which the delivery is necessary to be delivered [11].

From a different perspective of uncontrollable constraints, according to Oyola, Arntzen, & Woodruff [12], the Stochastic Vehicle Routing Problem (SVRP) is characterized by the presence of at least one random element in the system, resulting in system dynamics. There are three main variants of SVRP:

- The VRP with Stochastic Customers (VRPSC), where each customer has a probability, denoted by p, of making a request.
- The VRP with Stochastic Demands (VRPSD), where customer demands are random variables.
- The VRP with Stochastic Travel Times (VRPSTT), where both service time at a customer and travel time are uncontrollable variables.

Urban logistics operates within the critical last-mile segment of complex urban supply chains, involving multiple stakeholders such as carriers, stores, and customers. In addition to deliveries, urban logistics also encompasses pickups, thus extending the domain of the Vehicle Routing Problem (VRP). In 1989, Min presented a new approach to VRP, which involved Simultaneous Pickup and Delivery [13]. In this study, researchers developed a mathematical model for a scenario involving multiple vehicles, aiming to reduce the overall travel time while considering the capacity constraints of each vehicle. The VRPSPD was initially defined as an NP-hard combinatorial optimization problem, an extension of the general Pickup and Delivery Problem. Since then, significant advancements have been made in this field, including the development of metaheuristic solution approaches such as the Adaptive Memory (AM) framework [14].

Research on the VRPSPD has been enriched and examined by Koç, Laporte, and Tükenmez [15], who provided an overview of existing work, including case studies, mathematical formulations, variants, algorithms, and industrial uses. Additionally, Xie, Qiu, and Zhang [16] proposed a new heuristic approach to address the shortcomings of existing methods. Furthermore, Goksal, Karaoglan, and Altiparmak [17] introduced a hybrid discrete particle swarm optimization method for the VRPSPD, demonstrating its effectiveness in generating high-quality solutions. These research efforts reflect a continued commitment to developing efficient and effective solutions for the VRPSPD.

The study by [18] looks at the issue of heterogeneity in vehicle routing and discusses questions including different fleet routes, outsourcing scenarios, time slot availability, and state laws on driver stopovers. It develops mathematical models of the problem, methods for optimization of its effects, and decision-making support tools. However, the model, designed to minimize costs, presents significant limitations regarding customer satisfaction and environmental factors, which are ignored.

Authors in [19] discuss the challenges of Vehicle Routing with Vehicle Supply and Stochastic Time Windows (VRPSVTW). Their main objective is to efficiently meet delivery demands by combining a diverse fleet of company-owned business vehicles with stochastic crowd-sourced vehicles. The objective function of VRPSVTW mainly focuses on minimizing the total routing cost and the expected recourse cost. However, it has some limitations, and it fails to define customer satisfaction, hence the penalties associated with late delivery or failure to deliver within a certain time, which can lead to high costs. Optimizing Last-Mile Delivery (LMD) systems using the Heterogeneous Fleet Vehicle Routing Problem with Time Windows and External Costs (HFVRPTW-EC) model aims to reduce the overall cost of LMD while minimizing the negative effect of externalities [20]. The focus lies on optimizing LMD services based on both internal and external costs to reduce operational expenses while mitigating the negative impact of externalities on urban environments.

The primary challenge addressed in the article is optimizing the last-mile distribution system while considering both internal and external costs, reducing the negative impact of externalities such as air pollution and congestion, and all the previous challenges while minimizing total delivery costs. Regarding limitations concerning penalties for failing to meet delivery deadlines and customer satisfaction, the objective function aims to minimize internal and external costs. However, it may not account for penalties imposed for failing to meet delivery deadlines, potentially negatively impacting customer satisfaction. Furthermore, the objective function may not integrate direct measures of customer satisfaction, which could limit its ability to optimize service quality from the customer's perspective.

3. Problem Formulation

In last-mile delivery, the important problem is the misallocation of vehicle resources. Most of the time, any vehicle, regardless of type or capacity, is assigned to fulfil customer orders, which leads to unnecessarily costly trips and, consequently, non-quality transport service. Moreover, existing last-mile delivery solutions often disregard sustainability objectives that are increasingly prioritized in the world. In heterogeneous vehicle routing problems, a varied fleet of vehicles serves several consumers. Departing from a central depot, vehicles of different capacities meet consumer demands within specified time frames, with penalties for late arrivals. Vehicles return to the depot upon completing their routes. Based on the literature review, a mathematical model seeks to optimize a sustainable Vehicle Routing Problem (VRP) with time windows and heterogeneous vehicles. This model seeks to enhance the performance of sustainable last-mile delivery by optimizing route costs and planning a fleet of vehicles within a specified time window. This model meets key conditions of vehicle routing problems by ensuring each customer is served precisely once in a round, each vehicle is deployed once, travel time limitations are respected, and maximum loading capacities are not exceeded.

3.1. Mathematical Formulation

The model describes each parameter, set, and decision variable, with their respective definitions and roles detailed in Table 1.

Table 1. Parameters attached to the mathematical model

Elements	Description
V	Set of customers, where |V| = n.
K	Set of vehicles
D_i	Demand for customer $i \in V$
Cp_K	Capacity of vehicle $k \in K$.
Q_{iK}	The load of each vehicle *k* at customer *i*
S_i	Service time at customer $i \in V$.
e_i	Earliest allowable start time for customer *i*.
l_i	The latest allowable start time for customer *i*.
B_{ik}	The start time of service activities
t_{ij}	Travel time between customers *i* and *j*.
d_{ij}	Distance between customers *i* and *j*.
F_k	Fixed cost
c_k	Variable cost
s_{ijk}	Cost of carbon emission between customers *i* and *j*
$\propto$	Penalty cost for violating time windows.
β	Penalty cost for not serving a customer.
x_{ijk}	Binary variable that equals 1 if vehicle *k* travels directly from customer *i* to customer *j* and 0 otherwise.
y_{ik}	Binary variable that equals 1 if vehicle *k* starts travel from customer *i* and 0 otherwise.
AT_{ik}	Non-negative variable representing the time when vehicle *k* arrives at customer *i*.
DT_{ik}	Non-negative variable representing the time when vehicle *k* leaves the customer *i*.

