Optimization of Electric Vehicle Charging Routes Using Fuzzy Inference and Enhanced Gray Wolf Algorithm

Guanlong Jia*, Qianqian Pang, Xintong Lv, Feng Niu, Xiaoxue Wang
School of Electrical Engineering, Hebei University of Technology, Tianjin 300400, China
E-mail: jiagl@hebut.edu.cn, pangqianqian511@163.com, cuso4zinc@163.com, niufeng@hebut.edu.cn, xxwang@hebut.edu.cn
*Corresponding author

Keywords: electric vehicles, fuzzy inference, driving demands, charging route, enhanced Gray Wolf Algorithm

Received: June 26, 2025

Electric vehicles (EVs) help lower carbon emissions but face challenges from varied charging prices and long wait times. This study optimizes EV charging route planning to minimize user costs under diverse pricing and diverse driver preferences. Vague user preferences are converted into explicit weightings by employing a fuzzy inference system, and a total cost function covering economic, time, and carbon costs is defined. The optimal charging route is then determined by applying Depth-First Search combined with the Enhanced Gray Wolf Algorithm (EGWA). The method is tested on a single EV and a cluster of EVs. The results demonstrate that the combination of EGWA and fuzzy inference system can select the most compliant charging path for the user, thus effectively reducing the user's cost. Tests on single EV show EGWA consistently achieves the lowest comprehensive cost across weight combinations. Specifically, EGWA lowers costs by 12.47% on average compared to GWO, 9.27% over IWOA, and 5.08% over LPGA. EGWA also demonstrates faster convergence and better stability. These results highlight the benefit of integrating fuzzy modeling with metaheuristic optimization to support drivers in choosing cost-effective and environmentally friendly routes. The proposed method provides practical guidance for intelligent EV route planning systems.

Povzetek: Optimizacija poti polnjenja električnih vozil je izvedena z uporabo mehke logike za modeliranje preferenc uporabnikov in izboljšanega algoritma sivega volka. Metoda učinkovito zmanjša skupne stroške (ekonomske, časovne in okoljske) ter kaže hitro konvergenco in stabilnost.

1 Introduction

After the industrial revolution, the excessive carbon dioxide generated by the burning of a large number of fossil energy sources caused great negative effects on the earth [1]. To mitigate the environmental crisis, various countries have proposed carbon neutrality schedules that align with their national conditions to promote the implementation of energy conservation and emission reduction policies. All sectors are adopting certain measures in response to environmental protection policies. Among these, the issue of green vehicle routing in the transportation industry considers environmental factors from the perspectives of vehicles and logistic. Green vehicle routing problem (GVRP) includes GVRP for traditional fossil fuel vehicles, GVRP for alternative fuel vehicles and GVRP for hybrid vehicles [2]. With the development of lithium battery technology, the deployment and application of alternative fuel vehicles—namely electric vehicles (EVs)—have accelerated. And charging facilities have also become widespread [3].

The charging tariffs of charging stations are affected by a variety of factors [4], with different tariffs for the same charging station at different times, and different charging tariffs for different charging stations at the same time. Due to the battery characteristics of EVs, charging time is consumed for a long time [5]. As the number of EVs grows year after year [6], more vehicles use charging facilities and charging waiting time grows gradually. Economic cost and time cost become important factors affecting the charging route planning of EVs. To respond to the environmental protection policy, carbon emission should also be included in the consideration of route planning. How to carry out route planning according to drivers' needs has become the focus of research.

Most users' cost requirements cannot be accurately converted into specific values. Users' requirements cannot be directly entered into the optimization system. Moreover, the individual user's demand for the different costs is independent, and different users' demands for the costs are diverse, which increases the difficulty of charging path optimization. In order to address the diverse charging needs of users, it is decided to use a fuzzy inference system to convert user needs into weights. Fuzzy inference is a reasoning method based on fuzzy set theory to deal with uncertainty and ambiguity [7]. Fuzzy inference systems can be used to assist in autonomous driving technology [8]. The fuzzy inference system can also control EV charging and discharging based on the State of Charge (SOC) and the stay time of EV parked in the parking lot [9-10]. The new method combining hesitant fuzzy sets and multiplicative preference relations converts linguistic terms into hesitant fuzzy multiplicative elements to each criterion weight [11].

About economic costs, most studies on charging route planning consider time-of-use (TOU) charging pricing at charging stations [12]. For the Traveling Salesman Problem (TSP), Yang *et al.* [13] introduced a model for fast and scheduled charging of vehicles under TOU pricing. For cluster problems, a bi-level optimization model can also be utilized, which considers charging prices under TOU pricing [14]. However, none of this literature considers the different charging prices at different charging stations at the same time. The game between charging price and charging distance is also an important factor affecting the economic cost and time cost.

About time costs, Schoenberg *et al.* [5] propose a centralized database for route selection using mathematical methods to predict the waiting time in advance. Tan *et al.* [15] consider time-perceived fairness and waiting time, then propose a time-perceived fairness index. Literatures use either mathematical methods or heuristic algorithms to calculate. However, both methods have their advantages and disadvantages.

About carbon emission costs, Qiao *et al.* [16] proposed an operational model of coupled electricity-transportation network to achieve the goals of cost reduction and low carbon emissions while minimizing the self-consumption of each entity.

Mathematical methods, although straightforward, are complex to handle and require simplifying constraints to solve the problem [17-21]. The cooperative transportation network and distribution network scheduling method is designed which utilizes the combined distributed biased minimum consistency algorithm and the generalized Benders decomposition algorithm [22].

Heuristic algorithms are simple and easy to understand. However, heuristic algorithms usually find an approximate solution rather than an optimal solution within a certain period and they do not guarantee consistency of results [23]. The conventional algorithm requires extensive computation [24], necessitating improvements over traditional methods [25-32]. Deep learning algorithms can personalize travel routes, with the multi-objective shortest path approximation and single-objective average achievement rate both exceeding 93.36% [33]. The average charging cost of the path optimization model based on the improved topology and ant algorithm is 7%–26% lower than that of other models [34].

To fill the gap in the above literatures, the paper proposes the Enhanced Gray Wolf Algorithm (EGWA) with the fuzzy inference combined for solving the charging route optimization problem with different user demands when there are multiple charging stations with different charging prices. The core idea is to transform the fuzzy and independent diversified needs of users into the weights of the objective function for path finding optimization through fuzzy reasoning. EGWA is utilized to find the optimal charging path. The main contributions of this paper are two:

(1) A model for calculating the weights of the objective function using a fuzzy inference system is developed to convert the economic cost, time cost and carbon emission cost demands of the users, which cannot be accurately expressed in numbers when facing charging, into precise weight numbers to satisfy the different charging cost demands of the users.

(2) In order to improve the late convergence speed and solve the shortcomings of the traditional gray wolf optimization algorithm which is easy to fall into the local optimum, 2-opt and roulette wheel selection are combined with the traditional GWO to find the charging path with the lowest comprehensive cost to satisfy the users' needs.

The remainder of the paper is organized as follows. Section II establishes the model for EV route optimization. Section III describes the principles and improvements of algorithms. Section IV presents two case studies involving optimization. Section V provides a conclusion of the work.

2 System model

The charging price of EV charging stations is affected by many factors, the most important of which are energy cost, equipment investment and operation cost [35]. The charging price of each charging station is different, and the needs of users are different. Choosing the charging station that best meets the driver's needs becomes a necessary consideration.

According to its SOC, the EV charging route planning problem can be divided into the following two categories.

1) When the remaining charge of an EV is less than a certain value of the total charge, it is necessary to avoid a situation in which the charge runs out and travel is affected. In this case, the vehicle should immediately find the nearest charging station to its current location and plan the shortest route to the charging station.

