

An Electric Vehicle Optimal Charging Path Planning based on an Improved A* Algorithm

Xianyan Chen *

The School of Big Data and Intelligent Engineering, Chongqing Institute of International Business and Economics, Chongqing, 401520, China

* Corresponding author Email: 1985448584@qq.com

Abstract: This study aims to explore the optimal charging path planning for electric vehicles (EVs) based on an improved A* algorithm. During the path planning process, there are several issues such as excessive traversal of invalid nodes leading to low path search efficiency, an excessively fast search rate causing the algorithm to converge prematurely to a non-optimal path, or even being unable to find an effective path to the target, and the inability to balance the weights of exploring new paths and utilizing known information, which can lead the algorithm to fall into a local optimal solution or converge prematurely, thus failing to find the global optimal path. To address these issues, this study proposes the application of optimization goal-directed strategies, linear adaptation strategies, and exponential adaptation strategies. By integrating these strategies, the efficiency of the algorithm in searching for the optimal path is improved, enabling EVs to reach charging stations more quickly. The optimization goal-directed strategy adjusts the calculation method of the estimated cost in the heuristic function by introducing a square term, making the algorithm more inclined to choose nodes closer to the target direction when evaluating nodes. This enhances the directionality of the algorithm during the search process. The linear adaptation strategy dynamically adjusts the weight of the actual cost, guiding the algorithm to gradually slow down the search speed as it approaches the target point. This is more conducive to the algorithm's adaptation to the target location and improves the efficiency of path search. The exponential adaptation strategy dynamically adjusts the weight of the actual cost based on the progress of the path search, balancing the algorithm's choice between searching for new paths and utilizing known optimal paths, further improving search efficiency. This study experimentally verifies the effectiveness of these three strategies. The results show that by introducing these strategies, the search efficiency of the A* algorithm in the charging path planning of new energy vehicles has been significantly improved. These strategies contribute to the optimization of EV charging path planning and help promote the development of electric vehicles and intelligent transportation.

Keywords: A* Algorithm; Goal-oriented Strategies; Linear Adaptation Strategy; Exponential Adaptation Strategy.

1. Introduction

As global climate change and environmental issues become increasingly severe, reducing carbon emissions and promoting sustainable development have become a global consensus. Against this backdrop, electric vehicles (EVs) are gradually attracting global attention and popularity as a clean and efficient mode of transportation [1]. The trend of EV development is becoming increasingly apparent, driven by both market demand and technological innovation. The growth of market demand also provides strong momentum for the development of EVs[2]. As consumer awareness of environmental protection and energy conservation continues to increase, as well as their acceptance of new energy vehicle technology gradually growing, the market demand for EVs is showing a rapid growth trend[3]. Technological advancements and industrial innovation are the core drivers of EV development[4]. With breakthroughs in battery technology, the improvement of charging facilities, and the continuous development of autonomous driving technology, the performance and convenience of EVs have been significantly improved, providing consumers with a more convenient and efficient travel experience[5].

A comprehensive electric vehicle (EV) charging path planning system serves as the foundation for the widespread adoption of EVs, providing critical support for their convenient use[6]. By constructing a comprehensive, efficient, and intelligent charging network, not only can the range

anxiety of EV users be addressed, but their user experience can also be enhanced[7]. Further promoting the widespread adoption of EVs is not only a response to the environmental philosophy of green travel and low-carbon living, but also an important strategic measure to accelerate the revolution in energy consumption and promote the transformation and upgrading of energy structure[8]. This will help reduce dependence on fossil fuels, lower air pollution, and inject new momentum into the sustainable development of human technology.

Optimal charging path planning for electric vehicles (EVs) is a complex issue that involves multiple factors, including the range of the EV, charging speed, the location and availability of charging stations, and traffic conditions along the route[9]. The goal is to find an optimal path from the starting point to the destination that minimizes the total cost (such as total travel distance, total charging time, total energy consumption, etc.) while satisfying the driving and charging requirements of the EV. To address this problem, various optimization algorithms are typically employed, such as the A* algorithm and genetic algorithms[10]. The aim of this study is to optimize the application of the A* algorithm in EV path planning, aiming to improve its efficiency in navigating to known charging stations.

Currently, researchers have employed various methods to address the issue of optimal charging path planning for electric vehicles, including rule-based heuristic methods, optimization algorithm-based methods, and machine

learning-based methods[11]. Each of these methods has its own advantages and disadvantages, and can be selected based on specific scenarios and requirements. Researchers have not only considered basic factors such as distance and charging time, but have also begun to focus on other factors such as charging station availability, charging speed, charging cost, and user travel demands[12]. The comprehensive consideration of these factors makes optimal charging path planning more aligned with actual needs.

Jiang Haojie et al. addressed the shortcomings of the A* algorithm in the path planning process for electric sterilizing vehicles, such as long planning paths, low efficiency of unidirectional search, and non-smooth turning points. Starting from the heuristic function and search direction, they proposed an improved bidirectional A* search algorithm[13]. Nilgun Fescioglu-Unver et al. addressed customers' concerns about charging services by proposing research on improving the operation of electric vehicle charging services using machine learning models. Effective infrastructure planning, charging scheduling, charging pricing, and electric vehicle route planning can help reduce customer-perceived risks[14]. Cai Rong et al. proposed a study on the optimal planning of multi-energy complementary electric vehicle charging stations. Firstly, a charging station service division method based on Voronoi diagrams was proposed. Then, a charging capacity evaluation method for electric vehicle charging stations based on the M/G/K queuing model was proposed. Finally, a location and volume model was constructed and solved to determine the optimal construction plan for electric vehicle charging stations with the lowest total social cost[15]. The proposed charging station planning method is economical and effectively improves the charging convenience for electric vehicle users.

Compared to traditional fuel-powered vehicles, electric vehicles face the issue of reaching charging stations within the shortest range possible due to their energy replenishment methods[16]. To improve the efficiency of electric vehicle promotion and reduce operating costs, it is necessary to consider path planning strategies to plan reasonable charging routes that meet the goal of timely charging and range extension.