In this study, a variety of constants are present in the form of fixed costs, variable costs, penalty costs (including penalty for the violation time window and the unserved customer), as well as the cost of CO2 emissions. The objective function aims to reduce the cost by including the distance of the route, the capacity of the vehicles, compliance with time limits (with penalty if the time window is not respected), and CO2 emissions (environmental impact). Equation (1) Minimize the total cost, which is the sum of transportation costs, penalties, and sustainability costs:

$$min \sum_{k} \sum_{i \in V} F_k * y_{ik} + \sum_{k} \sum_{i \in V} \sum_{j \in V} c_k * t_{ij} * x_{ijk}$$

$$+ \sum_{k} \sum_{i \in V} \left(\alpha * max(0, AT_{ik} - l_i)\right)$$

$$+\beta * ((V-1) - \sum_{k} \sum_{i \in V} \sum_{j \in V} x_{ijk})$$

$$+ \sum_k \sum_{i \in V} \sum_{j \in V} \; s_{ijk} * d_{ij} * x_{ijk} \tag{1}$$

Constraint (2) The equation is set to equal zero, indicating that for each node h, the number of incoming trips must equal the number of outgoing trips for all vehicles k.

$$\sum_{i \neq h} x_{ihk} - \sum_{j \neq h} x_{hjk} = 0 \qquad \forall\, h \in V, k \in K \qquad (2)$$

Constraint (3-4) The constraint ensures that for each node, exactly one outgoing edge is selected across all vehicles. The "=1" at the end specifies that exactly one outgoing edge from the node should be selected.

$$\sum_{j \in V} \sum_{k \in K} x_{ijk} = 1 \qquad \forall\, i \in V \qquad (3)$$

$$\sum_{i \in V} \sum_{k \in K} x_{ijk} = 1 \qquad \forall\, j \in V \qquad (4)$$

Constraint (5) This constraint ensures that each vehicle initiates its journey from the depot, facilitating efficient routing planning.

$$\sum_{j \neq 1} x_{0jk} \leq 1 \qquad \forall\, k \in K \qquad (5)$$

Constraint (6) This constraint guarantees that each vehicle completes its journey by returning to the depot, ensuring proper resource utilization and completion of service operations.

$$\sum_{i \neq 1} x_{i0k} \leq 1 \qquad \forall\, k \in K \qquad (6)$$

Constraint (7) This constraint helps ensure that each customer is served by only one vehicle, preventing duplication of services and optimizing the routing plan.

$$\sum_{k} y_{ik} = 1 \qquad \forall\, i \in V \qquad (7)$$

Constraint (8) ensures that the initial capacity of the vehicle matches the number of customer requests on each route.

$$Q_{0k} = \sum_{i \in V} \sum_{\substack{j \in V \\ i \neq j}} D_j x_{ijk} \qquad \forall\, k \in K \qquad (8)$$

Constraint (9) ensures that the initial load limit of each vehicle is less than the vehicle capacity.

$$Q_{0k} \leq Cp_k \qquad \forall\, k \in K \qquad (9)$$

Constraint (10) ensures that the departure time from the depot for vehicle k (DT_{0k}) is not earlier than the earliest departure time e_0

$$DT_{0k} \geq e_0 - M(1 - y_{0k}) \qquad \forall i, j \in V, k \in K \qquad (10)$$

Constraint (11) ensures that the arrival time at the depot for vehicle k (AT_{0k}) is not later than the latest arrival time l_0.

$$AT_{0k} \leq e_0 + M(1 - y_{0k}) \qquad \forall i, j \in V, k \in K \qquad (11)$$

Constraint (12-13) the arrival time at the next customer after serving the previous customer.

$$AT_{jk} \geq DT_{ik} + t_{ij} - M\left(1 - x_{ijk}\right) \forall i, j \in V, k \in K \qquad (12)$$

$$AT_{jk} \leq DT_{ik} + t_{ij} + M\left(1 - x_{ijk}\right) \forall i, j \in V, k \in K \qquad (13)$$

Constraint (14) the start time of service activities at each customer (B_{ik}) must be the maximum of the arrival time(AT_{ik}) and the earliest start time e_i.

$$B_{ik} = max(AT_{ik}, e_i) \qquad \forall i, j \in V, k \in K \qquad (14)$$

Constraint (15-16) the departure time from each customer (DT_{jk}).

$$DT_{jk} \geq B_{ik} + S_i - M\left(1 - x_{ijk}\right) \forall i, j \in V, k \in K \qquad (15)$$

$$DT_{jk} \geq B_{ik} + S_i + M(1 - x_{ijk}) \forall i, j \in V, k \in K \qquad (16)$$

Constraint (17-18) related to the nature of the binary value decision variables for the determination of the vehicle in charge and the customer points visited by the vehicle.

$$y_{ik} \in \{0, 1\} \qquad \forall\, i \in V, k \in K \qquad (17)$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i, j \in V, k \in K \qquad (18)$$

Constraint (19-20) non-negative decision variable constraints.

$$AT_{ik} \geq 0 \qquad \forall\, i \in V, k \in K \qquad (19)$$

$$DT_{ik} \geq 0 \qquad \forall\, i \in V, k \in K \qquad (20)$$

3.1.1. Fixed Cost Component (First Term)

The first term in the equation (The fixed cost component) encapsulates the fixed expenses associated with operating the vehicle. It encompasses all vehicles involved in the transportation process in all periods to deliver to all customers. This mathematical expression calculates the cumulative fixed costs attributed to the use of each vehicle. Essentially, it quantifies the total fixed cost accrued by considering each instance where a vehicle transports demand in a given tour. In summary, the fixed cost component provides a valuation of the use of each vehicle across the entire transportation network.

$$\sum_{k} \sum_{i \in V} F_k * y_{ik} \qquad (21)$$

The "fixed cost" component of the transportation cost model combines several capital and operating expenses. The cost analysis includes the original purchase price of the vehicle, expected useful life, and regular costs such as licensing, insurance, and staff salary. The inputs have been calculated to accurately represent the real cost of maintaining and using the equipment during its service life.

$$F_k = Cost\ of\ vehicle\ ownership + taxe + \ insurance + staff\ salary \qquad (22)$$

3.1.2. Variable Cost Component (Second Term)

The variable cost component, constituting the second term of the equation, represents the dynamic costs linked to the operation of vehicles within the transport network. This component captures the cumulative variable costs associated with each vehicle's tour. the element c_k denotes the cost incurred for each unit of time associated with the specific vehicle, reflecting the expenses incurred for the use of the vehicle services for each type. t_{ij} means the travel time covered in the distance between the origin and destination customers. x_{ijk} serves as a binary decision variable, taking the value one when the vehicle transports demand directly from customer *i* to customer j and 0 if vehicle k does not take segment (*i*, *j*). The summation operation aggregates these costs for all customer vehicles, providing an assessment of the variable costs involved in traveling the different routes of the transport network.

$$\sum_k \sum_{i\in V} \sum_{j\in V} c_k * t_{ij} * x_{ijk} \quad (23)$$

The variable expenses include fuel and tires, as well as maintenance and repair. The calculations for each of these distinct components will be explained to provide the variable cost components.

$$c_k = cost\ of\ fuel + Tire\ cost + maintenance\ and\ repair \quad (24)$$

The cost of fuel is a variable factor that depends on the current market pricing. The cost of fuel may fluctuate based on factors such as the power rating of the engine, the speed at which the vehicle is traveling, the kind of road being travelled, and the total weight of the vehicle. Simultaneously, the velocity is dependent on the engine's power, the characteristics of the road, and the weight.

$$cost\ of\ fuel = fuel\ price * consumption\ of\ fuel \quad (25)$$

The combination of factors of tire wear and price calculates tire cost. Tires are weight-sensitive, which leads to increased wear as they accumulate additional weight. The durability of tires depends on the distance travelled.

$$cost\ of\ tire = \frac{price\ of\ tire}{uselife\ of\ tire} \quad (26)$$

In terms of maintenance and repair costs, there are long warranties for major vehicle components. Maintenance and repair costs vary depending on the product consumed (lubricating oil - oil filter - fuel filter, etc.), operating conditions, as well as the age of the equipment.

