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Dynamic Energy-Efficient Path Planning for Electric Vehicles Using an Enhanced Ant Colony Algorithm

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Abstract: Electric vehicles (EVs) energy efficient path planning is crucial for maximizing the range of EVs. However, existing path planning algorithms often prioritize least time or shortest path without considering energy efficiency, leading to issues such as long computation time, slow convergence, and suboptimal solutions in complex environments. To address these challenges, this study proposes an improved ant colony optimization (E-ACO) algorithm for dynamic energy efficient path planning of EVs. The E-ACO algorithm incorporates a traffic flow prediction model and an energy consumption model specific to EVs. By redesigning heuristic factors and state transition rules, the algorithm enhances the efficiency and accuracy of path planning. Moreover, to address the challenge of selecting optimal charging station locations based on existing battery levels, a charging path planning method is introduced. This method utilizes the E-ACO algorithm and employs charging station pre-screening strategies to identify the most suitable charging station for completing the charging process. Experimental results show that the E-ACO algorithm reduces energy consumption by approximately 7% compared to the traditional ant colony optimization (ACO) algorithm. Additionally, through data analysis, a pre-screening threshold of 10 charging stations is determined based on the relationship between distance and energy consumption. To provide a visual representation of the path planning results, software is used to display the optimized paths. This allows users to easily interpret and analyze the recommended routes. Overall, the proposed E-ACO algorithm offers an effective and efficient solution for energy-efficient path planning in EVs. The incorporation of charging station pre-screening strategies further enhances the charging process. The study's findings contribute to the development of more sustainable and efficient EV routing strategies, benefiting both EV users and the environment.

Keywords: ant colony (ACO); charging path planning; dynamic path planning; electric vehicle; energy efficient

1 INTRODUCTION

In recent years, in response to the escalating challenges posed by environmental pollution and resource scarcity, there has been a proactive push to advance the adoption of electric vehicles (EVs) as a pivotal direction in new energy development. By the close of 2019, China had already amassed 3.8 million new energy vehicles and over 1.2 million charging stations. In terms of industry policies, China has set forth a plan to establish an additional 4.8 million charging stations by 2020. The guidelines outlining the development of electric vehicle charging infrastructure ensure comprehensive support for the planning and execution of charging stations [1]. Several countries initiated the growth of the electric vehicle industry earlier on, and the corresponding infrastructure is progressively maturing [2]. Nonetheless, as the usage of new energy vehicles continues to surge, electric vehicles, when compared to their traditional fuel counterparts, confront noteworthy challenges and issues that demand attention. For instance, the limitations of pure electric vehicles in terms of their range and the convenience of charging significantly hinder the unfettered progression of electric vehicles [3, 4]. Currently, most navigation software falls short of providing comprehensive assistance when it comes to electric vehicle charging services. Conversely, when faced with diverse vehicle models, car owners frequently lack an intuitive grasp of the abstract numerical representation of power. This susceptibility to misjudgment can lead to instances of either improper charging or failure to charge in a timely manner. Moreover, due to the dynamic influence of traffic conditions, there are occasions when gauging whether the remaining power suffices to meet travel requirements based solely on driving distance becomes an uncertain endeavor. To address the challenges associated with electric vehicle travel and charging complexities, a comprehensive strategy is imperative, encompassing meticulous path planning that integrates various information facets, including vehicle specifications, road conditions, and electric capacity [5-7]. Electric vehicles can be categorized into public electric vehicles and private electric vehicles based on their intended use. Public electric vehicles concentrate on optimizing vehicle routes to enhance the operational efficiency of electric buses, electric logistics vehicles, electric taxis, and similar modes of transportation [8, 9]. On the other hand, private electric vehicles aim to enhance the travel experience, often prioritizing the shortest distance and quickest travel time. These vehicles also target charging stations with the lowest power consumption for their research objectives [10, 11]. Dynamic route planning contributes to more convenient electric vehicle travel. This approach involves a comprehensive consideration of real-time traffic data for all potential routes between the starting and ending points. Factors like time, traffic flow, distance, cost, and road conditions are integrated into the algorithm, serving as significant influencers in selecting the optimal path [12, 13]. Various research works have proposed innovative strategies for electric vehicle route planning. Zhang et al. [14] introduced a travel planning method utilizing multi-objective ant colony optimization within a dynamic stochastic road network environment. Basso et al. [15] integrated terrain data, vehicle speed distribution, and an enhanced energy consumption estimation approach to address electric vehicle path planning, focusing on energy consumption as the objective function. Liu et al. [16] presented a vehicle routing model incorporating a soft time window and an improved genetic algorithm for cost minimization. Yan et al. [17] devised a comprehensive system model integrating electric vehicles, distribution networks, and road traffic networks, and improved upon it, incorporating optimal charging station recommendations and path planning using road weight and Dijkstra's shortest path algorithm. Electric vehicles represent a transition from traditional vehicles to new energy alternatives and are seen as the primary choice for future transportation. However, helping users locate suitable charging stations and plan efficient routes remains a pressing issue. Various research endeavors have proposed solutions. Liu et al. [18] introduced a reserved charging decision model, optimizing for both driving time and charging cost through a K-shortest path algorithm. Hiermann et al. [19] considered load, battery capacity, operating cost, and time window aspects, utilizing an adaptive large-scale neighborhood search algorithm to determine suitable electric vehicle energy demand and consumption models. Jurik et al. [20] constructed a path selection optimization model based on traffic conditions and vehicle information, optimizing onboard power distribution between batteries and supercapacitors. Lin et al. [21] established a vehicle-road-network system comprising a road topology model, an impedance evaluation model, and a vehicle energy consumption model. Charging paths were planned using the A^* algorithm, optimizing for running time, energy consumption, and comprehensive factors. Gu et al. [22] introduced a novel heuristic energy consumption estimation cost to enhance the A^* algorithm and attain optimal energy consumption paths. Ding et al. [23] developed a power advance warning model for charging alerts, combining energy consumption factors, actual traffic data, and map information within the Dijkstra algorithm for EV path planning. Most of the path planning algorithms can get the optimal solution of the shortest path, but the efficiency is usually low. Moreover, without considering the future traffic flow through the road and the energy loss in the journey, the shortest path obtained is often not the optimal path in reality [24]. For example, genetic algorithms have good convergence and high robustness, but it cannot solve problems with large-scale computation. Tabu search algorithm has strong local search ability, but it has strong dependence on initial solution [25]. In contrast, the ant colony algorithm has strong robustness and can perform parallel computing; at the same time, it is easy to combine with other algorithms and more suitable for solving large-scale dynamic programming problems [26]. Given the foundation of shared road information and charging station data, this study introduces a dynamic energy-efficient path planning approach for electric vehicles. Leveraging enhancements to the Ant Colony Optimization (ACO) algorithm, this methodology is designed to tackle the challenges of limited driving range and charging difficulties encountered by electric vehicles. The primary innovations of this research can be outlined as follows:

