Research on Global Gath Planning for Mobile Robots Based on Improved Ant Colony Algorithm

Yongquan Zheng
School of Electrical and Control Engineering
Shenyang Jianzhu University
Shenyang, China
e-mail: 15503218397@163.com

Jialun Li
School of Mechanical Engineering
Shenyang Jianzhu University
Shenyang, China
e-mail: 18890499305@163.com

Junjie Deng
School of Electrical and Control Engineering
Shenyang Jianzhu University
Shenyang, China
e-mail: a15179400015@163.com

Yijie Wang
Ara Institute of Canterbury International Engineering College
Shenyang Jianzhu University
Shenyang, China
e-mail: 13050485608@163.com

Jin Zhao
School of Electrical and Control Engineering
Shenyang Jianzhu University
Shenyang, China
e-mail: 18842924415@163.com

Jing Hou*
Shenyang Jianzhu University
Shenyang, China
e-mail: dqhoujing@sjzu.edu.cn

***Abstract*- In the field of electric power and energy, the safety of important electric equipment stored in substations and power stations is a matter of great concern. The electric power inspection vehicle is an effective solution to the problem of low efficiency, inaccuracy, and high risk, as the current detection method is mainly manual inspection. The electric power inspection vehicle in addition to the realization of the basic requirements from the starting point to the end point, but also need to consider whether the inspection is convenient, whether it can automatically avoid obstacles in the emergency environment. In view of the above problems, this paper proposes an electric power inspection vehicle for real-time monitoring of important power equipment in power plants, which is able to avoid complex obstacles in the power plant, and at the same time enter different sub-areas within the power plant for inspection. Therefore, this paper focuses on the path planning and obstacle avoidance aspects of the vehicle, through the improvement of the Ant Colony Algorithm, constantly optimize the driving route, and constantly improve the obstacle avoidance ability.**

Keywords-path planning; artificial potential field gravity; obstacle repulsion factor; triangular pruning method

I. Introduction

In recent years, with China 's remarkable achievements in industry, energy and other fields, the power industry has ushered in rapid development. The safety inspection is the key link to ensure the stable operation of the power system. This paper takes the special application scenario of the power plant as the background. Due to the existence of high-voltage line risk and power equipment in the plant needs real-time detection, In this paper, a real-time monitoring of the electric power inspection vehicle in the plant area is proposed, which is able to avoid complex obstacles in the plant and at the same time to enter the plant within the different sub-areas for inspection. Therefore, this paper focuses on the path planning and obstacle avoidance of the vehicle. By improving the Ant Colony Algorithm, the driving route is continuously optimized and the obstacle avoidance ability is continuously improved.

Since the traditional Ant Colony Algorithm has problems such as insufficient orientation, slow convergence and easy to fall into local optimization[1], scholars at home and abroad have conducted research on this. Literature[1] through Dijkstra Algorithm for node selection, using Ant Colony Algorithm for optimization, updating the heuristic function, to achieve the optimization goal of shorter paths and fewer bending points. Literature[2] pheromone will be redistributed according to the new rules after optimization, and by dynamically adjusting the state transfer probability, the stagnation phenomenon of the algorithm can be effectively avoided, and the occurrence of the local optimum problem can be reduced. Literature[3] improves the initial pheromone concentration in the region by constructing a global optimal region, then seeks the optimization for each sub-region, and updates the optimal path pheromone in the region at the same time, finally, introduces the pheromone enhancement factor to improve the algorithm's ability to seek the optimization.

Aiming at the problem that the traditional Ant Colony Algorithm has insufficient guidance of the target point in the initial process of path planning[4], this paper enhances the guidance of the target point by introducing artificial potential field gravity, obstacle rejection factor, and adjusting the heuristic information function ; secondly, considering that the traditional algorithm is easy to fall into local optimum and the convergence speed is slow, this paper improves the pheromone update rule. On the basis of the original formula, the difference between the sum of pheromone concentrations carried by all ants on the optimal path and the worst path of the previous generation is added, so that the algorithm can dynamically update the pheromone increment. Finally, the triangular pruning method is utilized to remove redundant nodes and broken lines, which effectively reduces the path length and turning time of the electric power inspection vehicle.

II. GRID ENVIRONMENT

In this paper, the electric power inspection vehicle is regarded as a point-like object moving on a two-dimensional plane. Assuming that the is in a certain area from the starting point to the inspection point, the grid method is used to model the environment[5], as shown in figure 1 below.

