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Hybrid Ant Colony optimization and Variable Neighborhood Search algorithm for Electric and Fossil Fuel Vehicle Routing

Narges Khanlarzade[1], Babak Yousefi Yegane[1*]

[1]*Department of Industrial Engineering, Faculty of Engineering Management, Kermanshah University of Technology, Kermanshah, Iran*

Abstract

The use of eco-friendly energies has gained significant attention in recent years due to their high importance in preserving the environment. This study examines the vehicle routing problem, utilizing two categories of vehicles: owned vehicles and rented vehicles. The rented vehicles exclusively consist of electric vehicles, while the owned vehicles include both electric and fossil fuel-powered ones. To encourage the adoption of electric vehicles and discourage the use of fossil fuel-powered vehicles, government incentives are implemented. This approach aims to mitigate the harmful environmental impacts associated with fossil fuel consumption. This pioneering concept is formulated as the Close-Open Mixed-fleet Electric Vehicle Routing Problem with time window (COMF-EVRP), with a detailed mathematical framework provided. In the absence of real data, the performance of the proposed algorithm is evaluated using numerical examples involving 30 vehicles: 5 rental electric vehicles, 10 owned electric vehicles, and 15 fossil fuel-powered vehicles. The test problems differ in customer distribution, including random, clustered, and a combination of both scenarios. Key parameters such as vehicle capacities, customer demands, and charging stations were also considered. Due to the complexity of the mathematical model, a meta-heuristic approach based on the ant colony optimization algorithm is proposed to solve the problem. To improve the quality of the obtained solutions, they undergo a variable neighborhood search procedure. The computational results indicate that the proposed solution procedures are capable of achieving high-quality solutions in reasonable CPU time. These findings suggest that transportation companies could enhance their operational efficiency by implementing similar strategies.

Keywords: Vehicle Routing Problem; Electric Vehicle; close-open routing; Ant colony optimization

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[*] Corresponding Author

1. Introduction

In recent years, there has been a growing inclination towards the use of clean energies, driven by a collective awareness of the urgent need to address environmental challenges, such as global warming, increasing greenhouse gas emissions, and the depletion of natural resources. This shift, inspired by the pressing need to combat climate change and the harmful effects of air pollution, has sparked a renewed interest in the utilization of clean and renewable energy sources like solar, wind, and hydrogen power (IEA, 2022). This burgeoning appetite for clean energy, reflected in everything from policy initiatives to individual consumer behavior, is not merely a trend, but an imperative driven by health and environmental benefits. The transition to clean energy is no longer an option, but a necessity for a sustainable and resilient future.

The transportation sector, one of the largest contributors to global emissions, is undergoing a profound transformation with the rapid rise of electric vehicles (EVs). The global transportation industry accounts for nearly 24% of direct CO_2 emissions from fuel combustion, with road transport alone responsible for 18% of global emissions (IEA, 2023). Consequently, decarbonizing transportation is essential to achieving the climate goals set forth in the Paris Agreement, which seeks to limit global warming to 1.5°C above pre-industrial levels.

This shift holds vast implications for various sectors, including transportation, where a fascinating progression is taking place. There are two distinct approaches to achieving a reduction in pollution; the first is optimizing the use of existing resources, and the second is implementing new, eco-friendly technologies. The initial phase involves improving the utilization of resources at hand, such as reducing fuel consumption through smarter urban planning or the electrification of public transportation networks, achievable through the application of advanced routing planning optimization techniques and the implementation of smart distribution systems (Mancini, 2017). For example, algorithms based on artificial intelligence and machine learning are being employed to optimize vehicle routing, reducing fuel consumption and emissions while improving delivery efficiency in logistics systems(Yaiprasert & Hidayanto, 2024; Nozari et al., 2025).

For a substantial reduction in emissions, it is crucial to utilize eco-friendly technologies, such as Electric Vehicles (EVs), which may use batteries (battery electric vehicles (BEVs)) or solar cells for energy supply. Fuel cell electric vehicles (FCEVs), which run on hydrogen, are also emerging as a complementary solution for long-haul transportation, especially in heavy-duty trucks, where batteries alone may not be sufficient due to range limitations (Waseem et al., 2023).

Despite the advancements, the transition faces challenges, such as the high initial costs of EVs, limitations in charging infrastructure, and the environmental impact of battery production and disposal(Jannesar Niri et al., 2024). Moreover, the extraction of raw materials like lithium, cobalt, and nickel for EV batteries presents its own environmental and ethical concerns, including habitat destruction, water usage, and human rights violations in mining operations. Researchers are actively working on developing solid-state batteries, which promise greater energy density, faster charging times, and enhanced safety compared to conventional lithium-ion batteries (Alkhalidi et al., 2024; Nozari et al., 2024). Nevertheless, EVs are seen as a perfect transportation solution and a replacement for traditional vehicles because of environmental concerns. Numerous global governments are implementing strategies to decrease CO_2 emissions across all energy sectors, particularly in the transportation sector; For example, the European Union has set ambitious targets to reduce greenhouse gas emissions, including those from cars and trucks, as part of its wider plan to combat climate change. The European Green Deal aims to reduce emissions by at least 55% by 2030 compared to 1990 levels, with a significant focus on electrifying the transport sector (European Commission, 2020). Similarly, China has introduced measures to promote the use of electric vehicles and has been investing heavily in renewable energy sources to reduce its reliance on fossil fuels. In 2021, China accounted for more than half of the global EV sales, thanks to its robust policy support, subsidies, and the establishment of extensive EV infrastructure (Zhang & Qiu, 2024; Movahed et al., 2023); Moreover, the adoption of EVs is expected to play a critical role in global decarbonization efforts, reducing reliance on fossil fuels and enhancing energy security(Singh et al., 2023; Nozari, 2024). The importance of using clean energy has significantly increased in recent years, to the extent that global EV sales have increased from 125 thousand in 2012 to 6.75 million in 2021. EVs are gradually replacing conventional vehicles, as their market share has reached 8.3% in 2021 from 0.2% in less than a decade. Based on the International Energy Agency's (IEA) reports, the adoption of electric vehicles is rapidly expanding, as shown in Figure 1, which predicts the growth of electric vehicle usage across different countries by 2050 (IEA, 2023). The continued growth of EV markets across regions will depend on supportive policies, technological innovations, and the development of sustainable supply chains for raw materials, including lithium and cobalt, used in EV batteries. Furthermore, there is a need for international cooperation to standardize charging systems, ensure compatibility across borders, and develop shared recycling programs for EV batteries, minimizing their environmental impact (Gautam & Bolia, 2024,Abdi et al., 2023).