Based on the vehicle energy consumption model and combined with short-term traffic flow prediction, in this paper we improved the pheromone update rules of the ACO algorithm. The E-ACO algorithm can dynamically adapt to changes in road flow, minimize the energy consumption and provide users with reliable energy efficient path planning.

In order to meet the charging demand of electric vehicles under the range, we proposed the pre-screening strategies of charging stations according to the irregular distribution of charging stations in urban and suburban areas.

Based on the E-ACO algorithm, we proposed an optimal charging path planning method considering the path travel time, queuing time of charging stations and charging time.

Finally, to validate our approach, we conducted experiments using real-world data for comparative analysis, and the results were visually represented through path planning visualization.

The rest of the paper is organized as follows: Section 2 presents the dataset, related models and algorithms, Section 3 presents the experimental process and results; Section 4 summarizes the study.

2 METHODS

2.1 DataSet

The dataset used in this paper is the urban traffic index and trajectory data dataset in the Didi Gaia Open Data Project. The dataset contains nearly 40 million floating car trajectory data from October 1, 2018 to November 30, 2018 in Xi'an. The specific fields of the dataset are shown in Tab. 1.

Table 1 The table of dataset specific field

Field	Type	Instance	Remarks
Driver ID	String	glox.jrrlltBMvCh8n xqktdr2dtopmlH	Desensitized
Timestamp	String	1501584540	Unix timestamp in seconds
Longitude	String	104.04392	GCJ-02 coordinate system
Latitude	String	33.43	GCJ-02 coordinate system

According to the above data, the average speed and average acceleration of each road section in each time period are calculated. Then substitute into the subsequent electric vehicle energy consumption model to calculate the road estimated energy consumption.

2.2 Traffic Forecast Model

The inherent uncertainty within traffic systems poses significant challenges for traffic forecasting. Currently, various methods exist for short-term traffic flow prediction. The historical average method, while straightforward, suffers from limited predictive accuracy. On the other hand, the Kalman filter method offers high accuracy but involves intricate modeling processes [27]. In this study, we realize traffic flow prediction by constructing an enhanced architecture prediction model named All-Round-STN. The main process includes inputting historical traffic data information, filtering in the spatiotemporal convolution block, and then linking deep learning framework ELSTM layers and support vector regression model through dynamic networks to get the predicted traffic sequence. The time series convolution block includes the use of GLU and residual connection to complete the screening of effective information. The spatial convolution block utilizes the graph convolution technique, at the same time uses the trainable matrix parameters to modify the graph adjacency matrix to help better complete the mining of spatial information, and then outputs the predicted flow velocity sequence. The comprehensive architecture of the traffic flow prediction model is depicted in Fig. 1, encompassing the entire framework for prediction.