To further improve the performance and adaptability of the A* algorithm, this study introduces multiple strategies, including an optimized goal-directed strategy, a linear adaptation strategy, and an exponential adaptation strategy. The optimized goal-directed strategy is a method that guides the search process by adding heuristic information related to the target node. The linear adaptation strategy dynamically adjusts the weights of the heuristic function based on the search progress, introducing a linear factor to adjust the weights in the heuristic function, thus improving the adaptability and robustness of the A* algorithm. The exponential adaptation strategy adjusts the weights in the heuristic function using an exponential function. Unlike the linear adaptation strategy, the exponential adaptation strategy gradually adjusts the weights using an exponential function, making the search more biased towards the target node. As the search progresses, the exponential function can gradually adjust the weights to improve the search efficiency of the A* algorithm.

The main research content of this article is summarized as follows:

- The optimization goal-oriented strategy gradually slows down the search speed to better match the target location, and

effectively guides the algorithm to approach the target point using heuristic costs.

- The linear adaptation strategy optimizes the search direction by dynamically adjusting the actual cost weight, reducing ineffective searches.

- The exponential adaptation strategy dynamically adjusts heuristic weights based on different path lengths using an exponential function, further improving search efficiency. These strategies collectively enhance the performance and efficiency of the algorithm.

The remaining structure of this paper is organized as follows: Section Optimize A* algorithm introduces the theoretical framework of the innovative A* algorithm, Section Simulation analysis verifies the feasibility of the algorithm innovation through simulation experiments, and Section Conclusion discusses future research directions and suggestions.

2. Optimize A* Algorithm

The A* algorithm is a shortest path finding algorithm in graphs that is developed from the Dijkstra's algorithm. Unlike Dijkstra's algorithm, the A* algorithm not only considers the distance from the starting node to the candidate node but also takes into account the estimated distance from the current node to the goal node. The advantage of the A* algorithm is that it guarantees to find the optimal solution, and it can effectively prune the search process, avoiding the exploration of invalid states. The evaluation function of the A* algorithm is as follows:

$$F(n) = h(n) + g(n) \quad (1)$$

In the A* algorithm, the evaluation function $F(n)$ represents an estimated value of the minimum cost path from the starting node to the goal node through node n . This function is composed of two parts: $h(n)$, which represents the actual cost of the path traveled from the starting node to node n , and $g(n)$, which is an estimate of the potential optimal cost path from node n to the goal node. The function $g(n)$ reflects the heuristic information used by the algorithm, derived from people's understanding of path planning problems and based on certain empirical estimates. Based on $F(n)$, the cost of the current node can be calculated, and the next reachable nodes can be evaluated. By consistently selecting the node with the lowest $F(n)$ value to continue the search, the algorithm gradually finds the optimal path step by step. In the context of raster maps, heuristic functions usually have three different distance models:

(1) manhattan distance

The Hamanton distance is calculated based on the straight-line distance between two points, regardless of obstacles, and is the most intuitive but may not be very accurate model. Usually, the position where the robot is located is identified as the current location node, and the point expected to reach is defined as the target node. When the robot can only move along the four basic directions (i. e., front, back, left, right), the Hammanton distance is chosen as the heuristic function.

$$h(n) = abs(nx - gx) + abs(ny - gy) \quad (2)$$

(2) chebyshev distance

Chebyshev distance measures the maximum difference between the current position coordinates and the target position coordinates in all dimensions. It fully considers the possibility of diagonal movement, so it is suitable for robots with a higher flexibility to move. Usually used for robots that allow diagonal movement, it is computationally slightly more

complex than Manhattan distances.

$$h(n) = \max \left(\begin{matrix} \text{abs}(nx - gx), \\ \text{abs}(ny - gy) \end{matrix} \right) \quad (3)$$

Where, (nx, ny) represents the current position and coordinate of the robot, (gx, gy) representing the target position of the robot. When the robot can move freely in eight directions (including diagonal, vertical and horizontal directions), it is appropriate to choose the Chebyshev distance as a heuristic function. Chebyshev distance measures the maximum difference between the current position coordinates and the target position coordinates in all dimensions. It fully considers the possibility of diagonal movement, and therefore is suitable for robots with higher mobility flexibility.

(3) Euclidean distance

Considering the grid structure of the raster map, calculated according to the number of steps needed to move in the horizontal and vertical directions, it is suitable for robots that can only move along the grid direction.

$$h(n) = \sqrt{(nx - gx)^2 + (ny - gy)^2} \quad (4)$$

When the robot can move randomly, using the Euclidean distance.

The flowchart of the A* algorithm is shown in Figure 1, and its specific execution process is as follows: Firstly, the positions of the start node and the goal node are determined as the starting point and endpoint for path planning. Next, two lists are initialized: the open list is used to store the nodes to be examined, while the closed list is used to record the nodes that have already been examined. Subsequently, the A* algorithm begins to run, traversing the nodes around the start node and selecting the node with the minimum cost as the next search target based on certain evaluation criteria. This process is repeated as the path nodes are gradually determined. The algorithm continuously selects nodes from the open list, examines their surrounding nodes, and updates the open list and closed list until the goal position is finally reached, finding the optimal path from the start node to the goal node.