2) When the remaining charge of an EV is more than the certain value of its total charge, there are more charging stations to choose from. By comparing factors such as the charging price, waiting time and charging time, the most cost-effective charging route that meets the charging needs can be identified.

It is shown that N represents the traffic road nodes on the map. $N_{ch} \subset N$ represents the nodes of EV charging stations, where EVs can stay and complete charging tasks. The route from node i to node j is denoted as $(i,j) \in P$, and P is the set of all feasible routes.

The shortest charging route planning for EVs is to find the shortest route to the charging station with an objective function of

$$F_{dis}^{N_{ch}} = \sum_{(i,j)\in P} x_{ij,t} d_{ij} \tag{1}$$

where $x_{ij,t}$ indicates whether the EV passes through (i,j) at period of t . d_{ij} represents the distance from node i to node j (unit: km). If the route planning of the EV includes traveling from node i to node j, then $x_{ij}=1$; otherwise, $x_{ij}=0$. Eq.(1) represents the distance from the starting node to charging station N_{ch}.

The cost of charging an EV includes the economic cost, the time cost and the carbon emission cost. The current EV charging technology initially follows a constant current charging mode and switches to a constant voltage charging mode once a certain amount of charge is reached, with the former mode being faster and the latter slower and more time-consuming. To give due consideration to charging efficiency and maximize time savings, it is assumed that charging at the charging station will stop once the EV's battery reaches 80%. The economic cost refers to the expenses incurred at different charging stations. The time cost includes both charging time and waiting time. Electricity is a kind of clean energy, and the carbon emission of EVs when consuming electricity is small and negligible. During the use of EVs, the main carbon emissions are concentrated in the charging process. And the carbon emission in the charging process mainly depends on the energy structure of the local power grid. For the generality of the carbon emission index, the unit carbon emission is taken as 0.9kg/kWh [36]. The formulas are as follows:

$$Q_f = 80\% Q \tag{2}$$

$$F_{pr}^{N_{ch}} = (Q_f - e_{ch}) \times M_{N_{ch}} \tag{3}$$

$$F_{n_s,n_e}^{N_{ch}} = \sum_{(i,j)\in P} \frac{d_{ij}}{v_{ij}} x_{ij} + \frac{Q_f - e_{ch}}{P_{ch}} \tag{4}$$

$$F_{em}^{N_{ch}} = (Q_f - e_{ch}) \times 0.9 \tag{5}$$

where $M_{N_{ch}}$ represents the unit charging price at charging station N_{ch} (unit: ¥ /kWh), v_{ij} denotes the average speed of the vehicle (unit: km/h), and P_{ch} indicates the charging power at charging station N_{ch} (unit: kW). e_{ch} indicates the remaining charge of the EV upon reaching a charging station. Q represents the total battery capacity of the EV. The economic cost of charging the EV to Q_f at charging station N_{ch} is represented by (3), while the total time consumed from the starting point n_s to the endpoint n_e of the journey is represented by (4), including the time spent charging at charging station N_{ch}. Carbon emissions are calculated by multiplying the amount of charging power required by the carbon emissions per unit by (5).

Over long-term use, EV batteries are highly prone to incidents of false battery charge indications. In actual driving conditions, external environmental factors greatly affect the battery. For example, extreme cold weather can cause rapid depletion of battery charge. Therefore, to avoid the impact of false battery charge indications on the driver's journey, if the initial charge of the EV e_{start} is less than the certain value, it is imperative to immediately find the nearest charging station to the vehicle's location and plan the shortest charging route.

$$F = \min F_{dis}^{N_{ch}} \tag{6}$$

$$e_{ch} = e_{start} - r \sum_{(i,j)\in P} x_{ij} d_{ij} \geq 0 \tag{7}$$

$$\sum_{k\in N_{ch}} y_k = 1 \tag{8}$$

$$\sum_{(i,j)\in P} x_{ij} - \sum_{(i,j)\in P} x_{ji} = \begin{cases} 1, i = n_s \\ -1, i = n_e \\ 0, otherwise \end{cases} \tag{9}$$

$$a_{i,t+1} = \left| a_{i,t} + b_{i,t} - \sum_{(i,j)\in P} x_{ij,t} \right| \tag{10}$$

$$a_{i,t} = \sum_{(i,j)\in P, \tau<t} x_{ij,t+1} \tag{11}$$

$$\sum_{i\in N} (b_{i,t+1} + \sum_{j\in N,(i,j)\in P} x_{ij,t}) \leq 1 \tag{12}$$

$$P_{\min} \leq P_{ch} \leq P_{\max} \tag{13}$$

$$x_{ij}, y_k, a_{i,t}, b_{i,t} \in \{0,1\} \tag{14}$$

where $a_{i,t}$ denotes that the EV arrives at node i or leaves node i at period t, and $b_{i,t}$ denotes that the EV stays at node i at time period t. It is assumed the EV's energy consumption rate per unit distance is r (unit: kWh/km). $r \bullet d_{ij}$ indicates the amount of electricity consumed by the EV traveling from node i to node j. e_{start} is the remaining battery charge of the EV at the starting point. n_s signifies the starting point of the EV's journey, and n_e represents the endpoint of the journey. Equation (6) indicates that when the initial charge of the EV is less than the certain value of the total battery capacity, the sole objective is to find the shortest route to a charging station. Equation (7) specifies the power consumption from the starting point to the charging station and ensures that the remaining power at the arrival of the charging station is greater than 0, which means that the EV must have enough power to reach the charging station. The charging route planning selects only one charging station as the destination is guaranteed by equation (8). Equation (9) states that the driving route of the EV is a non-repeating route from the starting point to the charging station. Equation (10) restricts the EV to only three states throughout the process: arriving at a node or leaving a node, staying at a node, or traveling between nodes. Ensuring that the EV must leave the previous node before reaching the next node is guaranteed by equation (11). Constraint (12) ensures that if the EV leaves node i and drives to node j at time t, it cannot still be at node i at time t. The charging power is limited by constraint (13). Equation (14) shows that x_{ij}, y_k, $a_{i,t}$, $b_{i,t}$ are binary variables.

When the initial charge of the EV at the starting point is more than a certain value, it becomes feasible to consider the costs at multiple stations and select the most suitable charging route. In the situation, the economic cost is required to charge the vehicle, as well as the time cost is incurred during waiting and charging.

$$F = \min(\lambda F_{pr}^{N_{ch}} + \theta F_{n_s,n_e}^{N_{ch}} + \omega F_{em}^{N_{ch}}) \tag{15}$$

$$\lambda + \theta + \omega = 1 \tag{16}$$

where λ represents the weight of the economic cost, θ represents the weight of the time cost, and ω represents the weight of the carbon emission cost.

3 Solution approach

The framework of the whole algorithm is shown on Figure 1. The degree of driver's demand for cost is described as low, medium or high demand. The fuzzy and independent user demands are transformed into accurate weight figures and assigned to the corresponding objective functions by four steps: fuzzification of inputs, application of fuzzy rules, aggregation, and defuzzification [30]. In order to improve the optimization search rate, the Depth-First Search (DFS) algorithm is utilized to find all possible charging paths. Subsequently the path with the lowest overall cost is found by EGWA.

