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A combined genetic algorithm and A* search algorithm for the electric vehicle routing problem with time windows

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ABSTRACT

With growing environmental concerns, the focus on greenhouse gases (GHG) emissions in transportation has increased, and the combination of smart microgrids and electric vehicles (EVs) brings a new opportunity to solve this problem. Electric vehicle routing problem with time windows (EVRPTW) is an extension of the vehicle routing problem (VRP) problem, which can reach the combination of smart microgrids and EVs precisely by scheduling the EVs. However, the current genetic algorithm (GA) for solving this problem can easily fall into the dilemma of local optimization and slow iteration speed. In this paper, we present an integer hybrid planning model that introduces time of use and area price to enhance realism. We propose the GA-A* algorithm, which combines the A* algorithm and GA to improve global search capability and iteration speed. We conducted experiments on 16 benchmark cases, comparing the GA-A* algorithm with traditional GA and other search algorithms, results demonstrate significant enhancements in searchability and optimal solutions. In addition, we measured the grid load, and the model implements the vehicle-to-grid (V2G) mode, which serves as peak shaving and valley filling by integrating EVs into the grid for energy delivery and exchange through battery swapping. This research, ranging from model optimization to algorithm improvement, is an important step towards solving the EVRPTW problem and improving the environment.

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1. Introduction

With global warming and environmental problems intensifying, more and more attention has been paid to reducing greenhouse gas emissions in transportation. New energy vehicles have emerged globally as an environmentally friendly and energy-efficient alternative [1], but face challenges in practical applications due to limitations in battery technology and charging facilities [2]. To overcome these challenges, smart microgrids have emerged as a new type of energy management system, which can improve power sharing and power quality improvement and promote the sustainable development of new energy vehicles [3, 4]. Meanwhile, AI plays an important role in solving energy management problems in smart microgrids by applying various optimization methods and developing optimal energy management strategies, which can help to increase energy efficiency, reduce the total cost, and improve power quality [5].

EVRPTW as an optimization problem, aims to efficiently plan the routes of electric vehicles to meet the time window constraints and minimize the total cost or maximize the benefits. It optimizes the routes and charging strategies of electric vehicles to maximize the use of renewable energy and grid power for efficient energy management. By rationally arranging the use of charging stations and charging periods, it can reduce the dependence on the traditional grid and improve energy utilization. Meanwhile, by rationally planning the routes of electric vehicles, EVRPTW can reduce pollutant emissions and carbon footprint. Introducing EVs into smart microgrids and the whole grid, can promote the use of green energy and reduce dependence on oil and other limited resources.

Keskin and Çatay first started working on the EVRPTW problem in 2016 and specifically studied the allowed partial charging problem (EVRPTW-PR), where they formulated the problem as 0-1 mixed integer linear programming, developed an adaptive large neighborhood search (ALNS) algorithm, and used benchmark instances to test those solutions that can effectively find high quality solutions, As the result shows, the partial tolling scheme can substantially improve the routing decisions [6]. Keskin and Çatay reformulated the problem as mixed integer linear programming in 2018, where they built on the original by combining an ALNS method with an exact method equipped with various destroy-repair algorithms to efficiently explore neighborhoods and using CPLEX to strengthen the obtained routes [7]. In 2019, Wang *et al*. constructed a mathematical model to minimize the total cost based on EVRPTW considering time windows and battery swapping stations (2E-EVRPTW-BSS) for the two-stage vehicle path problem of electric vehicles and verified the validity of the model [8]. Gocken and Yaktubay solved the VRPTW problem by applying first clustering and then using genetic algorithm solution for planning. Meanwhile different clustering algorithms are compared and finally the superiority of K-means algorithm for initialising the population is concluded [9]. In 2020, Raeesi and Zografos developed a program utilizing a two-phase hybrid of dynamic programming and integer programming algorithms. The resulting program serves as the cornerstone of a robust, large neighborhood search algorithm, designed for the rapid resolution of instances related to EVRPTW-SMBS [10]. In 2021, Zhu *et al*. applied the elitist genetic algorithm to the EV path problem with a time window [11]. Deng *et al*. studied the EV path problem with a time window and nonlinear charging constraints (EVRPTW-NL) and proposed an improved hybrid algorithm combining an improved differential evolution (IDE) and several heuristics [12]. Bac and Erdem developed a series of neighborhood operators for the EVRPTW problem in the Variable Neighborhood Search (VNS) and Variable Neighborhood Drop (VND) heuristics for the local search process [13]. Lin *et al*. came out with EVRPTW (EVRPTW-TP) under time-varying tariffs, formulating it as an optimal problem, proposing a Lagrangian relaxation method and a mixed-variable neighborhood search/tabu search heuristic to obtain high-quality lower bounds and feasible solutions, respectively [14]. Lin *et al*. proposed an end-to-end deep reinforcement learning framework for solving the EVRPTW [15]. In 2022, Erdelić and Carić implemented the Adaptive Large Neighborhood Search (ALNS) meta-heuristic algorithm, utilizing the ruin-recreate strategy. This algorithm integrates a novel initial solution heuristic, partial search, path removal, and an exact procedure, resulting in the achievement of an optimal layout for charging stations. The results show that ALNS can find 38 new optimal solutions on the benchmark EVRPTW instance and that the advantages and disadvantages of using a partial charging strategy compared to a full charging strategy are evident [16]. In 2022, Niu *et al*. proposed the idea of consumers being able to choose multiple delivery addresses and used a large-scale neighbourhood search algorithm to facilitate further matching of logistics and distribution companies with customer needs [17]. In 2022, Liu *et al*. developed a hybrid Genetic Algorithm that combines the 2-opt algorithm with GA [18]. Ding designed an adaptive particle swarm optimization algorithm for the driving cycle based time window electric vehicle routing problem (EVRPTW-DC) to solve the problem [19]. In 2023, Kumar *et al*. proposed a firefly and ant colony algorithm with a new pad heuristic avoiding local optimums [20]. Kempton and Tomić first proposed electric vehicle-to-grid (V2G) technology, which utilizes large amounts of electric vehicle energy storage through interaction between electric vehicles and the grid to act as a buffer between the grid and renewable energy sources [21].

