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The close-open mixed-fleet electric vehicle routing problem

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ABSTRACT

The market of Electric Vehicles (EVs) has grown significantly in recent times. The transportation sector is expected to shift to EVs as well, but there are several significant challenges that make the shift difficult, mainly their capacity for transporting heavy payloads and their high acquisition costs. This research explores a novel business concept wherein a logistics company owns a small fleet of EVs, and rents additional EVs as needed, while providing the option to charge the owned EVs only after completing the final delivery. This concept is modeled as a Close-Open Mixed-fleet Electric Vehicle Routing Problem (COMF-EVRP), and the mathematical formulation is presented. Instances from the literature are adapted for the COMF-EVRP. To solve large instances, three discrete optimization swarm intelligence algorithms are employed, alongside a Variable Neighborhood Search algorithm. Lastly, a comprehensive evaluation of these algorithms' performance on the COMF-EVRP is provided.

1. Introduction

Electric Vehicles (EVs) have already started to infiltrate the transportation sector, and logistics operations are no exception (Ruan and Lv, 2022). Research on the subject of Vehicle Routing Problems with EVs (EVRP) has gained much interest since its introduction in Schneider et al. (2014). As a result, many variants of EVRP have been presented to date, solving most VRP variants but using EVs instead.

Logistics companies that transition to EVs face two issues. First, the battery technology is not yet up to par with traditional Internal Combustion Engine (ICE) vehicles in terms of driving range and refueling speed (Stamadianos et al., 2023). Secondly, the initial acquisition cost for EVs is higher than ICE vehicles, forcing companies to own a smaller fleet of vehicles and rent vehicles when their operations demand it.

In this research, a novel operational scenario is explored. It considers a logistics company that owns a small fleet of EVs that can satisfy their average daily operations, fits their budget, and rents more EVs as needed from an EV rental business. It is assumed that the rented EVs end their trips at Charging Stations (CSs), while the EVs of the owned fleet may end their routes either at a CS or the depot.

The described scenario is modeled as a Close-Open EVRP with a Mixed Fleet of owned and rented EVs. In this novel approach, the owned EVs are used first, and more EVs are rented only when necessary since renting adds to the total cost of operation. A close route means an EV begins and ends its trip at the depot, while an open one means that the EV leaves after the last customer has been served and goes to the closest CS. Since the vehicles are electric, they have to recharge after the end of their trip; therefore, the VRP model has to ensure the remaining energy is enough to visit a CS or go back to the depot. The routes of owned EVs may be either closed or open, while rented EV routes may only be open.

Last-mile delivery companies and ride-sharing companies are two examples of companies that could benefit from implementing this business model. Companies providing last-mile delivery services, such as e-commerce platforms or courier companies, can use this approach to optimize their EV fleet's operations. They can use their owned EVs for closed routes, starting and ending at the depot, to serve regular customers. When demand surges or there are areas not well-covered by owned EVs, they can rent additional EVs for open routes, ensuring efficient coverage without incurring unnecessary rental costs. Ride-sharing companies can utilize this approach to optimize their electric vehicle fleet. Owned electric cars can serve as the primary vehicles for standard routes and bookings. When the demand in a specific area increases due to events or special circumstances, rented EVs can be dispatched to accommodate the additional rides. This approach helps minimize the overall operational cost and reduces the need for a large fleet of owned vehicles.

Fig. 1 presents an example of the described scenario, where all the involved vehicles start their trip from the depot and finish at a CS.

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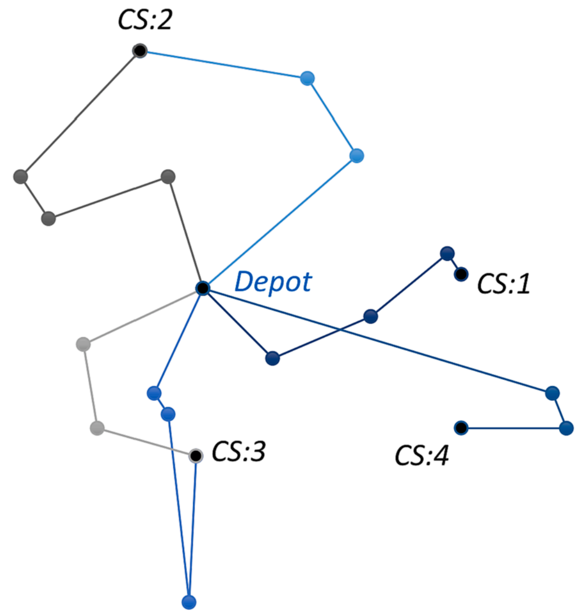

Fig. 1. Example of a COMF-EVRP plan.

Different routes are represented with varying shades of blue.

Small instances of the COMF-EVRP are solved both with the proposed algorithm and using the commercially available solver, Gurobi. To solve large instances, two discrete optimization swarm intelligence algorithms are employed, the Bee Colony Optimization (BCO) and two variants of the Ant Colony Optimization (ACO). In all cases, the swarm intelligence algorithms are combined with a Variable Neighborhood Search (VNS) algorithm.

The Bee System algorithm was first presented in Lucic and Teodorovic (2001), while the BCO was introduced in Teodorovic and Dell'Orco (2005). The implementation of BCO that inspired this variant was presented in Wong et al. (2008). The BCO approach exploits swarm behavior traits of the bees to tackle discrete optimization problems, unlike most other swarm intelligence algorithms developed to solve continuous optimization problems. In contrast to the BCO presented in Teodorovic and Dell'Orco (2005), the bees of this implementation lack the memory feature. In this case, the waggle dance takes place only after a complete, feasible solution has been created.

Ant Colony Optimization (ACO) algorithms are known for their exceptional performance on VRP, with the first variant introduced in Dorigo et al. (1996). In this case, two very potent variants, namely the Ant Colony System found in Dorigo and Gambardella (1997) and the Max–Min Ant System (MMAS) found in Stützle and Hoos (2000), were adapted for the proposed VRP.

The element that sets BCO and ACO apart is the memory component, which BCO lacks. The selected BCO and ACO implementations are both swarm intelligence algorithms and have a similar overall notion. The element that sets them apart from other swarm intelligence algorithms is their natural discrete nature, meaning that neither encoding nor decoding takes place. To further improve the BCO and ACO solutions, a VNS scheme is employed, using four local search operators. The proposed algorithm is evaluated on modified instances from the literature. The adaptation is described in detail and can be easily replicated for comparison purposes.

The contributions that stem from this paper are the following:

- The novel COMF-EVRP is introduced and its mathematical model is presented and solved.
- COMF-EVRP is the first VRP to consider a mixed fleet of owned and rented EVs, with the option of open routing for owned vehicles when necessary.
- A charging strategy that lowers the probability of delays caused by failures of the charging infrastructure is presented.
- Three discrete swarm intelligence algorithms are proposed and compared for solving large VRPs.

The structure of the research paper is the following. A literature review of research on related VRP variants is presented in Section 2. The COMF-EVRP model is presented in Section 3, and Section 4 presents the BCO and ACO solution algorithms. Section 5 discusses the computation experiment results. Lastly, Section 6 gives the overall conclusions and future research.

2. Related Literature

The variants of Close-Open VRP, Open VRP, and EVRP are related to COMF-EVRP and are analyzed in the following subsections.

2.1. Open Vehicle Routing Problems

The Open VRP (OVRP) variant was introduced in Schrage (1981), with external contractors conducting part of the deliveries as needed for a company with a high demand for deliveries and low demand for pickups.

In recent years, various adaptations of the original OVRP have been presented. In López-Sánchez et al. (2014), a heuristic algorithm was developed for OVRP, aiming to minimize the distance of the longest route. An improved Bumble Bee Mating algorithm for the OVRP, with an Iterated Local Search (ILS) in place of the flying equation, was presented in Marinakis and Marinaki (2014), leading to lower CPU times and better results. The OVRP with demand uncertainty was presented in Cao et al. (2014). The demand for each customer is not known a priori, but a range of potential demand for the customer is available. Vincent et al. (2016) explored a scenario in which the pickup and delivery are fully outsourced for the cross-docking OVRP. It was solved using a Simulated Annealing algorithm. OVRP with Decoupling Points was presented in Atefi et al. (2018). They explored the possibility of having multiple carriers for their deliveries and presented a case study. The OVRP with distance and load constraints was solved in Ruiz et al. (2019). The Multi-Depot OVRP (MD-OVRP) variant was solved in Soto et al. (2017) and Brandão (2020), with each employing a different heuristic algorithm. Another relevant variant is the Green OVRP. More recently, Niu et al. (2022) presented a three-level heuristic method for the Green OVRP. Their algorithm was validated on real-life instances. The goal in Niu et al. (2018) was to minimize the cost of fuel emissions using a hired fleet of vehicles and drivers. A multi-objective Green OVRP variant was presented in Kar et al. (2022).