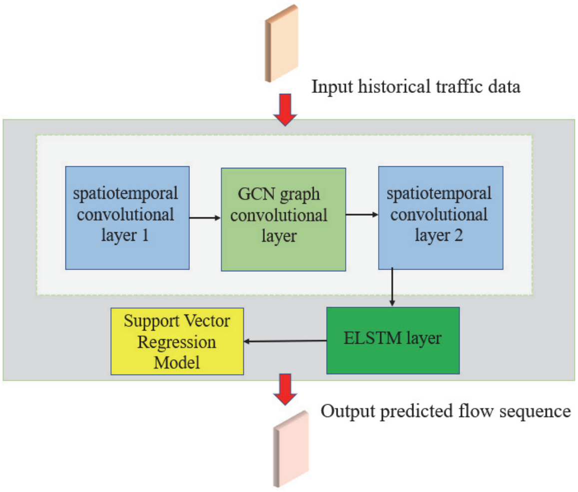


Figure 1 The traffic flow prediction model All-Round-STN

2.3 Electric Vehicle Energy Consumption Model

The introduction of the China Light-duty Vehicle Test Cycle (CLTC) addresses a significant challenge in China's nominal driving range predictions. Regrettably, so far most of the manufacturers still rely on NEDC [28]. Based on the current application of electric vehicles, vehicle energy consumption is an important reference factor whether it is in the process of driving or seeking charging, and it is also the most important factor and premise to help realize the path planning of electric vehicles in different situations. However, due to the battery capacity defect of the battery with relatively short cruising range, the charging problem of the pure electric vehicle is still an ongoing challenge. The cornerstone of this study lies in establishing an energy consumption model for vehicles, expressed as Eq. (1).

$$energy_i(t) = P_i(t)/\eta_M(t) \tag{1}$$

where $P_i(t)$ represents the energy consumption value of the vehicle in Eq. (2).

$$P_i(t) = n_i(t) \cdot T_i(t)/9550 \tag{2}$$

The $n_i(t)$ motor speed can be achieved by the vehicle power transmission in Eq. (3).

$$V_i(t) = 0.377\frac{n_i(t)\cdot r}{I_0} \tag{3}$$

$T_i(t)$ is obtained according to the balance equation of the driving force and driving resistance of the vehicle in Eq. (4).

$$\frac{T_i(t)\cdot i_0 \cdot \eta_r}{r} = fmg\cos\alpha + \frac{C_D A v_i(t)^2}{21.15} + mg\sin\alpha + \delta m\frac{\mathrm{d}(v_i(t)/3.6)}{\mathrm{d}t} \tag{4}$$

2.4 Dynamic Energy Efficient Path Planning Based on ACO Algorithm

The fluctuating vehicle velocities on roads, coupled with the ever-evolving road network information, render static planning methods unsuitable for achieving energy-efficient path planning within the practical road network context. In contrast, dynamic route planning stands as the cornerstone for real-time decision-making in urban route planning, often employing efficient heuristic algorithms. While the realm of dynamic path planning has achieved significant milestones, there remains a substantial scope for further exploration and optimization, particularly in the realm of enhancing and refining the dynamic planning of energy-efficient paths. Ant Colony Optimization (ACO) is a swarm intelligence algorithm, which is composed of a group of non-intelligent or slightly intelligent individuals (agents) through mutual cooperation to show intelligent behavior, and has strong robustness. It provides a new possibility for solving complex problems. Artificial ants represent a stochastic construction process of a solution, starting from an initial empty solution and building a complete solution by continuously adding solution components to partial solutions. This study introduces an innovative dynamic energy-efficient path planning technique utilizing an enhanced dynamic ant colony algorithm. This approach aims to tackle the evacuation path problem in the context of changing road network impedance. By refining the original ACO algorithm, the traditional transition probability based on path length and ant colony pheromones is replaced with vehicle energy consumption predictions as the guiding criterion. These predictions are combined with real-time road traffic flow speed and vehicle energy consumption for comprehensive calculation. Compared with the traditional ACO method, the E-ACO algorithm not only considers the real-time road traffic information, but also introduces a short-term road speed prediction model, and obtains the road network information adjacency matrix in the dynamic road network with real-time road condition information feedback. Aiming at the need of dynamic path planning in practical situations and expanding the global search ability of the algorithm, this paper redesigns the heuristic factors and state transition rules of the ant colony algorithm to help improve the fault tolerance rate of the pheromone update rules. Finally, the selection of the dynamic optimal path is realized, and the total energy consumption of the route can be calculated. The specific process of solving is shown in Fig. 2.

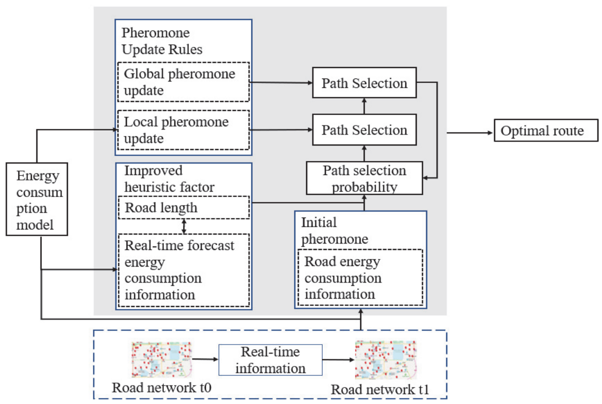


Figure 2 E-ACO algorithm

The heuristic factor $\eta_{ij}(t)$ in the ant colony algorithm will cause the ants lose the globality because they are only affected by the shortest path, resulting in the wrong selection of the next node and stuck in a local optimum.

Therefore, in order to improve the global search ability of the algorithm, combined with the energy consumption of the road, we improve the heuristic factor. The road transition probability of the original algorithm is expressed as follows in Eq. (5).

$$P_{ij}^{k}=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s\in J_k(j)}\left[\tau_{is}(t)\right]^{\alpha}\cdot\left[\eta_{is}(t)\right]^{\beta}} & j\in J_k(i)\\ 0,\ j\notin J_k(i)\end{cases} \tag{5}$$

Among them, the selection of heuristic information $\eta_{ij}(t)$ is the length of the road, and the improved ACO algorithm selection strategy is in Eq. (6).

$$\eta_{ij}(t)=e_{t(i,j)}\cdot d \tag{6}$$

$e_{t(i,j)}$ represents the time point t, "i, j" represent the previous average energy consumption, and "d" represents the distance between the two points.