3.1.3. Penalty for Time Window Violations (Third Term)

The third term of the equation is the penalty for violating time slots, which imposes a punitive cost for breaking from the specified window of time stated in the request. This term quantifies the cumulative penalty costs associated with each instance of a vehicle arriving outside of the designated time window for customer i.

For the quantification of waiting time, a function linked to customer dissatisfaction has been introduced. This function characterizes as output the estimated waiting time of customer *i*, which is part of the customer set N. This dissatisfaction function is notably integrated into the framework of penalty costs in the model. Within this model, the arrival time $AT_{ik}$with vehicle *k* at customer *i*, and the possible later time to arrive at the customer are the variables of this function. Therefore, the customer's perceived waiting time can be calculated using the following methodology:

$$waiting\ time = AT_{ik} - l_i \quad (27)$$

The parameter α represents the cost of the penalty incurred for each missing the time window constraints, which reflects the cost implications of not meeting deadlines. AT_{ik} denotes the actual arrival time of vehicle k at customer *i* while l_i represents the latest start time allowed for customer i, delimiting the time allowed for the start of the service.

The expression $max(0, AT_{ik} - l_i)$ captures any delay beyond the allowed time window, ensuring that only cases of delay incur penalties. By adding these penalty costs for all vehicles and all customers provides an assessment of the cost impact of violations of time window constraints on the entire transportation network.

$$\sum_k \sum_{i\in V} \left(\alpha * max(0, AT_{ik} - l_i)\right) \quad (28)$$

3.1.4. Penalty for Unserved Customers (Fourth Term)

The term introduced into the optimization equation penalizes cases where certain customers are not served during delivery. This term represents the cumulative penalty costs associated with unserved customers. The parameter β represents the penalty factor, indicating the costs incurred for each unserved customer.

The expression $(V-1) - \sum_k \sum_{i\in V} \sum_{j\in V} x_{ijk}$ evaluates the overall number of unserved customers, where V represents the overall number of customers. By subtracting the overall number of customers served from the total number of customers minus the depot, the term accurately reflects the number of customers not served. This ensures an assessment of costs resulting from customer dissatisfaction or missed service opportunities within the transportation network, ultimately guiding toward the optimization of service efficiency and customer satisfaction.

$$\beta * ((V-1) - \sum_k \sum_{i\in V} \sum_{j\in V} x_{ijk}) \quad (29)$$

3.1.5. Sustainability Metric s_{ijk}

The sustainability factor is the main indicator used to evaluate the environmental impact of using vehicles on each trip. Tinling li et al. introduce these terms as follows [21]. s_{ijk} introduces several aspects related to the environment. s_{ijk} represents the amount of fuel consumed. Calculating the exact s_{ijk} formula depends on many elements, such as the type of vehicle, fuel consumed, and distance travelled. Variables such as vehicle emissions standards, road conditions, and traffic congestion can also influence the s_{ijk} formula. By incorporating this sustainability indicator into the optimization model, it becomes possible to understand the environmental impacts of transport operations. Thus making more efficient and sustainable decisions in last-mile delivery.

$$\sum_k \sum_{i\in V} \sum_{j\in V} s_{ijk} * d_{ij} * x_{ijk} \quad (30)$$

Emissions generated by vehicles are closely linked to their fuel consumption and the type of vehicle used. In this part of the objective function, a formula is proposed for calculating the cost of carbon emissions during vehicle operation by introducing a carbon emission coefficient. To determine carbon emissions, we multiply the fuel consumption of the vehicle by the equivalent carbon emission coefficient, which returns this coefficient, which acts as a conversion factor. A linear equation is used to convert fuel usage to carbon dioxide emissions. In addition, it evaluates the financial impact of CO2 emissions by integrating the carbon tax into the overall cost. The equation expresses the costs associated with carbon emissions from vehicles:

$$s_{ijk} = c_s * \gamma * a \quad (31)$$

- s_{ijk} : represents the cost of CO2 emissions.
- c_s: means the carbon tax per unit of CO2 emission. This is the cost imposed per unit of CO2 emitted, typically measured in currency price per quantity of CO2 emitted.
- γ: means the CO2 emission coefficient. This is a measure of the quantity of CO2 emitted per unit of fuel consumed. It is usually provided in grams of CO2 emitted per unit of fuel (e.g., grams of CO2 emitted per liter of gasoline or diesel).
- a: represents the fuel consumption per kilometre. This is the quantity of fuel used by the vehicle to travel one kilometre. It is usually provided in litres per kilometre.

This equation serves as a fundamental framework for assessing and integrating the environmental costs of carbon emissions into the broader economic considerations of vehicle operation.

4. Experiments

To validate the model, this section offers a detailed description of the computational experiments. First, the problem-solving methods utilized in the experiments will be presented.

After that, describe the data used for the different variables of the model. Subsequently, the results from the experiments will be presented by employing both the exact algorithm and the genetic algorithm.

4.1. Optimization Methodology

In the realm of VRP, a variety of algorithms are widely employed to effectively address the challenges of vehicle routing. The different methods can be generally categorized into exact, heuristic, and metaheuristic algorithms [22].