Dasdemir et al. (2022) explored a bus routing problem from the perspective of OVRP, managing a fleet of buses transporting employees to their workplace. A crowdshiping service for small size deliveries modeled as a two-echelon OVRP, was explored in Wu et al. (2022). Lee et al. (2023) presented a ride-sharing application modeled as an OVRP.

Ahmed and Yousefikhoshbakht (2023) proposed a new tabu search algorithm for the heterogeneous OVRP, as well as an Ant Colony Optimization based approach for the same problem (Ahmed and Yousefikhoshbakht, 2023), including both fixed and variable costs. Ozcetin and Ozturk (2023) presented a variant of VNS for OVRP, while Bezerra et al. (2023) proposed a different VNS variant for the multi-depot OVRP.

A cutting-plane method for the split delivery OVRP was proposed in Ruiz et al. (2022), along with a case study that motivated the research. Zheng et al. (2023) also carried out research with a similar motivation, with the intention of allocating supplies with limited stock among customers, modeled as a multi-objective OVRP.

2.2. Close-Open Vehicle Routing Problems

The Close-Open VRP was introduced in Liu et al. (2010), and later in

Liu and Jiang (2012), as a Close-Open Mixed VRP, making deliveries with a fleet of owned and rented vehicles. The owned vehicles could end their trips only at the depot, while the rented ones end immediately after the last delivery. To date, this variant has received little study. The COVRP with Time Windows was presented in Brito et al. (2016) (available online in 2013), along with a proposed VNS algorithm, solving real-life and theoretical instances. Later, in Brito et al. (2015), the COVRP with Time Windows and fuzzy constraints was presented and solved using an ACO, GRASP, and VNS hybrid algorithm. In Azadeh and Farrokhi-Asl (2019), a variant of COVRP with mixed fleets and multiple depots was studied, aiming to minimize cost.

2.3. Electric Vehicle Routing Problems

The EVRP variant was introduced in Schneider et al. (2014) as EVRP with Time Windows and Recharging Stations. Since then, it has received great recognition from many researchers.

Researchers have been rightfully focused on energy consumption and replenishment. Desaulniers et al. (2016) created four variants of EVRPTW, each with a different charging scenario, and concluded that allowing multiple and partial recharges (PR) is the best option for en-route charging. Löffler et al. (2020) presented an EVRP allowing only one recharge, citing the better driving range of newer EVs and the non-productive idle time of charging. They also considered both partial and full charging policies.

Keskin and Çatay (2018) aimed to minimize the cost of recharging. A non-linear charging function (NLCF) was presented in Montoya et al. (2017), solving the EVRP-NL. An NLCF was also employed in Froger et al. (2017). Zuo et al. (2019) used a concave NLCF aiming to minimize the operational costs. Keskin et al. (2019) solved a variant with time-dependent waiting times for charging and highlighted the potential costs that might occur from charging delays. Çatay and Keskin (2017) showed the advantages of quick charging in EVRP. Ferro et al. (2018) considered charging parameters such as different energy pricing in relation to time and the efficiency of the EV's energy converter. In Schiffer et al. (2017), the potential of synchronizing driver breaks with charging was explored. A comparison to traditional vehicles showed that by this synchronization, the impact of charging is minimal.

Ding et al. (2015); and Froger et al. (2017) considered charging stations of limited capacity. A very innovative machine learning method was presented in Basso et al. (2021) to determine the EV's State of Charge (SoC). Charging and discharging were studied in Chakraborty et al. (2021) and Keskin et al. (2021). Lin et al. (2021) included in their research an innovative technology that allows the stored energy in the EV's battery to be supplied back to the grid when the vehicles are not used, always in a controlled environment. In Kyriakakis et al. (2022), the EVRP with Drones variant was introduced along with an energy consumption function that measures the amount of work needed to move the items by either type of vehicle.

The EVRP variant has to account for many external parameters due to the use of EVs. Their battery depletion is highly associated with the load they carry, effectively shortening their range. The research of Xiao et al. (2019) and Shao et al. (2017) considered both the speed of the vehicle and the load to determine the energy consumption of the EVs. In Lin et al. (2016) a case study was conducted based on real-world data to showcase the significant effect of load on energy consumption. Rastani et al. (2019) studied the temperature effect on EV energy consumption. In Zhang et al. (2018), vehicle load, speed, and friction from the tarmac were accounted for in the energy consumption calculation. The researchers aimed to minimize energy consumption instead of the total distance to prove that this approach provides solutions that demand less energy.

Electric bus routing problems and scheduling problems are also of interest, since they can have an even greater environmental impact if operated properly. For example, Liu et al. (2022) developed optimization models for charging plans using time-of-day electricity tariffs to minimize the electricity costs of electric bus operations, offering a practical solution for transit agencies to cut down on their operational expenses. He et al. (2022) presented a novel mixed-integer linear programming model to optimize the charging schedule for battery electric buses, successfully reducing charging costs by 15.56% based on real-world data, with implications for enhancing the planning of charging infrastructure.

Other studies have started to include parameters of uncertainty. Zhang et al. (2020) presented an EVRP with fuzzy travel and service times and fuzzy energy consumption. In Omidvar and Tavakkoli-Moghaddam (2012), vehicle speed is altered depending on the time of day to simulate the effect of traffic on the VRP. Kullman et al. (2018) presented a variant with private and public CSs, with the main distinction between the two being the uncertain waiting times at the latter.

More than one review of the EVRP literature has been published in the last few years. Xiao et al. (2021) discussed in detail issues such as charging strategies, energy consumption, and other relevant factors. In addition, the authors presented an EVRP model of their own with many realistic parameters. They carried out computational experiments that encouraged using larger batteries in EVs and showed the positive effect of variable speed compared to assuming a static one in the energy consumption function. They highlighted the lack of realism in the EVRP literature, which they attribute to the unique characteristics of EVs.

Abid et al. (2022) presented a very concise review on routing and charging operations, presenting a few general research directions. Huang et al. (2023) provided a systematic review on EVRP literature, analysing both EVRP variants as well as solution methodologies, and proposing charging station collaboration as a unique future research direction. Ye et al. (2022) identified four main EVRP research categories, load and battery life studies, time-window and charging studies, mixed fleet studies, and charging station location problems. Di Martino et al. (2022) analyzed energy consumption modeling strategies for EVs. In regards to VRP, the authors highlighted the importance of load, identifying the low level modeling that is commonly observed among EVRP variants. In their EVRP review, Su (2023) highlighted the lack of research on the Electric Team Orienteering Problem.

Lastly, Stamadianos et al. (2023) provide a comprehensive examination of electric mobility, presenting an analysis of technical vehicle specifications within the context of logistics applications and the VRP, as well as future research directions for EVs and other autonomous vehicles.

The present research combines the traditional COVRP with the emerging EVRP, presenting a novel mathematical formulation that distinguishes between owned and rented vehicles, leading to different solutions depending on the transportation demand. The proposed synergy capitalizes on the strengths of close-open routing and EVs, offering the potential for significant advancements in the field of operations research and contributing to the sustainable evolution of modern transportation systems.

3. The Close-Open Mixed-fleet Electric Vehicle Routing Problem

This research introduces an alternative operational model for logistics companies with the potential for real-world deployment. This section presents the key attributes of the COMF-EVRP and provides its mathematical formulation.