the urgency of addressing transportation-related emissions, coupled with the vital role of government policies in promoting clean energy solutions, makes this issue a focal point in the global fight against climate change. Given its significance for both environmental protection and policy-making, this paper aims to explore the impact of EVs and government interventions on reducing emissions. By examining these aspects, we address a critical challenge that holds the key to a sustainable and cleaner future. To achieve this, the study seeks to answer the following research questions:

1. What is the impact of financial policies and incentives on the adoption of electric vehicles within the Electric Vehicle Routing Problem (EVRP) framework?
2. How can the integration of financial policies and incentives enhance decision-making for sustainable transportation logistics

The remainder of the paper is structured as follows: Section 2 provides a comprehensive literature review, highlighting key studies in the field. Section 3 presents the problem description, focusing on the challenges and opportunities in reducing emissions through electric vehicles. In Section 4, we outline the solution procedure, detailing the methodology used in this research. Section 5 is dedicated to computational experiments, where the results are analyzed and validated. Section 6 offers managerial insights, discussing the practical implications for both industry and policymakers. Finally, Section 7 concludes the paper with findings, limitations, and future research directions.

2. Research Background

Transportation and distribution play pivotal roles in logistics, serving as key elements of supply chain management. These components not only ensure the efficient movement of goods from production facilities to end consumers but also significantly impact overall operational efficiency and customer satisfaction. By integrating advanced technologies and strategic planning, transportation and distribution can substantially enhance the effectiveness of the supply chain, promoting economic growth and sustainability. Research has shown that in today’s competitive environment, reducing distribution costs—particularly in fuel consumption—has a significant effect on operational expenses. Distribution costs depend on various criteria, such as load, speed, road conditions, fuel consumption rates, and fuel prices(Fallah et al., 2019).

i. Electric Vehicle Technology (EVs and PHEVs)

The Electric Vehicle Routing Problem (EVRP) was first introduced by Schneider et al. (2014), and since then, it has garnered substantial attention from researchers due to its high importance. Electric vehicle technology can be categorized into two main types: Battery Electric Vehicles (EVs) and Plug-In Hybrid Electric Vehicles (PHEVs) (Hamidi & Tavassoli, 2024). The term EV encompasses a wide range of vehicles that utilize electric motors for propulsion, including battery-powered EVs, hydrogen fuel-cell EVs, plug-in hybrids (Bahrami et al., 2020), and EVs with range-extending Internal Combustion Engines (ICEs)(Subramanyam et al., 2022).

ii. EVRP Models

Researchers have developed various models to address the EVRP. Desaulniers et al. (2016) developed four different versions of the Electric Vehicle Routing Problem with Time Windows (EVRPTW), each featuring distinct charging conditions. They found that the optimal charging strategy while en route allows for both multiple and partial recharges (PR). A Mixed Integer Linear Programming (MILP) model for time-dependent electric vehicles with time windows was formulated by Zhou et al. (2024), aimed at minimizing the total costs of energy consumption, travel distance, and the number of electric vehicles. A Variable Neighborhood Search (VNS) algorithm was employed to solve large-scale problems, while smaller instances were solved using the CPLEX solver.

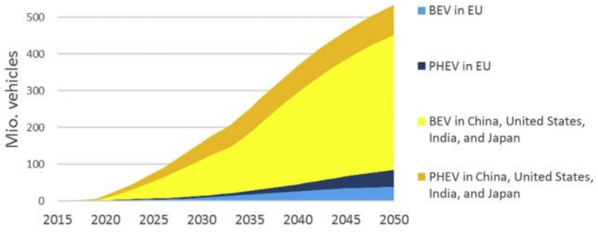

Figure1. Electric stock until 2050; reported by (Heitel et al., 2020)(BEV: battery EV; PHEV: plug-in hybrid EV)

iii. Specific Issues in EVRP: Charging, Costs, and Emissions

Last-mile transportation, regarded as a significant issue and an extension of the vehicle routing problem, was proposed by Zahedi-Anaraki et al. (2022). They applied a modified Benders decomposition technique in conjunction with the VNS algorithm to solve the mathematical model. Montoya et al. (2017) considered a nonlinear charging function for the EVRP and proposed a hybrid metaheuristic algorithm to address the complexity of the resulting mathematical model. Zuo et al. (2019) developed an MILP model for the EVRP with time windows, demonstrating that their model could achieve better electric vehicle logistics scheduling with improved charging time utilization.

Other significant contributions include a MILP model for EVs presented by Setak and Karimpour (2019), focusing on a multigraph with queuing at charging stations to minimize travel and charging costs, solved using a simulated annealing algorithm. Lin et al. (2021) proposed a Lagrangian relaxation approach along with a hybrid variable neighborhood search and tabu search heuristic to find feasible high-quality solutions for the EVRP with time windows under time-variant electricity prices. Mohammadbagher and Torabi (2022) introduced a bi-objective mathematical programming model, where cost optimization is prioritized as the first objective and minimizing pollutant emissions as the second. They utilized simulated annealing and epsilon-constraint methods to find Pareto-optimal solutions. A branch-and-cut approach to find feasible solutions for the EVRP with a nonlinear charging function was introduced by Schulz (2024), where infeasible solutions were added to the solution space, ultimately converging to optimal solutions.

For more detailed information on electric vehicles, the reader is referred to the review studies conducted by Kucukoglu et al. (2021) and Stamadianos et al. (2023).

2.1.Discussion about literature

Transportation and distribution are vital for supply chain management, directly affecting costs and customer satisfaction. Recent research highlights the Electric Vehicle Routing Problem (EVRP) and its focus on reducing distribution costs, particularly fuel consumption. Various optimization models have been developed, employing advanced techniques for logistics scheduling and route optimization. Recent advancements integrate machine learning and address uncertainties, thereby expanding research horizons. However, a significant gap exists in considering financial policies such as taxes and incentives, which remains an underexplored dimension of the EVRP. Given the increasing global emphasis on sustainability, understanding this interplay is critical for comprehensive insights into the economic and environmental implications of sustainable transportation logistics.

In light of this gap, this research seeks to delve into the intricate relationship between financial measures and sustainable transportation, focusing on their impact within the context of EVRP models. By evaluating the effectiveness of various economic-related policies and incentives, we aim to provide valuable insights into their potential to drive the adoption of electric vehicles and optimize transportation logistics. Additionally, our analysis will enhance understanding of the socio-economic implications of these policies, ultimately informing policymakers and stakeholders about strategies to advance sustainable transportation initiatives globally.