Table 2. Types of algorithms [20]

Exact algorithms	Heuristics	Metaheuristics
Branch and bound	Savings method	Genetics algorithms
Cutting plane method	Two-stage method	Simulation annealing
Dynamic programming	Scanning method	TABU search
Network flow method		Ant colony optimization

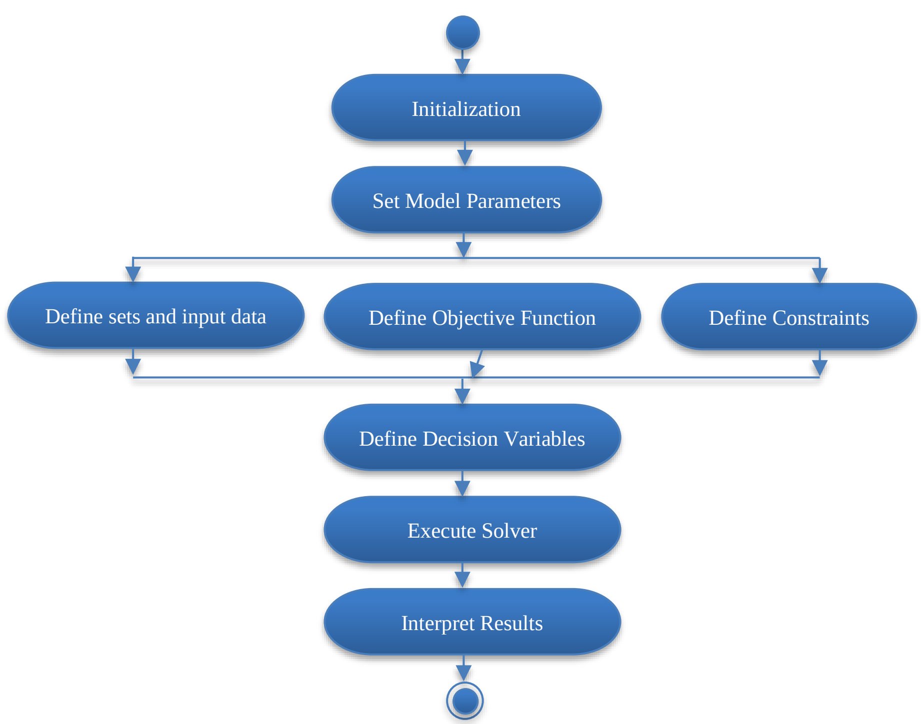

Fig. 1 Flow chart of the exact solution

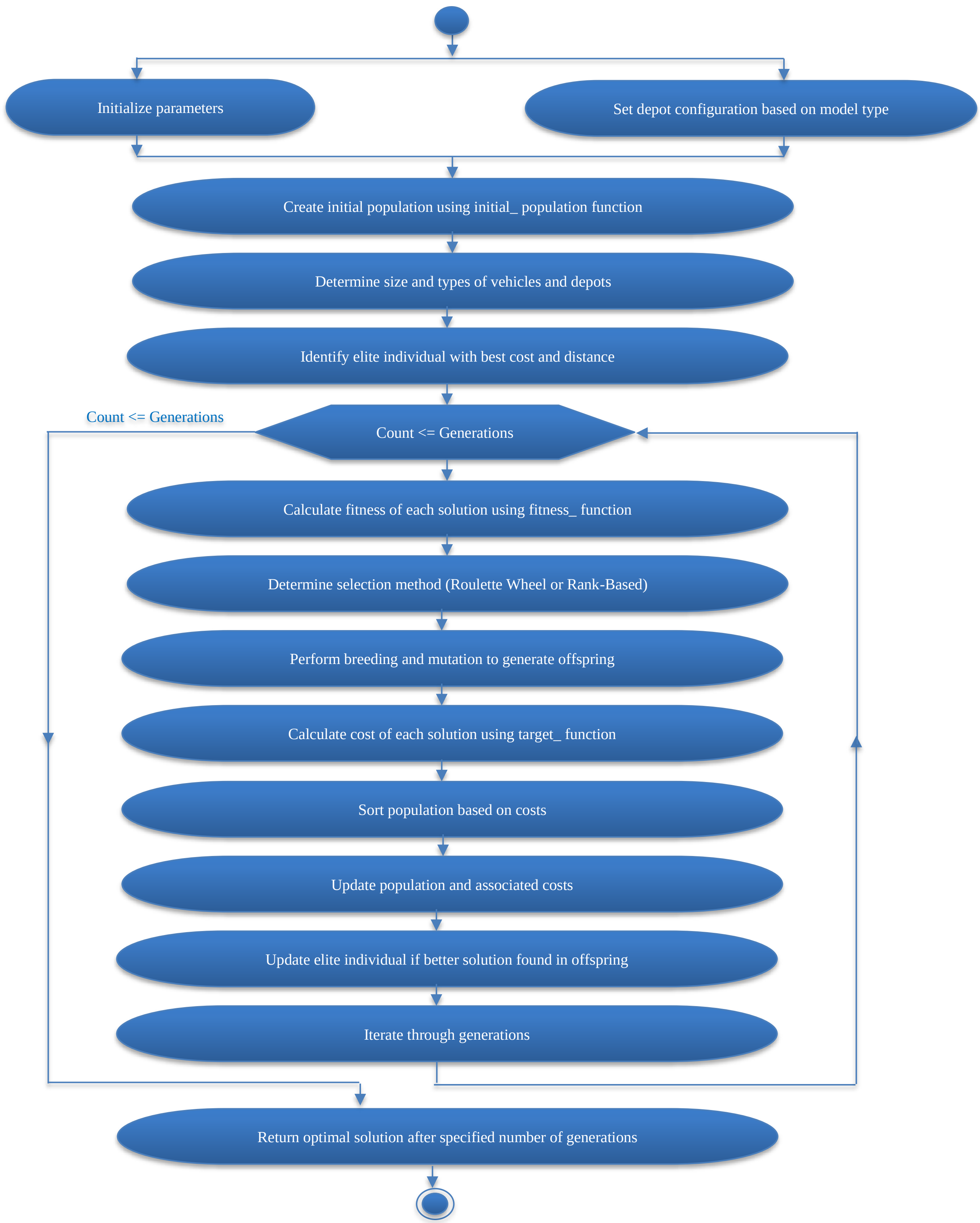

Fig. 2 Flow chart of the genetic algorithm

Regarding the study, the exact method, specifically Branch and Bound, was initially applied to find the optimal solution. Afterwards, the genetic algorithm was employed to reduce calculation time. It is considered shorter than exact methods, especially for large instances.The exact solution for the model starts with initialization, where defined sets and input data are provided. The model parameters are then established, including distances, times, time windows, demands, and costs. The Objective Function seeks to reduce costs associated with travel, fixed costs, penalties, and sustainability. The constraints guarantee that each customer is visited exactly once, that vehicles begin and finish their routes at the depot, that the capacity restrictions are not surpassed, and also that the time window is not exceeded. Decision variables reflect the paths taken by vehicles. An optimization solver in lingo is used to solve the model and identify the best solution, which includes building the route plan and calculating the associated costs. The Genetic Algorithm process starts by setting up parameters such as the start time, count, and maximum capacity. Additionally, the depot is configured according to the model type (VRP). Following that, the initial population function is used to construct an initial set of solutions, taking into account the size and types of the vehicles and depots. The population's solutions were evaluated for their cost using the target_function and then ranked accordingly. The fitness of each solution is determined by utilizing the fitness_function and using a selection technique based on the specified algorithm, Roulette Wheel or Rank-based. An elite individual, representing the best cost and distance, is identified. Genetic operations, such as breeding and mutation, operate on the population to generate offspring, therefore updating the population and associated costs. If a better solution is discovered in the offspring, the elite person is updated. The method continuously executes a predetermined number of generations. At last, after the required number of generations is finished, the best possible result is returned.