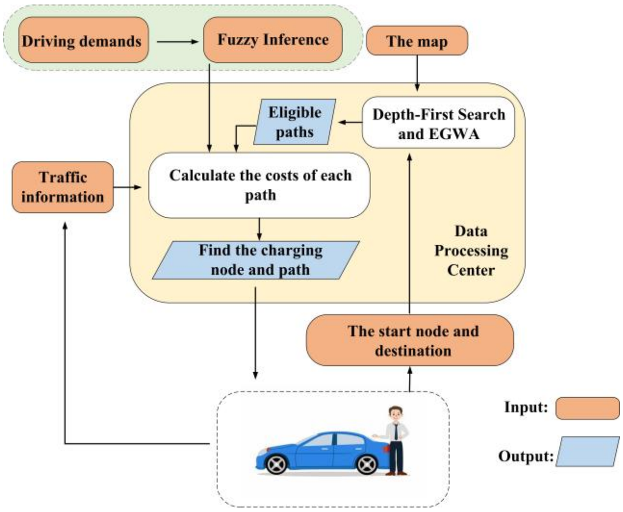


Figure 1: Outline of the proposed algorithm

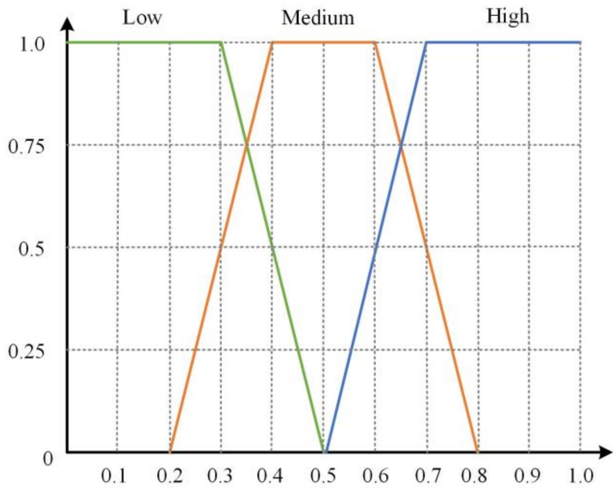


Figure 2: Output membership function

3.1 Fuzzy inference

The objective function consists of economic costs, time costs, and carbon emission costs. The degree of user demand for cost is categorized as low, medium and high demand, which are represented by the numbers "0", "0.5" and "1". These numbers are used as input variables. The input fuzzy function used for fuzzy inference is the Gaussian membership function, the output fuzzy function is the trapezoidal membership function, and the inference method used is the Mamdani inference method [10].

The Gaussian functions are highly practical in models requiring differential operations, such as neural networks, clustering, and fuzzy control, and are commonly used to model user preferences [37]. The general form of the Gaussian membership function is as follows

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{17}$$

where x is the input variable and $\mu(x)$ is the degree of affiliation which takes values in the range [0,1]. c is the mean value, which determines the center of the curve. σ is the standard deviation, which determines the width of the curve.

The trapezoidal membership represents the membership degree of an element in a fuzzy set by a trapezoid whose top side has a value of 1 and whose two non-parallel sides increase or decrease linearly. It has a simple structure and low computational complexity, making it particularly suitable for real-time systems that require fast computation. Providing feasible charging routes for electric vehicles is such a real-time system, where it is essential to deliver solutions to users promptly. The general form is as follows

$$\mu(x) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & x \ge d \end{cases} \tag{18}$$

where a and d control the left and right boundaries of the trapezoid which the part of the trapezoid with an affiliation of 0. b and c control the flat-top region of the trapezoid which the part of the trapezoid with an affiliation of 1. The implementation of weight with different types is shown in Figure 2.

The Mamdani method is commonly used to deal with systems with fuzzy rules that reason in the form of "IF-THEN" rules and deal with the relationship between inputs and outputs in the form of fuzzy sets. Each fuzzy rule is usually written as "IF ... THEN ..." which the relation-ship is $Rules=\{Rule_1, Rule_2, \ldots, Rule_n\}$.

$$\begin{cases} Rule_1 = \text{ IF } x_1 \text{ is } A_1 \text{ THEN } y_1 \text{ is } B_1 \\ Rule_2 = \text{ IF } x_2 \text{ is } A_2 \text{ THEN } y_2 \text{ is } B_2 \\ \ldots \\ Rule_n = \text{ IF } x_n \text{ is } A_n \text{ THEN } y_n \text{ is } B_n \end{cases} \tag{19}$$

$$Rule = \text{ IF } x \text{ is } A \text{ THEN } y \text{ is } B$$

A total of 27 rules is designed, with each rule mapping a specific combination of user requirements to a corresponding set of weights. During inference, relevant rules are activated, and the final weights are obtained through fuzzy aggregation and defuzzification.

The input variables are fuzzy using the Gaussian membership function and then evaluated according to the formulated rules. The fuzzy outputs of all the rules are computed based on the trapezoidal membership function to arrive at the final fuzzy set. The fuzzy outputs are transformed into exact outputs corresponding to the requirements as weights through defuzzification.

3.2 Depth-first search

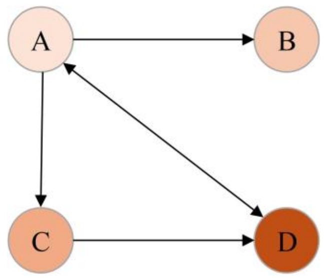


Figure 3: Principles of DFS

Traffic networks are composed of a series of nodes and the connecting lines between nodes [38]. The optimization of charging routes differs from standard route optimization problems in that the number of nodes included in each charging route can vary. Therefore, the methods for solving the charging route optimization problem need improvement.

The DFS algorithm is a graph traversal algorithm. Its basic principle is shown in Figure 3, it is visited A first and proceeded to visit the children of A, which are B, C, and D. Then if it is chosen B to visit first, B has no children. It is backtracked to A, and then visited another child node of A, C. C's children are A and D. A has already been visited, so visit D. D has no children. It is ended the traversal.

The number of nodes in the route can vary. Using binary algorithms to simply record whether a node has been visited with "0" or "1" is not feasible. The solution is to first use DFS to find all routes from the starting point to the endpoint and assign a number to each route. Then, it is randomly selected some routes and optimized them using the EGWA.

Algorithm 1 DFS

```
Initialize an empty list paths to store all found paths
Define internal recursive function dfs(currentPath):
    currentNode ← last node in currentPath
    If currentNode is in endPoints:
        Add currentPath to paths
    Return
    For each neighbor of currentNode in graph:
        If neighbor is not in currentPath:   // avoid cycles
            Call dfs(currentPath + neighbor)
Call dfs([startPoint])  // start the search from the starting point
Return paths
```

3.3 EGWA

GWO stratifies the population according to the social structure of grey wolves into four tiers, from top to bottom, α, β, δ and ω wolves. The α represents the best solution, the β represents the second-best solution, and the δ represents the third-best solution. The three wolves guide the movement of the ω wolves in encircling, harassing, and attacking the prey.

The mathematical model of the GWO is as follows. The wolves update their positions using the following position update equations and enable the population to adjust their positioning until the prey is encircled.

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{X_p(t)} - \overrightarrow{X(t)} \right| \tag{20}$$

$$\overrightarrow{X(t+1)} = \overrightarrow{X_p(t)} - \vec{A} \cdot \vec{D} \tag{21}$$

Equation (20) is used to calculate the distance between the grey wolves and the prey, while equation (21) is used to update the positions of the wolves. And the calculation formula is as follows.

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{22}$$

$$\vec{C} = 2\vec{r_2} \tag{23}$$

where $\vec{r_1}$ and $\vec{r_2}$ are both random vectors, with values ranging from 0 to 1. Consequently, the range of values for $\vec{A}$ is from $-\vec{a}$ to $\vec{a}$ and $\vec{C}$ can vary from 0 to 2.