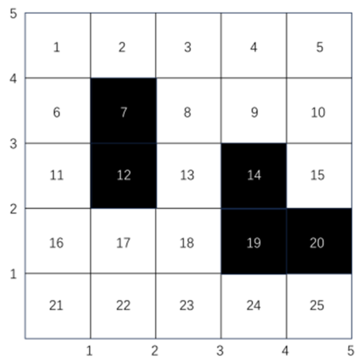

Figure 1. Grid Schematic

The grid graph Z is composed of grid Z_{ij}:

$$Z = \{Z_{ij} | Z_{ij} = S, 0, 1, E\} \tag{1}$$

Among them, $Z_{ij} = S$ represents the starting grid, $Z_{ij} = 0$ represents the free grid (white), $Z_{ij} = 1$ represents the obstacle grid (black), and$Z_{ij} = E$ represents the target grid.

III. TRADITIONAL ANT UOLONY ALGORITHM

Ant Colony Algorithm is an eight-character search algorithm that simulates ant foraging[6]: ants move from the starting point to the end point, and pheromones are released during the crawling process. The concentration of pheromones is proportional to the number of ants per unit time. The crawling logic of ants is based on the probability selection formula, and it will be calculated to determine the path crawling with a large concentration of pheromones. As a large number of ants continue to optimize, they will eventually find a shortest path. The traditional Ant Colony Algorithm steps are as follows.

A. Probability Selection

The traditional Ant Colony Algorithm uses the roulette method[7] to select the path according to the pheromone concentration and the movement distance. The probability selection formula is as follows, indicating that the probability of the ant from the node i to the node j is:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum_{s=allowed_k} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}, j \in allowed_k \\ 0, otherwise \end{cases} \tag{2}$$

Among them, $P_{ij}^{k}(t)$ represents the selection probability of the ant 's next arrival to the grid position, α is the pheromone importance factor, β is the importance factor of the expected heuristic function,$\tau_{ij}(t)$represents the pheromon concentration retained by the path (i, j), $\eta_{ij}(t)$ represents the heuristic factor from position i to j position, and $allowed_k$ represents the set of feasible regions.

B. Heuristic Function

The traditional heuristic function represents the reciprocal of the path length between the position i and the position j[8]. The formula is as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \tag{3}$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

where $\eta_{ij}(t)$ denotes the heuristic factor from position i to position j,d_{ij} is the distance between raster positions i, j.

C. Pheromone Update

As the ant crawl along the path, the concentration of pheromone released is higher and higher. When all ants complete an iteration, the pheromone concentration will be updated, and the concentration will be increased and volatilized according to the following formula.

$$T_{ij}(t + n) = (1 - P) \cdot T_{ij} + \Delta T_{ij}(t) \tag{5}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{6}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k}, \text{The path taken by Ant K}(i, j) \\ 0, \text{The path taken by Ant K}(i, j) \end{cases} \tag{7}$$

Among them, P is the pheromone volatilization coefficient, 1-P is the retention factor after pheromone volatilization, $\Delta\tau_{ij}(t)$ represents the sum of the pheromone increments left by m ants on the path node (i, j) after the first iteration, $\Delta\tau_{ij}^{k}(t)$ is the pheromone concentration left by the k-th ant on the path (i, j) ,Q is the pheromone intensity coefficient, and $L_k$is the path length of the k-th ant iteration.

IV. IMPROVED ANT COLONY ALGORITHM

A. Improved Heuristic Information Function

Since the traditional Ant Colony Algorithm adopts the eight-direction search method, there are numerous directions to explore, making the nodes less informative. In the unmanned scenario, searching in too many directions can lead to slow speeds and the risk of falling into a local optimum.

This paper emphasizes the enhancement of the heuristic function, by introducing artificial potential field gravity and obstacle repulsion factors. At the target point, gravity is introduced, while at obstacles, repulsion is imposed. This set up ensures that the force of gravity acting on the vehicle is directly proportional to the distance between the vehicle and the target point, and that the repulsive force from obstacles is inversely proportional to the distance between the vehicle and the obstacles. The introduction of these two functions enhances the targeting in the search process, effectively reduces unnecessary calculations, and improves the search efficiency of the algorithm. The improved heuristic function $\eta_{ij}(t)^{*}$ is

$$\eta_{ij}(t)^* = \frac{Y}{d_{ij}} \tag{8}$$

That is, the traditional heuristic function is augmented with a coefficient Y, which serves as a factor representing the gravity in the artificial potential field.