4.2. Experimental Sitting

As previously mentioned, this section presents the data from the experimental scenario used in the case study. The involved has 10 nodes, one of which represents the warehouses, which serve the other 9 customers. The vehicles used in this study depart the depot around 8:00 AM and come back at 12:00 PM, which represents the time window of the depot, to allow another tour to be performed in the afternoon with the same time window of four hours. Transportation costs can be divided into two costs: fixed costs and variable costs, each of which determines the overall efficiency and profitability of the transportation system. This study analysed these costs in the context of last-mile delivery based on three vehicle types: bicycles, motorcycles, and cars. For analysis purposes, it is assumed that all vehicles travel at a constant speed of 25 km/h. However, each vehicle type has a specific capacity that must not be exceeded. Transportation capacities are adapted to realistic operational constraints. Bicycles (CapB) can carry up to 10 parcels, motorcycles (CapM) are capable of carrying up to 50 parcels, and cars (CapC) have the largest capacity, with a maximum of 100 parcels. The capacity factor is a fundamental constraint for planning and optimizing delivery routes, as exceeding these limits can lead to operational inefficiencies. Some fixed costs, as discussed in the previous section, are costs that are incurred without any relation to the time element. These costs include vehicle ownership costs, taxes and insurance, whether the vehicle is used for one or multiple deliveries. Staff salaries are also fixed costs that reflect the costs incurred to hire staff to operate vehicles.

These fixed costs are important in understanding costs because they are the main overheads that must be covered to support delivery operations. Therefore, understanding the distribution of fixed costs across different vehicles helps to make final decisions on fleet composition and last-mile delivery strategies. This diversity allows for a balanced consideration of profitability and operational capacity, ensuring that the chosen vehicle mix is consistent with economic and logistical objectives. Table 3 presents each vehicle's fixed cost per how many times that vehicle has been used. Also, for the variable cost, each vehicle relates to a specific variable cost that represents the cost per unit of time.

The data in Table 4 describes the travel distances of the 10 nodes, from which the travel time between nodes can be extracted using the velocity equation. In Table 5, the dataset represents a distribution scenario involving a depot (DC) and ten customer nodes (C1 to C10) with varying time windows, service times, and parcel demands for each customer. The time window related to each node is represented by the earliest time allowed to visit the node and the last time allowed to be visited. Additionally, the data includes the service time for each customer. Linked to this data, the two types of penalties, α and β, are introduced, which respectively represent the coefficient of penalty in delay time for each node and the non-served customer. This coefficient is determined from historical customer satisfaction data. However, for this study, α is estimated at 0.2 $ and β at 1 $.

Table 3. Fixed and variable cost of each type of vehicle

	Bicycle	**Motorcycle**		**car**	
		e-M	M	e-car	car
Fixed cost / $	0.301	1.276	0.782	25.920	10.599
Variable cost / $	0.076	0.208	0.388	0.996	1.931
Cost of emission Co2 / $	0	0.595	1.190	3.807	7.613

For the impact of sustainability, the quantity of carbon emissions and the taxes paid for the emissions are used. For each type of vehicle (bicycle. motorcycle. car), the cost of CO2 emissions is presented in Table 3. In response to sustainability reasons, electric vehicles have been integrated into the experience to visualize the robustness of the model and the impact of green logistics. This integration introduced fixed and variable cost parameters different from those used in fuel vehicles, as presented in Table 3. The use of electric vehicles is significantly less polluting than that of fuel vehicles. A recent study has shown that the average electric vehicle emits over 50% less pollution than a diesel vehicle over its lifetime [23]. Furthermore, EVs also have lower operational CO2 emissions, with potential reductions of up to 31.6% in CO2 emissions by 2040 compared to traditional vehicles [24]. In comparison to diesel vehicles, electric cars have a 70% reduction in energy consumption [25]. In this study, reference is made to the research by Reichmuth, Dunn, and Anair [23], which states that the cost of Co2 emissions should be reduced by 50% when using electric vehicles. Twelve problems were extracted, ranging from low demand (5 nodes) to high demand (10 nodes). Scenario-specific information was provided regarding the volume of delivery demands D_i , travel distance d_{ij} , travel time t_{ij} and preferred visit time window. Vehicles used in this study are based on one of each type of vehicle (Bicycle, Motorcycle, Car).

4.3. Results of Exact Method

In the corresponding exact experimental resolution of each case, the aim was to come up with global and local optimal solutions through theoretical mathematical modelling. The study applied the linear dissatisfaction function approach as well as the standard time window framework to efficiently solve the optimization problem. The chosen approach was based on examining the exchanges between the different factors linked to delivery logistics and ensuring that the practical and theoretical solutions were reasonable. To apply the proposed mathematical model, the researchers had to utilize Lingo software, which is widely recognized for its optimization solutions. All the computational experiments were carried out on a computer with an Intel Core i5 1.6 GHz processor and 12 GB of RAM. The exact method set the intention to not only reach the global optimal solution, which is the optimal solution within the context of all objectives and constraints but also to attempt to achieve local optimal solutions that could offer satisfactory and feasible strategies near the global optimum. Table 6 below shows the results obtained from the use of gasoline vehicles in the study. After a quick view of the data, a clear fundamental distinction emerges between global and local optimal solutions. The global optimal solution is identified as the best possible solution in general. It represents the most efficient outcome.