3.1. Problem Description

The proposed COMF-EVRP offers several positive aspects from a business standpoint. It involves satisfying the company's average daily operations and budget constraints through the owned fleet while renting additional EVs from an external EV rental business as needed. Furthermore, the plan allows for flexibility in routing, as the owned fleet EVs may conclude their routes either at Charging Stations (CSs) or the company's depot. From a business standpoint, this approach offers potential advantages such as cost efficiency and scalability. Renting additional EVs instead of owning a large fleet upfront can result in cost savings, allowing the company to manage its budget effectively. Moreover, the flexibility in routing provides an opportunity to optimize operational logistics, reduce idle time, and enhance overall efficiency. In addition, the plan aligns with environmental sustainability goals by utilizing EVs as the primary mode of transportation. This approach addresses the growing demand for eco-friendly practices and positions the logistics company favorably in attracting environmentally conscious customers. By reducing carbon emissions through the use of EVs, the company can contribute to a greener transportation ecosystem and enhance its brand image.

However, the plan also presents certain negative aspects to consider. The dependency on the availability and reliability of the external EV rental business is a preeminent concern. Disruptions in the supply or service quality from the rental company could lead to operational challenges, potentially impacting customer satisfaction and overall business performance. Subsequently, having many rental business partners would be essential.

Additionally, the plan assumes the existence of adequate charging infrastructure at the CSs. In reality, there may be limitations in the charging infrastructure, such as insufficient capacity or congestion during peak times, which could hinder the smooth operation of the logistics company. This risk motivated the move of charging to the end of the routes. Moreover, the logistics company will face increased maintenance and long-term costs if the fleet expands. Proper planning, maintenance partnerships, and budget allocation will be necessary to address these potential challenges effectively.

The return strategy for owned EVs that conclude their trips at a CS is a critical aspect that warrants attention within the framework of efficient operations. Different companies can have different strategies, such as considering charging stops that allow drivers to rest before returning to the depot to restock their vehicles or opt to visit only fast CSs that would enable them to return to the depot after charging for only a few minutes.

Lastly, with the continuous advancement of technology and as economies of scale progress, it becomes necessary for companies following this model to assess their needs and adjust their fleet composition regularly.

3.2. Mathematical Formulation

The COMF-EVRP is an extension of EVRP that employs both owned and rented vehicles and explores an alternative charging scheme. All vehicles are assumed to be equipped with the same battery and have the same payload capacity. The carried weight is a characteristic with considerable influence on logistics; subsequently, the energy consumption is directly affected. In the presented problem, charging may occur only after the final delivery. Owned EVs can end their trips at the depot or a charging station, and rented EV trips may only end at a charging station.

The following assumptions are made in COMF-EVRP:

- All EVs have the maximum energy at the start of the trip.
- Customers are visited precisely once.
- There is an available charger at all times in each CS.
- Owned EVs end their trips at the closest possible location (depot or CS).
- Rented EVs end their journey at the closest CS.

It is crucial to highlight the prevalent assumption in VRPs that the routing of rented vehicles concludes once the last customer on the route has been visited. However, the reliance of EVs on battery power leads to additional issues and limitations. To ensure the EV's operational viability, it becomes necessary to maintain a sufficient battery level that allows for a visit to the closest CS.

Table 1
Notation used for the COMF-EVRP formulation.

	Sets & Characteristics
V_D	Depot set, $V_D = \{v_D\}$
V_C	Customers set, $V_C = \{v_{C1}, v_{C2}, \ldots, v_{Cn_c}\}$
CS	Charging Stations set, $CS = \{CS_1, CS_2, \ldots, CS_{n_{cs}}\}$
V_E	Ending nodes set, $V_E = V_D \cup CS$
V	Superset containing all the above sets, $V = V_D \cup V_C \cup CS$
d_{ij}	Distance from node i to node j
n_c	Number of customers
n_{cs}	Number of Charging Stations (CS)
q_i	Payload demand of customer i
K_1	Set of owned EVs
K_2	Set of rented EVs
K	Set of both owned and rented EVs
Q	Maximum payload capacity of EVs
E	Maximum energy capacity of EVs
	Decision Variables
f_{ijk}	Stores the payload of k EV coming from i.
x_{ijk}	If arc (i,j) is traversed, $x_{ijk} = 1$, otherwise $x_{ijk} = 0$.

The presented COMF-EVRP formulation is influenced by the work of Liu and Jiang (2012) that introduced the Close-Open VRP variant and from the model of Jie et al. (2019).

In Table 1 all the node sets, decision variables, and other parameters of the mathematical formulation are presented.

Objective Function:

$$min: \sum_{k\in K_2}\sum_{j\in V} x_{0jk} + \left(\sum_{i\in V}\sum_{j\in V}\sum_{k\in K}(1+f_{ijk}) \times d_{ij} \times x_{ijk}\right) \Big/ E \tag{1}$$

Subject to:

$$\sum_{k\in K}\sum_{j\in V, j\neq i} x_{ijk} = 1, \forall i \in V_C \tag{2}$$

$$\sum_{j\in V} x_{ijk} = \sum_{j\in(V_C\cup V_D)} x_{jik}, \forall i \in V_C, k \in K, i \neq j \tag{3}$$

$$\sum_{j\in V_C} x_{0jk} \leqslant 1, \forall k \in K \tag{4}$$

$$\sum_{i\in V_C} x_{i0k} = 0, \forall k \in K_2 \tag{5}$$

$$\sum_{j\in(V_C\cup V_D), j\neq i}\sum_{k\in K} f_{jik} - \sum_{j\in V, j\neq i}\sum_{k\in K} f_{ijk} = q_i, \forall i \in V_C \tag{6}$$

$$q_j \times x_{ijk} \leqslant f_{ijk} \leqslant (Q - q_j) \times x_{ijk}, \forall i \in V, j \in V_C, k \in K \tag{7}$$

$$\sum_{i\in V}\sum_{j\in V}(1+f_{ijk}) \times d_{ij} \times x_{ijk} \leqslant E, \forall k \in K \tag{8}$$

$$x_{ijk} = 0, \forall i \in V_D, j \in V_E, k \in K \tag{9}$$

$$x_{ijk} \in \{0,1\}, \forall i \in (V_C \cup V_D), j \in (V_C \cup V_E), k \in K, i \neq j \tag{10}$$

The proposed model is a Nonlinear Mixed-Integer Programming model. The model has a complex objective that stems from combining the need to minimize energy consumption and the number of vehicles, but most importantly, the number of rented ones. Subsequently, the objective function, Eq.(1), is separated into two parts. The first part serves the purpose of minimizing the number of rented vehicles. The second part sums up the total energy spent by all vehicles regardless of ownership, divided by the maximum energy. The division is necessary in order to have both parts of the objective function in the same order of magnitude. This scalarized approach allows for the simultaneous consideration of the two objectives and enables the optimization process to find a single solution that balances the trade-offs between these objectives.

The energy consumption calculation methodology is adopted from the research of Kyriakakis et al. (2022). Since the instance values are not expressed in real units of measurement, the work needed to deliver the items was selected, as it is a more appropriate method of energy consumption approximation in this case. In physics, work represents the amount of energy needed to move an item of a certain weight over a known distance.

Constraints (2) make sure all customers get visited and served precisely once. Constraints (3) equalize the input and output flow of each node, including the depot and the CSs. Constraints (4) limit the number of departures from the depot for each vehicle to be at most one. Constraints (5) prohibit the rented vehicles from ending their trips at the depot. Constraints (6) ensure that the payload when arriving at node i minus the payload when departing from node i is equal to the demand of node i. Constraints (7) set vehicle load constraints. If the arc (i,j) is not traversed, then the load is 0. Constraints (8) set vehicle energy constraints. Constraints (9) prohibit direct connections from the depot to an ending node. Constraints (10) represent the binary limitations of the decision variable x. The definition prevents unwanted connections from any node to itself, and prohibit direct connections originating from CSs to any other node, given that a CS may be visited after the completion of the deliveries.

The objective function and constraints described in Eq. (8) exhibit non-linear characteristics. It is important to highlight that the commercial solver utilized in this study automatically generates a piecewise-linear approximation for these non-linear components. As a result, the detailed explanation and inclusion of this approximation have been omitted from the current discussion. Eq. (8) is necessary as it limits the energy consumption of each vehicle, while the objective function ensures that the energy consumption is minimized.

4. Discrete Swarm Intelligence Algorithms

COMF-EVRP is an NP-hard problem; therefore, commercially available solvers cannot solve large problem instances optimally in a timely manner. Heuristic and meta-heuristic methods are appropriate in such cases.