2.2.Research implication

Exploring the integration of financial policies and incentives into EVRP enriches academic discussions on sustainable transportation logistics and holds profound implications for informed decision-making. By assessing the effectiveness of these policies in incentivizing electric vehicle adoption and promoting sustainable practices, researchers can provide valuable insights for decision-makers (DMs) aiming to address environmental concerns and mitigate carbon emissions.

Furthermore, this research direction fosters collaboration between academia, industry, and government bodies, facilitating the development and implementation of holistic strategies for advancing sustainable transportation practices globally. Through interdisciplinary approaches and stakeholder engagement, this research has the potential to catalyze transformative changes in transportation systems, paving the way towards a greener and more resilient future for generations to come.

3.Problem Description

Consider a collection of two categories of vehicles, the first group comprises vehicles under ownership, and the second group consists of rental vehicles. In the first category, two types of vehicles are used: the first type runs on fossil fuel (FFV) and the second type is electric (EV); Additionally, all rental vehicles are electric. In order to protect the environment and help reduce greenhouse gas emissions, the government has implemented a penalty for using any fossil fuel-powered vehicle and an incentive for using any electric vehicle.

All vehicles start their trip from the depot indicated by n_0 and if the edge between node i and node j covered with vehicle j, the binary variable $x_{ij\vartheta}$ equals to 1; otherwise equals to 0; also, distance of d_{ij} between customer i and j within a time period of t_{ij} with unloading time p_j for node j to satisfy its demand as d_i is considered; The arrival time of vehicle ϑ at customer j is indicated by variable $At_{j\vartheta}$.

The time window of a customer refers to the time period during which the customer can be served; each customer has a time window $[e_j, l_j]$ where e_j and l_j are the earliest and latest delivery time of customer j respectively. The other symbols and parameters used in the problem are as follows:

Sets and indices	
i, j	Index that represents customers
ϑ	Index that represents vehicles
Parameters	
FV	Set of owned vehicles with fossil fuels
OEV	Set of owned EVs
REV	Set of rented EVs

V	Set of all vehicles: $V = FV \cup OEV \cup REV$
ω^{+}	Government Penalty for using fossil fuels for each vehicle
ω^{-}	Government subsidy for using fossil fuels for each vehicle
d_{ij}	Distance between node i and node j
t_{ij}	Traveling time between node i and node j
p_j	unloading time for node j
N_D	Depot set, $N_D = \{D_1, D_2, \dots\}$
N_C	Customer set, $N_C = \{C_1, C_2, \dots\}$
N_{CH}	Charging station set, $V_{CH} = \{CH_1, CH_2, \dots\}$
Γ	Set of all nodes $N_D \cup N_C \cup N_{CH}$
θ_i	Demand of customer i
q_{ϑ}	Capacity of vehicle ϑ
τ	Battery consumption rate per kilometer
BC_{max}	Maximum battery capacity
Decision variables	
$x_{ij\vartheta}$	Binary variable denoting if path between node i and node j covered with vehicle j
$At_{j\vartheta}$	Arrival time of vehicle ϑ at customer j
Bc_j	Battery charge upon the arrival at customer j
Bc'_{ϑ}	Battery charge upon the arrival of vehicle ϑ at depot

The other assumptions are as follows:

- fleet of fossil-fueled vehicles is homogeneous;
- The fleet of all electric vehicles (owned or rented) is homogeneous.
- All electric vehicles (owned or rented) are full charge at the start of the trip;
- Each customer is visited only once by one of the available transportation methods and split delivery is not permitted.
- Each charging station has a charger accessible at all times.
- EVs under ownership conclude their trip at the nearest feasible location, which may be a charging station or depot but rented EVs end their trips at the closest charging station.

Considering all the above points, the problem can be formulated as follows:

$\boldsymbol{P1}: min \sum_{i \in N_D \cup N_C} \sum_{j \in N_D \cup N_C} \sum_{\vartheta \in FV \cup OEV} d_{ij} . x_{ij\vartheta} + \sum_{\vartheta \in REV} \sum_{j \in \Gamma} x_{0j\vartheta} + \omega^{+} \sum_{\vartheta \in FV} \sum_{j \in \Gamma} x_{0j\vartheta} - \omega^{-} \sum_{\vartheta \in OEV} \sum_{j \in \Gamma} x_{0j\vartheta}$	(1)
$\sum_{\vartheta \in V} \sum_{j \in \Gamma, j \neq i} x_{ij\vartheta} = 1 \quad \forall i \in N_C$	(2)
$\sum_{j \in \Gamma, j \neq i} x_{ij\vartheta} = \sum_{j \in \Gamma, j \neq i} x_{ji\vartheta} \quad \forall i \in N_C, \vartheta \in V$	(3)
$\sum_{j \in \Gamma} x_{0j\vartheta} \leq 1 \ \forall \vartheta \in V$	(4)
$\sum_{j \in \Gamma} x_{0j\vartheta} = 0 \ \forall \vartheta \in V_3$	(5)
$At_{i\vartheta} + (p_i + t_{ij}) x_{ij\vartheta} - At_{j\vartheta} \leq (1 - x_{ij\vartheta}) M \quad \forall \vartheta \in V, i, j \in \Gamma$	(6)
$At_{j\vartheta} \geq e_j \sum_j x_{ij\vartheta} \ \forall \vartheta \in V, i \in \Gamma$	(7)
$At_{j\vartheta} \leq l_j \sum_j x_{ij\vartheta} \ \forall \vartheta \in V, i \in \Gamma$	(8)

$\sum_{i\in N_C}\left(\theta_i \sum_{i\in\Gamma} x_{ij\vartheta}\right) \leq q_{\vartheta} \; \forall\, \vartheta \in V$	(9)
$Bc_j = BC_{max} \;\; \forall\, j \in N_D \cup N_{CH}$	(10)
$Bc_j \leq Bc_i - \tau.d_{ij} + BC_{max}.(1 - x_{ij\vartheta}) \; \forall\, \vartheta \in OEV \cup REV, i, j(i \neq j) \in N_C \cup N_{CH}$	(11)
$Bc_j \geq \tau\left(d_{ij}.x_{j0\vartheta}\right) \; \forall\, \vartheta \in OEV, i, j(i \neq j) \in N_C \cup N_{CH}$	(12)
$x_{ij\vartheta} \in \{0,1\} : \forall\, \vartheta \in V, i, j \in \Gamma$	(13)
$Bc_j \geq 0 : j \in N_C$	(14)
$At_{i\vartheta} \geq 0 \;\; \forall\, \vartheta \in V, i \in \Gamma$	(15)