In 2018, Shao *et al*. solved the EVRP model based on a hybrid genetic algorithm and used the dynamic Dijkstra algorithm to make some improvements to the classical Dijkstra algorithm [22]. In the same year, Wang *et al*. proposed to solve complex multi-objective problems based on a heuristic algorithm (ST-VNSGA) consisting of a variable neighbourhood search method and GA considering the spatiotemporal distance [23]. Zhu *et al*. investigated the path algorithm, and then used the elitist genetic algorithm and proposed an improved neighbour path initialization method to solve the EV routing problem [24]. Hien *et al*. proposed a greedy search algorithm GSGA inspired by clustering [25]. Wang *et al*. used Montecarlo tree search algorithm to improve the genetic algorithm, taking into account the flexibility of the paths and saving allocation time. The more complex the composition of the road network, the better the results obtained by the algorithm [26]. In 2023, Amiri *et al*. proposed developed two meta-heuristic algorithms including Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Adaptive Large Neighbourhood Search (ALNS), and combined with multi-objective solution methods (e.g. weighted and epsilon constraints and hybrid methods) [27].

In this paper, based on the previous research, firstly, established an integer hybrid planning model for the EVRPTW problem that comprehensively considers multiple factors, including vehicle fixed cost, energy cost, time cost, and penalty cost for violating constraints, which is closer to the actual engineering background. Meanwhile, the Time of use Pricing and Area price are introduced, and the EVs into the grid based on the V2G model realize the formation of a smart microgrid, which effectively acquires and delivers energy by means of the EVs swap under the dual perspectives of time and space. In particular, the use of the A* algorithm in the initializing population step allows for a better initial solution, which avoids the problem of slow iteration speed and satisfies the stochastic nature of genetic algorithms. Experiments demonstrate that the GA-A* algorithm performs well in solving the EVRPTW problem, applies to different sizes of arithmetic cases, and outperforms the traditional GA algorithm and other path planning algorithms. In addition, it helps the smart microgrid not only achieves the successful reduction of the system's load peak-to-valley difference rate and mean square deviation based on the V2G model by incorporating EVs into the grid, effectively utilizing EVs to reduce the grid's volatility and improve the quality of power but also enables the EVs to rationally distribute energy in the grid by prioritizing the delivery of energy during peak hours of power consumption and acquiring energy during the trough hours of power consumption, which achieves a reasonable distribution of power.

2. Methodology

2.1 Math model

The main problem investigated in this paper is the Electric-Vehicle Routing Problem with Time Windows (EVRPTW), which is described as a number of EVs transporting the required supplies from a distribution center to various customer nodes, where they can be charged or discharged at a charging station, which adopts battery swapping. On the one hand, swapping batteries simplifies the model complexity, on the other hand, the replaced batteries can be used as part of a microgrid for charging and discharging operations, bringing profit to the grid operator. Verma confirmed that battery swapping leads to better path planning options for electric vehicles [28]. The objective function is to minimize the total cost including vehicle fixed cost, energy cost which considers the temperature coefficient, time cost, penalty cost for violating the load constraint, penalty cost for violating the time window, penalty cost for violating the power constraint, and charging and discharging cost.

EVs are subject to constraints:

- Each customer has a fixed amount of demand and is allowed to be served by only one vehicle and only once;
- EVs exist that the maximum load cannot exceed the maximum load capacity;
- EVs have a battery capacity that cannot exceed the maximum battery capacity or a battery capacity that is less than zero;

- EVs depart from the distribution center in a fully charged state and eventually return to the charging center;
- EVs are allowed to visit the charging station multiple times;
- EVs are required to arrive by the latest time window or pay a penalty cost;
- EVs arriving early at the customer node are not required to pay penalty costs, only time costs according to time.

In the problem, the Time of use Pricing and area price are introduced to charge different prices for 24 hours of the day according to different periods and in different areas. Higher prices are charged during the periods and areas with excessive electricity demand; conversely, the prices are lowered. The base load is referred to the data provided by Xiao *et al*. [29]. Fig. 1 shows the 24 hours area price and the grid load at each moment, and the area price is set with reference to the data provided by Fu *et al*. [30]. Fig. 2 shows the area price and the grid load in different areas. Huo has demonstrated that ambient temperature has a great influence on the energy consumption of EVs, and Fig. 3 shows the temperature curve fitted according to the data of this article [31]. Fig. 4 shows the annual time-averaged temperature profile for Beijing in 2022, with data from the National Oceanic and Atmospheric Administration (NOAA) National Center for Environmental Information (NCEI).