In this research, the Bee Colony Optimization (BCO) algorithm and two Ant Colony Optimization (ACO) algorithms are employed to construct solutions alongside a Variable Neighborhood Search (VNS) algorithm that further improves upon them. These methods were selected because they are some of the few swarm intelligence methods designed with discrete optimization in mind while having differences that separate them. A detailed analysis of the described methods is provided in the following subsections.

4.1. The proposed Bee Colony Optimization algorithm

The first bee-inspired algorithm was introduced in Lucic and Teodorovic (2001), while the first BCO algorithm was later proposed in Teodorovic and Dell'Orco (2005). The BCO method is a population-based metaheuristic in which each member of the population of agents, bees, in this case, generates a complete solution. Each bee starts its trip from the depot and keeps visiting customers until no further customers may be added. Then, depending on the type of vehicle (owned or rented), the bee either returns to the depot or visits a CS to end the trip of the current EV. The bee keeps repeating this pattern until all customers have been visited. Only feasible solutions are accepted.

Algorithm 1 presents the described meta-heuristic approach.

Algorithm 1: Bee Colony Optimzation algorithm

Algorithm 1: Bee Colony Optimzation algorithm

Data: Instance, BCO_{it}, λ, β
Result: Global best solution

```
Initialize λ, β ;
Generate random initial solution ;
for each iteration of BCO_it do
    for each bee in Bees do
        Observe the waggle dances of previous bees ;
        Initialize new solution ;
        while termination criteria not met do
            Select a customer;
            if the selected customer can be serviced then
                Add selected customer to the solution;
            Update termination criteria;
        if the solution quality allows a waggle dance then
            Perform waggle dance;
    Find the best bee of the iteration;
    Apply VNS;
    if the current solution is better than the global best then
        Re-apply VNS;
        Set current solution as the global best;
return Global best solution;
```

The initial solution BCO uses is created using the initial solution mechanism from the Greedy Randomized Adaptive Search Procedure (GRASP) originally presented in Feo and Resende (1995). This method helps generate a diverse set of initial solutions.

4.1.1. Transition Rules

In the solution creation stage, the node selection (transition) is affected by two parameters, λ, and β, representing the randomness and greediness of the selection, respectively. β is responsible for regulating the heuristic part of the method, which is the inverse of the distance between two nodes.

The BCO transition rules are given in Eq.(11):

$$p_{ij} = \begin{cases} \dfrac{[\rho_{ij}][\frac{1}{d_{ij}}]^{\beta}}{\sum_{l \in L_i} [\rho_{il}][\frac{1}{d_{il}}]^{\beta}}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where L_i is the set of customers not visited, and ρ_{ij} defines the quality of $arc(i,j)$ given in Eq.(12):

$$\rho_{ij} = \begin{cases} \lambda, & \text{if } j \in F_i \\ \dfrac{1 - \lambda \cdot |L_i \cap F_i|}{|L_i| - |L_i \cap F_i|}, & \text{otherwise} \end{cases} \tag{12}$$

where F_i is the most favorable node to transition to, based on the waggle dance, and $\lambda \in (0,1)$.

4.1.2. Waggle Dance

When a bee completes a solution, a waggle dance may be performed to share information about the achieved solution quality. The dance may only occur if the quality improves the personal best record.

When a bee performs the waggle dance, the rest of them have the option of adopting that bee's solution or not, depending on the characteristics of the solution (those with a lower energy consumption have a greater chance of being adopted).

The scoring method used to calculate the probability of selection was originally proposed in Wong et al. (2008). The score rules are displayed in Table 2. The selection chance SC for each bee is equal to the inverse of the cost of the solution the bee created, $SC_{bee} = 1/cost(S_{bee})$. For the population, the average score is calculated by $\overline{SC}_{colony} = \frac{\sum_{bee \in bees} SC_{bee}}{numBees}$. They are used to determine the probability of being followed.

4.2. The proposed Ant Colony Optimization algorithms

The Ant Colony Optimization framework is a well-studied family of swarm intelligence algorithms that base their solution searching strategy on the way ants search for food. In nature, the ants utilize pheromone trails to inform each other about the quality of food sources. They lay pheromone on the ground for other ants to follow and reach the food source. This indirect form of communication, though alterations in the surrounding environment, is called stigmergy. Paths with large amounts of pheromone are more likely to be chosen by other ants, while the pheromone in less favorable ones tends to diminish through evaporation. Slowly, the ant colony converges to the best one, and the lines of ants frequently observed in nature are formed.

The first algorithm to utilize the food foraging strategy of biological ants is the Ant System, proposed by Dorigo et al. (1996). Numerous variants of ACO algorithms have been proposed, improving the convergence behavior of the artificial colony. The Ant Colony System (ACS) presented in Dorigo and Gambardella (1997) uses a local pheromone evaporation mechanism to increase the exploration properties of the colony during solution construction and avoid premature convergence. The Max–Min Ant System (MMAS), introduced in Stützle and Hoos (2000), utilizes minimum and maximum values in the pheromone trails in order to keep a more diversified solution population even in the later iterations of the algorithm. Further insights into the many variants of the ACO are presented in Mohan and Baskaran (2012).

In both ACO variants, each ant represents a solution of the COMF-EVRP. Every ant begins its journey from the depot, adding customers to the route until a further addition violates one of the constraints. The ant then has the option to either return to the depot or go to a charging station. If there are customers still not visited, the ant starts another journey. This process is repeated until all the customer demand has been satisfied. If the generated solution is infeasible, the solution generation process is repeated. Each ACO variant utilizes its own set of transition rules in order to decide which node will be added to the solution. The following subsections present the ACS and MMAS transition and pheromone update rules.

Algorithm 2 and Algorithm 3 outline the ACS and MMAS variants, respectively. The following subsections describe their individual elements and steps.

Algorithm 2: ACS + LS

Algorithm 2: ACS+LS

Data: Instance, $ACSiters, NumAnts, q_0, \rho, \beta, LSiters$
Result: S^{BSF}

Initialize τ, η ;
for $iter \leftarrow 1$ *to* $ACSiters$ **do**
    for $ant \leftarrow 1$ *to* $NumAnts$ **do**
        $S_{ant} \leftarrow$ ConstructACSsolution(τ, η, q_0, β);
        LocalPheromoneUpdate$(\tau, \rho, S[ant])$;
        if $cost(S_{ant}) < cost(S^{IB})$ **then**
            $S^{IB} \leftarrow S_{ant}$;
    LocalSearch$(S^{IB}, LSiters)$;
    if $cost(S^{IB}) < cost(S^{BSF})$ **then**
        $S^{BSF} \leftarrow S^{IB}$;
    GlobalPheromoneUpdate(τ, ρ, S^{BSF}) ;
return S^{BSF};

Algorithm 3: MMAS + LS

Algorithm 3: MMAS+LS

Data: Instance, $MMASiters, NumAnts, Q, \rho, \alpha, \beta, LSiters, NBS = \{NB_1, NB_2, ..\}$

Result: S^{BSF}

Initialize $\tau, \eta, \tau_{max}, \tau_{min}$;
for $iter \leftarrow 1$ *to* $MMASiters$ **do**
  for $ant \leftarrow 1$ *to* $NumAnts$ **do**
    $S_{ant} \leftarrow$ConstructMMASSolution$(\tau, \eta, \alpha, \beta)$;
    if $cost(S_{ant}) < cost(S^{IB})$ **then**
      $S^{IB} \leftarrow S_{ant}$;
  LocalSearch$(S^{IB}, LSiters)$;
  if $cost(S^{IB}) < cost(S^{BSF})$ **then**
    $S^{BSF} \leftarrow S^{IB}$;
  EvaporatePheromone(τ_{min}, ρ) ;
  ApplyPheromone(τ_{max}, S^{BSF});
return S^{BSF};

Table 2
Score Rules.