The objective function (Eq. (1)) is multifaceted, aiming to minimize total travel distance, decrease fossil fuel vehicle usage, and maximize the deployment of electric vehicles; Each customer is visited only once and by a vehicle among sets of available vehicles, as indicated by constraint (2) and Eq. (3) represents the equality of inflow and outflow followed by vehicle l, i.e., If a vehicle arrives at a node, it must depart from that node as well, ensuring continuity in its trip; each vehicle departs from the depot only once, as specified in constraint (4); Eq. (5) indicates that rental vehicles do not end their trips at the depot; arrival time for each node is presented by Eq.(6) and Eq. (7) and (8) are Time window constraints. Eq. (9) indicates the capacity constraint of each vehicle. Eq. (10) sets the value of battery charge equal to BC_{max} at the departure from the depot and reset it up to BC_{max} upon visit a recharging station. Eq. (11) indicates the battery charge level upon arrival at each node and Eq. (12) ruled the battery charge level must be sufficient for returning to depot. The domains of decision variables are sets by constraints (13-15).

4.Solution Procedure

As the vehicle routing problem and all of its extensions are NP-hard (Lenstra & Kan, 1981), many efforts have been made by researchers to solve the problem using heuristics approaches, metaheuristic methods, and even exact algorithms. Exact algorithms are only efficient for small problem instances. Heuristics and metaheuristics are often more suitable for practical applications, because real-life problems are considerably larger in scale (e.g., a company may need to supply thousands of customers from dozens of depots with numerous vehicles and subject to a variety of constraints)(Braekers et al., 2016);

In this research two metaheuristic approaches based on ant colony optimization have been conducted to tackle with the complexity of the proposed problem which is described in the following subsection.

4.1.Hybrid Ant colony -Variable Neighborhood Search algorithm

The Hybrid Ant Colony-Variable Neighborhood Search (ACO-VNS) algorithm combines the strengths of two powerful optimization techniques to solve complex combinatorial problems. While ACO effectively constructs solutions by simulating the foraging behavior of ants and using a pheromone-based learning mechanism, VNS enhances the exploration of the solution space by systematically changing neighborhoods. This hybridization allows for improved solution quality and a more robust search process, helping to overcome the limitations of each individual algorithm.

In the following sections, we will examine each algorithm separately to provide a clearer understanding of their roles and contributions.

4.1.1. Ant colony optimization algorithm

Ant Colony Optimization (ACO) algorithms create solutions for optimization problems by blending a pheromone model's guidance with insights from greedy functions. This pheromone model represents the collective knowledge of the algorithm about good solutions. The algorithm then adjusts this model based on the performance of the best solutions found in current or previous iterations, reinforcing paths that lead to superior outcomes. For applying an ACO metaheuristic to a combinatorial optimization problem, it is suitable to depict the problem using a graph $G(\phi, \eta)$, where ϕ and η representing the nodes the edges respectively. We employ the ACO algorithm detailed in (Yousefi Yegane et al., 2020); our approach focuses on improving solutions through the incorporation of variable neighborhood search algorithms, aiming for superior quality results. For local search, 1-1 intra-route swap and 1-1 inter rout swap is applied:

4.1.2.Variable Neighborhood Search (VNS)

The VNS algorithm is used to systematically explore the neighborhood of the current solution by changing its structure, which helps escape local optima. By integrating VNS with ACO, the search space is expanded, enabling the algorithm to explore new solutions that may not have been discovered by ACO alone. This hybrid approach enhances the exploration and exploitation balance, ultimately improving the quality of the solutions.

Local Search Steps:

a.1-0 Relocate*: a randomly selected customer is removed from his original vehicle and placed in a different one. Both the place within the new vehicle and the vehicle itself are selected at random*. (Figure 2)

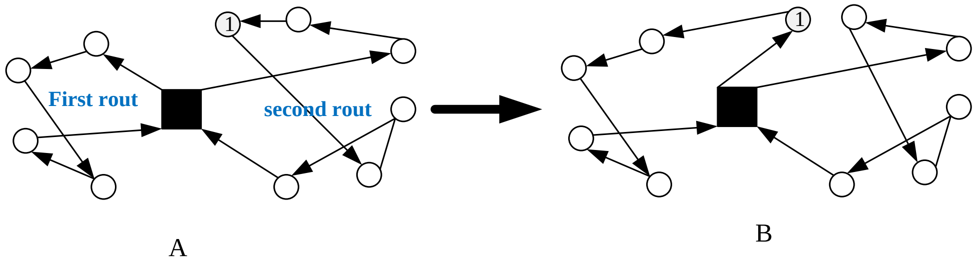

Figure 2. 1-0 Relocate procedure where customer 1 is removed from second rout and add to the first rout

b.1-1 inter route swap*: two randomly selected customers from two different vehicles exchange their places* (Figure 2).

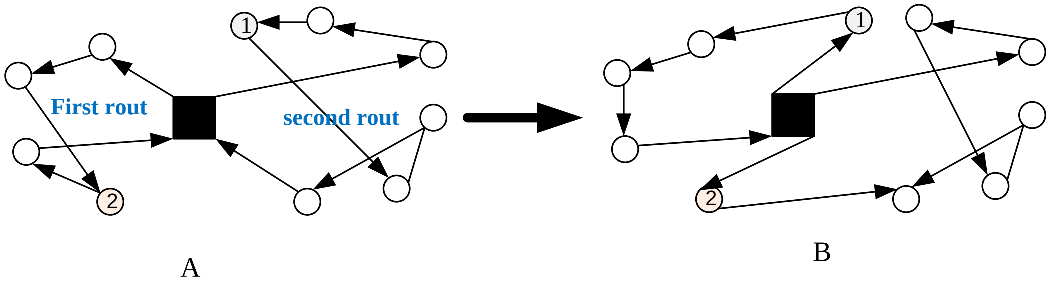

Figure 3. 1-1 inter route swap procedure where customer 1 and 2 are exchange their places

4.1.3.Advantages of Combining ACO and VNS

he combination of ACO and VNS provides several advantages. ACO is effective at building good initial solutions by simulating the behavior of ants in finding optimal paths. However, ACO may sometimes converge prematurely to local optima. By incorporating VNS, which systematically explores alternative neighborhoods, the algorithm can escape these local optima and find better solutions. This hybrid approach ensures more robust optimization and consistently yields higher-quality solutions compared to using ACO or VNS alone.