$$Y = \mu^{fa \cdot h} \tag{9}$$

$$fa = \lambda \cdot d(i, E) \tag{10}$$

$$h = \frac{1}{2}\left(1 + cos\frac{\theta}{2}\right) \tag{11}$$

Substituting the above equation into the heuristic function gives $\eta_{ij}(t)^*$

$$\eta_{ij}(t)^* = \frac{\mu^{\lambda \cdot d(i,E) \cdot \frac{1}{2}\left(1+cos\frac{\theta}{2}\right)}}{d_{ij}} \tag{12}$$

Where Y is the factor of joining the artificial potential field gravity, fa is the artificial potential field gravity from the current node j to the target point, h is the obstacle rejection factor, θ represents the angle between the line from the vehicle to the obstacle and the line from the vehicle to the target point, μ is a constant with the value range of $(0,1)$;λ is the positive scale factor, $d(i, E)$ is the distance from the current node$i$ to the target point E . As the distance increases, the magnitude of the potential energy that the vehicle is subjected to correspondingly augments; conversely, as the distance decreases, the magnitude of the potential energy that the vehicle experiences diminish.

When The electric power inspection vehicle in the starting position point A, the angle $\theta_1 < 90^{\circ}$,$\cos\frac{\theta_1}{2}$ reduce rate slowly, at this time the obstacle repulsion factor $h \approx 1$, that is, the vehicle at the same time by the obstacle repulsive force and the target point of gravity, obstacle repulsive factor does not play a role; when the vehicle is located in the B point, the angle $\theta_2 > 90^{\circ}$ $cos\frac{\theta_2}{2}$reduce the rate of faster, obstacle repulsive factor$h$ gradually reduce and reduce the rate of fast, so that the inspiration function increases rapidly . At this time, the vehicle is almost unaffected by the obstacle repulsion, only by the gravitational force of the target point, to avoid the vehicle deviating from the ideal path due to the repulsive force is too large, as shown in figure 2.

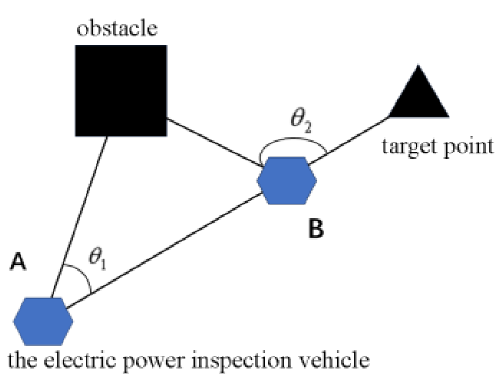

Figure 2. Effect of Obstacle Exclusion Factors on Vehicles at Different Locations

B. Improved Pheromone Update Rules

In the traditional Ant Colony Algorithm, as the ant colony continues to iterate, the pheromone concentration on the path gradually increases, and if the ants in front of them choose the wrong path, it may lead to the ants behind them to walk towards this path, which is easy to lead to a local optimum.

In this paper, an adaptive pheromone regulation mechanism is proposed, which involves adding the total pheromone concentration carried by all ants on the optimal path from the previous generation to the original pheromone increment, and subtracting the sum of pheromone concentrations carried by all ants on the worst path, to obtain the adaptive regulation pheromone $\Delta\tau_{ij}^*(t)$, which is updated as shown in the following equation.

$$\tau(t+1)^* = (1 - P) \cdot \tau_{ij} + \Delta\tau_{ij}(t) + \Delta\tau_{ij}^*(t) \tag{13}$$

$$\Delta\tau_{ij}^*(t) = \sum_{k=1}^{m} \Delta^*\tau_{ij}^k(t) \tag{14}$$

$$\Delta^*\tau_{ij}^k(t) = v \times \frac{Q}{Lmax_{min}} \tag{15}$$

where $\Delta\tau_{ij}^*(t)$ is the additional pheromone increment; $\Delta^*\tau_{ij}^k(t)$ is the pheromone increment left by the k ant on path (i, j), k is the number of ants on the worst path of this cycle, v is the number of ants on the optimal path of this cycle, L_{min} is the length of the optimal path of this iteration, and L_{max} is the length of the worst path of this iteration.

The improved pheromone updating rule can promote the accumulation of pheromone in the early iteration period, thus enhancing the convergence efficiency of the algorithm; it can inhibit the accumulation of pheromone in the late iteration period, thus avoiding the algorithm from falling into the local optimal situation.