In the process of ants traversing the city, while releasing pheromone, the intensity of the pheromone on the connection paths between cities is gradually disappearing through volatilization and other methods. Using the local pheromone update rule, whenever the ants select a road segment, the pheromone concentration of the road segment they pass through is correspondingly reduced, so as to achieve the purpose of local adjustment and reduce the probability of selecting the road segment again. To describe this feature, let $\rho(0 < \rho < 1)$ denote the degree of volatilization of the pheromone. In this way, after all the ants have completely walked through all the cities, the information concentration on the connecting paths between the cities is in Eq. (7).

$$\begin{cases}\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\rho\Delta\tau_{ij}\\ \Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}\end{cases} \tag{7}$$

Among them, $\Delta\tau_{ij}^{k}$ is the pheromone concentration increased by the kth ant releasing pheromone on the connection path between city i and city j; $\Delta\tau_{ij}$ is the pheromone concentration increased by all ants releasing pheromone on the connecting path between city i and city j, which is a positive feedback mechanism. The E-ACO algorithm is based on the short-term road speed prediction model, the vehicle energy consumption model and the ant colony algorithm to solve the optimal energy-efficient path problem, which can be divided into the following four steps: ① Input road network information adjacency matrix "G", short-term vehicle speed change table "T", energy consumption model "M", starting point position "S" and destination position "E". ② At the beginning of the algorithm, all parameters of the algorithm are initialized, the number of iterations "N", the number of ants "m", "α", "β", "ρ", "τ_{ij}". ③ When $N > 0$, m ants are randomly placed at different evacuation points, for any k belonging to m, the energy consumption value of the road is obtained by using the energy consumption model M, and the next road section is selected; when the ant k arrives at the destination, the local pheromone update is completed; the path cost of each ant is calculated by the road distance, and the optimal solution of the current iteration is saved. ④ Output the planning path "P".

2.5 Charging Path Planning Algorithm Based on E-ACO Algorithm

Solving the charging problem is a major challenge to improve the utilization rate of electric vehicles. When electric vehicles have charging needs, how to find the nearest charging pile as soon as possible and plan a most suitable path based on the remaining power is an urgent problem to be solved. In addition, the concurrent charging requirements of a large number of users and the path planning requirements of charging stations in different states are also issues that need to be considered. Therefore, based on the data sharing of charging stations and the above-mentioned electric vehicle energy consumption model, this paper proposes a dynamic path planning algorithm for electric vehicles under charging demand. The charging path planning process based on data sharing is as follows: ① Information initialization. At the beginning of route planning, the latest road traffic data is obtained from the server, and the average speed of each street is calculated through the traffic prediction model, this information is used as the input of the energy consumption model. In addition, the information such as location of each charging station and remaining charging piles should be obtained in real time to provide data support for charging station pre-screening and charging path planning. ② Pre-screening of charging stations. After obtaining the location information of the charging station, the optimal solution of the charging station set is screened out through the dynamic screening strategy, which improves the efficiency of path planning. ③ Charging path planning. Calculate the optimal path planning scheme and select the appropriate charging station. ④ Update the charging station data. After confirming the destination charging station, upload the route planning result and update the charging station data.

(1) Pre-screening strategies for charging stations.

The distribution of charging piles in cities is usually very irregular, areas closer to the city center are denser, and areas farther away from the city center are sparser. When the user is close to the city center, there may be many charging stations to choose from. If the system traverses all charging stations and calculates the distance and energy consumption from each charging station to the starting point, it will seriously affect the operating efficiency of the system, which consumes a lot of computing resources, so it is necessary to pre-screen the charging station data, and screen out the charging stations that are far away from the user and are not considered temporarily. Screening of charging piles within the range of the user's location as the center of the circle and a specific distance as the radius will be difficult to apply in actual scenarios due to the irregular distribution of charging stations. This paper takes the specific number of charging stations closest to the user's location as the screening condition, selects a certain number of charging stations to meet the diverse needs of users, and can adjust the number to expand the selection range to achieve high-quality charging pile screening. At the same time, in order to solve the problem that the optimal solution may be missed when the urban charging stations are too dense and the suburban charging stations are too few, resulting in unnecessary time overhead, this paper adopts the method of dynamically adjusting the screening conditions. Suppose all the charging stations are arranged in ascending order of the distance from the starting point, in the initial case, select the first k charging stations (such as k = 10) $\{P_1, P_2, P_3, ..., P_k\}$ into the candidate queue, if the difference between the distance from the charging station P_k to the departure point and the distance from the charging station P_{k+1} to the departure point is less than 300 meters, meanwhile, the charging stations in this area are densely distributed, the charging station P_{k+1} is added to the candidate queue, and the number of candidate stations k is increased by 1 until the distance between the nearest candidate charging station P_{k+1} and the farthest candidate charging station P_k exceeds 300 meters. If the difference between the distance from the charging station P_k to the departure point and the distance from the charging station P_{k-1} to the departure point is greater than 5 kilometers, it can be judged that the distribution of charging stations in this area is sparse. The specific process is shown in Fig. 3.