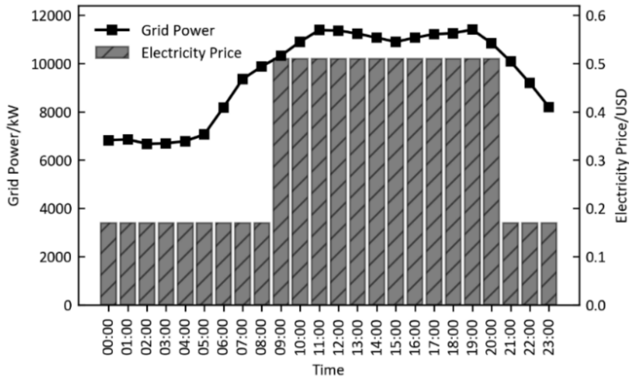

Fig. 1 Time of use pricing and grid loads

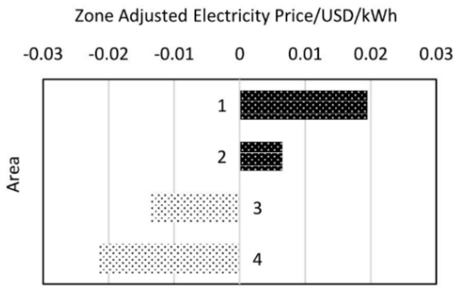

Fig. 2 Area price adjustment

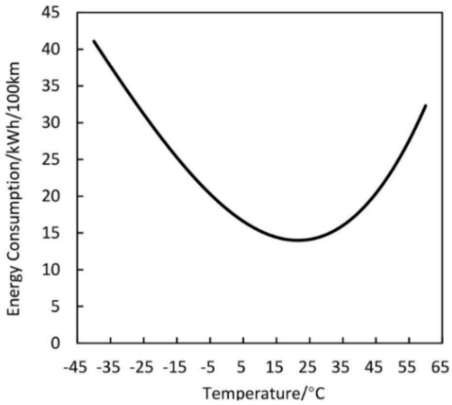

Fig. 3 Temperature-energy consumption per 100 km curve

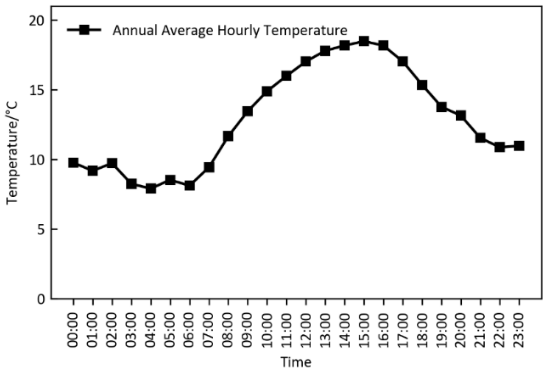

Fig. 4 Beijing's annual average temperature time curve

$$y = 0.000052307x^3 + 0.0069952x^2 - 0.37395x + 18.276 \quad (1)$$

Eq. 1 shows the fitted temperature-energy consumption per 100 km curve.

Due to the short driving range of EVs, they need to be recharged at the charging station during the driving process. In this paper, electric energy is recharged by swapping batteries and connected to the power grid to deliver/acquire energy. According to the impact of the Time of use Pricing and the area price, electricity is sold to the power grid for profit. V2G technology is introduced by simulating V2G based on the Time of use Pricing and the area price. This paper divides a day into 24 time periods, each with different electricity prices. During periods of high electricity demand, it is the peak period of electricity consumption, and the Time of use Pricing is higher. Conversely, it is a low valley stage, and the Time of use Pricing is lower. Divide the entire map into different regions based on different datasets. In areas of peak electricity consumption, area prices are higher; conversely, area prices are lower. When the vehicle is charging, replace the battery with a fully charged battery at the charging station; When the vehicle is discharged, replace the battery at the charging station with enough power to support the next charging station or distribution center.

The EVRPTW model studied in this paper is, given a graph $G = (N \cup E, A)$, where the point set $N = \{0,1,\cdots,n\}$ represents a set of n customers' points, where 0 represents a distribution center, $E = \{n, n+1, \cdots, n+m\}$ represents m charging stations, $A = \{(i,j)|i,j \in N \cup E, i \neq j|\}$ represents all connected arcs in $N \cup E$.

The symbol descriptions in the model are shown in Table 1.

Table 1 Symbol description

Symbol	Instructions
O	Distribution center
N	Customer node set
K	Set of the number of EVs used
E	Charging Station set
V	All node set
d_{ij}	Node i to node j traveling distance
D_i	Customer node i demand
L_{mc}	Max. loading capacity of the vehicle
L_{ik}	Remaining load at arrival of vehicle k at node i
B_Q	Max. battery capacity of vehicle
B_{aik}	Remaining capacity at arrival of vehicle k at node i
B_{lik}	Remaining capacity at left of vehicle k at node i
E_i	Customer node i's earliest service time, $i \in N$
L_i	Customer node i's latest service time, $i \in N$
t_{aik}	Time at arrival of vehicle k at node i, $i \in N$
t_{lik}	Time at leaving of vehicle k at node i, $i \in N$
t_{wik}	Waiting Time of vehicle k at node i, $i \in N$
t_{mik}	Missing Time of vehicle k at node i, $i \in N$
t_{sik}	Service/Swap Time of vehicle k at node i, $i \in N$
t_{ijk}	Time at driving of vehicle k from node i to node j, $i, j \in N$
v	velocity of vehicles traveling in distribution
μ	Battery consumption rate
$Tem_{\gamma k}$	γ time vehicle k traveling ambient temperature coefficient
C_d	Cost per distance
C_1	Penalty costs for violating load constraints
C_2	Penalty costs for violating the time window
C_3	Penalty costs for violating electricity constraints
C_t	Cost per time
$S_{\gamma\theta}$	γ time area θ price
$P_{L\gamma\theta}$	No EVs in the original grid γ time area θ power

The EVRPTW model proposed in this paper is improved from the mathematical model proposed by Li *et al*. [32], and on this basis, increases the Time of use Pricing, Area price, and ambient temperature coefficient. On the one hand, it is closer to the real working environment, and on the other hand, it can help regulate and store electricity in space, which can better improve energy quality and play a role in energy distribution. According to the description of the EVRPTW problem, the objective function includes vehicle fixed cost, energy cost which considers the temperature coefficient, time cost, penalty cost for violating load constraints, penalty cost for violating time windows, penalty cost for violating energy constraints, and charging and discharging cost. A mathematical model for this problem is established.