To solve the complex charging route planning problem discussed in this paper, GWO is chosen in this paper because of its simplicity, ease of implementation and wide applicability. However, GWO has two drawbacks, one is the slow convergence speed at the later stage, and the other is that it is easy to fall into the local optimum. Therefore, it is used the 2-opt algorithm and the roulette wheel selection method to solve these two problems in turn.

Algorithm 2 EGWA

```
Initialize the value of α, β and δ as +∞
Initialize the position of the grey wolves
iter = 1
while iter ≤ maxiter :
 For each wolf
    update the position and numerical value of α, β and δ
 end
 Record the value of α
 For each wolf i not in {α, β, δ}:
     Select two pairs of sides to swap
      if newdistance < routedistance do
         Update Fitness and paths for wolf i
      end
 end
 If no improvement over several iterations:
     Update the value of α probabilistically
  end
iter += 1
Return the value of α
```

3.3.1 2-opt

The 2-opt algorithm was initially proposed as an optimization method for solving the TSP. Its main goal is to find a shorter one by making improvements. It iterates through each edge in the route. It randomly swaps the positions of two points and then compares the length of the new route to the original one, as shown in Figure 4. If the new route is shorter, it is retained. Otherwise, the path continues to be updated until no shorter path can be found or the set number of iterations is reached.

To address the slow convergence speed in the later stages of the GWO, it is integrated the 2-opt algorithm into the GWO. After a position update is completed by the GWO, the 2-opt algorithm is used to optimize the original route, reducing its length. Then, it is proceeded to the next iteration of the GWO, sought the shortest route length to assign to the α, β and δ wolves for a new round of position updates.

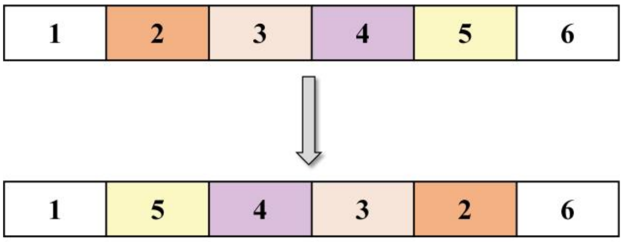


Figure 4: Principles of 2-opt

3.3.2 Roulette wheel selection

A common example of the roulette wheel selection is a spinning wheel lottery, where the area occupying the largest section of the wheel has the highest probability of being selected. It reflects the fundamental idea of the roulette wheel selection that the probability of each segment being selected is directly proportional to its relative size within the whole. Integrating the concept of roulette wheel selection into the algorithm, the relative size is replaced by the fitness value, with the calculation formula as follows:

$$p(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{24}$$

$$q_i = \sum_{j=1}^{i} f(x_j) \tag{25}$$

where $f(x_i)$ represents the fitness value of an individual, and $\sum_{j=1}^{N} f(x_i)$ represents the total fitness value of the population. Equation (24) calculates the proportion of an individual's fitness value. Equation (25) calculates the cumulative probability from 1 to i. When selecting individuals, it is made choice based on the cumulative probability. It is generated a random number between 0 and 1. If q_i is greater than the random number, then corresponding individual x_i is selected.

If the best fitness value of the α wolf in GWO does not change after 10 iterations, it is determined that it has fallen into local optimality. Roulette wheel selection can be used to select one of the best fitness values of the alpha wolf in the past, assign that value to the best fitness value of the alpha, and continue to optimize until the algorithm falls into another local optimum or reaches a predetermined number of iterations. After many iterations of roulette wheel selection, if the same best fit value is determined to be a local optimum several times, it is certain that the value is a global optimum.

4 Numerical experiments

To verify the feasibility of the proposed solution, it is abstracted the traffic roads of a certain city into the traffic map as shown in Figure 5. The map contains a total of 34 nodes. Nodes 10, 16, and 31 are the locations of charging stations where EVs can complete their charging tasks. The EV starts from node 1 and has its destination at node 34. To ensure the universality of the verification, the Tesla Model Y 2023 Long Range All-Wheel Drive version is selected, which has a high sales volume [39]. The vehicle has a total battery capacity of 78.4 kWh and a power consumption of 13.4 kWh per 100 km. It is assumed the driving speed of the EV is 60 km/h, and the charging power at the charging stations is 22 kW [40].