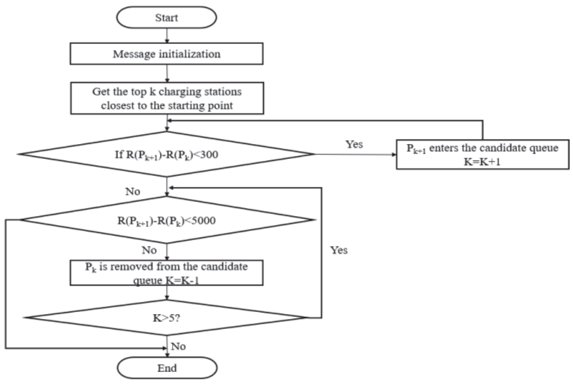


Figure 3 Flowchart of the pre-screening strategy

(2) Optimal charging path planning.

How to meet the charge as soon as possible to the nearby charging station to continue your journey. In this paper, the user's travel time cost T_{route} is established, which mainly includes the path travel time T_{drive} from the starting point to the charging station, the charging station queue waiting time T_{wait}, and the charging time T_{charge} in Eq. (8).

$$T_{route} = T_{drive} + T_{wait} + T_{charge} \tag{8}$$

According to the traffic prediction model described above, the average road speed of each street in the next hour V_i can be obtained, and the optimal energy-efficient path to each charging station can be acquired by using the E-ACO algorithm. The travel time T_{drive} is calculated according to the road information in the optimal energy-saving route, and the length of the passing street is D_i, then the route travel time T_{drive} can be expressed in Eq. (9).

$$T_{drive} = \sum \frac{D_i}{V_i} \tag{9}$$

When there are m spare charging piles in the charging station, if there are n vehicles going to the charging station, and n is less than the number of spare charging piles, the waiting time T_{wait} is 0. Conversely, if n is greater than the number of vacant charging piles, let the estimated arrival time of each vehicle be T_i, if $T_{drive} < T_m$, T_m is the mth vehicle that arrives first, then the waiting time T_{wait} is 0. If none of the above conditions are satisfied, let T_j be the remaining charging time of the charging vehicle, then the estimated waiting time is in Eq. (10).

$$T_{wait} = \sum_{j=0}^{n-m} T_j - T_{drive} \tag{10}$$

The existing charging mode of the charging station generally uses a certain high power to charge about 80% of the capacity of the electric vehicle, and then switches to a low power until it is fully charged, so as to achieve the purpose of protecting the battery. Therefore, this paper only considers the period of charging to 80% when calculating the charging time T_{charge}, E_i is the rated capacity of the electric vehicle, E_q is the current remaining power, P_e is the charging power, and E_d is the driving energy consumption, then the charging time is in Eq. (11).

$$T_{charge} = \frac{80\% E_i - E_q + E_d}{P_e} \tag{11}$$

Among them, P_e takes 30 kwh/h for fast charging piles, 7 kwh/h for slow charging piles, and E_j takes 50 kwh. E_d can be obtained by ant colony algorithm, and E_q is user input. The driving energy consumption E_d from the starting point to each charging station is calculated by the ant colony algorithm, the unreachable charging stations are screened out, and then the travel time T_{route} to each charging station is calculated by the ant colony algorithm, then the path with the shortest time is selected.

3 RESULTS AND DISCUSSION

3.1 E-ACO Path Planning Results

Based on the traffic flow prediction network and energy consumption model, input the starting point and destination point, and compare with the original ACO algorithm. The experimental results are shown in Fig. 4 and Fig. 5 below.

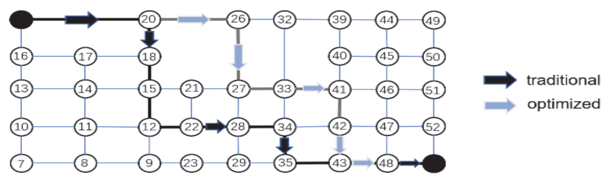


Figure 4 Comparison results of path planning

It can be seen that the road obtained by using the improved EACO dynamic path planning algorithm in this project can effectively reduce energy consumption. Although the driving range is slightly increased, the driving speed is increased and the energy consumption is reduced by about 7%. It is shown that this algorithm can find a more suitable path to save energy when electric vehicles face the problem of low power.