C. Path Optimization and Updates

When the electric power inspection vehicle is searching for paths, the searched paths may have a large number of redundant nodes and turning points, and the vehicle not only needs to turn several times, resulting in the inability to increase the speed, but also travels through the paths to be on the long side, which is not conducive to the vehicle to quickly and accurately reach the vicinity of the destination.

Since the search rule of traditional Ant Colony Algorithm is the eight search method, which only randomly searches the eight directions around, it can not break the limitation that the step size is 1 or root 2. Therefore, in this paper, the triangular pruning method is used to remove the redundant turning points and folding lines, and the core idea is: the first node is connected separately to several other nodes according to the distance, if it does not pass through the obstacles, the node is discarded, and if it passes through the obstacles, the previous node is selected as the target point of the vehicle at the next moment, as shown in figure 3 below.

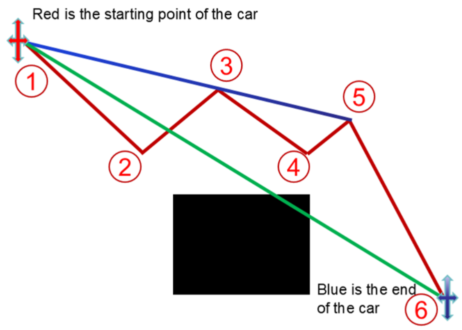

Figure 3. Schematic Diagram of Triangle Pruning

Let the sequential set φ be the set of checkpoints, $P = \{P_1, P_2, \dots, P_n\}$ be the set of turnpoints of the path to be optimized, R be the set of all the points on the line connecting the turnpoints P_i of the point φ_i to be checked, and T be the set of obstacles. Add the to-be-optimized turning point P_1 to the set of checkpoints, and then sequentially connect the set of turning points in P to the first element in the set φ, and add the points on the connecting line to the set R. If $T \cap R = \varphi$, then the current connection is used; if $T \cap R \neq \varphi$, then the current connection is not used; and add the elements of the set P to the first position of the set φ in order to verify, until all the elements of P are added to the set φ, the verification is completed. After judging all the turning nodes in turn, the path optimization is completed, and the optimized path points in the figure are 1-5-6.

D. Algorithm Flow

- Step 1: establish the grid environment model. Utilize the grid method to create 20×20 and 30×30 grid environments, determine the grid specifications, divide the free and obstacle grids, and set the starting point S and target point E.
- Step 2: initialize basic parameters. Focus on the pheromone importance factor α,the expected heuristic information importance factor β, the pheromone Volatilization Coefficient ρ, the maximum number of iterations of initialization parameter K and the number of ants M;
- Step 3: determine the path node. According to the probability selection principle of formula (2), the next target point of ants is determined, and all target points are added to the $TABU_K$ table until all m ants in this iteration reach the target point.
- Step 4: summarize the total number of ants corresponding to all paths, mark the ant path and path length of each iteration with different colors in the process of K iterations, stack the number of ants in the same path. Finally, all data are summarized and written into the cell storage cell.
- Step 5: update the pheromone. Based on the data in $TABU_K$ and cell, the optimal path and the worst path of each iteration are distinguished, and the number of ants is summarized. Use formula (13), (14), (15) to update pheromone concentration in real time.
- Step 6: complete the iteration, and determine whether iteration is required based on the maximum number of iterations K. If it is less than K, clear the taboo list and return to step 3. If it is equal to K, output the optimal path and its convergence curve.
- Step 7: optimize the output optimal path, optimize the output optimal path by combining with the triangle pruning method, and output the path map before and after optimization.

V. Experimental Simulation and Analysis

To verify the effectiveness of the improved Ant Colony Optimization algorithm in different grid environments, this paper conducts simulation experiments in grid environments of 20×20 and 30×30, with the proportion of obstacles being no less than 30% of the total grid count. The experimental environment is the MATLAB R2024a simulation platform. The values of the important parameters are: maximum number of iterations K = 200, number of ants M = 50, number of elite ants b = 5, pheromone importance factor α = 1, heuristic information importance factor β = 2, pheromone volatility = 0.8, pheromone increment Q = 10, and potential field constant *sigma* = 0.05.