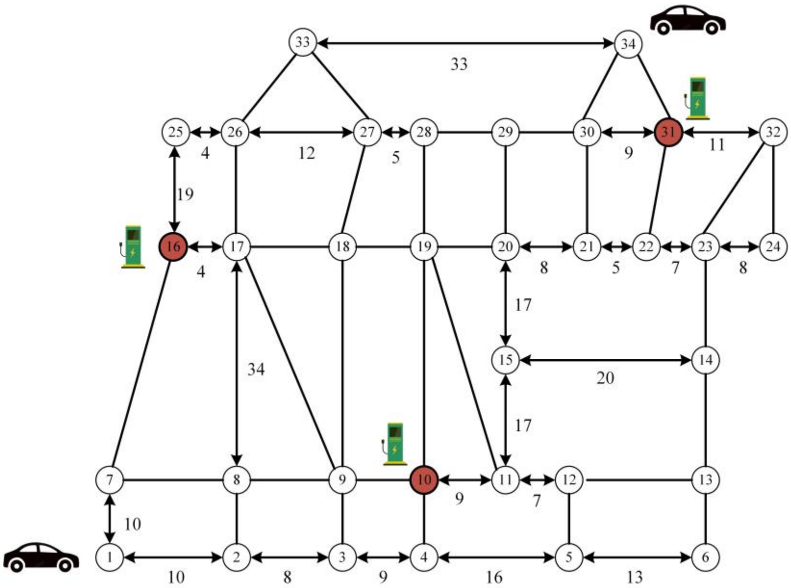


Figure 5: The map of the test section

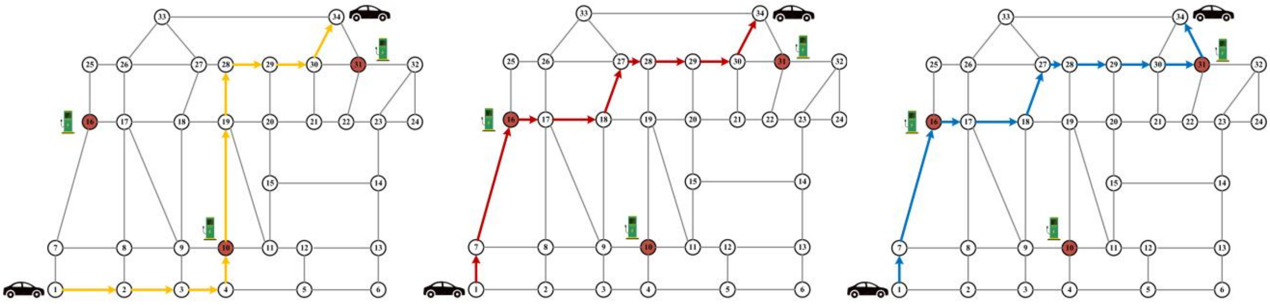
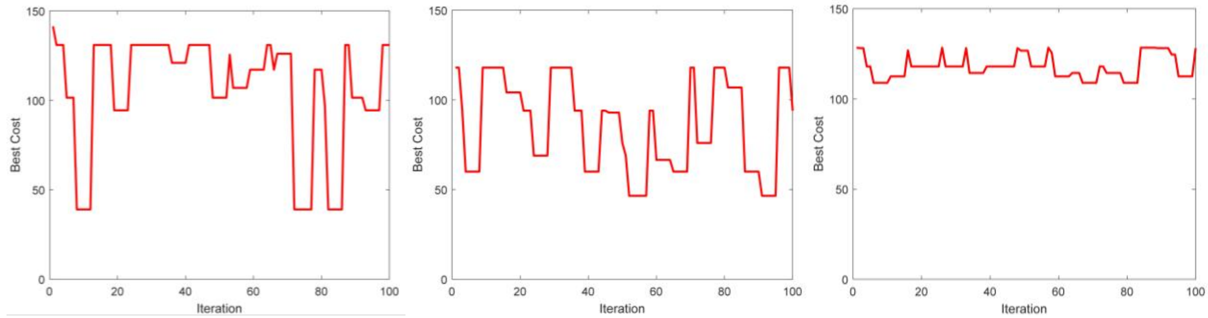
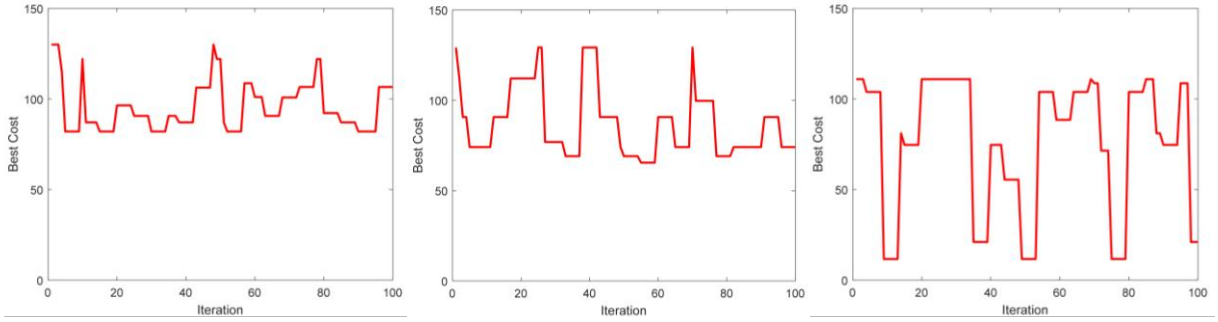


Figure 6: The shortest route from start node to destination



(a) from node 1 to 10 (b) from node 1 to 16 (c) from node 1 to 31



(d) from node 10 to 34 (e) from node 16 to 34 (f) from node 31 to 34

Figure 7: The iterative process for the shortest route

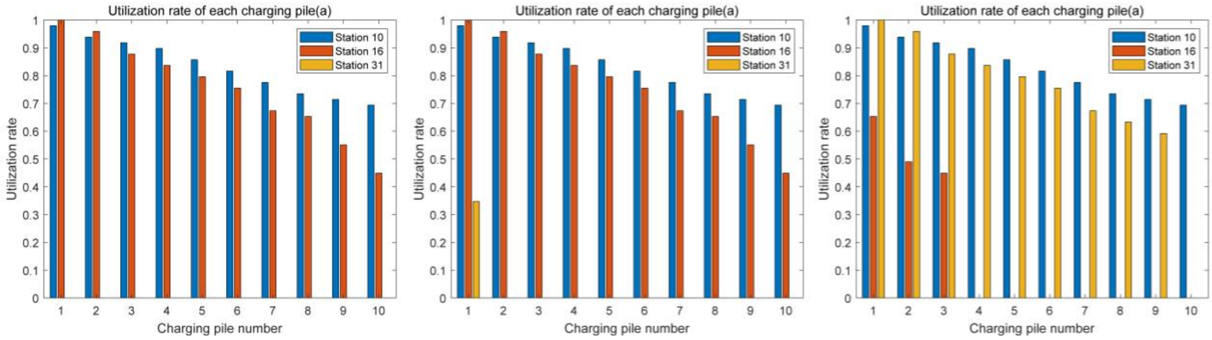
4.1 Charging route planning for a single EV

First, a specific value of 20% of the total charge is assumed. When the initial charge of the EV at the start node 1 is less than 20% of the total charge, the algorithm searches for the shortest route to a particular charging node and ensures that the EV has the charge to reach the charging station. The shortest route to each node is shown in Figure 6. The distance of the shortest route to node 10 is 39 km, the distance of the shortest route to node 16 is 46.53 km, and the distance of the shortest route to node 31 is 108.94 km. After arriving at the charging station, the electric vehicle is charged. After charging is completed, the shortest route to the destination should be planned. The shortest route lengths from the three charging nodes to the destination are as follows: the shortest route length through node 10 is 82.08 km, the shortest route length through node 16 is 65.50 km, and the shortest route length through node 31 is 11.70 km. The iterative process of the shortest path is shown in Figure 7. From the shortest path lengths obtained by EGWA, the roulette wheel algorithm can prove that the results obtained are globally optimal to a certain extent, which reduces the cases of falling into local optimization.

The route planning for a single EV is relatively simple, as it does not need to consider the waiting time at charging stations. It is assumed that the EV has 40% of its battery remaining at node 1. It is assumed the charging cost at node 10 is ¥1.3 per hour, at node 16 is ¥1 per hour, and at node 31 is ¥0.7 [41-42]. Considering the costs of each route, the driver can choose the appropriate charging station according to their needs. According to the fuzzy inference system, the user can derive an objective function that meets drivers' needs, as in equation (15). Assuming that the user attaches great importance to economic costs, input "1" to the fuzzy inference system and "0" for the rest of the costs. The system outputs the weights $\lambda = 0.72$, $\theta = 0.14$, $\omega = 0.14$. Assuming that the user attaches great importance to economic costs and time costs, input "1" to the fuzzy inference system and "0" for carbon emission cost. The system output weights $\lambda = 0.45$, $\theta = 0.45$, $\omega = 0.10$. Assuming that the user needs to balance the three costs, the system outputs $\lambda = 0.33$, $\theta = 0.33$, $\omega = 0.33$. The charging station choices for various user requirements are shown in Table 1.

Table 1: Charging options for vehicles with different needs

Inputs to the Fuzzy Inference System			Weights			Charging Station
Economic Cost	Time Cost	Emission Cost	λ	θ	ω	
1	0	0	0.72	0.14	0.14	31
0	1	0	0.14	0.72	0.14	16
0	0	1	0.14	0.14	0.72	16
1	1	0	0.45	0.45	0.1	31
0	1	1	0.1	0.45	0.45	16
1	0	1	0.45	0.1	0.45	16
1	0.5	0	0.56	0.33	0.11	31
1	1	1	0.33	0.33	0.33	16



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Figure 8: Utilization rate of charging pile under different scenarios

Table 2: Number of cars charged at each node

Scenario 1		Scenario 2		Scenario 3	
Node	Number of vehicles	Node	Number of vehicles	Node	Number of vehicles
10	24	10	24	10	24
16	26	16	25	16	10
31	0	31	1	31	16

4.3 Comparison of methods

To highlight the advantages of EGWA, EGWA is compared with other optimization algorithms in terms of minimum route length and minimum cost.

4.3.1 Minimum route length

To verify the performance of EGWA used for searching shortest paths in this paper, we have chosen GWO, LPGA [13], IWOA [42] and EGWA for comparison. The objective of optimization is to search for the shortest path from node 1 to node 10.

According to Figure 9 and Table 3, GWO finds the optimal solution 108.94 at the 47th iteration. IWOA finds the optimal solution 39 at the 64th iteration. LPGA finds the optimal solution 39 at the 84th iteration, and EGWA finds the optimal solution 39 at the 23rd iteration. EGWA keeps jumping out of the optimal solution to prove that the current optimal solution is a global optimal solution. EGWA is much better than other algorithms in terms of path finding efficiency and accuracy.