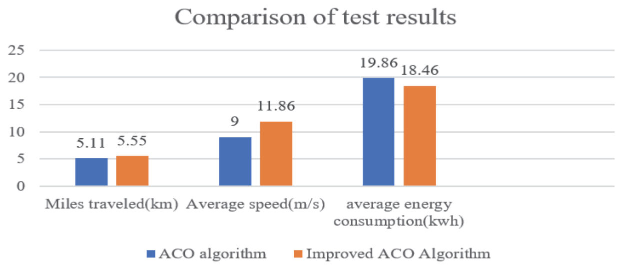


Figure 5 Comparison results of path planning

3.2 Charging Pile Pre-screening Experiment

In order to determine the quantitative criteria for screening charging stations, this paper examines the driving distance and energy consumption to nearby charging stations when they are in different locations. This paper selects Xi 'an urban area and Xi 'an suburban area respectively as the starting point for screening and analysis of charging piles. The experimental data are shown in Tab. 2 and Tab. 3. The straight-line distance in the table is calculated from the longitude and latitude coordinates of the starting point to the charging station, and the driving distance is after the path planning. The driving energy consumption is calculated by the energy consumption model described above, and the types of the charging pile are obtained through the data interface of the BAIC charging bar. It can be seen from Tab. 2 that in the city center, when the straight-line distance between two points is not much different, the positive correlation between the straight-line distance and the driving distance is not obvious. As shown in Tab. 2 No. 3 and No. 4, although No. 3 has a shorter straight-line distance, but the driving distance is farther, this is because of the complex urban roads that may require detours to get to certain points, and the driving distance will be longer. But when the straight-line distance difference is too large, such as No. 6 and No. 7 in Tab. 2, because the circumstance of detours is usually in block units, when the straight-line distance difference is too large, this situation can be ignored. In addition, a large number of experiments has proved that within eight charging stations, the straight-line distance of two charging stations often changes by leaps, which is also determined by the layout design of charging stations. Since the driving energy consumption is positively related to the driving distance, the charging station reached with the lowest energy consumption can be found within the eight charging stations. At the same time, in order to comprehensively consider factors such as charging price, charging speed of charging piles, etc., this algorithm sets the urban pre-screening standard to 10 to meet the diverse needs of users. As can be seen from Tab. 3, the distribution of charging stations in the suburbs is very sparse, the number of charging piles is small, and the straight-line distance between each charging station and the starting point is quite different, so the number of charging stations is screened by a smaller number instead of 10. Instead, the number of pre-screened charging stations is reduced on a 10-digit basis and a threshold is passed to prevent the number of participating charging stations from being too low.

Table 2 The table of experimental data from Xi'an center

Serial number	Starting point	Charging station	Charging pile type	Straight line distance / m	Driving distance / m	Driving energy consumption / kwh
1	Post Building	No. 14, Gaoxin 4th Road	Slow charge	408	569	0.105423056
2	Post Building	No. 58, Keji 1st Road	Slow charge	480	956	0.177125556
3	Post Building	No. 26, Keji 1st Road	Fast charge	533	941	1.174346389
4	Post Building	No. 38 Keji Road	Slow charge	645	896	0.166008889
5	Post Building	Xi'an Customs, Tangyan Road and Keji 2nd Road	Fast charge	833	1537	0.284771944
6	Post Building	Intersection of Fenghui Road and Keji 2nd Road	Slow charge	996	1396	0.258647778
7	Post Building	Intersection of Keji 2nd Road and Zhangba North Road	Fast charge	1637	2457	0.4552275
8	Post Building	No. 256, Zhangba North Road	Slow charge	1723	3005	0.556759722
9	Post Building	No. 80, Gaoxin Road	Fast charge	1738	2645	0.4990059722
10	Post Building	Yanta District Lock Building	Fast charge	1990	3272	0.606228889
11	Post Building	No. 34, Fenghui South Road, High-tech Zone	Fast charge /Slow charge	2236	2912	0.539528889
12	Post Building	No. 34, Fenghui South Road, High-tech Zone	Fast charge /Slow charge	2324	2924	0.541752222

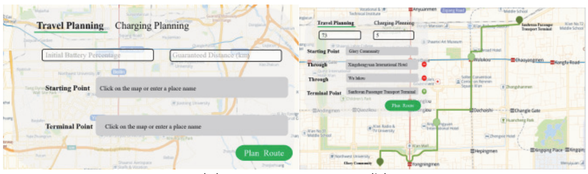
Table 3 The table of experimental data from Xi'an suburb

Serial number	Starting point	Charging station	Charging pile type	Straight line distance / m	Driving distance / m	Driving energy consumption / kwh
1	Xi'an GuoYou Business Hotel	No. 451, Xijin Road, Gaoling District	Fast charge	4418	6814	1.262482778
2	Xi'an GuoYou Business Hotel	Hanyang Mausoleum Museum	Slow charge	4901	21559	3.994403611
3	Xi'an GuoYou Business Hotel	Baqiao Rich Nong Livestock and Poultry Development Co., Ltd.	Fast charge	9231	18456	3.421154167
4	Xi'an GuoYou Business Hotel	No. 9 Gangwu Avenue, Baqiao District	Fast charge /Slow charge	9594	15182	2.812887222
5	Xi'an GuoYou Business Hotel	Hancheng Street, Wei yang District	Fast charge	11848	13920	2.579066667
6	Xi'an GuoYou Business Hotel	Baqiao District G210 Armed Police Second Detachment two kilometers	Fast charge /Slow charge	14375	21808	4.040537778
7	Xi'an GuoYou Business Hotel	Chuanhua Logistics Park, Gangxing 1st Road, Baqiao District	Fast charge	21509	28039	5.195003611

The results show that this experiment provides a research basis for the electric vehicle path planning method, which takes traffic flow, driving energy consumption and charging pile information into consideration in planning, improves the utilization rate of electric vehicle charging piles, and reduces the waste of charging pile resources. It reduces congestion, avoids charging queuing and waiting, provides a basis for charging time saving, and improves traffic smoothness. And to a certain extent, it reduces the mileage anxiety of electric vehicle users, makes it easier for users to find and use charging facilities, and improves user satisfaction and experience. The convenient performance of charging piles promotes the popularization of EVs through reasonable path planning. In conclusion, dynamic energy-efficient path planning for electric vehicles is important for promoting the popularization of EVs, optimizing energy use, improving user experience and achieving sustainable development.