A. Simulation Results and Analysis for 20×20

In a 20×20 grid environment, this paper conducts simulation experiments based on MATLAB R2024a, comparing the movement trajectories and convergence curves of the electric power inspection vehicle using both traditional and improved Ant Colony Optimization algorithms. To further optimize the movement path generated by the improved Ant Colony Optimization algorithm, the Triangle Pruning Method is employed for secondary optimization of the planned path, removing redundant turning points. In the figure below, the path without optimization using the Triangle Pruning Method is shown in red, while the optimized path with redundant nodes removed after applying the Triangle Pruning Method is shown in blue, as shown in figures 4, 5, 6, and 7 below.

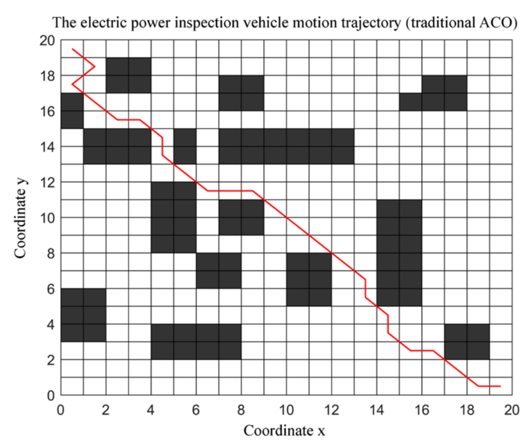

Figure 4. Path Planning Using Traditional Ant Colony Algorithm

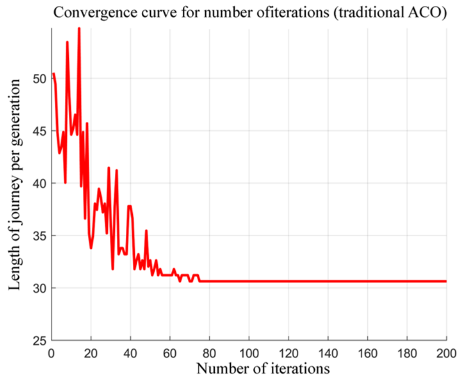

Figure 5. Convergence Curve of Traditional Ant Colony Algorithm

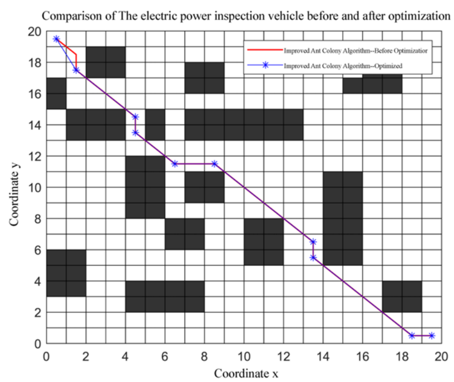

Figure 6. Path Planning Using Improved Ant Colony Optimization Algorithm

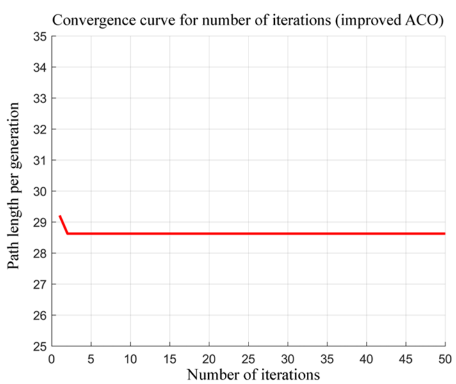

Figure 7. Convergence Curve of Improved Ant Colony Optimization Algorithm

In the 20×20 grid environment using the traditional Ant Colony Optimization algorithm, the path length of the electric power inspection vehicle is 30.63 centimeters, the running time is 8.07 seconds, there are 15 turning points, and convergence is achieved after 77 iterations. In the improved Ant Colony Optimization algorithm, the optimal path length of the electric power inspection vehicle is 28.45 centimeters, the running time is 3.61 seconds, there are 8 turning points, and convergence is achieved after 2 iterations.

Based on the above operational results, this paper compares the improved Ant Colony Optimization algorithm with the traditional Ant Colony Optimization. The optimal path length is reduced by 7.12%, the running time is reduced by 55.27%, and the number of turning points is reduced by 46.67%.

This indicates that the improved Ant Colony Optimization algorithm presented in this paper significantly reduces the path length, significantly accelerates the running time, significantly enhances the convergence speed, and significantly decreases the number of turning points. As shown in Table 1 below.