Decision variables:

$$X_{ijk} = \begin{cases} 1, \text{Vehicle } k \text{ from customer } i \text{ to customer } j \\ 0, \text{otherwise} \end{cases}$$

$$Y_k = \begin{cases} 1, & \text{vehicle } k \text{ violated the power constraints} \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{aligned} minC = C_o \sum_{k \in K} X_k + C_1 \sum_{k \in K} max[0, D_k - L_{mc}] + C_2 \sum_{i \in V} \sum_{k \in K} t_{mik} \\ + C_3 \sum_{k \in K} Y_k + C_d \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{\gamma=1}^{24} Tem_{\gamma k} d_{ij} x_{ijk} \\ + C_t \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} (t_{ijk} + t_{sjk}) + \sum_{\gamma=1}^{24} \sum_{\theta=1}^{n} \sum_{k \in K} \left| P_{\gamma k} \right| S_{\gamma\theta} \end{aligned} \tag{2}$$

$$\sum_{i \in N, i \neq j} X_{ijk} = 1, \forall j \in N, k \in K \tag{3}$$

$$\sum_{j \in V,\ i \neq j} X_{0jk} \leq 1\,, k \in K \tag{4}$$

$$\sum_{i \in V i \neq j} X_{ijk} - \sum_{i \in V i \neq j} X_{jik} = 0, \forall j \in V, k \in K \tag{5}$$

$$0 \leq D_j \leq L_{ik} - D_i, i \in V, j \in V, k \in K \tag{6}$$

$$0 \leq \sum_{i \in N} D_{ik} \leq L_{mc}, \forall k \in K \tag{7}$$

$$0 \leq B_{ajk} \leq B_{lik} + Tem_{\gamma k} d_{ij} X_{ijk} \mu, \forall i \in N, j \in N, k \in K \tag{8}$$

$$\sum_{i,j \in V} Tem_{\gamma k} d_{ij} X_{ijk} \mu \leq B_{li} \leq B_Q, i \in G \tag{9}$$

$$0 \leq B_{aik} \leq B_Q, \forall i \in V, k \in K \tag{10}$$

$$B_{aik} = B_{lik}, \forall i \in V, k \in K \tag{11}$$

$$t_{wik} = max[0, e_i - t_{aik}], \forall i \in N, k \in K \tag{12}$$

$$t_{mik} = max[0, t_{aik} - l_i], \forall i \in N, k \in K \tag{13}$$

$$t_{lik} = t_{aik} + t_{sik} + t_{wik}, \forall i \in N \cup G \tag{14}$$

$$t_{ijk} = \frac{d_{ijk}}{v}, \forall i \in V, j \in V, k \in K \tag{15}$$

$$t_{ajk} = (t_{lik} + t_{ijk}) X_{ijk}, \forall\, i \in V, j \in N \cup G, k \in K \tag{16}$$

$$X_{ijk} = \{0,1\}, \forall\, i \in V, j \in V, k \in K \tag{17}$$

$$Y_k = \{0,1\}, \forall k \in K \tag{18}$$

The objective function (Eq. 2) represents the minimum total cost, including vehicle fixed cost, energy consumption cost, time cost, charging and discharging cost, and penalty cost. Among them $S_{\gamma\theta}$ are the Time of use Pricing and Area price. When the battery is discharged, $S_{\gamma\theta}$ is negative, i.e. when the cost of charging and discharging is negative, it means that the charging and discharging process is generally profitable. Constraint Eq. 3 indicates that each customer is served only once. In the cost of time penalty, waiting time is not included in the penalty, but rather placed within the cost of time. We believe that this can improve the efficiency of resource allocation. Constraint Eq. 4 indicates that only one transport vehicle is arranged for each distribution route. Constraint Eq. 5 indicates equal number of vehicles entering and exiting. Constraint Eq. 6 indicates that the demand of the vehicle at the next node cannot be higher than the remaining demand of the vehicle at the current node minus the demand at the current node. Constraint Eq. 7 indicates that all demands of a transportation route must not exceed the maximum load capacity. Constraint Eq. 8 indicates that the remaining power upon reaching the next node must not be less than the current node's power minus the power consumption from that node to the next node. Constraint Eq. 9 indicates that the energy consumption after charging and discharging at the charging station is not less than the energy consumption of the sub path and not higher than the maximum energy consumption. Constraint Eq. 10 indicates that the remaining electricity at any point is not negative. Constraint Eq. 11 indicates that the remaining electricity is unchanged before and after the vehicle visits the customer node. Constraint Eq. 12 represents the calculation method of waiting time. Constraint Eq. 13 represents the calculation method of late time. Constraint Eq. 14 indicates that the time of a vehicle leaves the node is the sum of arrival time, waiting time, and service time. Constraint Eq. 15 represents the calculation method of the time taken by the vehicle from node i to node j. Constraint 16 indicates that the time for the vehicle to reach the next node is equal to the sum of the time to leave the current node and the time spent on the journey. Constraints Eqs. 17 and 18 are binary 0-1 variables.