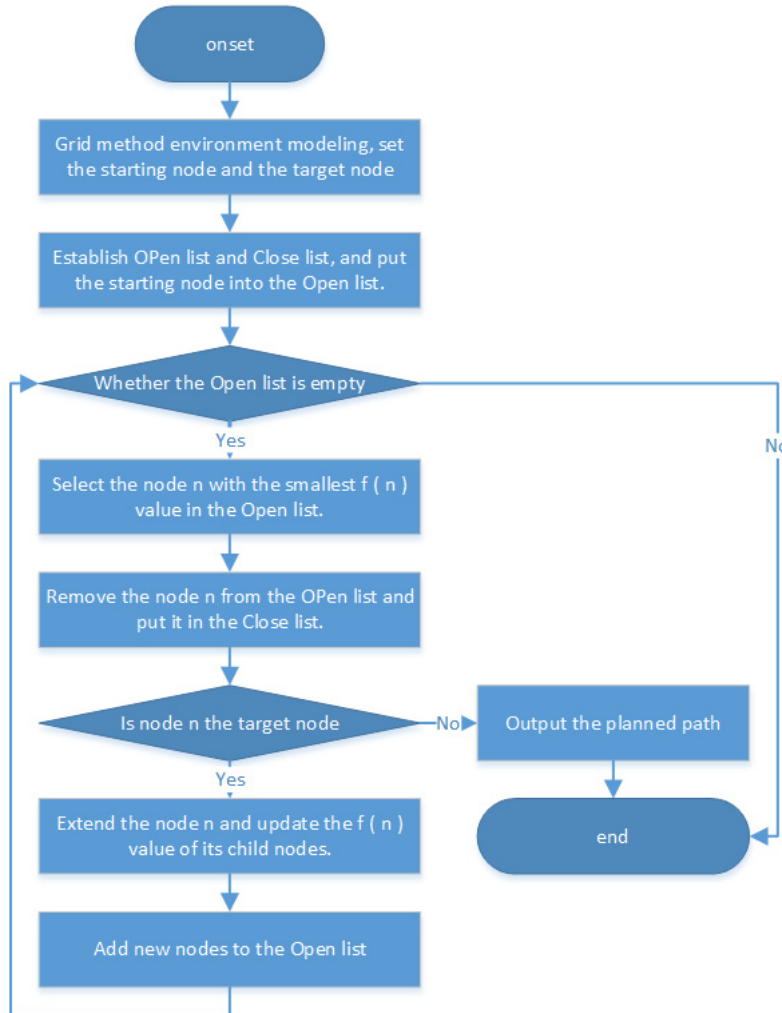


Figure 1. Flow chart of the A* algorithm

A* algorithm is widely used in the field of robot path planning. When the algorithm is applied to the petroleum analysis scenario, the searched path still has disadvantages such as excessive bending, too long planning time, and weak path search direction. Therefore, the algorithm needs to be optimized.

3. Optimization Goal-Directed Strategy

The goal-directed strategy for path search is a method that guides the search process by utilizing information about the target and the current location. The main idea behind this strategy is to prioritize paths or regions that are more likely to lead to the target node. Heuristic search is a common example

of a goal-directed strategy. In this method, a heuristic function is used to estimate the cost from the current node to the target. The search algorithm preferentially selects nodes with lower heuristic costs, enabling a faster approach towards the target.

The optimized goal-directed strategy for path search mainly focuses on how to more effectively utilize target information to guide the robot's search process from its current location, in order to find high-quality paths more quickly. To optimize the directionality of the path search, a squared term is added to the distance function $g(n)$ in the heuristic function. This is because the squared term imposes a stricter penalty on distance, making the search algorithm more inclined to choose paths that are closer to the target. This adjustment allows the search algorithm to focus more on the target direction, reducing unnecessary searches and deviations from the target. By adding the squared term, the heuristic function can better reflect the cost of the predicted path and guide the search process to approach the target more efficiently. This adjustment has a positive impact on improving the accuracy and efficiency of path search.

$$totalCost = historicCost + (heuristicCost)^2 \quad (5)$$

In this context, "totalCost" represents the estimated cost of the path from the starting point to the endpoint, "historicCost" denotes the cost of the already traversed path, and "heuristicCost" refers to the estimated cost of the path from the current node to the endpoint. The node with the lowest "totalCost" value is selected as the optimal node, which represents the next path node to be followed.

This goal optimization strategy gradually reduces its effectiveness as the target location is approached, slowing down the search speed and focusing the search process more on finding the target point. This adjustment allows the algorithm to better adapt to the search for the target point, improving the accuracy and efficiency of the search. By employing this optimization strategy, the goal-directed path search can better handle complex environments and changes, enhancing the accuracy and efficiency of the search. This enhancement method is significant in many practical applications, such as autonomous driving, robot navigation, and logistics delivery.

4. Optimization of Goal-Directed Strategy with Linear Adaptation

During the process of path planning, the strategy of optimizing goal-directedness utilizes target information to guide the search process. By dynamically adjusting goal-directed parameters, the algorithm can adaptively modify the search progress based on changes in positional distance, ensuring that the search always proceeds in the most promising direction. This further enhances the efficiency of path planning.

The objective function is the core of path planning, representing the cost of the path. In an optimized goal-directed strategy, we can define the objective function as a function based on the target node, used to evaluate the closeness of the path to the target. By automatically adjusting the parameters of the objective function, we can optimize the influence of the search algorithm on the target node.

An adaptive strategy involves dynamically adjusting path planning parameters as the search location changes. We can define an adaptive function to reflect changes in positional distance and form dynamic parameters, which can then be used to adjust the objective function. In this way, the search

algorithm can adaptively adjust its search strategy based on the progress of the search, better adapting to different situations and changes.

To describe the implementation of optimized goal-directed and adaptive strategies, a formula for dynamic parameter adjustment can be introduced. This formula adjusts the parameter values of the objective function based on changes in the distance from the current node to the target node and changes in the distance from the current node to the starting node. By dynamically altering the objectives of the path planning evaluation function, the search algorithm can better adapt to environmental changes and uncertainties.

$$(totalCost)_h = k_1(historicCost) + (heuristicCost)^2 \quad (6)$$

$$k_1 = \frac{heuristicCost}{historicCost} \quad (7)$$

In this context, represents the estimated cost that combines optimized goal-directedness with linear adaptation strategies. The represents the linear adaptation function.

The formula for optimizing goal-directedness and adaptability combines the definition of the objective function, the introduction of the adaptability function, and the dynamic parameter adjustment formula. Through dynamic parameter adjustment, the adaptability strategy can adaptively modify the search strategy based on the progress of the search, further enhancing search efficiency.

5. Optimization of Goal-Directedness with Exponential Adaptation Strategy

In the process of path planning, the optimization of goal-directedness with an exponential adaptation strategy combines goal-directedness with adaptive adjustment. This strategy uses an exponential function to adjust the strength of goal-directedness, gradually increasing its influence as the search progresses.