Table 1. Comparison of Experimental Results in a 20×20 Grid Environment

Algorithm	Optimal Path Length /cm	Running Time /s	Convergence Iterations	Turning Points
Traditional ACO	30.63	8.07	77	8.07
Algorithm in Literature[9]	29.21	6.54	21	6.54
Improved ACO	28.45	3.61	2	3.61

B. *Simulation Results and Analysis for 30×30*

To further validate the superiority of the improved algorithm presented in this paper, simulation experiments are conducted in a more complex 30×30 grid environment with unchanged parameters, as shown in figures 8, 9, 10, and 11 below.

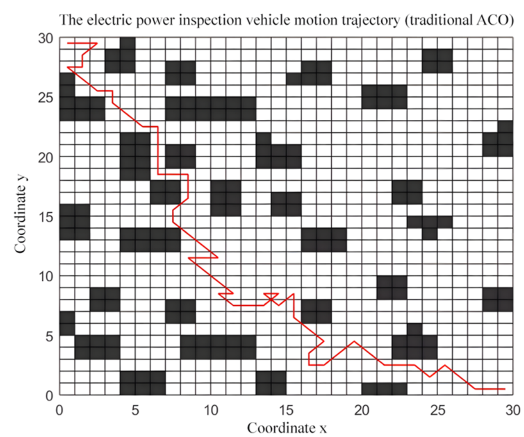

Figure 8. Path Planning Using Traditional Ant Colony Algorithm

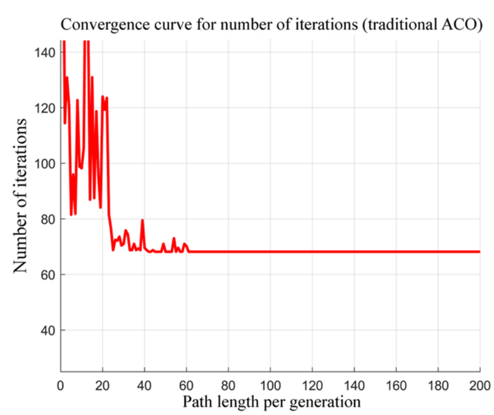

Figure 9. Convergence Curve of Traditional Ant Colony Algorithm

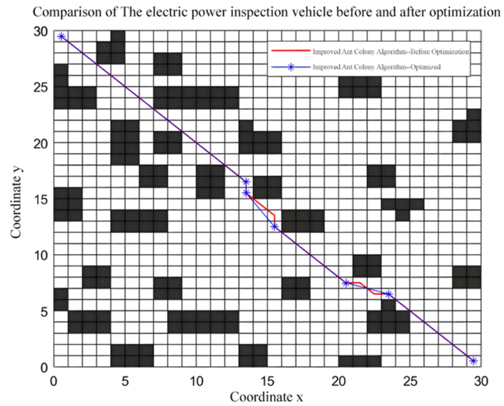

Figure 10. Path Planning Using improved Ant Colony Optimization Algorithm

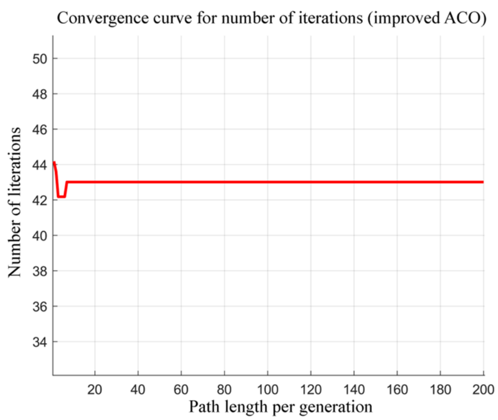

Figure 11. Convergence Curve of improved Ant Colony Optimization Algorithm

In a 30×30 grid environment using the traditional Ant Colony Optimization algorithm, the path length of the vehicle is 76.43 centimeters, the running time is 38.83 seconds, there are 35 turning points, and convergence is achieved after 62 iterations. In the improved Ant Colony Algorithm, the optimal path length of the vehicle is 41.71 centimeters, the running time is 31.58 seconds, there are 5 turning points, and convergence is achieved after 9 iterations.

Based on the above operational results, this paper compares the improved Ant Colony Algorithm with the traditional Ant Colony Algorithm. The optimal path length is reduced by 45.43%, the running time is reduced by 18.67%, and the number of turning points is reduced by 85.71%.