Starting from the depot, each ant sets off on its route, progressively integrating customers until a constraint violation is encountered, prompting the ant to decide whether to return to the depot or proceed to a charging station; an ant uses the following transition rule to select a customer j with the probability of q_0:

$$i = arg\ max\left\{\tau_{ij}\eta_{ij}^{\beta}\right\} \tag{16}$$

Where τ_{ij} and η_{ij} are the pheromone trail and heuristic information between node i and j respectively and β is a positive parameter denoting the relative importance of the heuristic information versus the pheromone trail. In other words, η_{ij} demonstrates the favorability of selecting node j after departing node i. With the probability of $(1 - q_0)$ the ant selects customer j using following equation:

$$p_{ij} = \frac{\tau_{ij}\eta_{ij}^{\beta}}{\sum_{j=1}^{N}\tau_{ij}\eta_{ij}^{\beta}} \tag{17}$$

Parameter η_{ij} is determined as follow:

$$\eta_{ij} = \frac{d_{ij}}{\sum_j d_{ij}} \tag{18}$$

After constructing an assignment, an ant modifies the pheromone intensity of path by applying local updating rule as follows:

$$\tau_{ij} = (1 - \rho_0)\tau_{ij} + \rho_0\tau_0 \tag{19}$$

τ_0 is the initial value of the pheromone trails and ρ_0 is the local evaporation rate of pheromone trail $(0 < \rho_0 \leq 1)$.

After ants have constructed their solution, the intensity of pheromone on each path between every pair of nodes is adjusted by applying global updating rule:

$$\tau_{ij} = (1 - \rho)\tau_{ij} + \rho\tau_0\left(\frac{d_{ij}}{d_{best}}\right) \tag{20}$$

$\rho(0 < \rho \leq 1)$ is global pheromone trail evaporation rate; $d_{best}$is the length of the most efficient solution has been stablished.

Prior to the final refinement of the paths' pheromones (Equation 24), the solution is undergone through local search.

The general framework of the proposed algorithm is as follows:

Algorithm1

```
Initializing step
    Set parameters
        $ant\_size(Number\ of\ ants)$
        $\tau_0(initial\ pheromone\ trail)$
        $\rho_0, \rho(local\ and\ global\ evaporation\ rate)$
        $q_0(acceptance\ probability)$
        $iter_{max}$
 $z_{best} \leftarrow +\infty$
// start
  $Route = \emptyset$        //solution set
   for $itter = 1$ to $iter_{max}$
       for $ant = 1$ to $ant\_size$
           $S(ant) = \emptyset$
               while no constraint is violated Do:
                   $S(ant) \leftarrow$ construct a solution using transition rule
                   Local pheromone update using $S(itter, ant)$
               End while
           $Objectiv\_Function(S(ant)) \leftarrow objective\ function\ of\ constructed\ solution$
             Variable Neighborhood Search procedure (VNS)
                 update the $S(ant)$ if VNS improve the solution
                 $if\ the\ solution\ is\ improved$: $update\ Objectiv\_Function(S(ant))$
               if $Objectiv\_Function(S(ant)) < z_{best}$
                   $z_{best} \leftarrow Objectiv\_Function(S(ant))$
                   $Route \leftarrow S(ant)$
               end if
           Global update pheromone trail
           next ant
       next itter
print $Route$; $z_{best}$
```

5. Computational Experiments

This section, presents numerical results on the performance of the proposed hybrid ACO. The algorithm has been implemented in the C# programming language and executed on a Core i5 processor 2.5 GHz Pentium IV processor with 8 GB of RAM. Before providing the experimental results, the generation of test problems and parameter settings are discussed.

5.1.Test problems and parameter setting

Given that no real data are available for the mathematical model presented in this research, it is imperative to evaluate the performance of the developed algorithm adequately before commencing the solution, so the sets of numerical examples provided in (Schneider et al., 2014) are used and the results are given in Table 1 where m and f indicate the number of vehicles and travel distance in that order. The last number in each sample problem also represents the number of customers. For example, the number of customers in $C206 - 5$ is 5, $RC102 - 10$ has 10 customers, and $R102 - 15$ has 15 customers. The sample examples used differ in various aspects, with the most significant being the distribution of customers, which is considered in random(R), clustered(C), and a combination of both scenarios (RC); In addition to these factors, parameters such as vehicle capacities, customer demands, and charging stations are also considered in the sample problems, consistent with the elements accounted for in (Schneider et al., 2014). A total of 30 vehicles have been considered, with five of them being rental electric vehicles and the remaining being owned. Among the owned vehicles, 10 are electric, and the other 15 vehicles operate on fossil fuels.

To set the numeric parameters of the proposed algorithm, we adopted a comprehensive experimental approach, which is a well-established methodology for parameter tuning in metaheuristic optimization algorithms. In optimization problems, there is no universally optimal set of parameters, and their performance depends significantly on the problem's specific nature.