The optimization of goal-directedness with an exponential adaptation strategy utilizes the objective function to evaluate the closeness of the path to the target. Subsequently, it introduces an exponential function to dynamically adjust the parameters of the objective function. This exponential function takes the distances from the current location to both the starting point and the target point as inputs and outputs an adjustment coefficient. As the search progresses, the value of the exponential function gradually increases, thereby enhancing the strength of goal-directedness.

$$(totalCost)_L = k_2(historicCost) + (heuristicCost)^2 \quad (8)$$

$$k_2 = e^{\frac{heuristicCost}{historicCost}} \quad (9)$$

In this context, represents the estimated cost associated with the optimization of goal-directedness combined with an exponential adaptation strategy. The represents the exponential adaptation function.

By doing so, the optimization of goal-directedness with an exponential adaptation strategy provides greater freedom to the algorithm in the early stages of the search, allowing for the exploration of different paths and regions. As the search progresses, the strategy gradually enhances the influence of goal-directedness, directing the search process more towards paths that are closer to the target. This adaptive adjustment approach helps improve search efficiency and accuracy, especially in complex and dynamic environments where it

exhibits significant advantages.

6. Simulation Analysis

This section of the experiment was conducted on a Lenovo computer with a frequency of 2.40MHz and 4GB of memory using MATLAB 2018a. The experiment constructed an electric vehicle and charging environment of 100dm x 100dm, dividing it into squares with a side length of 1dm. Obstacle positions were randomly set on the map. The black areas represent non-viable regions, while the white parts are the viable regions. During the construction of the map, the edges of the black obstacles were dilated to create a safety zone around them. This safety distance is also represented in the black area.

7. Comparison Experiment before and after Introducing the Optimization of Goal-directedness Strategy

In the traditional A* algorithm, attention is typically focused solely on finding the shortest path from the starting point to the end point. This approach has the advantage of quickly locating direct paths, but sometimes it may not be the most optimal or suitable solution. For path planning with a fixed target location, by utilizing an optimization goal-directed strategy, the A* algorithm can be made to focus more on specific goals, making the path search more targeted. To facilitate discussion, the A* algorithm that incorporates the optimization goal-directed strategy will be referred to uniformly as the A*-T algorithm.

To validate the impact of introducing the optimization of goal-directedness strategy on path planning, we conducted comparison experiments while keeping other conditions constant. Comparison experiment before and after introducing the optimization of Goal-Directedness strategy is as shown in Figure 2, during the path planning process, the black areas represent obstacles, the white areas represent viable regions, and the gray areas indicate the regions that have been traversed. The starting point is located at the top

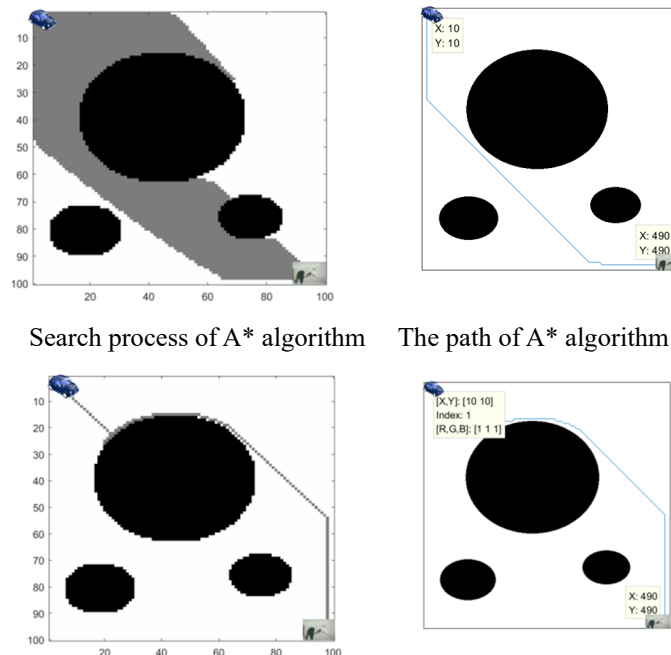
left corner of each experimental map (10, 10), and the destination is at the bottom right corner (490, 490). Under the optimized goal-directedness strategy, the A* algorithm searches for an optimal path from the starting point to the destination.

In the analysis of simulation experiments, the A* algorithm is observed to require the exploration of all feasible nodes near the starting point as well as all feasible nodes adjacent to the path nodes in order to find the optimal path. This leads to excessive computation of redundant nodes in the path cost calculation. However, the A*-T algorithm, guided by the target node, restricts the search direction to paths that are more likely to reach the target, allowing for precise selection of expansion nodes. This approach reduces the computation of redundant nodes, increasing the efficiency and effectiveness of the algorithm. By focusing the search on more promising paths, the A*-T algorithm is able to locate the optimal path more quickly and with less computational overhead.

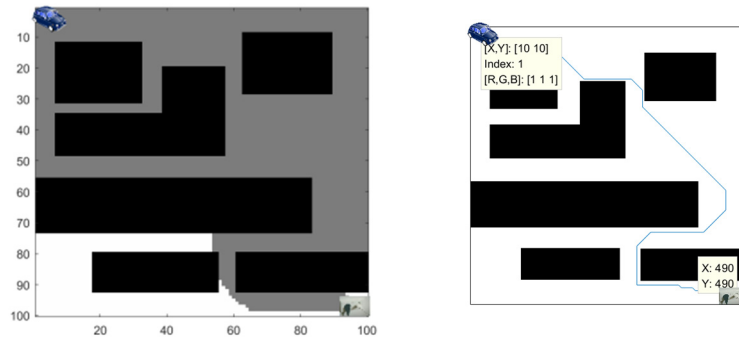
By comparing the simulation experiments of the A* algorithm and the A*-T algorithm, we obtained the results presented in Table 1.

Upon analyzing the experimental data, it can be observed that the average path planning efficiency for the A* algorithm is 5.21, while the average path planning efficiency for the A*-T algorithm is 44.76. This indicates an improvement in path planning efficiency by a factor of 7.59 with the optimized A*-T algorithm.