Table 4. Data of 10 customers (time window - service time-demand)

d_{ij}	d_0	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}
d_0	0	4.1	0.7	1.5	7.3	7.2	1.2	8.1	1.3	8.0	3.7
d_1	4.1	0	6.9	9.3	6.5	3.3	3.5	2.9	2.9	5.9	8.8
d_2	0.7	6.9	0	2.1	3.4	3.5	3.7	4.2	1.5	5.2	3.7
d_3	1.5	9.3	2.1	0	6.8	4.4	5.6	3.8	8.8	4.1	3.8
d_4	7.3	6.5	3.4	6.8	0	8.9	4.7	5.5	6.1	3.1	3.1
d_5	7.2	3.3	3.5	4.4	8.9	0	5.0	0.8	2.2	0.1	8.0
d_6	1.2	3.5	3.7	5.6	4.7	5.0	0	0.7	3.1	8.2	7.5
d_7	8.1	2.9	4.2	3.8	5.5	0.8	0.7	0	9.6	3.3	5.3
d_8	1.3	2.9	1.5	8.8	6.1	2.2	3.1	9.6	0	7	4.4
d_9	8.0	5.9	5.2	4.1	3.1	0.1	8.2	3.3	7	0	7.0
d_{10}	3.7	8.8	3.7	3.8	3.1	8.0	7.5	5.3	4.4	7.0	0

Table 5. Distance between each customer

		Time Window/min			Demand
N	Name of nodes	Open	Close	Service time	Deliver / parcels
0	DC	0	240	0	0
1	C1	90	210	6	4
2	C2	150	190	7	10
3	C3	160	200	5	4
4	C4	50	120	8	6
5	C5	30	100	3	6
6	C6	0	200	8	6
7	C7	40	70	12	10
8	C8	60	240	7	10
9	C9	100	200	3	6
10	C10	90	150	6	4

Table 6. Result of GOS and LOS for fuel vehicle

<table>
<tr><th rowspan="2" colspan="2"></th><th colspan="3">FUEL VEHICLE RESULT</th></tr>
<tr><th>OF</th><th>Solution</th><th>Runtime seconds</th></tr>
<tr><td rowspan="2">N5F-V</td><td>GOS</td><td>12.007</td><td rowspan="2">B= D0 →C1→C4 →D0
M= D0 →C3 →C2 →D0</td><td>0.40</td></tr>
<tr><td>LOS</td><td>12.007</td><td>0.31</td></tr>
<tr><td rowspan="2">N6F-V</td><td>GOS</td><td>28.255</td><td rowspan="2">B= D0 →C4→C3 →D0
M= D0 →C1→C5→C2 →D0</td><td>0.57</td></tr>
<tr><td>LOS</td><td>28.255</td><td>11.65</td></tr>
<tr><td rowspan="2">N7F-V</td><td>GOS</td><td>14.573</td><td>B= D0 →C4→C3 →D0
M= D0 →C6→ C1→C5→C2 →D0</td><td>101.27</td></tr>
<tr><td>LOS</td><td>18.179</td><td>B= D0 →C5→C3 →D0
M= D0 →C6→ C1→C4→C2 →D0</td><td>11.46</td></tr>
<tr><td rowspan="2">N8F-V</td><td>GOS</td><td>24.835</td><td rowspan="2">B= D0 →C1 →C4 →D0
M= D0 →C6 →C7 →C5→C2→C3→D0</td><td>4.61</td></tr>
<tr><td>LOS</td><td>24.835</td><td>4.62</td></tr>
<tr><td rowspan="2">N9F-V</td><td>GOS</td><td>25.506</td><td rowspan="2">B= D0 →C4→C1 →D0
M= D0 →C6 →C7 →C5 →C8→C2→C3→D0</td><td>5.48</td></tr>
<tr><td>LOS</td><td>25.506</td><td>64.53</td></tr>
<tr><td rowspan="2">N10F-V</td><td>GOS</td><td>48.323</td><td>B= D0 →C4 →C3 →D0
M= D0 →C6→C7→C5 →C9→C1→C8→D0
C= D0 →C2→ D0</td><td>30.90</td></tr>
<tr><td>LOS</td><td>74.988</td><td>B= D0 →C3→C9 →D0
M= D0 →C4→C8 →C5→C7→C1 →C6→D0
C= D0 → C2→ D0</td><td>507.03</td></tr>
</table>

Table 7. Result of GOS and LOS for electric vehicle

<table>
<tr><th rowspan="2" colspan="2"></th><th colspan="3">ELECTRIC VEHICLE RESULT</th></tr>
<tr><th>OF</th><th>Solution</th><th>Runtime seconds</th></tr>
<tr><td rowspan="2">N5E-V</td><td>GOS</td><td>7.427</td><td rowspan="2">B= D0 →C1→C4 →D0
M= D0 →C3 →C2 →D0</td><td>0.40</td></tr>
<tr><td>LOS</td><td>7.427</td><td>0.27</td></tr>
<tr><td rowspan="2">N6E-V</td><td>GOS</td><td>16.110</td><td rowspan="2">B= D0 →C4→C3 →D0
M= D0 →C1→C5→C2 →D0</td><td>0.56</td></tr>
<tr><td>LOS</td><td>16.110</td><td>6.33</td></tr>
<tr><td rowspan="2">N7E-V</td><td>GOS</td><td>16.756</td><td>B= D0 →C5→C1 →D0
M= D0 →C6→ C4→C2→C3 →D0</td><td>4.10</td></tr>
<tr><td>LOS</td><td>20.186</td><td>B= D0 →C4 →D0
M= D0 →C6→ C1→C5→C2→ C3 →D0</td><td>57.97</td></tr>
<tr><td rowspan="2">N8E-V</td><td>GOS</td><td>14.482</td><td>B= D0 →C1 →C4 →D0
M= D0 →C6 →C7 →C5→C2→C3→D0</td><td>3.76</td></tr>
<tr><td>LOS</td><td>108.818</td><td>B= D0 →C4→C1 →D0
M= D0 →C5→C6 →D0
C= D0 → C7→ C3→ C2→ D0</td><td>10.38</td></tr>
<tr><td rowspan="2">N9E-V</td><td>GOS</td><td>14.973</td><td rowspan="2">B= D0 →C1→C4 →D0
M= D0 →C6 →C7 →C5 →C8→C2→C3→D0</td><td>4.06</td></tr>
<tr><td>LOS</td><td>14.973</td><td>46.06</td></tr>
<tr><td rowspan="2">N10E-V</td><td>GOS</td><td>25.996</td><td>B= D0 →C4 →C3 →D0
M= D0 →C6→C7→C5 →C9→C1→C8→D0
C= D0 →C2→ D0</td><td>20.66</td></tr>
<tr><td>LOS</td><td>31.678</td><td>B= D0 →C1→C4 →D0
M= D0 →C6→C8 →C5→C7→C9 →C3→D0
C= D0 → C2→ D0</td><td>3870.75</td></tr>
</table>

However, obtaining this solution can be challenging, especially in the context of complex optimization problems, due to the complex and intensive nature of the computations required. On the other hand, the local optimal solutions are more easily achievable due to runtime execution. Despite their relative ease of discovery, local optimal solutions do not always match the optimal objectives of the system. As seen in a broader context, they may not represent the most efficient outcome for the system and may deviate from the optimum. In analyzing the consequences of deploying electric vehicles in the creation of the last-mile delivery optimization model, especially the integration of sustainability into the process, improvements are observed in Table 7. The transition from traditional vehicles to green vehicles is an effective improvement in the global optimal solution, especially regarding general optimization.