2.2 Algorithm

To solve the Electric-Vehicle Routing Problem with Time Windows, this paper proposes an improved genetic algorithm GA-A*. Genetic algorithm has the advantages of starting from the population, having potential for parallelism, using evaluation functions for inspiration, simple processes, probability mechanisms for iteration, and randomness. However, genetic algorithms have certain dependencies in initial population selection, which may lead to the problem of falling into local optimal solutions.

To overcome these problems, this paper introduces the A* algorithm as part of the improved genetic algorithm. The A* algorithm is a heuristic search algorithm that guides the search process by evaluating the cost function and heuristic function of nodes. It has high efficiency and accuracy in path search. The purpose of introducing the A* algorithm is to optimize the initial set of points by solving for the optimal path and cutting it into seed nodes. Then, by randomly creating other nodes as genes, the initialized population is formed. Such an improvement measure aims to improve the search efficiency and effectively avoid the occurrence of local optimal solutions.

This paper chooses to introduce the A* algorithm. Firstly, it can evaluate nodes through heuristic functions to quickly find the optimal path. Secondly, the A* algorithm has good performance and accuracy in solving the optimal path problem. By applying the A* algorithm to the optimization of the initial point set, the quality of the initial population can be improved, providing a better starting point for the search process of genetic algorithms. Finally, this improvement by introducing the A* algorithm helps to improve the overall algorithm's ability to solve the EVRPTW and provides better results.

The pseudo-code of the GA-A* algorithm is shown in Fig. 5. Through this improvement, this paper aims to overcome the limitations of traditional genetic algorithms and improve the efficiency and quality of solving path planning problems.

Firstly, based on the A* algorithm, the optimal path passing through all nodes is obtained and the path is divided into sub-paths according to the needs of the customer nodes. Then sort the remaining unincorporated nodes by time window order, and insert randomly signed charging station nodes to generate multiple genes as the initial population. Using decimal signed encoding to represent genes, including information such as customer nodes, charging nodes, and distribution centers. The fitness function considers vehicle costs, energy consumption costs, time costs, and penalty costs for constraint violations. Selection, using the roulette selection method. Crossover, using the first 1/3 encoding after crossover to replace the last 1/3 encoding before crossover. Variation, using an elitist strategy to retain elitist individuals, varies general genes, generates multiple genes, and calculates the fitness to retain the highest term. Multiple iterations are performed to obtain the final path encoding.

Algorithm 1 GA-A* algorithm

Input: V, A, d_{ij}, $Station\_area$, D_i, t_{sik}, t_{ijk}, E_i, L_i,C_0,C_1,C_2,C_3,C_d,C_t,
Output: $Best\ \ path$

```
class S object:
Dis ← S.var
npath ← Priority_Que()
napth.S
while npath ≠ ∅ do
    if len(npath) = num_cities then
        path ← npath
    end if
    visited[current] ← True
    for neighbor ← 0 to num_cities − 1 do
        if neighbor in charging_stations.keys() then
            continue
        end if
        if not visited[neighbor] then
            has_gone_to_charging ← 0
            if has_gone_to_charging = 0 then
                has_gone_to_charging ← 1
                find min cost with Station
            else if has_gone_to_charging == 1 then
                find min cost without Station
            end if
            continue
        end if
    end for
end while
path ← npath
for index, pos in enumerate(path) do
    Path encoding is segmented based on demand
end for
for sub_path in(path) do
    Each sub_path code arranged in TW and randomly sorted by grouping the
remaining codes
end for
for i ← 1 to k do
    chosen_pop ← choose(pop)
    crossed_pop ← cross(chosen_pop)
    pop ← mergeGenes(pop, crossed_pop)
    pop ← vary(pop)
    key ← gene : fitness_pop(gene)[0]
    pop.sort(reverse = True, key = key)
end for
```

Fig. 5 GA-A* pseudo-code

2.3 Experimental design

To evaluate the performance of the model and algorithm. In this paper, 16 test cases were selected. Test cases are derived from a shared database [33]. In these cases, each customer node has different requirements, and each example has a different charging station and number of customers. For example, the case "R-2-C-40" means that there are two charging stations and forty customers in the case. To test the performance of the GA-A* algorithm, experiments were designed to test it against the conventional GA, and referred to the data made by Li et al using adaptive large neighbourhood search (ALNS), large neighbourhood search (LNS), and variable neighbourhood search (VNS) algorithms [32] for comparison. The algorithm is written in Python and the test platform is Intel Xeon E5-2680 v4.

3. Result

3.1 Simulation results

The algorithm was used to test the optimal path under 16 groups of different cases, Some of the initial maps are shown in Fig. 6 for 30, 50, 70 and 120 charging station nodes.

Fig. 7 shows the paths plotted from the optimal paths derived from the GA-A* operation with other methods.