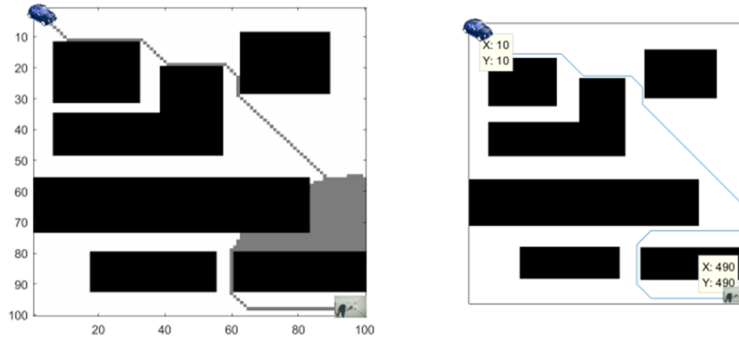
To more intuitively analyze the changes in path planning time of the A* algorithm under different conditions, the collected data on path planning time from the experiments were organized. These data were presented through a bar chart to facilitate the observation of the distribution and trends of the A* algorithm's path planning time under various conditions. Bar chart of experimental results before and after introducing the optimization of Goal-Directedness strategy is as shown in Figure 3. Upon observing the experimental data, it can be noted that the path lengths remain nearly unchanged. Therefore, a bar chart analysis will be conducted solely on the path planning time.



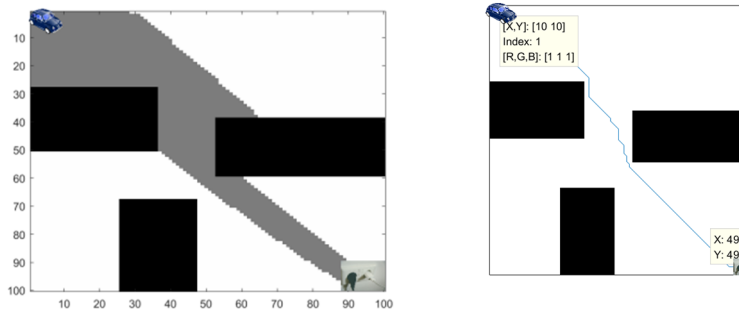
The search process of A* algorithm The path of A* algorithm
 The search process of A* -T algorithm The path of A* -T algorithm
 Fig 2 Experiment 1



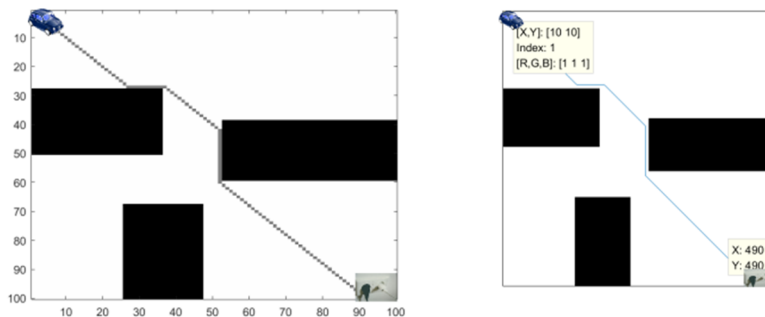
Search process of A* algorithm The path of A* algorithm



The search process of A* -T algorithm The path of A* -T algorithm
Fig 2 Experiment 2



Search process of A* algorithm The path of A* algorithm



The search process of A* -T algorithm The path of A* -T algorithm
Fig 2 Experiment 3

Figure 2. The path search process comparison experiment of A* algorithm and A* -T algorithm is carried out

Table 1. Experimental Data for A* Algorithm and A*-T Algorithm

Algorithm	Optimized	Plan the time 10 ² /s	The length of the path 10 ² /dm	efficiency of path planning
Experiment I	A*	2.934	7.755	2.64
	A*-T	0.094	7.754	82.49
Experiment II	A*	2.416	10.448	4.32
	A*-T	0.848	10.408	12.27
Experiment III	A*	0.845	7.315	8.66
	A*-T	0.185	7.315	39.54



Figure 3. Bar Chart of Path Planning Experimental Results for A* Algorithm and A*-T Algorithm

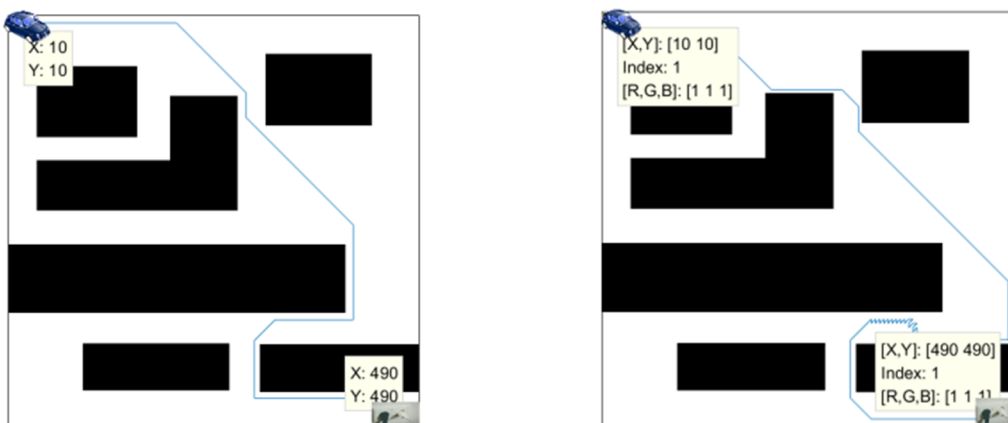
According to the experimental results, after optimizing the path planning algorithm, the path length remains approximately the same, but the path search time is significantly reduced by two orders of magnitude. Based on these findings, the following conclusions can be drawn: The A*-T algorithm exhibits higher path planning efficiency and fewer redundant nodes compared to the A* algorithm. This implies that the optimized algorithm is capable of finding the optimal path more rapidly. By restricting the search direction, the algorithm is able to more precisely select the next expansion node, thus avoiding excessive ineffective searches and guiding the search accurately to the target point. In summary, the A*-T algorithm demonstrates superior efficiency and accuracy in path planning, enabling the identification of shorter optimal paths.

strategy is introduced to enhance the A* algorithm, resulting in a new algorithm called A*-LT. This algorithm builds upon the strengths of the A* algorithm while dynamically adjusting its search strategy based on environmental changes. In the A* algorithm, a squared heuristic function is used to calculate the cost from the current node to the goal node. This heuristic function is typically based on prior knowledge and guides the search direction. However, when the environment changes, this fixed heuristic function may not adapt well to the new conditions, leading to reduced search efficiency. By introducing a linear adaptation strategy, the heuristic function can be adaptively adjusted based on the progress of the search.