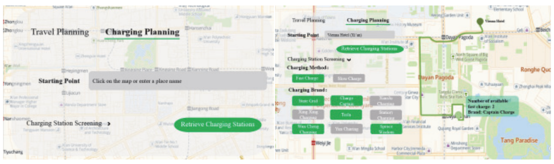
3.3 Visual Display

Finally, we visually display the path planning method proposed in this paper. In Fig. 6, we set the initial electric quantity and minimum distance parameters on the interface, input the starting point, current point and end point, and click the route planning button. Then, the system takes the starting point or the current stopover point to the end point or the next stopover point as a section, and plans the travel path step by step. In addition, the system will retrieve and mark the optimal charging post location, detailed information and driving route on the map based on the starting point, charging preference, etc., as shown in Fig. 7.



(a) (b)

Figure 6 Travel planning results



(a) (b)

Figure 7 Charging planning results

4 CONCLUSION

The development of electric vehicles faces challenges related to cruising range and inconvenient charging, and existing path planning schemes often neglect the energy-saving aspect for EVs. Thus, this paper addresses the problem of energy-efficient path planning for EVs and proposes a charging station finding scheme, which holds great significance for EV development. The key contributions of this paper are as follows: 1) A traffic flow prediction model and an EV energy consumption model are introduced to dynamically adapt the path planning algorithm to changing road traffic conditions while considering EV energy consumption. By predicting future traffic flow and vehicle speed, the energy consumption of each road section is obtained. 2) The ant colony algorithm is employed for path planning. To enhance the algorithm's global search ability and incorporate road energy consumption, the heuristic factor is improved, leading to the proposed E-ACO algorithm. 3) In conjunction with travel time, charging queue time, and charging time under the E-ACO algorithm, an optimal charging path planning algorithm is devised for candidate charging stations after preliminary screening. This approach selects the most suitable charging station for the current EV status. 4) Experimental results validate the effectiveness of the E-ACO algorithm in enhancing driving efficiency for EV energy-efficient path planning and charging path planning. The proposed model has potential applications in dynamic vehicle scheduling and traffic flow control for various congestion scenarios. However, this paper lacks a comparison with other energy-saving algorithms, which is a major limitation. Future research should explore the use of alternative energy-saving algorithms and further investigate the influence of real-time road information, battery charging efficiency, and other factors on route and charging planning. Additionally, efforts should focus on improving the accuracy of traffic prediction models and energy consumption models. In conclusion, this study lays a foundation for energy-efficient path planning in EV travel and contributes to the advancement of EV technology. Further research is needed to address the mentioned limitations and advance the field of EV path planning.

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5 REFERENCES

[1] Guidelines for the development of electric vehicle charging infrastructure (2015-2020). (2015). National Development and Reform Commission.

[2] Weiss, P. (2019). Charger collaborations power global electric vehicle expansion. *Engineering*, *5*(06), 2. https://doi.org/10.1016/j.eng.2019.10.010

[3] Li, Z., Khajepour, A., & Song, J. (2019). A comprehensive review of the key technologies for pure electric vehicles. *Energy*, *182,* (SEP.1), 824-839. https://doi.org/10.1016/j.energy.2019.06.077

[4] Liu, J. Y., Liu, S. F., & Gong, D. Q. (2021). Electric Vehicle Charging Station Layout Based on Particle Swarm Simulation. *Int. Journal of Simulation Modelling*, *20*(4), 754-765. https://doi.org/10.2507/IJSIMM20-4-CO17

[5] Xing, Q., Chen, Z., Leng, Z., Lu, Y., & Liu, Y. (2020). Electric vehicle path planning and charging navigation strategy based on real-time traffic information. *Proceedings of the CSEE*, *40*(02), 534-550.

[6] Baum, M., Dibbelt, J., & Gemsa, A. (2019). Shortest feasible paths with charging stops for battery electric vehicles. *Transportation Science*, *53*(06), 1627-1655. https://doi.org/10.1287/trsc.2018.0889

[7] Liu, L., Chen, T., Gao, S., Liu, Y., Yang, S., & Wang, X. (2021). Optimization of Agricultural Machinery Allocation in Heilongjiang Reclamation Area Based on Particle Swarm Optimization Algorithm. *Tehnički vjesnik*, *28*(6), 1885-1893. https://doi.org/10.17559/TV-20210427163416

[8] Duarte, G., Baptista, P., & Rolim, C. (2016). How battery electric vehicles can contribute to sustainable urban logistics: A real-world application in Lisbon, Portugal. *Sustainable Energy Technologies and Assessments*, *15*, 71-78. https://doi.org/10.1016/j.seta.2016.03.006

[9] Liu, M. L., Yao, X. Z., Huang, J. Y., & Zhang, C. (2022). Optimization of Unmanned Vehicle Scheduling and Order