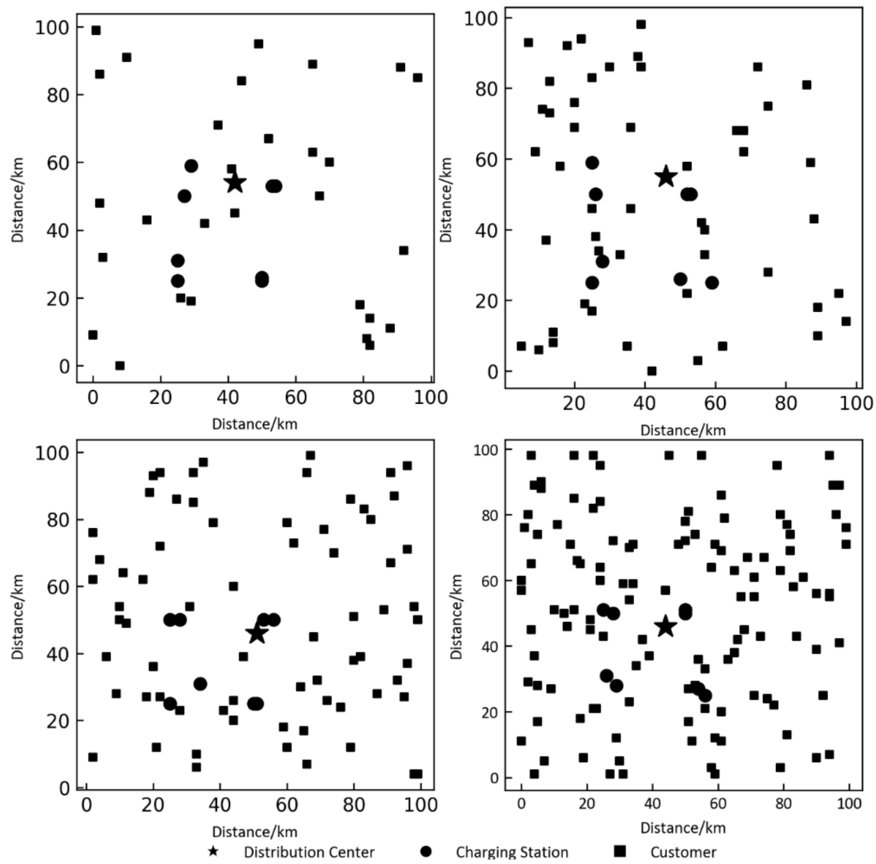

Fig. 6 Initial map

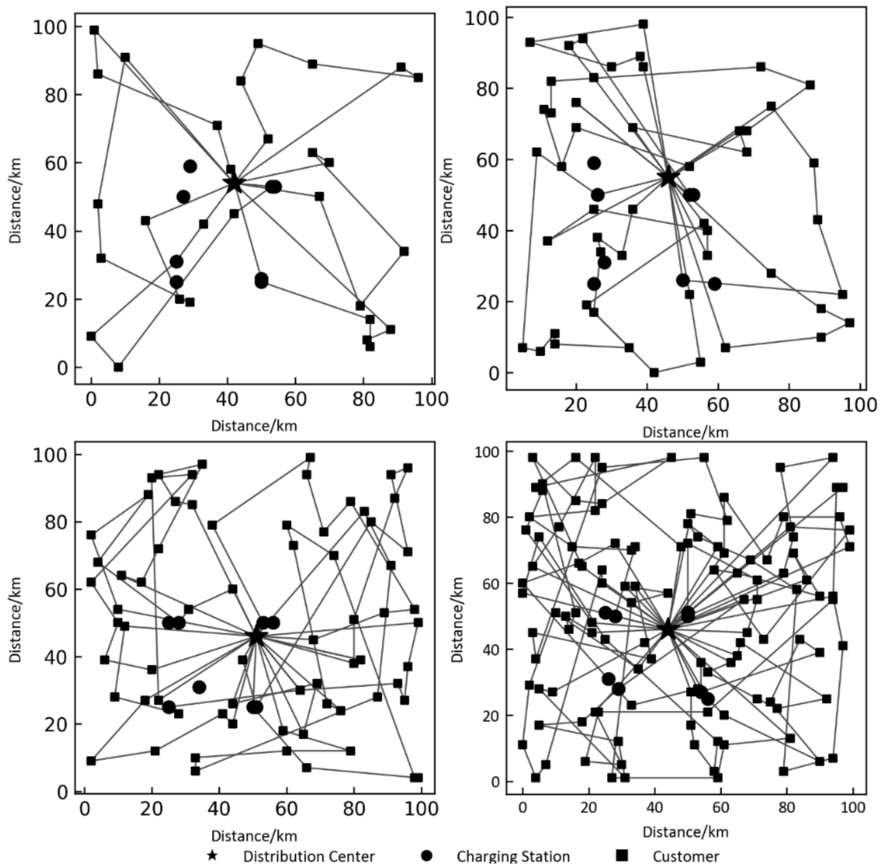

Fig. 7 Route map

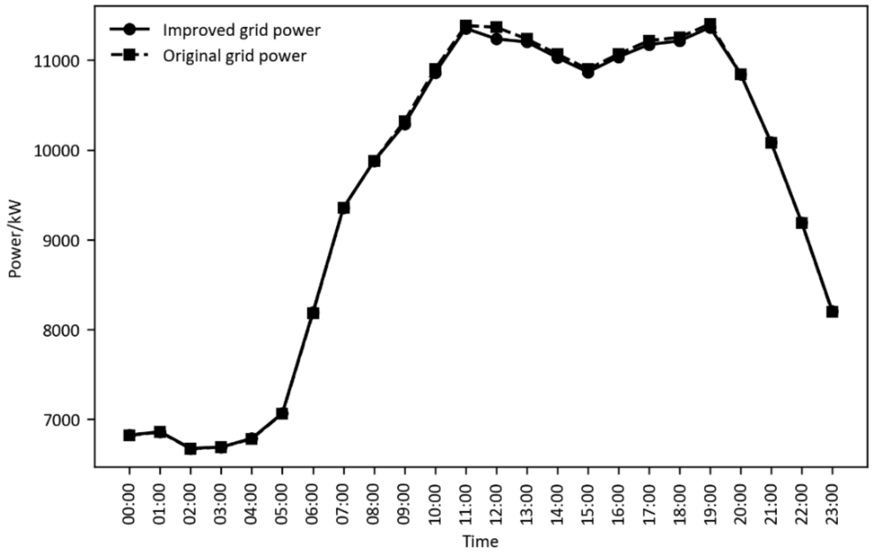

Fig. 8 Grid load comparison

As shown in Fig. 7, the algorithm can find the route that fulfils the conditions and ensures the correctness of the solution. After that, the paper tests the effect of the GA-A* algorithm on the power grid at different times, and the experimental results show that the GA-A* algorithm has a good effect on power sharing and power quality.

Fig. 8 shows better power distribution under the GA-A* algorithm scheduling. Most of the charging time is concentrated between 21:00 and 3:00 the next day, which is in the off-peak period of electricity consumption. The discharge time is concentrated from 9:00 to 19:00, which is in the peak period of power consumption, the peak load decreases from the original 11403.73 kW to 11365.10 kW, and the peak differential rate decreases from the original 41.50-41.27 %. Charging when the electricity price is low and discharging when the electricity price is high, fully shows that the scheduling function of the GA-A* algorithm can cut peak and fill the valley and reduce the charging cost. As shown in Table 2.