Table1. Computational results for test problems

Instances	CPLEX			VNS/TS		HACO			ACO		
	m	f	t(s)	f	t(s)	F^w	F^b	t(s)	F^w	F^b	t(s)
C101-5	2	257.75	81	257.75	0.21	269.3	257.75	0.33	278.1	257.75	0.23
C103-5	1	176.05	5	176.05	0.12	182.1	176.05	0.21	189.6	176.05	0.16
C206-5	1	242.55	518	242.55	0.14	253.8	242.55	0.18	259.1	242.55	0.16
C208-5	1	158.48	15	158.48	0.11	169.2	158.48	0.14	174.9	158.48	0.12
R104-5	2	136.69	1	136.69	0.13	155.2	136.69	0.22	162.2	136.69	0.15
R105-5	2	156.08	3	156.08	0.11	159.1	156.08	0.17	167.1	156.08	0.12
R202-5	1	128.78	1	128.78	0.11	143.5	128.78	0.14	138.9	128.78	0.14
R203-5	1	179.06	5	179.06	0.15	199.2	179.06	0.19	205.8	179.06	0.16
RC105-5	2	241.30	764	241.30	0.14	259.7	241.30	0.14	276.7	241.30	0.13
RC108-5	1	253.93	311	253.93	0.17	262.2	253.93	0.2	269.4	253.93	0.19
RC204-5	1	176.39	54	176.39	0.15	194.7	176.39	0.12	197.2	176.39	0.14
RC208-5	1	167.98	21	167.98	0.13	173.8	167.98	0.15	169.6	167.98	0.12
C101-10	3	393.76	171	393.76	0.77	410.6	393.76	0.58	407.8	393.76	0.66
C104-10	2	273.93	360	273.93	0.95	289.2	273.93	1.12	297.3	273.93	0.87
C202-10	1	304.06	300	304.06	0.71	310.1	304.06	0.68	315.7	304.06	0.66
C205-10	2	228.28	4	228.28	0.49	237.1	228.28	0.61	246.1	228.28	0.52
R102-10	3	249.19	389	249.19	0.65	254.1	249.19	0.71	258.9	249.19	0.6
R103-10	2	207.05	119	207.05	0.72	217.6	207.05	0.61	233.5	207.05	0.58
R201-10	1	241.51	177	241.51	0.78	247.1	241.51	0.96	255.8	241.51	0.81
R203-10	1	218.21	573	218.21	0.71	225.9	218.21	0.94	231.6	218.21	0.73
RC102-10	4	423.51	810	423.51	0.69	438.2	423.51	0.73	447.1	423.51	0.7
RC108-10	3	345.93	39	345.93	0.90	352.8	345.93	1.2	355.3	345.93	0.92
RC201-10	1	412.86	7200	412.86	0.90	425.3	412.86	1.25	431.2	412.86	0.87
RC205-10	2	325.98	17	325.98	0.81	337.2	325.98	1.14	331.4	325.98	0.97
C103-15	3	384.29	7200	384.29	15.37	393.8	384.29	13.67	400.6	384.29	11.34
C106-15	3	275.13	5060	275.13	14.94	288.7	275.13	14.21	294.2	275.13	12.7
C202-15	2	383.62	7200	383.62	13.41	392.1	383.62	8.62	389.3	383.62	7.61
C208-15	2	300.55	7200	300.55	11.08	308.3	300.55	9.11	312.7	300.55	8.43
R102-15	5	413.93	7200	413.93	19.55	426.8	413.93	16.32	424.7	413.93	14.86
R105-15	4	336.15	7200	336.15	13.35	345.7	336.15	15.21	354.2	336.15	12.22
R202-15	2	358.00	7200	358.00	13.17	365.8	358.00	11.54	374.7	358.00	11.28
R209-15	1	313.24	7200	313.24	13.73	319.1	313.24	10.96	325.2	313.24	9.67
RC103-15	4	397.67	7200	397.67	14.62	406.2	397.67	12.07	414.3	397.67	11.32
RC108-15	3	370.25	7200	370.25	12.92	378.9	370.25	10.38	391.2	370.25	11.17
RC202-15	2	394.39	7200	394.39	12.74	402.5	394.39	10.21	405.4	394.39	10.3
RC204-15	1	407.45	7200	407.45	15.57	413.8	407.45	17.87	423.9	407.45	16.97

For this reason, extensive parameter tuning through experimental trials is essential to achieve robust and effective results. During the preliminary phase of our research, numerous combinations of parameter values were systematically tested across various experimental scenarios. We aimed to strike an optimal balance between exploration and exploitation, ensuring that the algorithm thoroughly explores the solution space while also efficiently converging towards high-quality solutions. Our tests revealed that the following parameter settings consistently produced satisfactory results: ant size= 25, initial pheromone trail = 10^{-10} , $\beta = 1$, $\rho = 0.1$, $q_0 = 0.9$ and the algorithms will be stopped after 5000 iterations. These parameters were selected based on their impact on both convergence speed and solution quality.

The choice of these parameters is grounded in both **empirical validation** and **sensitivity analysis**. Specifically, the pheromone evaporation rate ($\rho = 0.1$) controls the balance between retaining useful information from past iterations and avoiding the risk of premature convergence to suboptimal solutions. Similarly, the parameter $q_0 = 0.9$, which influences the probability of exploiting the best-known path, was fine-tuned to maximize solution quality without stifling diversity in the search process. Additionally, our sensitivity analysis confirmed the robustness of these parameter values, demonstrating that moderate variations in the parameters did not lead to significant degradation in algorithmic performance.

This experimental tuning process follows best practices in the literature, where fine-tuning through trial and error is considered one of the most reliable techniques for optimizing performance in metaheuristics. For instance, recent studies in the field of Ant Colony Optimization and Variable Neighborhood Search highlight the importance of tailoring parameters to the specific characteristics of the problem at hand to achieve optimal performance. Our approach not only adheres to these best practices but also contributes valuable insights into parameter tuning for combinatorial optimization problems, offering a solid foundation for further research in this area.

In conclusion, the parameters selected through our empirical methodology are robust and well-suited for this particular problem, ensuring that the algorithm achieves high performance and delivers reliable results

Table 1 presents the results of the Ant Colony Algorithm hybridized with a local search engine (HACO), alongside the results of the ACO without utilizing a local search procedure, all of which are compared with the exact solution of sample problems found by GAMS software(CPLEX Solver), as well as the results of the VNS/TS algorithm applied by (Schneider et al., 2014), have been compared. The proposed ACOs algorithms were executed 10 times on each sample problem and the numerical report were generated for the best (F^b) and worst (F^w) solutions obtained. The proposed ACO and HACO, as utilized in the research, exhibit remarkable capabilities. It has shown exceptional performance in terms of time efficiency, solving sample problems in a reasonable time. Furthermore, it has consistently converged to the optimal solution, demonstrating its high capability. These results collectively highlight the algorithm's significant potential. According to the findings, now the proposed ACOs is applied to the mathematical model of this study and the results are presented in Table 2 based on instances provided in (Schneider et al., 2014) with 100 customers; Taxation and subsidy strategies implemented by governments to mitigate carbon emissions and improve the environmental pollution indices are quantified at 40 and 25 for each fuel and electrical vehicle respectively, mirroring established research findings in this domain.