Allocation. *Int. Journal of Simulation Modelling*, *21*(3), 477-488. https://doi.org/10.2507/IJSIMM21-3-613
[10] Chen, Z., Ma, L., Liu, P., & Li, Z. (2017). Electric vehicle development in China: A charging behavior and power sector supply balance analysis. *Chemical Engineering Research and Design*, *131*, 671-685. https://doi.org/10.1016/j.cherd.2017.11.016
[11] Zhang, B., Li, X., & Yan, X. (2017). Comparative analysis on the development of electric vehicle technologies in China and USA: patent view. *Journal of Harbin Institute of Technology*, *49*(07), 86-92.
[12] Song, Q., Zhao, Q., Wang, S., Liu, Q., & Chen, X. (2020). Dynamic path planning for unmanned vehicles based on fuzzy logic and improved ant colony optimization. *IEEE ACCESS*, *8*, 62107-62115. https://doi.org/10.1109/ACCESS.2020.2984695
[13] Wang, S. R. & Huang, Q. (2022). A Hybrid Code Genetic Algorithm for VRP in Public-Private Emergency Collaborations. *Int. Journal of Simulation Modelling*, *21*(1), 124-135. https://doi.org/10.2507/IJSIMM21-1-595
[14] Zhang, S., Luo, Y., & Li, K. (2016). Multi-objective optimization for traveling plan of fully electric vehicles in dynamic traffic environments. *Journal of Tsinghua University (Science and Technology)*, *56*(02), 130-136.
[15] Basso, R., Kulcsar, B., Egardt, B., Lindroth, P., & Sanchez-Diaz, I. (2019). Energy consumption estimation integrated into the electric vehicle routing problem. *Transportation Research*, *69*, 141-167. https://doi.org/10.1016/j.trd.2019.01.006
[16] Liu, M. L., Zhang, C., Wu, Q. L., & Meng, B. R. (2021). Vehicle Routing Problem with Soft Time Windows of Cargo Transport O2O Platforms. *Int. Journal of Simulation Modelling*, *20*(2), 351-362. https://doi.org/10.2507/IJSIMM20-2-564
[17] Yan, Y., Luo, Y., Zhu, T., & Li, K. (2015). Optimal charging route recommendation method based on transportation and distribution information. *Proceedings of the CSEE*, *35*(02), 310-318.
[18] Liu, H., Yin, W., Yuan, X., & Niu, M. (2018). Reserving charging decision-making model and route plan for electric vehicles considering information of traffic and charging station. *Sustainability*, *10*(5), 1324. https://doi.org/10.3390/su10051324
[19] Hiermann, G., Puchinger, J., Ropke, S., & Hartl, R. F. (2016). The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research*, *252*(03), 995-1018. https://doi.org/10.1016/j.ejor.2016.01.038
[20] Jurik, T., Cela, A., Hamouche, R., Reama, A., Natowicz, R., Niculescu, S., Villedieu, Ch., & Pachetau, D. (2012). Energy optimal real-time navigation system: Application to a hybrid electrical vehicle. *IEEE International Conference on Intelligent Transportation Systems-ITSC*, 409-414. https://doi.org/10.1109/ITSC.2013.6728514
[21] Lin, X., Zhou, B., & Xia, Y. (2021). Electric vehicle charging path planning strategy integrating dynamic energy consumption and road network information. *China Mechanical Engineering*, *32*(06), 705-713.
[22] Gu, Q., Dou, F., & Ma, F. (2015). Optimal path planning of electric vehicle energy consumption based on improved A* algorithm. *Transactions of the Chinese Society for Agricultural Machinery*, *46*(12), 316-322.
[23] Ding, D., Li, J., Tu, P., Wang, H., Cao, T., & Zhang, F. (2020). Electric vehicle charging warning and path planning method based on spark. *IEEE ACCESS*, *8*, 8543-8553. https://doi.org/10.1109/ACCESS.2020.2964307
[24] Zhang, X. & Wang, J. Q. (2011). Application of hybrid ant colony algorithm in vehicle routing problem. *Computer Engineering*, *2011*, *37*(24), 190-192.
[25] Qiu, M., Fu, Z., Eglese, R., & Tang, Q. (2018). A Tabu Search algorithm for the vehicle routing problem with discrete split deliveries and pickups. *Computers & Operations Research*, *12*(100), 102-116. https://doi.org/10.1016/j.cor.2018.07.021
[26] Duan, Z., Yang, D., & Wang, S. (2010). An improved ant colony algorithm for time dependent vehicle routing problem. *Journal of control theory and applications*, *27*(11), 1557-1563. https://doi.org/10.1061/41139(387)466
[27] Chen, M., Gan, K., Li, K., Chen, F., & Fan, Y. (2021). A Spatial-temporal Graph Convolutional Network Model for Accurate and Robust Traffic Flow Prediction Based on Real-time Multimodal Spatial-temporal Data. *Journal of Highway and Transportation Research and Development*, *38*(08), 134-139.
[28] Guo, J., Jiang, Y., Liu, C., Zhao, D., & Yu, Y. (2021). Integrated multistep Markov-based velocity predictor of energy consumption prediction model for battery electric vehicles. *Transportmetrica B: Transport Dynamics*, *9*(01), 399-414. https://doi.org/10.1080/21680566.2020.1867664

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