Table 8. Comparative table of the use of electric vehicles and fuel vehicles in the global optimal solution

N° nodes	OF F-V	Runtime F-V	OF E-V	Runtime E-V	% OF E-V/V	%Time E-V/V	GAP OF	GAP Time
5	12.007	0.4	7.427	0.4	62%	100%	38%	0%
6	28.255	0.57	16.110	0.56	57%	98%	43%	2%
7	14.573	101.27	16.756	4.1	115%	4%	-15%	96%
8	24.835	4.61	14.482	3.76	58%	82%	42%	18%
9	25.506	5.48	14.973	4.06	59%	74%	41%	26%
10	48.323	30.9	25.996	20.66	54%	67%	46%	33%
Average:							33%	29%

Table 9. Comparative table of the use of electric vehicles and fuel vehicles in the local optimal solution

N° nodes	OF F-V	Runtime F-V	OF E-V	Runtime E-V	%OF E-V /V	%Time E-V /V	GAP OF	GAP Time
5	12.007	0.31	7.427	0.27	62%	87%	38%	13%
6	28.255	11.65	16.110	6.33	57%	54%	43%	46%
7	18.179	11.46	20.186	57.97	111%	506%	-11%	-406%
8	108.818	17.43	108.818	10.38	100%	60%	0%	40%
9	25.506	64.53	14.973	46.06	59%	71%	41%	29%
10	74.988	507.03	31.678	3870.75	42%	763%	58%	-663%
Average:							28%	-157%

The introduction of electric vehicles, with their lower environmental impact, registers these companies as environmentally-friendly companies that respect the environment. Additionally, it increases opportunities for companies to save money on fuel and even earn money. Therefore, the type of vehicle used has a significant effect on the calculation of the GOS, which is an indicator of the maximum amount of optimality regarding the model. Indeed, some variables, such as the operational cost and emissions of electric cars, are liabilities that are taken into account when searching for the optimal solution. By incorporating sustainability criteria into the model, the focus is on solutions that satisfy not only the logistical need but also the ecological objective, thus enhancing the value of the identified objective for the optimal solution. The table shows the performance comparison between F-V and E-V in various scenarios, which are represented by the number of nodes in the network, as shown in Table 8 below. The analysed metrics consist of the Objective function, which represents the performance cost related to a particular path, as well as the time taken to reach the given solutions. The table presents on a percentage basis the similar objective function value of EVs compared to fuel vehicles. Also, it was found that the "GAP OF" and "GAP Time" reflect the percentage difference between EVs and fuel vehicles in terms of the value of the objective function and operating time, respectively, and it proved that EVs are in a better position in terms of cost. The average value of the objective function value of EVs compared to fuel vehicles is 33%, so in terms of environmental and economic efficiency, EVs can have some advantages. Table 9 contains the comparison of the objective function gap in local optimal solutions between Electric Vehicles (EVs) and fuel vehicles (FVs). The results show that the objective function gap for EVs is slightly lower by 28% compared to FVs. This reduction means that even in cases where the aim is to achieve the best local solution, EVs maintain a competitive advantage in terms of objective function results. This result is significant and highlights the generality of EVs in the form of different optimization problems. Such a competitive performance of EVs in local optimization might be taken advantage of in strategic planning. The analysis of the results obtained when solving the optimization problems in reference to this study is adequately illustrated in Figure 3-4, presenting a graphical representation of the number of client points and the Runtime required to solve them. Therefore, with the growth of the number of client points, a significant increase in the Runtime is observed, which is particularly notable in cases involving FV and EV. In these cases, the execution time presents a quadratic growth in terms of time complexity to find both Local Optimal Solutions (LOS) and Global Optimal Solutions (GOS). This quadratic increase in execution time indicates that, as the number of nodes rises, and thus the complexity of the dataset in the search space, the time required to solve search problems increases. This step leads to a higher computational time, which also becomes a major issue in practical situations where decision-making should be done within a short period. To solve this problem and find solutions close to the optimum within an acceptable time, it is, therefore, necessary to use algorithms that can be designed to achieve the balance between optimality and efficiency. With such algorithms, researchers would be able to understand the trade-off between obtaining optimal solutions and the time required to solve these problems. With the application of these new algorithms, it is, therefore, possible to work with larger and more complex data sets while achieving near-optimal quality results and implementing them in real problems.

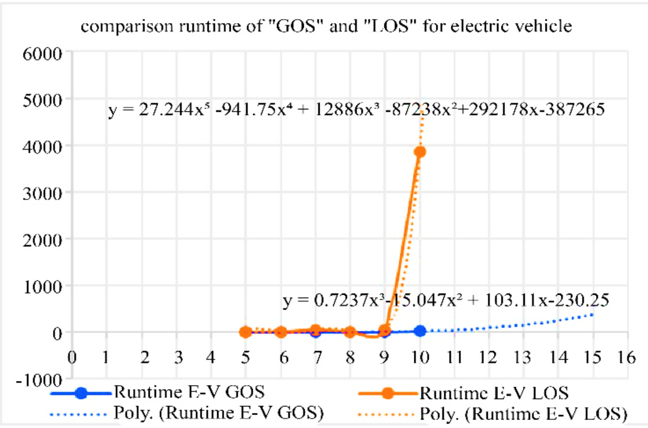

Fig. 3 Graph of runtime by number of nodes for E-V

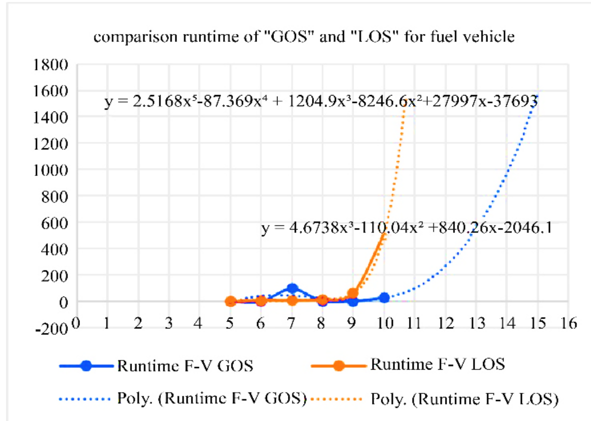

Fig. 4 Graph of run time by number of nodes for F-V

Table 10. Comparative table of the global optimal solution and genetic algorithm in the case of electric vehicle