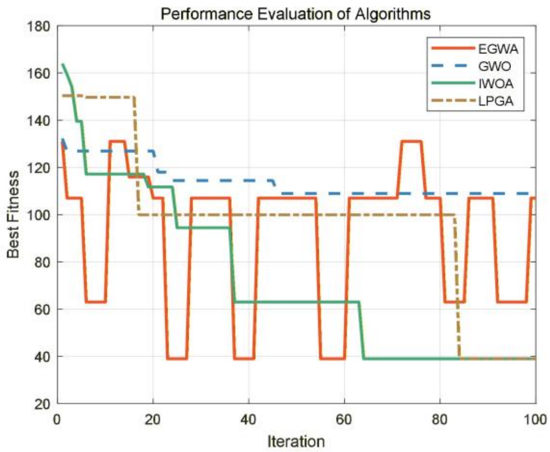
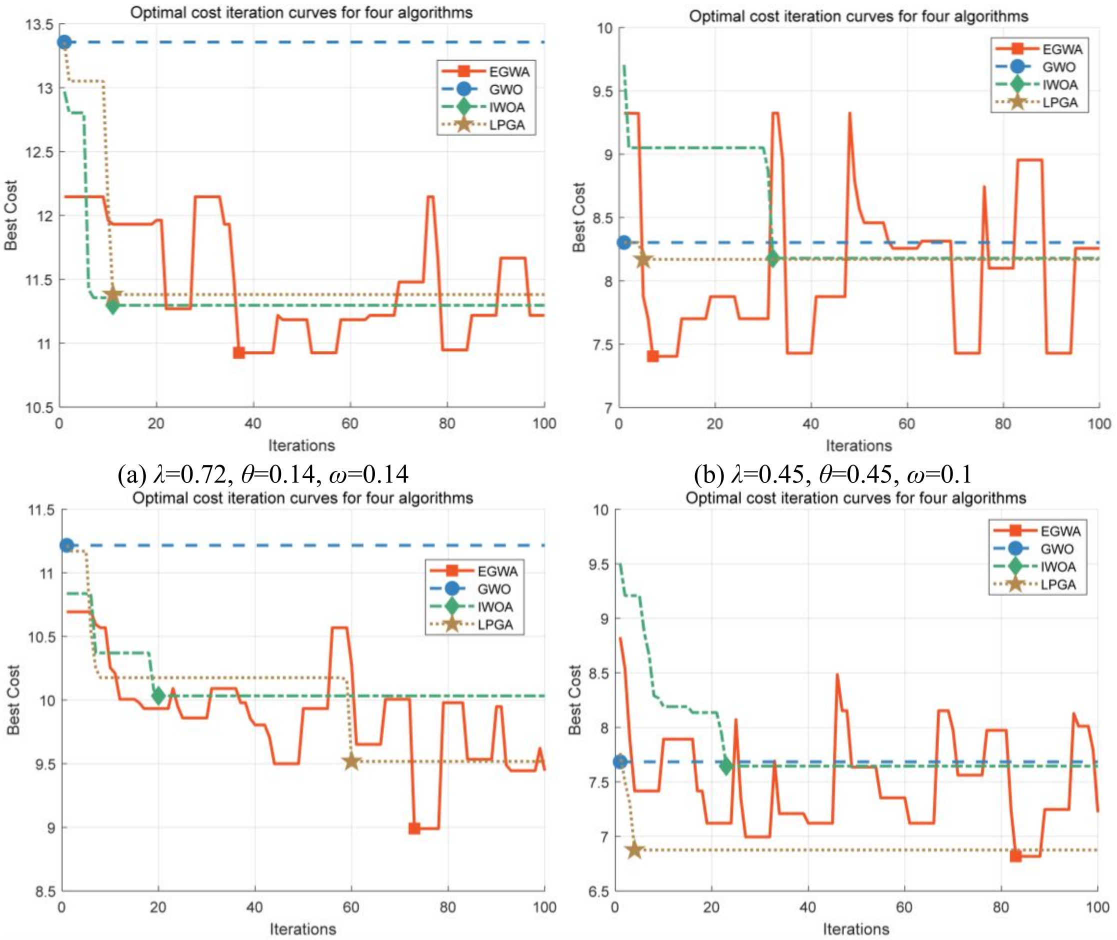


Figure 9: The comparison between EGWA, GWO, IWOA and LPGA

Table 3: Algorithm performance comparison

Algorithm	Optimal value	Number of iterations to reach the optimum
EGWA	39	23
GWO	108.94	47
IWOA	39	64
LPGA	39	84

4.3.2 Minimum cost



(a) λ=0.72, θ=0.14, ω=0.14 (b) λ=0.45, θ=0.45, ω=0.1

(c) λ=0.56, θ=0.33, ω=0.11 (d) λ=0.33, θ=0.33, ω=0.33

Figure 10: Iterative process of optimal solution with different cost weights

Table 4: Algorithm performance comparison

Weights	Algorithm	Optimal value	Number of iterations to reach the optimum	Cost savings achieved by EGWA over other algorithms
λ=0.72 θ=0.14 ω=0.14	EGWA	10.9247	37	\
	GWO	13.3566	1	22.26%
	IWOA	11.2970	11	3.41%
	LPGA	11.3809	11	4.18%
λ=0.45 θ=0.45 ω=0.1	EGWA	7.4048	7	\
	GWO	8.3028	1	12.13%
	IWOA	8.1792	32	10.46%
	LPGA	8.1700	5	10.33%
λ=0.56 θ=0.33 ω=0.11	EGWA	8.9903	73	\
	GWO	11.2161	1	24.76%
	IWOA	10.0331	20	11.60%
	LPGA	9.5184	60	5.87%
λ=0.33 θ=0.33 ω=0.33	EGWA	6.8174	83	\
	GWO	7.6840	1	12.71%
	IWOA	7.6448	23	12.14%
	LPGA	6.8755	4	0.85%

Table 5: Economic, time, and emission costs under λ=0.14, θ=0.14, ω=0.72

	Economic Cost	Cost savings achieved by EGWA	Time Cost	Cost savings achieved by EGWA	Emission Cost	Cost savings achieved by EGWA	Total Cost	Cost savings achieved by EGWA
EGWA	15.5751	\	2.1141	\	3.3994	\	4.9241	\
GWO	19.2983	23.90%	3.2130	51.98%	5.1665	51.98%	6.8715	39.55%
IWOA	15.5570	-0.11%	2.7055	27.97%	4.3505	27.98%	5.6889	15.53%
LPAG	16.2522	4.35%	2.2475	6.31%	3.6140	6.31%	5.1921	5.44%

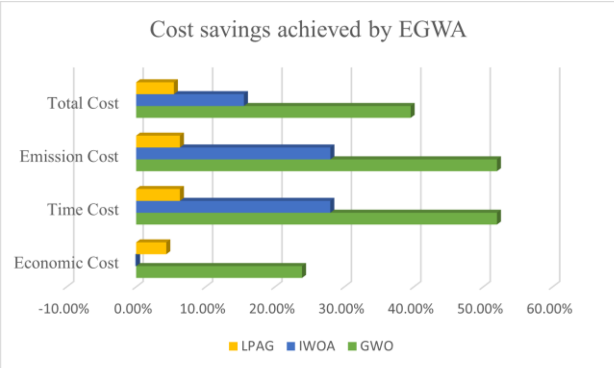


Figure 11: Cost savings achieved by EGWA over other algorithms

To highlight the superiority of EGWA in charging path cost optimization, four different cost weighting optimization iteration processes are presented.