Score	$P_{followed}$
$SC_{bee} < 0.5\overline{SC}_{colony}$	0.60
$0.5\overline{SC}_{colony} \leqslant SC_{bee} < 0.65\overline{SC}_{colony}$	0.20
$0.65\overline{SC}_{colony} \leqslant SC_{bee} < 0.85\overline{SC}_{colony}$	0.02
$0.85\overline{SC}_{colony} \leqslant SC_{bee}$	0.00

4.2.1. *Ant Colony System*

In order to determine the next node to add to the solution, ACS utilizes the parameter q_0 to regulate the greediness. Larger q_0 values increase the probability of the ant to traverse the most promising path. Parameter β controls the relative importance of the heuristic information η. Given L_i, the set of customers not visited yet and τ_{ij} the pheromone in the arc connecting customer i and j, the following transition rules are applied:

$$j = \begin{cases} \underset{l \in L_i}{\operatorname{argmax}} [\tau_{il}][\eta_{il}]^{\beta}, & \text{if } q \leqslant q_0 \\ Z, & \text{otherwise} \end{cases} \tag{13}$$

where $q \in [0, 1]$ is a uniformly generated random number, Z is the node selected according to probability distribution in (14).

$$p_{ij} = \begin{cases} \dfrac{[\tau_{ij}][\eta_{ij}]^{\beta}}{\sum_{l \in L_i} [\tau_{il}][\eta_{il}]^{\beta}}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

The pheromone trails in the ACS implementation are updated in two points within the solution process. As a new solution is constructed, the pheromone gets removed from the trails, making the other ants less likely to follow the same path. This local update mechanism offers additional exploratory properties to the algorithm. To calculate the pheromone levels, Eq. (15) is used:

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \rho\tau_0 \tag{15}$$

$$\tau_0 = 1/(n \times C^{IS}) \tag{16}$$

where τ_0 is the starting pheromone, C^{IS} the cost of the initial solution, and n customers.

The second pheromone update mechanism utilized by the ACS is the global update. In each iteration, the pheromone levels are updated by best-so-far (BSF) ant by laying pheromone inversely proportional to cost C^{BSF}, as seen in Eq. (17):

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \Delta\tau_{ij}^{BSF} \tag{17}$$

$$\Delta\tau_{ij}^{BSF} = 1 \Big/ C^{BSF} \tag{18}$$

where ρ is the rate of evaporation.

4.2.2. *Max–Min Ant System*

Similarly to the ACS, the MMAS uses two parameters Q_0 and β. β has the same function as in ACS, moderating the relative importance of the heuristic, while Q_0 limits the lower pheromone limit. The probability of an ant traversing arc (i,j) for the MMAS is presented in (19).

$$p_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in L_i} [\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}}, & \text{if } j \in L_i \\ 0, & \text{otherwise} \end{cases} \tag{19}$$

where α is the significance of the pheromone.

The MMAS imposes limits to the pheromone levels; thus, the values range between $[\tau_{min}, \tau_{max}]$. This mechanism keeps less attractive arcs relevant even in later stages of the algorithm, prompting further exploration. The initial pheromone values is τ_{max}; subsequently, all nodes can be potentially visited. The minimum and maximum values of the range are calculated using Eqs. (21) and (20):

$$\tau_{max} = 1/\rho C^{IS} \tag{20}$$

$$\tau_{min} = \tau_{max}/Q_0 \tag{21}$$

In MMAS the best so far ant is the only one allowed to update pheromone, following Eq. (22):

$$\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \Delta\tau_{ij}^{BSF} \tag{22}$$

$$\Delta\tau_{ij}^{BSF} = 1 \Big/ C^{BSF} \quad (23)$$

where ρ is again the rate of evaporation.

4.3. Local search

The Variable Neighborhood Search (VNS) metaheuristic was first presented in Mladenović and Hansen (1997). Its mechanism may be divided into three phases: shaking, local search, and moving. First, a random solution is selected at the shaking phase, followed by the local search application, and finally, making a move. The process is repeated until the maximum number of iterations has been reached.

For the local search phase of the proposed VNS, four operators were employed, *k-Opt*, *1–1 Inter-route Swap*, *1–1 Intra-route Swap*, and *1–0 Relocate*.

- *k-Opt*: two randomly selected customers from the same vehicle are used to determine the part of the route to be visited in the reverse order.
- *1–1 Inter-route Swap*: two randomly selected customers from two different vehicles exchange their places.
- *1–1 Intra-route Swap*: two randomly selected customers from the same vehicle exchange their places. Although both customers belong to the same route, the potential difference in the weight allocation within the route may result in an infeasible final route which is not acceptable.
- *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.

5. Computational Study

Numerous experiments were carried out to ensure the quality of the proposed BCO algorithm. The BCO results for small instances were compared to those of the Gurobi Optimizer (version 9.1.2).

The BCO algorithm was implemented in C++ (C++20 standard) programming language and was compiled in Microsoft Visual Studio 2019 (community edition). The Gurobi Optimizer model was constructed in Python (version 3.9.1). A computer equipped with an Intel (R) Core(TM) i3-8130u @2.20 GHz, and 12 GB of DDR4 RAM @2400Mhz, was employed for all the experiments.

5.1. Problem Instances

The instances introduced in Schneider et al. (2014) are the most popular among EVRP variants and have been modified and used in numerous cases. They are based on the VRP with Time Windows instances, presented in Solomon (1987). In this research, the instances of Schneider et al. (2014) were lightly modified to fit the new COMF-EVRP model.

There are instances of five, ten, fifteen, and one hundred customers. They are further separated based on the type of customer distribution. Three distributions are present: random, clustered, and a combination of both, referred to as 'r', 'c', and 'rc', respectively.

The elements carried over from the Schneider et al. (2014) instances are the following:

- Depot, customer, and CS coordinates
- Customer demand
- Maximum vehicle payload.

The missing elements are the number of vehicles and their maximum energy capacity. The original instances did not include a maximum vehicle number, but their number is a crucial parameter in this variant. This number was determined through preliminary tests, resulting in ten vehicles total. Three of the vehicles are owned by the company, while seven more may be rented. These tests were carried out on the hundred customer instances, with three, five, and seven owned vehicles. The results indicated that three vehicles are sufficient for almost half of the small instances.

An additional observation concerning the number of vehicles is that if an owned vehicle is available and there is the option of employing it to lower the total energy consumption of the operation by as many units of energy as the energy capacity of a vehicle, then the extra owned vehicle will be used.

As for the energy capacity of small instances, it was augmented in proportion to the energy capacity of the original ones, resulting in 2333 units of energy for those of type 'c' and 'rc', and 1818 units of energy for instances of type 'r'. Large instances were allocated 15000 units of energy. Since the energy units and the distances of the benchmarks are not real-world units, the energy was set in such a way that would keep the total number of vehicles below 10.

5.2. Computational Experiments

The parameter values displayed in Table 3 were used for all of the presented experiments.

The results of the COMF-EVRP benchmark instances described are presented in the following subsections. All the reported number of vehicles include the owned and the rented ones. It is worth reminding that the objective function minimizes only the number of rented vehicles.

5.2.1. Small Instances

For instances of up to fifteen customers, the results of the Gurobi Optimizer and the proposed BCO, ACS, and MMAS algorithms are given.

The computational results for five, ten, and fifteen-customer instances are given in Tables 4–6, respectively.

As seen in Tables 4 and 5, the results of Gurobi and all the proposed algorithms coincided. In both tables, the first column displays the instance name. The following three columns present the Best Found Value (BFV), containing the objective function and the two parts that comprise it; as well as the number of vehicles and the total energy consumption.

In Table 6, the first four columns are created similarly to the previous two tables; however, four more columns are added to display the gap between Gurobi and the proposed algorithms from the BFV. It is worth noting that the objective function comprises two parts, one concerned with the number of employed vehicles and the other with the total energy consumption.

The following observations were made based on the analysis of the results:

- The number of employed vehicles was identical among all methods for all instances.
- The total energy consumption is the only differentiating factor when the BFV is not reached
- All five-customer instances were solved to optimality by Gurobi.
- Only three of the ten-customer instances were solved to optimality by Gurobi.
- None of the fifteen-customer instances were solved to optimality by Gurobi.
- In two of the fifteen-customer instances, Gurobi failed to reach the BFV.
- All of the proposed meta-heuristics reached the BFV in all small instances.

Gurobi solved only the small five-customer instances and three ten-customer instances to optimality. For the instances at which Gurobi reached the time limit (900 s), optimality cannot be guaranteed, even if the two methods performed identically. Lastly, the average gap of Gurobi from the BFV was 0.05%.

Table 3
Parameter description and settings.