The following is a comparative experiment that illustrates the path search performance of the A* algorithm and the A*-LT algorithm, as shown in Figure 4.

8. Comparison Experiment Before and After Introducing the Linear Adaptation Strategy

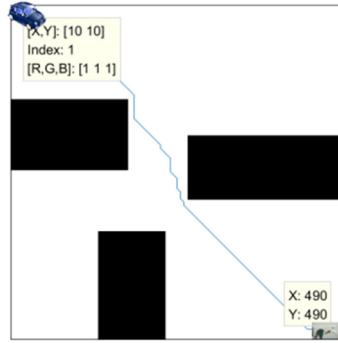
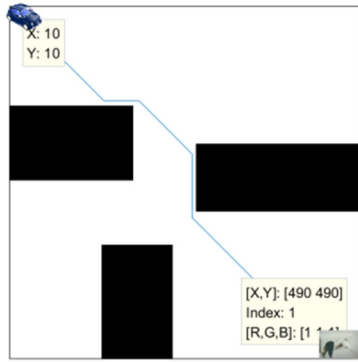
To further improve search efficiency, a linear adaptation



A* algorithm

A*-LT algorithm

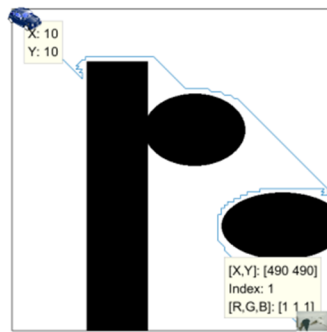
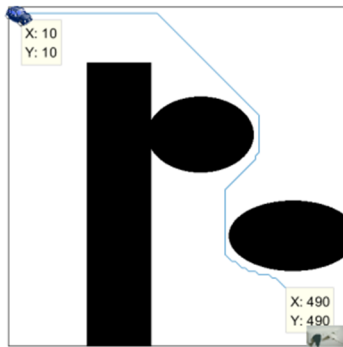
Fig 4 Experiment 1



A* algorithm

A*-LT algorithm

Fig 4 Experiment 2



A* algorithm

A*-LT algorithm

Fig 4 Experiment 3

Figure 4. The path comparison experiment of A* algorithm and A* -LT algorithm planning is carried out

Upon analyzing the experimental results, the linear adaptation strategy provides the algorithm with a clearer search direction by adjusting the weight of the actual cost. This enables the algorithm to be closer to the optimal path when selecting the next node at each step, thus reducing unnecessary searches and backtracking. The algorithm avoids entering regions that are obviously not optimal solutions during the search process. By adjusting the weights, the

algorithm can more accurately evaluate the priority of nodes, thereby reducing the time spent on ineffective searches.

After comparing the experiments of the A* algorithm and the A*-LT algorithm, a set of data was obtained to accurately reflect the time taken for path search. Next, the changes in path planning time will be visually presented in the form of a chart, as shown in Figure 5.

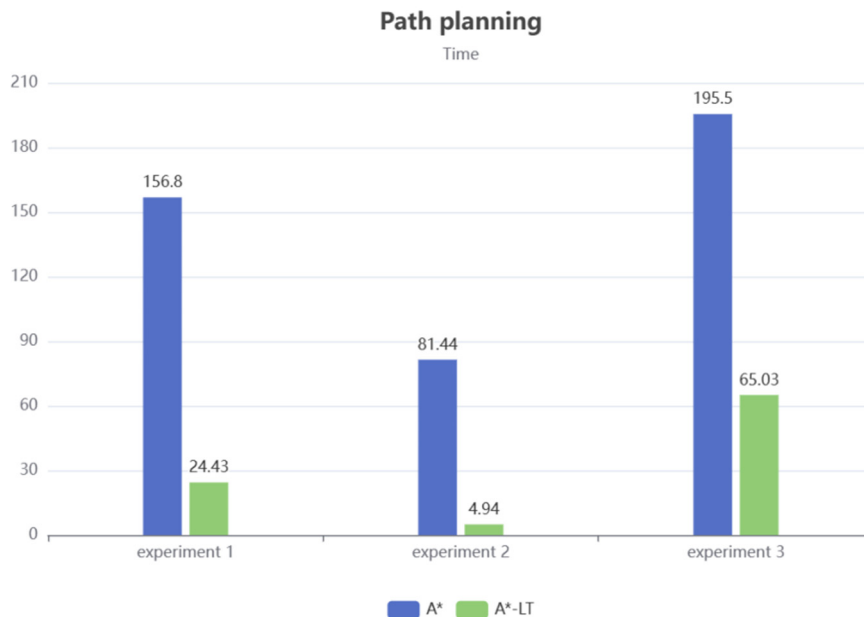


Figure 5. A* algorithm and A* -LT algorithm path planning experimental results histogram

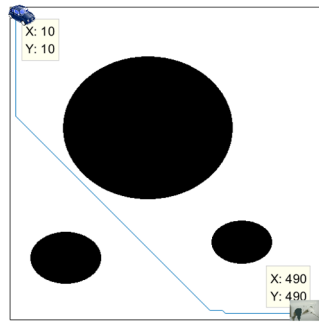
Upon analyzing the experimental data, it can be observed that the introduction of the linear adaptation strategy into the A* algorithm results in a significant reduction in path search time. The average path planning time for the A* algorithm is 132.58 seconds, while the average path planning time for the A*-LT algorithm is 51.05 seconds. This represents an average reduction of 61.50% in path planning time with the optimized algorithm.