Dealing with discrete path optimization, the position update formula of GWO is not suitable for discrete problems, and the lack of sufficient perturbation after updates leads to no population renewal, resulting in no change in the optimal value during subsequent iterations. Although IWOA and LPGA [4] can find local optima, they are prone to getting trapped in local optima, making it difficult to find the global optimum. The GWO improved by applying the 2-opt method and roulette wheel selection performs better in both population updating and optimal value searching. As shown in the Figure.10 and Table. 4, EGWA consistently achieves the lowest cost under different weight settings. On average, EGWA saves 12.47% more cost than GWO, 9.27% more than IWOA, and 5.08% more than LPGA.

According to the Figure. 11 and Table. 5, the use of EGWA results in an average reduction of 28.76% in carbon emission costs. A comparison between EGWA and IWOA shows that although EGWA does not achieve the lowest value for every individual cost component, its disadvantage in economic cost, whose weight is relatively small in the total objective function, is offset by its advantage in carbon emission cost, which has a higher weight. As a result, EGWA achieves a 15.53% reduction in the overall cost. This demonstrates that even if EGWA does not find the optimal solution for all sub-objectives, the overall cost is primarily determined by the sub-objectives with larger weightings. Therefore, achieving better performance in the dominant sub-objectives can still significantly reduce the overall cost.

5 Conclusion

This paper focuses on the charging route optimization problem under the scenario of multiple charging stations with different charging tariffs and different objective functions. A fuzzy inference system is used to allocate weights to the objective function, providing greater flexibility and comprehensiveness. By applying Depth-First Search (DFS) and an Improved Grey Wolf Optimizer (EGWA), suitable charging routes can be selected to improve the accuracy and efficiency of route optimization. Simulation of an EV fleet shows that node charging prices and waiting times have significant impacts on drivers' route choices. Simulation of a single EV demonstrates that EGWA has an irreplaceable advantage in minimizing charging costs. However, in real-world studies, battery degradation of EVs is inevitable, and aging may lead to inaccurate estimation of available energy and charging demand. In addition, carbon emission factors and charging prices may fluctuate with grid load, time, and regional policies. Traffic flow in route planning is also critical, as its dynamic changes can significantly affect waiting times. Therefore, future work will couple traffic flow and road network relationships, take into account the impact of battery aging on available energy, and establish a system model that is closer to real-world conditions. This will improve the realism and robustness of the optimization model and further refine the algorithm to achieve better results in EV charging route planning.

References

[1] A. D. Asiegbu, M. T. E. Kahn and A. M. Almaktoof, "Green hydrogen: A clean energy solution for Germany's transportation sector," *SAIEE Africa Research Journal*, vol. 115, no. 1, pp. 16-23, March 2024, doi: 10.23919/SAIEE.2024.10463751.

[2] S. Sabet and B. Farooq, "Green Vehicle Routing Problem: State of the Art and Future Directions," *IEEE Access*, vol. 10, pp. 101622-101642, 2022, doi: 10.1109/ACCESS.2022.3208899.

[3] Y. Li et al., "Key Technologies and Prospects for EVs Within Emerging Power Systems: Insights from Five Aspects," *CSEE Journal of Power and Energy Systems*, vol. 10, no. 2, pp. 439-447, March 2024, doi: 10.17775/CSEEJPES.2024.00190.

[4] Z. Zhao and C. K. M. Lee, "Dynamic Pricing for EV Charging Stations: A Deep Reinforcement Learning Approach," *IEEE Transactions on Transportation*

Electrification, vol. 8, no. 2, pp. 2456-2468, June 2022, doi: 10.1109/TTE.2021.3139674.

[5] S. Schoenberg and F. Dressler, "Reducing Waiting Times at Charging Stations with Adaptive EV Route Planning," *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 1, pp. 95-107, Jan. 2023, doi: 10.1109/TIV.2022.3140894.

[6] X. Li and Q. Han, "An EV Charging Station Load Prediction Method Considering Distribution Network Upgrade," *IEEE Transactions on Power Systems*, vol. 39, no. 2, pp. 4360-4371, March 2024, doi: 10.1109/TPWRS.2023.3311795.

[7] H. Seki and M. Mizumoto, "On the Equivalence Conditions of Fuzzy Inference Methods—Part 1: Basic Concept and Definition," in IEEE Transactions on Fuzzy Systems, vol. 19, no. 6, pp. 1097-1106, Dec. 2011, doi: 10.1109/TFUZZ.2011.2160268.

[8] Gao, D., Wang, J., & Chai, R. (2024). Intelligent Car Autonomous Driving Tracking Technology Based on Fuzzy Information and Multi-sensor Fusion. *Informatica (Slovenia)*, *48*(21), 37 - 50. https://doi.org/10.31449/inf.v48i21.6636

[9] S. Hussain, M. A. Ahmed and Y. -C. Kim, "Efficient Power Management Algorithm Based on Fuzzy Logic Inference for Electric Vehicles Parking Lot," in IEEE Access, vol. 7, pp. 65467-65485, 2019, doi: 10.1109/ACCESS.2019.2917297.

[10] S. Hussain, Y. -S. Kim, S. Thakur and J. G. Breslin, "Optimization of Waiting Time for Electric Vehicles Using a Fuzzy Inference System," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 9, pp. 15396-15407, Sept. 2022, doi: 10.1109/TITS.2022.3140461.

[11] Narang, M., Joshi, M. C., & Pal, A. K. (2022). A Hesitant Fuzzy Multiplicative Base-criterion Multi-criteria Group Decision Making Method. *Informatica (Slovenia)*, *46*(2), 235 - 242. https://doi.org/10.31449/inf.v46i2.3452

[12] V. Sharma, S. M. Aziz, M. H. Haque and T. Kauschke, "Energy Economy of Households with Photovoltaic System and Battery Storage Under Time of Use Tariff with Demand Charge," in IEEE Access, vol. 10, pp. 33069-33082, 2022, doi: 10.1109/ACCESS.2022.3158677.

[13] H. Yang, S. Yang, Y. Xu, E. Cao, M. Lai and Z. Dong, "Electric Vehicle Route Optimization Considering Time-of-Use Electricity Price by Learnable Partheno-Genetic Algorithm," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 657-666, March 2015, doi: 10.1109/TSG.2014.2382684.

[14] C. Yao, S. Chen, M. Salazar and Z. Yang, "Joint Routing and Charging Problem of Electric Vehicles with Incentive-Aware Customers Considering Spatio-Temporal Charging Prices," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 11, pp. 12215-12226, Nov. 2023, doi: 10.1109/TITS.2023.3286952.

[15] M. Tan, Y. Ren, R. Pan, L. Wang and J. Chen, "Fair and Efficient Electric Vehicle Charging Scheduling Optimization Considering the Maximum Individual Waiting Time and Operating Cost," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 8, pp. 9808-9820, Aug. 2023, doi: 10.1109/TVT.2023.3257547.

[16] W. Qiao, Y. Han, F. Si, J. Wang and Q. Zhao, "A Carbon-Tax-Based Pricing Scheme for Vehicle Scheduling in Coupled Power-Traffic Networks," in IEEE Transactions on Transportation Electrification, vol. 10, no. 2, pp. 4029-4041, June 2024, doi: 10.1109/TTE.2023.3313125.

[17] S. Zhang and K. -C. Leung, "Joint Optimal Power Flow Routing and Vehicle-to-Grid Scheduling: Theory and Algorithms," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 1, pp. 499-512, Jan. 2022, doi: 10.1109/TITS.2020.3012489.

[18] G. Ferro, M. Paolucci and M. Robba, "Optimal Charging and Routing of Electric Vehicles with Power Constraints and Time-of-Use Energy Prices," in IEEE Transactions on Vehicular Technology, vol. 69, no. 12, pp. 14436-14447, Dec. 2020, doi: 10.1109/TVT.2020.3038049.