N° nodes	OF E-V GOS	Time E-V GOS	OF E-V GA	Time E-V GA	%OF E-V GA/GOS	%Time E-V GA/GOS	GAP OF	GAP TIME
5	7.427	0.4	7.882	0.33	106%	83%	-6%	18%
6	16.110	0.56	9.531	0.62	59%	111%	41%	-11%
7	16.756	4.1	7.713	0.86	46%	21%	54%	79%
8	14.482	3.76	15.5	0.62	107%	16%	-7%	84%
9	14.973	4.06	46.176	0.94	308%	23%	-208%	77%
10	25.996	20.66	45.654	0.98	176%	5%	-76%	95%
Average:							-34%	57%

Table 7. Parameter values generations, population_size, mutation_rate

Generations	Population_size	Mutation_rate	Objective function	Runtime [S]
50	5	0.05	55.835	2.35
		0.1	45.055	2.96
		0.2	44.224	2.34
	10	0.05	55.2	5.04
		0.1	53.271	5.06
		0.2	44.158	6.05
	15	0.05	47.784	9.57
		0.1	50.333	8.55
		0.2	45.179	9.68
100	5	0.05	48.499	1.72
		0.1	47.127	2.2
		0.2	53.171	1.56
	10	0.05	45.686	3.77
		0.1	45.179	3.77
		0.2	53.271	3.63
	15	0.05	45.91	6.22
		0.1	53.271	5
		0.2	53.271	5.44
200	5	0.05	53.271	2.96
		0.1	45.686	3.49
		0.2	53.271	3.15
	10	0.05	43.165	7.18
		0.1	53.271	6.43
		0.2	53.271	6.34
	15	0.05	53.271	10.46
		0.1	49.029	11.19
		0.2	47.127	10.93

Table 8. Response table for signal-to-noise ratios

Level	Generations	Population_size	Mutation_rate
1	-50.76	-50.86	-50.91
2	-50.86	-50.86	-50.8
3	-50.97	-50.86	-50.88
Delta	0.21	0	0.11
Rang	1	3	2

4.4. Results of Genetic Algorithm

The Genetic Algorithm (GA) is an efficient and adaptable approach to solving challenging situations associated with routing vehicles with different characteristics. These challenges generally involve time constraints and constraints on the capacity of heterogeneous vehicles. Utilizing concepts derived from natural selection and evolution, GA systematically optimizes solutions to identify the most optimum or nearly optimal routes for a fleet of vehicles that are engaged in servicing several sites.

The performance analysis algorithm has been made specifically to solve the problem with the use of limited heterogeneous vehicles, limited capacity, and soft-time windows. Several scenarios were tested, and a sensitivity analysis was conducted to see how appropriate the algorithm designed to solve the problem. The six groups of scenarios and the test results obtained show that the GA algorithm is designed to be capable of approaching the optimal solution in Table 10. Moreover, the required computation time is 57% shorter than the time needed to identify the optimal solution.

To analyse the results and the magnitude of the effect of each parameter on the quality of the solution and the required computation time, each determined parameter will be changed in value. Using data from 10 nodes and 3 heterogeneous vehicles, the results obtained for changes in parameter values generations, population_size, and mutation_rate are shown in Table 12. Determining the best parameter value in the GA uses the Taguchi method, which is capable of producing efficient parameter settings. In the Taguchi method, there are two factors: signal factor and noise factor. To get the best results, the smallest option was selected. The classification and grouping of each level can be seen in Table 11.

Figure 5 presents the results of the combined analysis, which includes the evaluation of each parameter at different levels. This diagram provides a comprehensive perspective on how the parameters interact and their impact on the overall results.

Table 9. Best GA parameters

Parameter	Value
Generations	50
population_size	15
mutation_rate	0.1

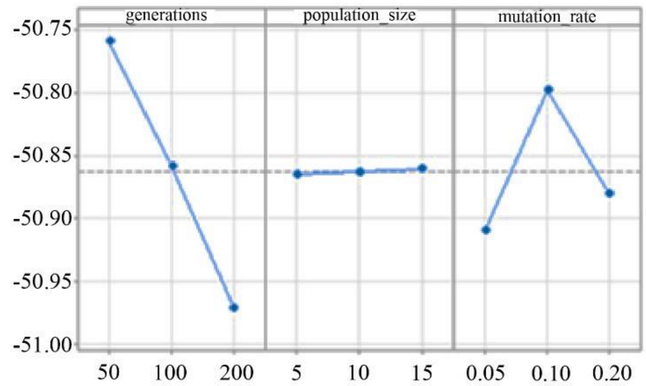

Fig. 5 Main effects graph for signal-to-noise ratio

Table 12 provides a brief, in-depth summary of the data. The values of each parameter analysed are included in the table. The Taguchi method was used to determine the optimal combinations of parametric conditions used in the genetic algorithm. The results show that a generation of 50, a population of 15 and a mutation rate of 0.5 brought results close to optimal.

5. Conclusion

The objective of addressing the Vehicle Routing Problem (VRP) is to determine the most efficient delivery routes that not only serve consumers efficiently but also reduce last-mile logistics and delivery costs. This study involved the extensive development of a linear programming model to solve a sustainable heterogeneous Vehicle Routing (VRP) problem with time windows. Lingo software was used to verify this model, and the evaluation was conducted using two different vehicle types: electric and gasoline. This allowed the inclusion of sustainability features in the evaluation process. Initial experiments were conducted on small-scale scenarios with 5, 6, 8, 9, and 10 customer points. These tests showed that the objective function gap in the solutions between electric and gasoline vehicles was 33%, while the computation time differed by 29%.

However, a quadratic escalation of the execution time was observed as the number of nodes increased, suggesting the increasing computational difficulty involved in determining optimal solutions for larger datasets. In order to identify solutions to these issues, a genetic algorithm (GA) was employed to efficiently solve complex optimization problems via an iterative procedure that includes selection, crossover, and mutation. From the results obtained and the comparisons carried out, this approach is considered to provide a solution as good as the analytical solution with 34% closer and with a much faster runtime equal to 57%. It is concluded that the approach developed based on the genetic algorithm provides a good solution, approaching the optimal solution for the sustainable VRP model with limited heterogeneous vehicles and soft time windows with reasonable calculation time. Moreover, this research sets itself apart by including many elements, such as consumer satisfaction and sustainability issues, that are typically overlooked in the literature. This study fills a significant vacuum in the current literature by specifically examining a heterogeneous fleet with flexible delivery time windows and a focus on long-lasting performance during the last stage of transportation. Previous studies have mostly focused on minimizing costs without giving enough attention to sustainability and customer satisfaction. Regarding future perspectives, this study emphasizes the possibility of further advances in the sustainable Vehicle Routing Problem (VRP). Future studies could explore the use of more advanced metaheuristic algorithms, such as particle Ant Colony Optimization (ACO) and Particle swarm Optimization (PSO), to improve the efficiency of the solutions. Integrating dynamic components, such as real-time traffic data and stochastics customer demand, into the model could provide more practical solutions for real-world applications.

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