Similarly, with reference to the data on the Ant Colony Algorithm in literature[10], this paper concludes that in a 30×30 grid environment, the improved Ant Colony Algorithm demonstrates significant advantages in four aspects: optimal path length, running time, number of iterations to convergence, and number of turning points, compared to both the traditional Ant Colony Algorithm and the algorithm described in literature[10]. This indicates that the improved Ant Colony Algorithm proposed in this paper outperforms the traditional Ant Colony Algorithm, as well as the algorithms described in literature[9]and literature[10], in both simple and complex grid environments. As shown in Table 2 below.

Table 2. Comparison of Experimental Results in a 30×30 Grid Environment

Algorithm	Optimal Path Length /cm	Running Time /s	Convergence Iterations	Turning Points
Traditional ACO	76.43	38.83	62	35
Algorithm in Literature[10]	66.84	35.49	34	13
Improved ACO	41.71	31.58	9	5

VI. ROS SIMULATION EXPERIMENT VERIFICATION

In order to verify that the improved Ant Colony Algorithm algorithm is suitable for the power plant environment, this paper carries out ROS simulation experimental environment verification to compare the path differences before and after the algorithm improvement by simulating the real environment.

This paper examines the problem of power inspection in a power plant environment in the field of power and energy. The electric power inspection vehicle needs to move to each plant in real time to detect the operation of electric equipment, The vehicle is currently located in the first plant on the right, clockwise order is the second, third, four plants, four plants are stored in the important power equipment, the vehicle needs to move in real time to each plant to detect the operation of the power equipment, in the movement of the path there must be obstacles. and there must be obstacles in the path of movement. Obstacles, this paper uses a cylinder to replace the obstacles, built in the simulation environment. Then use Rviz for visualization, the 3D map is scanned into a complete 2D planar map, as shown in figure 12 below.

Figure 12. Two Dimensional Plane Map

The electric power inspection vehicle is enabled for navigation in ROS and placed on the right side of the first plant, which is considered as the starting point, and the path planner is opened in Rviz and the electric power inspection vehicle is given a goal command to move along the generated path towards the second plant. The electric power inspection vehicle is made to generate different navigation paths in the same power plant environment by calling traditional and improved algorithms, the path diagrams of Rviz and Gazebo are shown below. Where the green line is the movement path of the vehicle and the red arc is the obstacle edge line, as shown in figures 13 and 14 below.

Figure 13. Path Diagram of Traditional Algorithm

Figure 14. Path Diagram of Improved Algorithm

The above is based on the existence of static obstacles in the power plant under the conditions of the vehicle to plan the movement path, if the power plant suddenly appeared in the dynamic obstacles similar to people or vehicles, this paper's improved algorithm can also be adjusted in real time to the original route, to avoid collision at the same time continue to travel to the second power plant, as shown in figures 15, 16, 17, and 18 below.

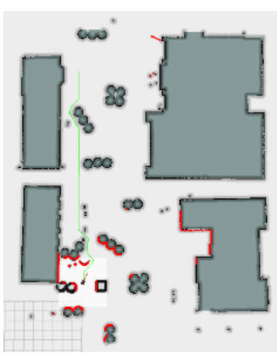

Figure 15. Path Map of Temporary Obstacles (Traditional Algorithm)

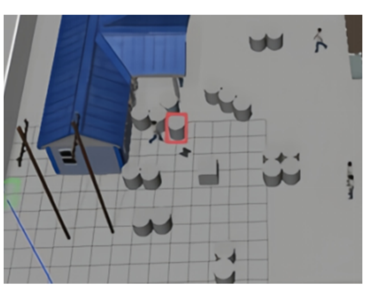

Figure 16. Gazebo Simulation Environment with Temporary Obstacles (Traditional Algorithm)

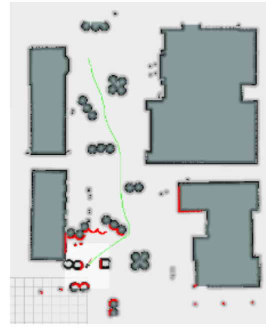

Figure 17. Path Map of Temporary Obstacles (improved algorithm)

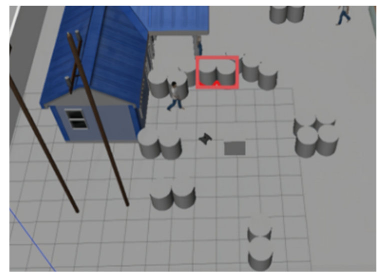

Figure 18. Gazebo Simulation Environment with Temporary Obstacles (Improved Algorithm)

When static obstacles exist in the power plant, observing the path diagrams of Figure 13 and Figure 14, The electric power inspection vehicle, if it moves along the path of the traditional algorithm, has a high probability of colliding with the static obstacles in front of the first plant, whereas the improved algorithm can avoid this problem. When there are dynamic obstacles in the power plant, observing the path diagrams in Figure 15 and Figure 17, the traditional algorithm still suffers from the above problem, while the improved algorithm can re-plan the path so as to bypass the obstacles that are dangerous.