Due to the existence of area price, the area price can be used to regulate loads in different areas of the grid. As shown in Fig. 9, if the charging station is in a region with low electricity prices, the route is more concerned with charging in this region; if it is in a region with high electricity prices, the route is more concerned with discharging in this region.

Table 2 Load characteristic index in the different scenarios

scenarios	Max. load (kW)	Min. load (kW)	mean square	peak-to-valley ratio (%)
original grid	11403.73	6670.81	1846.76	41.50
GA-A*	11365.10	6675.15	1825.69	41.27

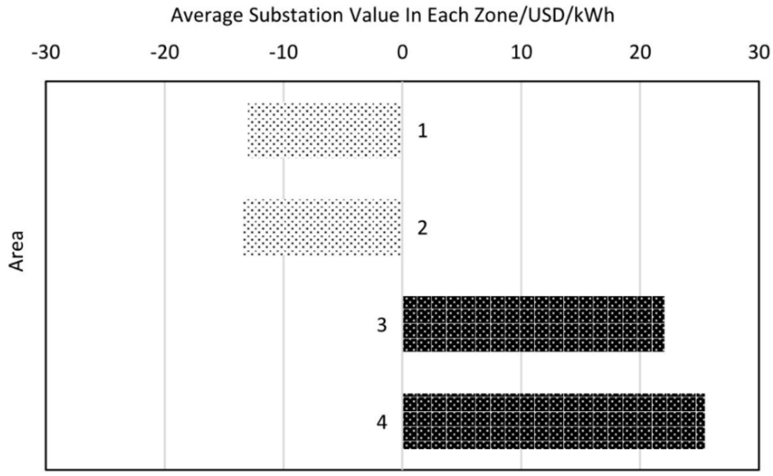

Fig. 9 Zonal grid load changes

3.2 Comparison with other methods

Fig. 10 shows the comparison between the GA-A* algorithm and the traditional GA algorithm. As shown in the figure, the iteration speed of GA-A* is significantly faster than that of the GA algorithm, and it enters the low value region 89 times and completes the iteration quickly. The shortest distance produced by GA-A* is also significantly smaller than the optimal solution produced by GA.

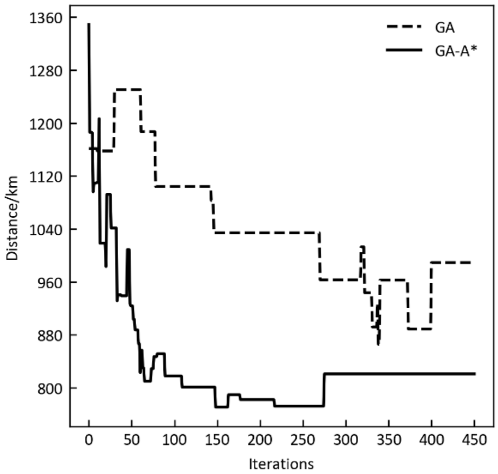

Fig. 10 GA-A* versus GA

Table 3 shows the comparison results between GA-A* and the other three algorithms. It is found that the GA-A* algorithm has a better optimization effect than the other three algorithms. In comparison to LNS, VNS, and ALNS, the average reduction is 281.41, -67.43, and 207.80 km, respectively. The results show that the optimization effect of GA-A* is significantly higher than that of LNS and ALNS.