Table2. Computational results for large-Scale problems

Instances	CPLEX		HACO			ACO			No. of vehicles for each Instance		
	Best Bound	t(s)	F^w	F^b	t(s)	F^w	F^b	t(s)	RV	OFV	OEV
C101	1048.24	>7200	1032.15	1005.89	132.14	1035.96	1014.36	121.19	3	4	5
C102	1069.47	>7200	1052.98	1026.64	146.27	1059.12	1036.18	127.35	3	3	5
C103	1022.53	>7200	1006.43	983.17	112.96	1017	997	101.37	3	2	5
C104	1067.94	>7200	1031	1015	121.26	1046	1028	106.98	3	2	5
C105	1051.86	>7200	1028	1011	122.67	1034	1023	105.65	3	3	5
C106	1047.31	>7200	1021	1009	118.93	1031	1017	102.18	3	3	5
C107	1015.7	>7200	998	972	112.45	1008	981	995.65	3	3	5
C108	1086.13	>7200	1047	1032	154.32	1044	1036	131.48	3	2	5
C109	1046.78	>7200	1026	1013	129.12	1034	1021	110.17	3	2	4
C201	616.32	>7200	573	532	87.41	592	541	64.57	0	2	2
C202	621.34	>7200	596	582	88.13	610	593	72.19	0	2	2
C203	637.12	>7200	591	573	87.90	599	585	60.23	0	2	2
C204	645.19	>7200	617	601	89.14	639	623	62.16	0	2	2
C205	626.86	>7200	598	582	88.04	612	602	60.37	0	2	2
C206	610.17	>7200	592	577	82.39	590	582	55.92	0	2	2
C207	618.76	>7200	610	600	83.34	608	597	66.49	0	2	2
C208	613.14	>7200	601	589	82.57	605	592	60.36	0	2	2
r101	1567.34	>7200	1487	1421	191.52	1485	1437	183.21	5	6	7

r102	1418.16	>7200	1398	1381	189.76	1403	1392	164.53	4	5	7
r103	1235.98	>7200	1202	1173	174.56	1210	1193	158.93	3	5	5
r104	1037.62	>7200	1002	983	131.54	1114	999	108.76	3	4	4
r105	1387.24	>7200	1321	1295	168.46	1326	1295	143.95	4	5	5
r106	1271.19	>7200	1246	1208	162.98	1238	1215	142.84	3	5	5
r107	1098.83	>7200	1032	1003	158.37	1047	1012	143.72	3	4	5
r108	986.13	>7200	932	912	103.64	937	921	88.00	2	4	5
r109	1134.76	>7200	1076	1023	168.28	1091	1047	143.52	3	4	5
r110	1159.98	>7200	1082	1039	169.41	1096	1047	147.91	3	4	5
r111	1083.29	>7200	1042	1017	155.62	1064	1032	143.17	2	4	5
r112	965.42	>7200	931	901	98.53	956	912	80.00	2	4	5
r201	1254.89	>7200	1138	1087	160.89	1149	1110	146.22	0	1	2
r202	945.62	>7200	921	873	101.12	934	902	92.13	0	1	2
r203	916.54	>7200	902	893	99.31	908	900	90.42	0	1	2
r204	735.61	>7200	706	682	88.49	712	693	75.62	0	1	1
r205	905.12	>7200	891	863	96.74	894	877	80.17	0	1	2
r206	912.18	>7200	894	881	96.89	899	886	80.00	0	1	2
r207	789.53	>7200	753	727	91.26	751	736	80.32	0	1	1
r208	707.47	>7200	691	674	83.92	698	676	75.12	0	1	1
r209	817.65	>7200	801	785	92.38	810	803	81.42	0	1	2
r210	824.17	>7200	803	792	93.00	803	796	80.11	0	1	2
r211	816.75	>7200	799	783	92.17	806	789	84.31	0	1	1
rc101	1653.94	>7200	1612	1592	217.87	1623	1597	172.86	4	6	6
rc102	1463.16	>7200	1407	1387	192.45	1426	1395	164.35	4	5	6
rc103	1318.97	>7200	1299	1283	176.57	1306	1283	132.12	3	5	5
rc104	1153.11	>7200	1098	1072	168.33	1116	1095	141.00	3	4	4
rc105	1403.8	>7200	1364	1325	189.76	1382	1341	155.00	4	5	5
rc106	1374.92	>7200	1326	1308	177.00	1342	1316	146.71	3	5	5
rc107	1213.23	>7200	1201	1187	174.32	1203	1194	152.12	3	4	5
rc108	1143.86	>7200	1111	1091	166.00	1125	1106	140.37	2	4	5
rc201	1379.31	>7200	1321	1286	179.37	1315	1293	153.31	1	1	2
rc202	1328.76	>7200	1296	1253	175.62	1310	1287	156.67	1	1	1
rc203	937.16	>7200	905	893	99.44	912	899	80.44	1	1	1
rc204	815.64	>7200	792	775	93.64	802	781	82.16	1	1	1
rc205	1254.95	>7200	1167	1132	175.00	1193	1142	149.42	1	1	1
rc206	1113.53	>7200	1096	1064	163.83	1103	1079	147.31	1	1	1
rc207	896.14	>7200	842	815	95.67	857	831	81.35	1	1	1
rc208	765.19	>7200	739	710	98.47	745	721	82.00	1	1	1

To solve sample problems with 100 customers, all of the sample problems were coded in GAMS 24.7.4 software and CPLEX solver have been utilized. Findings were are reported by Table 2, indicate that optimal solutions have not been obtained for any of the problems within the time limit of 7200 seconds, and the reported values for the objective function represent the best bounds obtained by CPLEX. In the subsequent columns of the Table 2, the best and worst values obtained are related to two proposed algorithms, Ant Colony Optimization (ACO) and Hybrid Ant Colony Optimization (HACO). Noteworthy in the results is the improvement in the objective function values in the HACO algorithm compared to ACO, attributed to enhanced solutions through local search, which also leads to increased solution time. This observation can be inferred by comparing the solution times obtained in Table 2. In Table 2, the number of vehicles used by each group is also presented separately. Since there is no distinction between vehicles (except for the method of energy supply), in most cases, a sample of each of the three categories has been used. Considering the incentive provided in most cases, the set of electric vehicles is used more than the number of vehicles running on fossil fuels. To investigate a sensitivity analysis, we increase/decrease the number of owned electric vehicles/fossil fuel vehicles, and the sample scenarios are solved again using the provided algorithms, with the results of the solutions presented solely in terms of the number of vehicles used in

Table 3. By referring to the Table 3, it is observed that with the considered tax and incentive rate, there is still a tendency to use electric vehicles in various sample scenarios.

Now, by keeping the number of vehicles constant, we alter the taxation and incentives considered, and evaluate the impact of these changes on the number of vehicles used again, the results of which are observable in Table 4. As expected, with an increase in incentives or taxation, the inclination towards using electric vehicles also increases, which the obtained results confirm.