Through the above ROS simulation experiment results, the path length and the number of turning points of the improved algorithm are significantly better than the traditional algorithm, and the vehicle can avoid obstacles and reach the target point with the shortest distance in both static and dynamic environments, which verifies the feasibility of the improved algorithm in this paper in the real 3D power plant environment.

VII. CONCLUSION

In this paper, an improved Ant Colony Algorithm is proposed for the high-voltage line risk and power equipment detection problems of power plants: (1) the gravitational force and obstacle repulsion factor of the artificial potential field are introduced, so that the heuristic function is affected by the joint action of the target point and the obstacle, and the eight-degree-of-freedom search principle of the traditional Ant Colony Algorithm is abandoned, and the convergence speed and optimization ability are accelerated; (2) In terms of pheromone update, the difference between the pheromone concentration of the optimal path and the worst path of the previous generation is added to dynamically update the pheromone increment and improve the path optimization ability. (3) The triangular pruning method is used to remove redundant nodes and broken lines, and the path length and the number of turns are reduced.

Through the comparison of Matlab and ROS simulation experiments, the results show that the improved algorithm significantly optimizes the path and reduces the collision risk, which is more effective and stable than the traditional Ant Colony Algorithm in the 20×20, 30×30 grid environment or in the real simulation environment.

REFERENCES

[1] Themistoklis Stamadianos, Andromachi Taxidou, Magdalene Marinaki, Yannis Marinakis. Swarm intelligence and nature inspired algorithms for solving vehicle routing problems [J]. Operational Research, 2024, 24 (3): 47-47.

[2] Wayan Firdaus Mahmudy, Agus Wahyu Widodo, Alfabiet Husien Haikal. Challenges and Opportunities for Applying Meta-Heuristic Methods in Vehicle Routing Problems[J]. Engineering Proceedings, 2024, 63 (1): 12-.

[3] Dubey Ghanshyam Prasad, Stalin Shalini, Alqahtani Omar, Alasiry Areej, Sharma Madhu, Aleryani Aliya, Shukla Piyush Kumar, Alouane M. Turki-Hadj. Optimal path selection using reinforcement learning based ant colony optimization algorithm in IoT-Based wireless sensor networks with 5G technology[J]. Computer Communications, 2023, 212 377-389.

[4] Jing Zeyuan, Kuang Huan, Leite Walter L., Marcoulides Katerina M., Fisk Charles L..Model Specification Searches in Structural Equation Modeling with a Hybrid Ant Colony Optimization Algorithm[J]. Structural Equation Modeling: A Multidisciplinary Journal, 2022, 29 (5): 655-666.

[5] Cai Jun, Zhong Zhiyuan.Path planning of a meal delivery robot based on an improved Ant Colony Algorithm [J]. CAAI Transactions on Intelligent Systems,2024,19(2):370-380.

[6] Wu Shuai, Wei Wenhong, Zhang Yuhui. Path planning of mobile robot based on improved Ant Colony Algorithm[J]. Journal of Dongguan University of Technology. 2023,30(01):24-34.

[7] Chen Danfeng, Lei Hao, Liu Junlang, He Jun. Research on Robot Path Planning Based on Enhanced Ant Colony Algorithm[J] Journal of Ordnance Equipment Engineering.2023,44(06):239-245+303.

[8] Xing Xiehong, Huang Kunrong, Tang Dewen. Robot path planning based on improved Ant Colony Algorithm[J]. Mechanical Management and Development,2023,38(11):1-4+9.)

[9] Yu Lianzhi, Qin Tian. Research on improved Ant Colony Algorithm in path planning of logistics robots [J]. Intelligent Computer and Application, 2022,12(10):62-67.)

[10] He Yaying, Fan Xinwei. Application of improved Ant Colony Algorithm in robot path planning[J]. Computer Engineering and Applications, 2021, 57(16):276-282.)