Table 3 Load characteristic index in the different scenarios

case	optimal solution /km			
	GA-A*	LNS	VNS	ALNS
r-8-c-120	3282.46	3617.30	3160.50	3602.10
r-8-c-70	2067.05	2382.70	1938.40	2242.20
r-8-c-50	1401.98	1672.30	1419.90	1646.70
r-8-c-30	947.25	1333.30	983.60	1145.50
r-6-c-120	2428.78	2132.90	1841.20	2479.10
r-6-c-70	1791.31	2196.80	1767.40	2057.80
r-6-c-50	1536.47	2417.70	1556.90	1784.40
r-6-c-30	820.92	1469.90	828.50	1009.10
r-4-c-80	2249.17	2369.50	2181.10	2465.90
r-4-c-70	1975.49	2305.20	2117.10	2310.90
r-4-c-50	1469.40	1532.80	1327.90	1583.60
r-4-c-30	849.50	1087.90	881.10	1043.10
r-2-c-90	2455.17	2722.80	2285.50	2707.10
r-2-c-70	1934.04	2054.20	1842.20	2099.90
r-2-c-50	1369.70	1575.50	1357.60	1569.80
r-2-c-30	873.24	1083.70	884.20	1029.50

4. Discussion

In the process of solving the EVRPTW problem, in order to reduce the total cost in the transportation process and make the model closer to the actual engineering background, we comprehensively consider several factors and establish the model by using integer mixed programming. These factors include the fixed cost of the vehicle, energy cost which considers the temperature coefficient, the cost of time, the penalty cost of violating the load constraint, the penalty cost of violating the time window, and the penalty cost of violating the power constraint and the charge and discharge cost. Through such comprehensive consideration, we obtained a model of EVRPTW that is more in line with the actual engineering context.

By introducing the Time of use Pricing and Area price, we have reached the V2G model, integrating EVs into the grid, and realizing the transportation and exchange of energy is realized. By means of power swapping for electric vehicles, we have achieved the purpose of forming a smart microgrid. In this mode, EVs can choose to deliver energy during peak hours of electricity consumption and obtain energy during low hours of electricity consumption according to the demand of the power grid, rationalizing the distribution of electric energy, reducing the peaks and valleys and volatility of the load on the power grid, and improving the quality of electric energy. V2G mode makes EVs become part of the power grid, participate in the transportation and exchange of energy, and make full use of the energy storage capacity and flexibility of EVs through intelligent energy scheduling and control.

In terms of algorithm, we improve the steps of initializing the population and introduce the A* algorithm to obtain a better initial solution. By combining GA and A* algorithm, we not only avoid the problem of slow iteration speed of the genetic algorithm but also meet the randomness requirement of GA. Experimental results show that this GA-A* algorithm can provide correct path planning, and has better iteration speed and optimization quality when solving EVRPTW problem. Compared with the traditional genetic algorithm, our algorithm shows obvious advantages in iteration speed and optimal solution quality. Compared with other different types of path planning algorithms, such as LNS, ALNS, and VNS algorithms, our algorithm also shows better performance and can get good results in different scale examples. In some specific cases as shown in Table 3 it can be seen that the distance of GA-A* is less than the solution derived by VNS for small scale cases with eighty client nodes, but in large scale cases VNS shows better performance. This paper argues that the implementation of the VNS algorithm searches a wider space of solutions in variable neighbourhoods, no matter the size of the arithmetic case can find a better solution by means of global search. VNS follows this feature for solutions at different scales, whereas GA-A*, which has fixity in its initialisation, shows better performance in small scale solving. In this paper, we argue that GA-A* has significantly outperformed other algorithms under the path length perspective for small-scale problems, and some algorithms for large-scale problems; it outperforms other algorithms under the perspective for spatio-temporal deployment of energy consumption. The algorithm has been initialised in such a way as to find the optimal solution passing through all nodes, so that there is a certain degree of similarity between the initialised population and the final solution for the small-scale example in the global solution; the algorithm outperforms other algorithms in terms of energy consumption because it takes into account the spatio-temporal tariffs. There are also some weaknesses in that the initialised population is still somewhat fixed even with the addition of random values, so larger than large-scale arithmetic cases lack global search capability. So introduction of the A* algorithm as part of the initialization allows the genetic algorithm to start searching for a better initial solution. This combination can fully utilize the advantages of the two algorithms and improve the search efficiency and solution quality of the algorithm.

In summary, by comprehensively considering multiple practical factors and establishing an integer mixed programming model, introducing Time of use Pricing and Area price as well as the V2G model, and combining the genetic algorithm and A* algorithm for optimization, we have made remarkable progress in solving EVRPTW problem. Our model and algorithm can better conform to the actual engineering background, obtain a better solution, improve the efficiency and quality of power grid energy management, and bring a positive impact on the operation of smart microgrid and the entire power grid. Such as Wang *et al*. used heuristics and collision avoidance algorithms for collaborative scheduling planning of multiple AGVs [34]. GA-A* can be generalised to AGVs in industrial manufacturing for logistics optimisation tasks such as optimal routing through improvements.

5. Conclusion

To solve the EVRPTW, this paper comprehensively considers multiple factors in reality and takes the minimum total cost as the model proposes the GA-A* algorithm which introduces the A* algorithm, and tests 16 cases of four groups of different scales. Experiments show that compared with the traditional GA algorithm and other algorithms, it has a certain optimization effect. The algorithm itself can provide a solution to the np-hard problem and get the right route. At the same time, based on the V2G mode, the smart microgrid can reduce fluctuations and improve power quality, and the reasonable spatio-temporal allocation of EVs plays a role in peaking and valley filling for the entire power grid.

The GA-A* algorithm introduced in this paper can provide better path planning in the search process, but it may face the problem of too long computation time when dealing with large-scale problems. Therefore, for larger scale EVRPTW problems, it may be necessary to further optimize the efficiency of the algorithm. At the same time, in practical problems, there are often multiple conflicting objectives that need to be optimized, The GA-A* algorithm can be further extended. Therefore, to solve the above problems, we can consider further optimizing the efficiency of the algorithm, such as introducing a pruning strategy or parallel computing. Multi-Objective Optimization can be supported by improvement, such as considering the problem of simultaneously optimizing total cost and total time.

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