Parameter	Description	Values tested
	BCO	
Bees	Total population of bees	10
λ	Moderates the greediness in the construction phase	$\{0.1,\ldots,0.9\}$
β	Moderates the effect of the heuristic data	$\{1,\ldots,9\}$
	ACS	
Ants	Total population of ants	10
q_0	Moderates the greediness in the construction phase	$\{0.1,\ldots,0.9\}$
β	Moderates the effect of the heuristic data	$\{1,\ldots,9\}$
ρ	Pheromone evaporation rate	0.01
	MMAS	
Ants	Total population of ants	10
Q_0	Moderates the greediness in the construction phase	$\{300, 600, 900\}$
β	Moderates the effect of the heuristic data	$\{1,\ldots,9\}$
ρ	Pheromone evaporation rate	0.02
α	Moderates the pheromone significance	1
	Other	
VNS_{it}	Total VNS iterations	25000
K_1	Number of owned vehicles	3

Table 4
5-customer instances.

	BFV		
Instance	Objective	Vehicles	Energy
c101c5	1.57	3	3662.75
c103c5	1.16	3	2698.09
c206c5	1.16	3	2704.75
c208c5	2.05	3	4779.94
r104c5	1.17	3	2134.89
r105c5	0.63	3	1153.61
r202c5	0.86	3	1568.07
r203c5	1.56	3	2828.08
rc105c5	2.50	3	5832.05
rc108c5	2.39	3	5579.50
rc204c5	2.39	3	5584.75
rc208c5	1.00	3	2330.96
Average	1.54	3	3404.79

Between Gurobi and the meta-heuristics, the execution times differ significantly. Nonetheless, they cannot be directly compared, given that Gurobi may fully utilize all four CPU threads while the C++ applications of BCO, ACS, and MMAS are single-threaded. All three meta-heuristics solved each instance in a matter of a few seconds while generating the same or better results. As expected, Gurobi solved the small five-customer instances in a few seconds, but execution times dramatically increased for the larger ones. This difference in execution time suggests that the proposed meta-heuristics are a better option for solving the larger instances, in addition to the previously mentioned gaps. Table 7 presents the average execution times for generating a single solution by Gurobi and BCO. Results of ACS and MMAS are omitted since they each took between 5 and 10 ms for all small instances.

Table 5
10-customer instances.

	BFV		
Instance	Objective	Vehicles	Energy
c101c10	2.12	5	7754.12
c104c10	2.38	4	6411.92
c202c10	3.04	4	8215.19
c205c10	1.26	4	6004.50
r102c10	2.28	4	4864.67
r103c10	3.01	3	3469.88
r201c10	2.77	4	4342.45
r203c10	1.47	3	4170.31
rc102c10	1.33	4	7741.89
rc108c10	0.96	4	5371.85
rc201c10	1.08	3	6027.02
rc205c10	2.79	4	6493.61
Average	2.04	3.83	5905.62

5.2.2. *Large Instances*

Besides the small instances, instances of 100 customers, 20 CSs, and a depot (which doubles as a charging station) were also presented in Schneider et al. (2014). In Table 8, the results of the experiments on the large instances are presented. The displayed values in each case are the best-obtained results for each one. In addition, the EV energy capacity was set at 15, 000 units of energy.

The first column of Table 8 presents the instance name. The following two columns display the value of the objective function and the number of vehicles used for the Best Found Value (BFV). The last six columns present the gaps for the objective function and the number of vehicles for each algorithm.

5.3. *Result Analysis*

Further analysis was carried out on the large instances to observe the behavior of the parameters used by each meta-heuristic.

There are three types of instances in this study distinguished by the distribution of the included customers, which may be clustered, random, or a combination of both. They are referred to as ’c’, ’r’, and ’rc’, respectively. More specifically, 17 instances are of type ’c’, 23 are of type ’r’, and 16 are of type ’rc’.

Of the three meta-heuristics, ACS set 37 BFVs, MMAS set 10, and BCO set 9. ACS was the dominant method, providing the most BFVs for each customer distribution type. The average gap of ACS from the BFV was 0.17%, that of MMAS from the BFV was 0.99%, and the largest was that of BCO at 2.05%. In all cases, ACS used the same number of vehicles found in the BFV, MMAS used an extra one in three instances, and BCO used an additional vehicle in 14 instances. It is worth noting that all algorithms used the same number of vehicles as the BFV in ’rc’ instances.

In Table 9 the average results per type of instance and per algorithm are given. As observed, instances with customers in clusters required the most vehicles on average, while instances with random customer distribution required the fewest. This could be a side-effect of the number of clusters in some instances, compared to the randomly placed customers. Moreover, regardless of the customer distribution, BCO required the most vehicles and ACS the fewest.

Figs. 2 presents the average gap percentage of the average objective function values in relation to the parameters of BCO. Similarly, Figs. 3 and 4 present the results of ACS and MMAS, respectively.

In Fig. 2, the parameters λ and β, employed by BCO, are displayed. λ represents the randomness, and β, represents the greediness of the node selection method. As seen, lower levels of randomness in combination

Table 6
15-customer instances.

	BFV			Gap(BFV)			
Instance	Objective	Vehicles	Energy	Gurobi	BCO	ACS	MMAS
c103c15	6.24	5	9886.41	0,00%	0,00%	0,00%	0,00%
c106c15	3.34	4	5465.16	0,00%	0,00%	0,00%	0,00%
c202c15	5.70	5	8638.77	0.30%	0,00%	0,00%	0,00%
c208c15	5.61	5	8414.41	0,00%	0,00%	0,00%	0,00%
r102c15	4.30	4	5991.06	0,00%	0,00%	0,00%	0,00%
r105c15	5.20	5	5826.06	0,00%	0,00%	0,00%	0,00%
r202c15	7.50	6	8174.28	0.34%	0,00%	0,00%	0,00%
r209c15	7.06	6	7379.29	0,00%	0,00%	0,00%	0,00%
rc103c15	5.27	5	7630.15	0,00%	0,00%	0,00%	0,00%
rc108c15	8.09	6	11867.36	0,00%	0,00%	0,00%	0,00%
rc202c15	6.05	5	9454.51	0,00%	0,00%	0,00%	0,00%
rc204c15	8.07	6	11839.63	0,00%	0,00%	0,00%	0,00%
Average	6.04	5.17	8380.59	0.05%	0,00%	0,00%	0,00%

Table 7
Execution time for small instances (in seconds).

5-customers			10-customers			15-customers		
Instance	Gurobi	BCO	Instance	Gurobi	BCO	Instance	Gurobi	BCO
c101c5	1.1	1.1	c101c10	900.0	1.1	c103c15	900.0	1.8
c103c5	1.0	1.8	c104c10	900.0	1.3	c106c15	900.0	1.8
c206c5	1.1	1.3	c202c10	900.0	1.4	c202c15	900.0	1.6
c208c5	1.2	0.8	c205c10	900.0	1.4	c208c15	900.0	1.5
r104c5	1.7	1.2	r102c10	900.0	1.2	r102c15	900.0	2.1
r105c5	2.9	1.2	r103c10	64.4	1.6	r105c15	900.0	1.7
r202c5	2.8	1.6	r201c10	900.0	1.3	r202c15	900.0	1.4
r203c5	1.2	0.9	r203c10	72.3	1.5	r209c15	900.0	1.2
rc105c5	0.6	0.8	rc102c10	900.0	1.2	rc103c15	900.0	1.6
rc108c5	0.5	0.6	rc108c10	900.0	1.3	rc108c15	900.0	1.6
rc204c5	1.7	0.9	rc201c10	20.1	1.5	rc202c15	900.0	1.8
rc208c5	1.2	1.4	rc205c10	900.0	1.4	rc204c15	900.0	1.4
Average	1.4	1.1	Average	688	1.3	Average	900.0	1.6

Table 8
Results for 100-customer instances.