9. Comparison Experiment Before and After Introducing the Exponential Adaptation Strategy

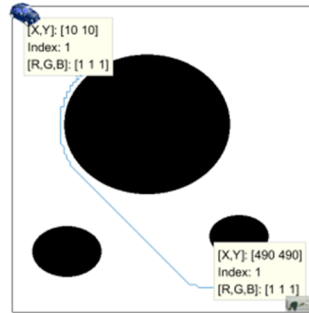
The A* algorithm evaluates the quality of paths by combining the actual path length with an estimated remaining

distance to select the optimal path. However, to improve the performance and adaptability of the A* algorithm, an exponential adaptation strategy can be introduced to form a new algorithm called A*-IT. This primarily involves adjustments to the calculation of $h(n)$, which affects the path selection process.

The exponential adaptation strategy is an improved approach that dynamically adjusts the calculation method, enabling the A* algorithm to better adapt to different search environments and requirements. This strategy involves the application of an exponential function to adjust its impact on the search process. As shown in Figure 6, experiments were conducted by running both the A* algorithm and the A*-IT algorithm on each map, obtaining the search path for each iteration, and recording the search time accordingly.

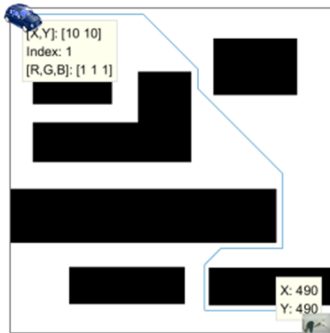


A* algorithm

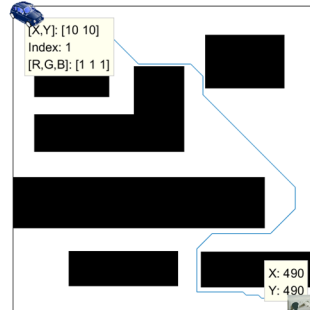


A*-IT algorithm

Experiment 1

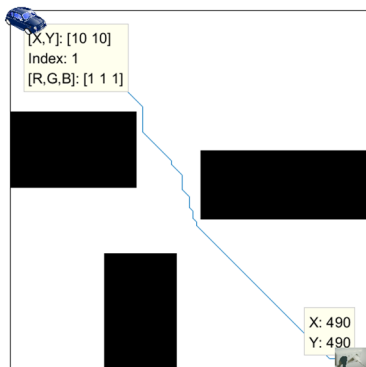


A* algorithm

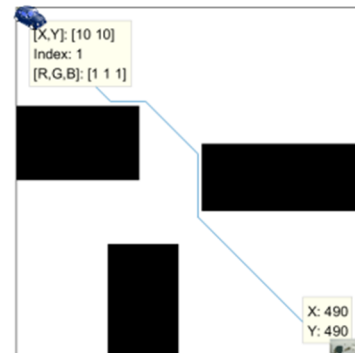


A*-IT algorithm

Experiment 2



A* algorithm



A*-IT algorithm

Experiment 3

Figure 6. A* algorithm and A* -IT algorithm path planning comparison experiment

Analyzing the experimental results, the introduction of the exponential adaptation strategy allows the algorithm to dynamically adjust the weight of the actual cost during the search process. This means that the algorithm can optimize the search direction based on the current progress of the search and the characteristics of the environment, thereby reducing unnecessary search efforts. On the other hand, by adjusting the weights, the A* algorithm with the exponential adaptation strategy can more accurately select the next node to expand during the search. This selection is closer to the optimal path, thus reducing backtracking and duplicate work

during the search process, which in turn shortens the search time. The exponential adaptation strategy helps the algorithm avoid or reduce entering regions that are obviously not optimal solutions during the search process. This reduces the time spent on ineffective searches. The algorithm can focus more quickly on regions that are more likely to contain optimal solutions, thereby improving search efficiency.

By comparing the path planning simulation experiments of the A* algorithm and the A*-IT algorithm, the results shown in Figure 7 can be obtained.



Figure 7. A* algorithm and A* -IT algorithm path planning experimental results histogram

The experimental results indicate that the introduction of the exponential adaptation strategy into the A* algorithm significantly reduces the time taken for path search. The average path planning time for the A* algorithm is 177.21 seconds, while the average path planning time for the A*-IT algorithm is 28.35 seconds. This represents an average reduction of 84% in path planning time with the optimized algorithm. Compared to the A*-LT algorithm, the path planning time of the A*-IT algorithm is reduced by an additional 23.5%, further improving the efficiency of path planning.

This improvement not only enhances the efficiency of the algorithm, but also further confirms the important role of adaptive strategies in optimizing the search process. The exponential adaptive strategy balances exploring new path areas and exploiting known areas by dynamically adjusting the weights of actual distances. This ensures that the algorithm can explore new possible paths while avoiding excessive exploitation of known but suboptimal paths, thereby reducing unnecessary searches. This is demonstrated by the significant reduction in search time in the experimental results.

In the process of robot path planning, Genetic Algorithm (GA) is a method that simulates the natural evolution process to search for the optimal solution, used to help the robot find the optimal or near-optimal path from the starting point to the endpoint. A comparison of genetic algorithms, the A* algorithm, and the A*-IT algorithm is presented in Table 2.

The efficiency of path planning algorithms can be reflected by the ratio of path length to planning time, which indicates the algorithm's ability to plan paths per unit of time. A higher ratio signifies higher path planning efficiency. Upon analyzing the experimental data, it can be found that the path planning efficiency of the A*-IT algorithm is improved by

9.28 times compared to the genetic algorithm.

Table 2. The simulation comparison experiment of genetic algorithm and A* -IT algorithm

Experimental data	Plan time $10^2/s$	Path length $10^2/dm$	Planning efficiency
GA	0.937	9.24	9.86
A* Algorithm	1.566	10.448	6.67
A*-IT algorithm	0.270	11.408	42.25

10. Conclusion

This study aims to plan the optimal charging paths for electric vehicles by improving the A* algorithm. To achieve this goal, we combined optimized goal-directed strategies, linear adaptation strategies, and exponential adaptation strategies. Through MATLAB simulation experiments, we verified that the improved algorithm exhibits higher path search efficiency. Compared to the A* algorithm, the path planning efficiency of the A*-T algorithm is improved by 7.59 times. The average path planning time of the A*-LT algorithm is reduced by 61.50%, while the average path planning time of the A*-IT algorithm is reduced by 84%.