[19] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard and W. Su, "Optimal Routing and Charging of an EV Fleet for High-Efficiency Dynamic Transit Systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3563-3572, July 2018, doi: 10.1109/TSG.2016.2635025.

[20] C. Yao, S. Chen and Z. Yang, "Joint Routing and Charging Problem of Multiple EVs: A Fast Optimization Algorithm," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 8184-8193, July 2022, doi: 10.1109/TITS.2021.3076601.

[21] Y. Xiang, J. Yang, X. Li, C. Gu and S. Zhang, "Routing Optimization of EVs for Charging with Event-Driven Pricing Strategy," *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 1, pp. 7-20, Jan. 2022, doi: 10.1109/TASE.2021.3102997.

[22] J. Liu, G. Lin, S. Huang, Y. Zhou, C. Rehtanz and Y. Li, "Collaborative EV Routing and Charging Scheduling with Power Distribution and Traffic Networks Interaction," *IEEE Transactions on Power Systems*, vol. 37, no. 5, pp. 3923-3936, Sept. 2022, doi: 10.1109/TPWRS.2022.3142256.

[23] Y. Jin, J. Xu, S. Wu, L. Xu and D. Yang, "Enabling the Wireless Charging via Bus Network: Route Scheduling for EVs," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1827-1839, March 2021, doi: 10.1109/TITS.2020.3023695.

[24] B. Al-Hanahi, I. Ahmad, D. Habibi, P. Pradhan and M. A. S. Masoum, "A Charging Strategy for Large Commercial EV Fleets," *IEEE Access*, vol. 12, pp. 46042-46058, 2024, doi: 10.1109/ACCESS.2024.3382219.

[25] M. Farahani, S. H. Zegordi and A. H. Kashan, "A Tailored Meta-Heuristic for the Autonomous EV Routing Problem Considering the Mixed Fleet," *IEEE Access*, vol. 11, pp. 8207-8222, 2023, doi:

10.1109/ACCESS.2023.3237481.
[26] R. Zhang, J. Guo and J. Wang, "A Time-Dependent EV Routing Problem with Congestion Tolls," *IEEE Transactions on Engineering Management*, vol. 69, no. 4, pp. 861-873, Aug. 2022, doi: 10.1109/TEM.2019.2959701.
[27] Y. Shen, L. Yu and J. Li, "Robust EV Routing Problem with Time Windows under Demand Uncertainty and Weight-Related Energy Consumption," *Complex System Modeling and Simulation*, vol. 2, no. 1, pp. 18-34, March 2022, doi: 10.23919/CSMS.2022.0005.
[28] X. Zhu, R. Yan, Z. Huang, W. Wei, J. Yang and S. Kudratova, "Logistic Optimization for Multi Depots Loading Capacitated Electric Vehicle Routing Problem from Low Carbon Perspective," in IEEE Access, vol. 8, pp. 31934-31947, 2020, doi: 10.1109/ACCESS.2020.2971220.
[29] Y. Zhu, K. Y. Lee and Y. Wang, "Adaptive Elitist Genetic Algorithm with Improved Neighbor Routing Initialization for EV Routing Problems," *IEEE Access*, vol. 9, pp. 16661-16671, 2021, doi: 10.1109/ACCESS.2021.3053285.
[30] Z. Liu, X. Zuo, M. Zhou, W. Guan and Y. Al-Turki, "EV Routing Problem with Variable Vehicle Speed and Soft Time Windows for Perishable Product Delivery," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 6, pp. 6178-6190, June 2023, doi: 10.1109/TITS.2023.3249403.
[31] H. Mao, J. Shi, Y. Zhou and G. Zhang, "The Electric Vehicle Routing Problem with Time Windows and Multiple Recharging Options," in IEEE Access, vol. 8, pp. 114864-114875, 2020, doi: 10.1109/ACCESS.2020.3003000.
[32] Y. -H. Jia, Y. Mei and M. Zhang, " Confidence-Based Ant Colony Optimization for Capacitated EV Routing Problem with Comparison of Different Encoding Schemes," *IEEE Transactions on Evolutionary Computation*, vol. 26, no. 6, pp. 1394-1408, Dec. 2022, doi: 10.1109/TEVC.2022.3144142.
[33] Ziyue, Z. (2024). A Deep Intelligent Ant Colony-Ba sed Approach to Personalized and Customized Rout e Optimization for Smart Tourism. *Informatica (Slo venia)*, *48*(21), 139 – 154. https://doi.org/10.31449/i nf.v48i21.6572
[34] Wei, L. (2025). An Improved Topology Graph and A nt Colony Optimization Approach for Optimizing E lectric Vehicle Travel Path Considering Time and C harging Cost. *Informatica (Slovenia)*, *49*(17), 67 – 8 0. https://doi.org/10.31449/inf.v49i17.6669
[35] C. Fang, H. Lu, Y. Hong, S. Liu and J. Chang, "Dyn amic Pricing for Electric Vehicle Extreme Fast Char ging," *IEEE Transactions on Intelligent Transportat ion Systems*, vol. 22, no. 1, pp. 531-541, Jan. 2021, doi: 10.1109/TITS.2020.2983385.
[36] C. Zhang and Y. Kuang, "Low-Carbon Economy Optimization of Integrated Energy System Considering Electric Vehicles Charging Mode and Multi-Energy Coupling," in IEEE Transactions on Power Systems, vol. 39, no. 2, pp. 3649-3660, March 2024, doi: 10.1109/TPWRS.2023.3280067.
[37] E. Boopathi Kumar and M. Sundaresan, "Edge detection using trapezoidal membership function based on fuzzy's mamdani inference system," 2014 International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2014, pp. 515-518, doi: 10.1109/IndiaCom.2014.6828012.
[38] S. Hulagu and H. B. Celikoglu, "EV Location Routing Problem with Vehicle Motion Dynamics-Based Energy Consumption and Recovery," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 10275-10286, Aug. 2022, doi: 10.1109/TITS.2021.3089675.
[39] Li, Jiayi. “Research on the Marketing Strategy of Tesla Vehicle in China.” *Advances in Economics, Management and Political Sciences* (2023): n. pag, DOI:10.54254/2754-1169/4/2022912.
[40] B. Liu, W. Ni, R. P. Liu, Y. J. Guo and H. Zhu, "Optimal Electric Vehicle Charging Strategies for Long-Distance Driving," in IEEE Transactions on Vehicular Technology, vol. 73, no. 4, pp. 4949-4960, April 2024, doi: 10.1109/TVT.2023.3332097.
[41] Oxford Institute for Energy Studies. (n.d.). *Electric vehicles*. Chinese Climate Policy. Retrieved July 31, 2025, from https://chineseclimatepolicy.oxfordenergy.org/book-content/domestic-policies/vehicles/electric-vehicles/
[42] Chon Man Tam, I-Yun Lisa Hsieh, Xin Sun, assessing levelized cost of electric vehicle recharging in China, iScience, Volume 27, Issue 9, 2024,110690, ISSN 2589-0042, https://doi.org/10.1016/j.isci.2024.110690.
[43] H. Bao, Y. Wang, H. Zhu and D. Wang, "Area Complete Coverage Path Planning for Offshore Seabed Organisms Fishing Autonomous Underwater Vehicle Based on Improved Whale Optimization Algorithm," in IEEE Sensors Journal, vol. 24, no. 8, pp. 12887-12903, 15 April15, 2024, doi: 10.1109/JSEN.2024.3371497.