6. Managerial Insights

In the dynamic landscape of transportation, managerial decisions play a pivotal role in shaping the trajectory of electric and fossil fuel vehicle usage, particularly within the realms of rental and ownership-based transportation. This section aims to explore the strategic considerations and managerial insights essential for navigating the transition towards electric mobility and sustainable transportation practices. As the global community intensifies its efforts to combat climate change and reduce dependence on fossil fuels, managers face a myriad of challenges and opportunities. From crafting taxation policies to incentivize electric vehicle adoption to developing infrastructure conducive to electric vehicle usage, managerial decisions wield significant influence over the direction of transportation systems.

Table3. Sensitivity Analysis for changing in number of vehicles

$25\%^{+}-25\%^{-}$								
	c101	**c104**	**c108**	**c208**	**r101**	**r104**	**r201**	**r208**
RV	3	3	2	0	6	3	0	0
OFV	4	2	2	2	4	2	1	1
OEV	5	5	6	2	8	5	2	1
$50\%^{+}-50\%^{-}$								
RV	3	2	1	0	5	3	0	0
OFV	3	1	1	1	3	1	0	0
OEV	7	7	8	3	10	6	3	2
$75\%^{+}-75\%^{-}$								
RV	3	2	1	0	5	3	0	0
OFV	3	1	1	0	2	1	0	0
OEV	7	7	8	4	11	6	3	2

Table4. Sensitivity Analysis for changing in financial policies tariffs

$25\%^{+}-25\%^{-}$								
	c101	**c104**	**c108**	**c108**	**r101**	**r104**	**r201**	**r208**
RV	3	3	2	0	6	3	0	0
OFV	3	1	1	1	3	1	0	0
OEV	7	6	7	3	9	6	3	2
$50\%^{+}-50\%^{-}$								
RV	3	3	2	0	6	3	0	0
OFV	1	0	0	0	1	0	0	0
OEV	9	7	8	4	11	7	3	2
$75\%^{+}-75\%^{-}$								
RV	2	2	1	0	4	2	0	0
OFV	0	0	0	0	0	0	0	0
OEV	11	8	9	4	14	8	3	2

In this section, we delve into key managerial insights pertaining to taxation policies, incentive structures, infrastructure development, regulatory frameworks, public awareness initiatives, and research and development investments. By analyzing these aspects, we aim to provide a comprehensive understanding of the managerial strategies necessary for fostering the widespread adoption of electric vehicles and advancing sustainable transportation goals. Now, let us embark on an exploration of these managerial insights and their implications for shaping the future of transportation.

- **Taxation Policies**: In the face of escalating environmental concerns and the imperative to mitigate climate change, taxation policies emerge as potent tools for incentivizing sustainable transportation choices. By levying higher taxes on fossil fuel vehicles and offering tax breaks or incentives for electric vehicle adoption, managers can steer consumers towards environmentally friendly alternatives.

- **Incentive Policy Determination**: Crafting incentive structures that align with broader environmental and economic objectives requires careful consideration. Managers must evaluate the effectiveness of various incentives, such as financial discounts, preferential parking, or access to High Occupancy Vehicle (HOV) lanes, in driving electric vehicle uptake while balancing financial constraints and societal goals.

- **Infrastructure Development**: Building the necessary infrastructure to support electric vehicle usage represents a critical managerial challenge. Managers must invest in charging stations, upgrade grid infrastructure, and expand public transportation networks to accommodate electric vehicles effectively. Moreover, strategic partnerships with utilities and government agencies can facilitate the deployment of charging infrastructure at scale.

- **Regulatory Framework Enhancement**: Enhancing regulatory frameworks is essential to create a level playing field for electric vehicles and fossil fuel vehicles. Managers must advocate for clear and consistent regulations governing vehicle emissions, safety standards, and incentives for clean technology adoption. Additionally, collaboration with policymakers and industry stakeholders is vital to ensure that regulations support rather than hinder the transition to electric mobility.

- **Public Awareness and Education Initiatives**: Engaging with consumers through public awareness campaigns and educational initiatives is crucial for fostering acceptance and adoption of electric vehicles. Managers can collaborate with government agencies, non-profit organizations, and industry partners to disseminate accurate information about the benefits of electric transportation and dispel common misconceptions.

- **Research and Development Investment**: Strategic investment in research and development is indispensable for advancing electric vehicle technology and driving down costs. Managers must allocate resources towards battery research, charging infrastructure innovation, and vehicle design to enhance performance, affordability, and consumer acceptance of electric vehicles.

7.Conclusion, findings, limitation and future direction

In this section, we provide a comprehensive summary of our research findings and their implications. The conclusion is organized into four distinct sections to enhance clarity and guide the reader through our main insights, the limitations of our study, potential avenues for future research, and the practical applications of our findings. This structured approach aims to facilitate a better understanding of the contributions made by this research and to highlight areas for further exploration.

7.1. The Main Conclusion

In this research, we addressed the vehicle routing problem by considering two types of transportation facilities: rental-based and ownership-based, focusing on electric and fossil fuel vehicles. Recognizing the environmental implications of fossil fuel vehicles, we introduced a tax to deter their use while simultaneously offering incentives for the adoption of electric vehicles. This dual approach aims to significantly reduce environmental impact and promote sustainable transportation solutions. A linear programming model was meticulously developed to represent the problem, and given its inherent complexity, we employed a hybrid algorithm that combines Ant Colony Optimization (ACO) with a local search method. This combination enhances the solution quality, allowing us to effectively tackle the problem's high-dimensional nature.

7.2. Limitations

This study acknowledges several limitations. Notably, it does not account for crucial real-world variables such as vehicle speed, traffic conditions, and reliability, which could enhance the model's realism. Additionally, the dynamic nature of customer demand, where orders may change before delivery, was not considered.

7.3. Future Research

Future research could delve into these aspects using simulation-based models, thereby improving the practical applicability of the findings. Furthermore, exploring competitive leader-follower models involving multiple transportation companies with varied vehicle compositions or incorporating drones to improve delivery speed presents exciting avenues for future inquiry. Another intriguing extension could involve the transportation of perishable goods or medical products like blood, which introduces critical time constraints and service quality considerations.

7.4. Applications

The insights gained from this research are valuable for policymakers and transportation companies seeking to optimize their fleets while minimizing environmental impacts. The findings can inform the design of effective financial policies and incentives, contributing to the broader goal of promoting sustainable transportation practices globally.

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