Firstly, the optimized goal-directed strategy enhances the influence of heuristic cost during the search process, guiding the algorithm to slow down the search speed as it gradually approaches the target point. This strategy ensures that the algorithm can search more finely when nearing the target location, thereby improving the accuracy of finding the optimal charging path. Secondly, the linear adaptation strategy dynamically adjusts the weight of actual costs, optimizing the search direction and effectively reducing

ineffective searches. This strategy allows the algorithm to flexibly adjust the search strategy based on the current search state, improving search efficiency. Additionally, the exponential adaptation strategy dynamically adjusts the heuristic weight in an exponential manner based on different path lengths. This strategy is particularly suitable for long-distance path planning, significantly improving search efficiency and helping the algorithm find the optimal solution faster. Through MATLAB simulation experiments, the performance of the improved algorithm was compared with the original A* algorithm. Experimental results show that the improved algorithm outperforms the original algorithm in terms of search speed. Specifically, the improved algorithm can find the optimal charging path faster, thereby contributing to improving the driving range of electric vehicles.

In summary, this study successfully improved the A* algorithm by introducing optimized goal-directed strategies, linear adaptation strategies, and exponential adaptation strategies. The effectiveness of the improved algorithm was verified through MATLAB simulation experiments. These improvements not only enhance the performance and efficiency of the algorithm but also provide a new solution for optimal charging path planning for electric vehicles. In the future, we will continue to optimize the algorithm and explore its potential in practical applications.

Data Availability Statement

All data generated or analyzed during this study are included in this published article.

Author Contributions

Chen Xianyan wrote the main manuscript text.

Competing Interests

The authors declare no competing interests.

Acknowledgments

This work has been supported by Chongqing University of International Business and Economics (KYZK2024037).

References

- [1] Ran Jing, Chen Yuan, Hamidreza Rezaei, et al. Assessments on energy and greenhouse gas emissions of internal combustion engine automobiles and electric automobiles in the USA, *Journal of Environmental Sciences*, Volume 90, 2020, Pages 297-309.
- [2] Fulan Wu, Pei Li, Xuebing Dong, et al. Exploring the effectiveness of China's dual credit policy in a differentiated automobile market when some consumers are environmentally aware, *Energy Economics*, Volume 111, 2022, 106077, ISSN 0140-9883.
- [3] Xiaohong Dong, Zhiwei Feng, Xiaodan Yu, et al. Evolution prediction method for electric private car ownership considering the decision-making behaviour of consumers, *Energy Reports*, Volume 11, 2024, Pages 498-509.
- [4] Bakheit Mohammed Nur. A case study of socio-cultural and technical factors in automobile design: Discourses between designers and potential users on a new electric vehicle in Africa, *Technology in Society*, Volume 63, 2020, 101398.
- [5] Alpaslan Alkan, Mehmet Sait İnan. Experimental investigation of the effects of compressor types on the performance of an automobile air conditioning system using R1234yf, *International Journal of Refrigeration*, Volume 155, 2023, Pages 58-66, ISSN 0140-7007.
- [6] Yoshitomo Yamasaki, Noboru Noguchi. Optimal route planning and a turning method for an electric vehicle robot in an irregularly shaped vineyard, *IFAC-PapersOnLine*, Volume 55, Issue 32, 2022, Pages 1-5, ISSN 2405-8963.
- [7] Miguel Campaña, Esteban Inga. Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition, *Energy Reports*, Volume 9, 2023, Pages 5246-5268, ISSN 2352-4847.
- [8] Kangoh Lee. Bold fiscal policies for a net-zero EU: Promotion of electric vehicles and expansion of green energy, *Energy Reports*, Volume 10, 2023, Pages 2944-2949, ISSN 2352-4847.
- [9] Mansoor Davoodi, Marjan Abedin, Bahareh Banyassady, et al. An optimal algorithm for two robots path planning problem on the grid, *Robotics and Autonomous Systems*, Volume 61, Issue 12, 2013, Pages 1406-1414, ISSN 0921-8890.
- [10] Yibing Cui, Wei Hu, Ahmed Rahmani. Multi-robot path planning using learning-based Artificial Bee Colony algorithm, *Engineering Applications of Artificial Intelligence*, Volume 129, 2024, 107579, ISSN 0952-1976.
- [11] Yang Jiang, Yifan Yu, Ruohuai Sun, et al. Research on dynamic path planning method of electric inspection robot based on fuzzy neural network, *Energy Reports*, Volume 9, Supplement 8, 2023, Pages 483-491, ISSN 2352-4847.
- [12] Yisheng An, Yuxin Gao, Naiqi Wu, et al. Optimal scheduling of electric vehicle charging operations considering real-time traffic condition and travel distance, *Expert Systems with Applications*, Volume 213, Part B, 2023, 118941, ISSN 0957-4174.
- [13] Haojie Jiang, Yuan Sun. Research on global path planning of electric disinfection vehicle based on improved A* algorithm, *Energy Reports*, Volume 7, Supplement 7, 2021, Pages 1270-1279, ISSN 2352-4847.
- [14] Nilgun Fescioglu-Unver, Melike Yıldız Aktaş, et al. Electric vehicle charging service operations: A review of machine learning applications for infrastructure planning, control, pricing and routing, *Renewable and Sustainable Energy Reviews*, Volume 188, 2023, 113873, ISSN 1364-0321.
- [15] Rong Cai, Kun Huang, Shu Zheng, et al. Including research on optimization planning of multi-energy complementary electric vehicle charging station, *Energy Reports*, Volume 9, Supplement 7, 2023, Pages 1037-1047, ISSN 2352-4847.
- [16] Yiming Ye, Hanchen Wang, Bin Xu, et al. An imitation learning-based energy management strategy for electric vehicles considering battery aging, *Energy*, Volume 283, 2023, 128537, ISSN 0360-5442.