	BFV		BCO		ACS		MMAS	
Instance	Objective	Veh.	$Gap_{Obj.}$	$Gap_{Veh.}$	$Gap_{Obj.}$	$Gap_{Veh.}$	$Gap_{Obj.}$	$Gap_{Veh.}$
c101	11,53	10	**0,00**%	0	0,02%	0	0,22%	0
c102	11,55	10	0,25%	0	**0,00**%	0	0,12%	0
c103	11,54	10	0,54%	0	**0,00**%	0	0,07%	0
c104	11,53	10	0,37%	0	**0,00**%	0	0,08%	0
c105	11,53	10	**0,00**%	0	0,05%	0	0,21%	0
c106	11,54	10	0,13%	0	**0,00**%	0	0,06%	0
c107	11,54	10	0,11%	0	**0,00**%	0	0,01%	0
c108	11,54	10	0,23%	0	**0,00**%	0	0,14%	0
c109	11,53	10	0,35%	0	**0,00**%	0	0,28%	0
c201	9,62	7	6,99%	+1	**0,00**%	0	1,86%	0
c202	9,72	7	2,40%	0	**0,00**%	0	3,07%	0
c203	9,81	7	5,16%	+1	**0,00**%	0	0,46%	0
c204	9,67	7	6,66%	+1	**0,00**%	0	6,09%	+1
c205	9,71	7	5,79%	+1	2,44%	0	**0,00**%	0
c206	9,68	7	6,24%	+1	0,63%	0	**0,00**%	0
c207	9,93	7	3,74%	+1	0,01%	0	**0,00**%	0
c208	9,79	7	3,78%	0	1,97%	0	**0,00**%	0
r101	8,90	8	0,23%	0	**0,00**%	0	0,88%	0
r102	8,86	8	0,12%	0	**0,00**%	0	0,88%	0
r103	8,87	8	0,15%	0	**0,00**%	0	0,40%	0
r104	8,85	8	**0,00**%	0	0,60%	0	0,65%	0
r105	8,89	8	0,30%	0	**0,00**%	0	0,49%	0
r106	8,90	8	0,36%	0	**0,00**%	0	0,39%	0
r107	8,90	8	**0,00**%	0	0,30%	0	0,05%	0
r108	8,85	8	1,38%	0	**0,00**%	0	1,20%	0
r109	8,83	8	0,65%	0	**0,00**%	0	0,72%	0
r110	8,90	8	0,68%	0	0,01%	0	**0,00**%	0
r111	8,91	8	0,05%	0	0,27%	0	**0,00**%	0
r112	8,89	8	0,44%	0	0,11%	0	**0,00**%	0
r201	7,61	6	7,73%	+1	**0,00**%	0	3,48%	0

(continued on next page)

Table 8 (*continued*)

	BFV		BCO		ACS		MMAS	
Instance	Objective	Veh.	$Gap_{Obj.}$	$Gap_{Veh.}$	$Gap_{Obj.}$	$Gap_{Veh.}$	$Gap_{Obj.}$	$Gap_{Veh.}$
r202	7,60	6	**0,00%**	0	1,20%	0	7,27%	+1
r203	7,75	6	1,95%	0	**0,00%**	0	0,30%	0
r204	7,69	6	**0,00%**	0	0,08%	0	0,10%	0
r205	7,67	6	7,68%	+1	**0,00%**	0	5,55%	+1
r206	7,74	6	5,88%	+1	**0,00%**	0	1,14%	0
r207	7,70	6	6,96%	+1	**0,00%**	0	2,12%	0
r208	7,71	6	6,88%	+1	**0,00%**	0	1,54%	0
r209	7,72	6	5,22%	+1	**0,00%**	0	2,28%	0
r210	7,75	6	4,99%	+1	**0,00%**	0	1,15%	0
r211	7,64	6	7,78%	+1	**0,00%**	0	2,06%	0
rc101	11,57	9	0,51%	0	**0,00%**	0	1,12%	0
rc102	11,59	9	2,37%	0	**0,00%**	0	0,03%	0
rc103	11,59	9	1,32%	0	**0,00%**	0	0,58%	0
rc104	11,53	9	2,10%	0	0,03%	0	**0,00%**	0
rc105	11,53	9	**0,00%**	0	0,60%	0	1,09%	0
rc106	11,56	9	1,02%	0	0,11%	0	**0,00%**	0
rc107	11,55	9	**0,00%**	0	0,24%	0	1,17%	0
rc108	11,61	9	0,50%	0	**0,00%**	0	0,52%	0
rc201	10,45	8	0,05%	0	0,27%	0	**0,00%**	0
rc202	10,41	8	0,82%	0	**0,00%**	0	1,08%	0
rc203	10,38	8	1,36%	0	**0,00%**	0	0,38%	0
rc204	10,42	8	**0,00%**	0	0,45%	0	0,72%	0
rc205	10,45	8	0,05%	0	**0,00%**	0	0,59%	0
rc206	10,45	8	0,23%	0	**0,00%**	0	1,13%	0
rc207	10,41	8	0,68%	0	**0,00%**	0	0,58%	0
rc208	10,41	8	1,79%	0	**0,00%**	0	1,32%	0
Average	9,80	7,93	2,05%	+0.25	0,17%	0,00%	0,99%	+0.05

Table 9
Average results per instance type.

	BCO		ACS		MMAS		
Distribution	Obj_{avg}	Veh_{avg}	Obj_{avg}	Veh_{avg}	Obj_{avg}	Veh_{avg}	**Avg.**
c	10,94	9,13	10,72	8,80	10,77	8,87	8.93
r	8,51	7,43	8,32	7,13	8,42	7,22	7.26
rc	11,08	8,38	11,01	8,25	11,07	8,25	8.29
Avg.	10,18	8.31	10,02	8.06	10,08	8.11	N/A

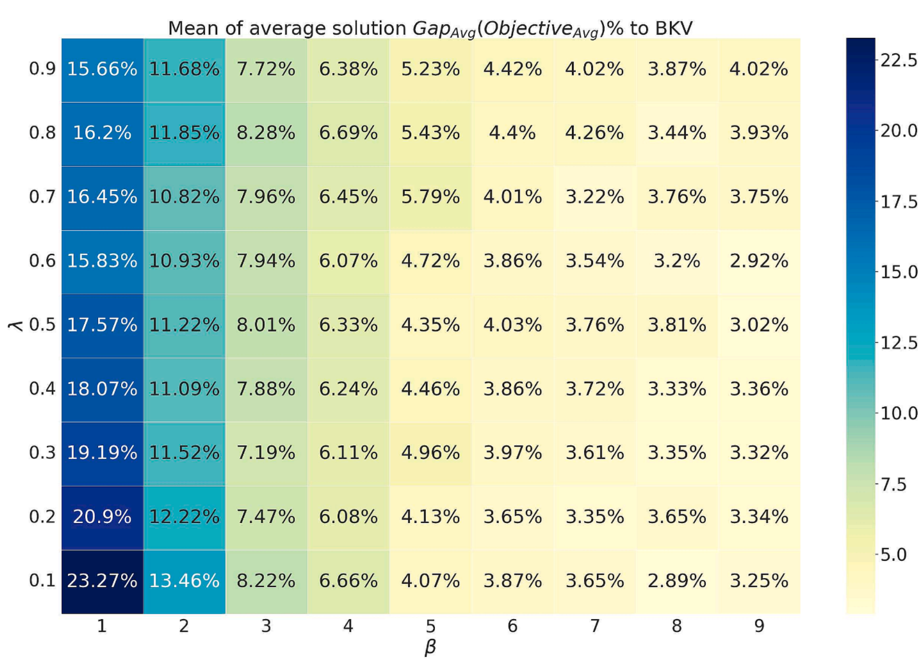

Fig. 2. Sensitivity analysis for the BCO algorithm.

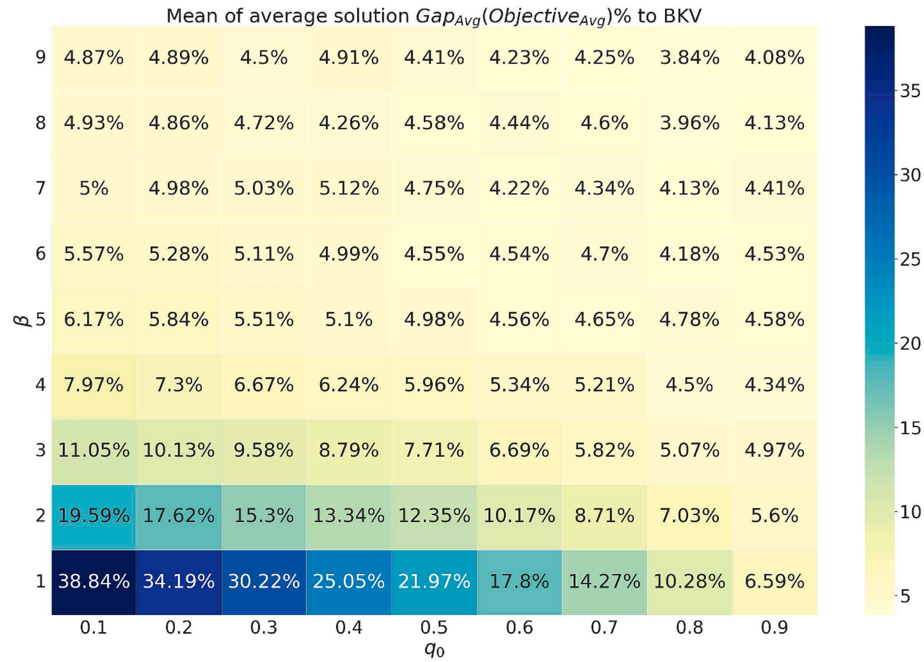

Fig. 3. Sensitivity analysis for the ACS algorithm.

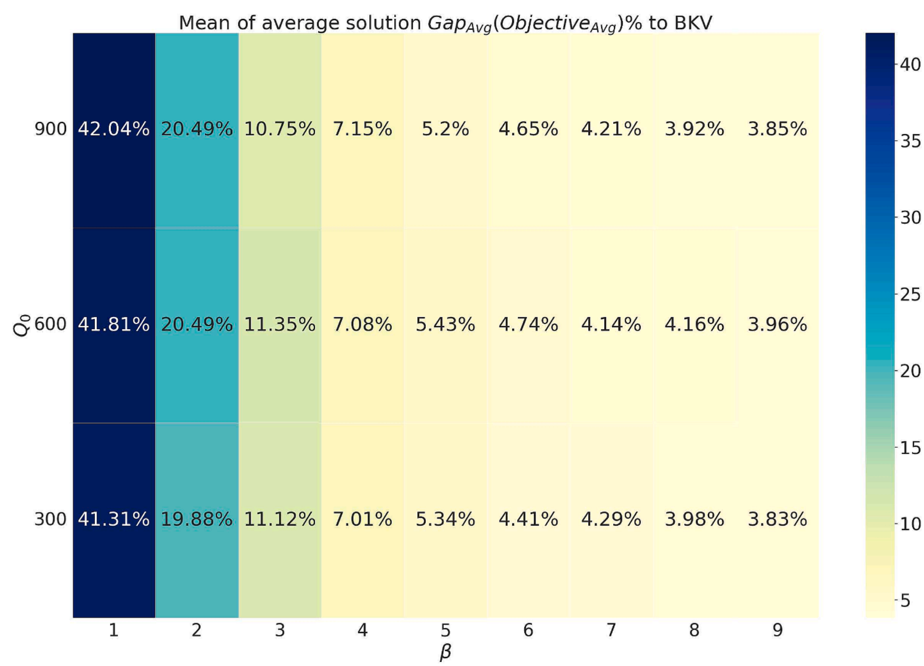

Fig. 4. Sensitivity analysis for the MMAS algorithm.

with higher greediness provided better solutions. For values of $\beta >= 6$, the change is quite limited, with randomness having seemingly no effect on the results.

Fig. 3 presents the parameter analysis for the ACS algorithm. Parameter q_0 controls the exploitation in the solution generation process, while β controls the importance of the heuristic data. Compared to BCO, ACS is less sensitive to the parameter settings. It is worth noting that for values of $\beta \geqslant 0$, any changes in the results become negligible; however, the best results were acquired with $q_0 = 0.8$. Interestingly, for lower values of $\beta, q_0 = 0.9$ is the better option.

Lastly, Fig. 4 explores the parameter settings of MMAS. Q is a parameter used to determine the lower bound of pheromone levels that helps mitigate the possibility of rapid convergence. In this case, the results were primarily affected by the value of β that controls the importance of the heuristic data, similar to ACS. For $\beta >= 5$, the percentage change was insignificant regardless of Q.

Overall, ACS performed the best, providing 37 out of the 56 BFVs while being less sensitive to the parameters it employs. The advantage of ACS and MMAS over BCO is their ability to generate initial solutions. On the other hand, the initial solution mechanism found in GRASP is employed by BCO to acquire initial solutions. Subsequently, BCO used more vehicles on average compared to ACS and MMAS. ACS managed to outperform MMAS because of its intermediate local pheromone update stage, providing feedback faster than MMAS, in which evaporation takes place after the completion of a full solution.

6. Conclusions

EVs have steadily gained market share and have become more popular over the last few years. Despite all the perks of EVs, some drawbacks still deter people from shifting to them. Three main issues are the range, the charging speed, and the initial purchase cost. The sector of logistics is affected by all three of them.

A significant issue EV drivers face currently is not related to their vehicles but to the CSs. On some occasions, chargers may be out of order, or if there are only a few, they may be occupied. Subsequently, relying on a CS to be available and operational at any time is unrealistic. By eliminating the charging aspect from mid-trip and placing it at the end of the trip, routing is carried in a traditional fashion while avoiding these setbacks.

This research explored a new concept of operation for logistics companies. More specifically, it considers that a logistics company owns a small fleet of EVs for daily operations. Additional EVs may be rented when the owned fleet can not satisfy the demand. The rented EVs end their trips at CSs. The owned EVs may also visit a CS after completing their deliveries to recharge.

The described scenario was modeled as the Close-Open Mixed-Fleet Electric Vehicle Routing Problem (COMF-EVRP). The mathematical formulation, accounting for all the constraints of the vehicles and the proposed charging method, was presented. The COMF-EVRP combines the Close-Open Mixed-Fleet variant with EVs for the first time and suggests a charging strategy different from the commonly used charging strategy in EVRP that leads to more reliable delivery plans.

Small COMF-EVRP instances were solved by the commercially available software, Gurobi Optimizer, and by the proposed swarm intelligence algorithms; however, the high CPU times did not allow Gurobi to be used for larger instances. A Bee Colony Optimization meta-heuristic, an Ant Colony System meta-heuristic, and a Max–Min Ant System meta-heuristic were developed to solve hundred-customer instances. A Variable Neighborhood Search (VNS) was employed following the solution of the meta-heuristics. The VNS algorithm included four local search operators,*k-Opt*, *1–1 Intra-route Swap*, *1–1 Inter-route Swap*, and *1–0 Relocate*. Instances found in the literature were adapted for COMF-EVRP, requiring only minor modifications and no additional data; thus, they can be replicated easily.

The hundred customer instances were solved exclusively with meta-heuristics since they were proven successful and vastly quicker than Gurobi. The average values of the obtained results were presented along with an extensive parameter analysis. Of the 56 instances, ACS provided the BFV for 37, MMAS provided the BFV for 10, and BCO provided the BFV for 9. A parameter sensitivity analysis was conducted for all three methods.

This study has some practical limitations mostly pertaining to the EV characteristics and cost. Combining owned and rented EVs can lead to a heterogeneous fleet in terms of age, condition, and maintenance history. Maintaining consistency and reliability across the entire fleet may require additional effort and resources, as vehicles of the same characteristics may behave differently. Optimizing the routing and scheduling of a mixed fleet with different vehicle types, energy capacities, and operational characteristics can be complex. The cost structure of renting EVs may be less predictable compared to owning a fixed fleet. Fluctuations in rental rates and availability can make it challenging to forecast and manage operating costs effectively. Depending on the rental terms and the frequency of renting, this can significantly add to the operational expenses. Companies must carefully assess the cost-effectiveness of renting versus owning additional vehicles. Moreover, the availability of rental EVs may not always align with demand, especially during peak periods. Rental vehicles might be unavailable when needed most, which can result in service disruptions and customer dissatisfaction. Furthermore, to ensure that both owned and rented EVs can recharge at the end of their trips, a robust charging infrastructure is necessary. In some regions, the availability of charging stations may be limited, which can hinder the feasibility of the approach.

Besides research on the previously mentioned practical limitations, in the future, researchers may direct their attention to various parts. First and foremost, including other elements in the model of the problem will lead to more realistic representations of the actual routing scenarios. Some examples are the weather (given the effect ambient temperature has on battery efficiency), variable speed profiles that could also accommodate kinetic energy recovery systems and many other examples discussed in the present study and related literature. Another valuable contribution would be the procurement and presentation of realistic instances. Alternative objective functions could be employed to achieve different goals. Lastly, more meta-heuristics and different local search algorithms could be tested.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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