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Research on Path Optimization of Intelligent Inspection in Petrochemical Plant Area

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Abstract

Particle swarm optimization(PSO) and ant colony optimization(ACO) are commonly used methods to solve the inspection problem in path planning. Because the environment in petrochemical plant areas is mostly very complex, robots using a single algorithm to perform inspections often have problems such as overlapping paths and long time-consuming. In order to solve the above problems, this paper proposes a hybrid algorithm based on PSO to optimize the parameters of ACO while improving the pheromone update method. First, the PSO is used to optimize the relevant parameters of ACO, and then the pheromone is continuously updated during the particle operation and the entire algorithm solving process. In order to prove the superiority of this method, this method was compared with several other methods. Experimental results show that the method proposed in this paper converges faster, has fewer iterations, and under the same conditions, the optimal path is shorter. It provides a theoretical reference for path optimization in a closed environment.

Keywords

Intelligent Inspection; PSO; ACO; PSO-ACO; Path Optimization.

1. Introduction

With the increasing demand for energy in various countries around the world, petrochemical enterprises are the main channel of international energy supply, and their internal production safety and fire safety are the foundation of the development of the enterprise and the foundation [1]. Risk monitoring in the petrochemical plant area is an important part of plant safety. Accurate and rapid risk elimination can provide a reliable guarantee for safe operations [2]. Strengthening daily inspections and maintenance within the enterprise is one of the effective measures to reduce accidents and eliminate risks. However, due to the large internal area, multiple equipment, high degree of automation, complex environment, and many harmful and toxic substances in the petrochemical plant area, manual on-site inspections often rely on experience, and are low in efficiency, time-consuming and labor-intensive, and it is not always possible to accurately find faults [3]. But as smart energy has become an important part of the construction of modern energy industry. For the petroleum industry, the application of enabling technologies such as data transmission, Internet of Things, and big data analysis to the construction of plant areas can fill the gap in the application of smart technology in energy facility systems [4]. The emergence of intelligent inspection robots completely compensates for these shortcomings, greatly improves the feasibility of inspections, and reduces the probability of production safety risks. However, when intelligent robots perform inspections in complex petrochemical plant areas, most of them have problems such as overlapping paths and excessive time-consuming [5]. In response to the above-mentioned problems, this paper proposes a path optimization algorithm using particle swarm optimization to optimize the ant colony, so as to improve the efficiency of inspection, reduce the management cost of the enterprise, and provide better security guarantee.

Duguleana, M. et al. proposed a new method to solve the problem of autonomous movement of robots in the environment of static and dynamic obstacles, using Q-learning and neural network algorithms to provide mobile robots with uncertain work in stationary and moving entities Collision-free trajectory in space [6]. Xiong, N. Z. et al. proposed the Time Taboo Ant Colony Optimization Algorithm (TTACO), which improves the slow convergence speed, poor global search ability, and unknown time-varying dynamic obstacles in ant colony optimization path planning in a dynamic environment [7]. Huang, MD et al. proposed a new transition probability function, combining the angle factor function and the visibility function, and setting the penalty function through the new pheromone update model. The computer simulation experiment results prove that it is superior to the global path planning problem. Genetic algorithm and traditional ACO [8]. Porta, G. M. et al. proposed a new solution based on the simple ant colony optimization meta-heuristic (SACO-MH) to solve the path planning problem of mobile robots. The distance between the source point and the target point plays a role in path planning. Simulation experiments prove that the improved scheme improves the speed of path planning and effectively performs static and dynamic obstacle avoidance [9]. Xuan, R. Z. et al. proposed an improved A* algorithm that optimizes the A* algorithm through the ACO. The improved A* algorithm has shorter search paths, less time-consuming, smaller total corners, and smoother paths [10]. Lv, Q.D et al. proposed an improved particle swarm optimization algorithm and an objective function for path planning. The inverse learning strategy is used to initialize the particle swarm, while dynamically adjusting the inertia weight and learning factor to improve the global search ability, convergence accuracy and stability of the optimization algorithm [11]. Miao, Y. et al. proposed an improved PSO algorithm combining Simulated Annealing from three aspects: parameter adjustment, organizational structure and evolution, and topological structure. Four commonly used test functions are then used to test the optimized performance of the improved PSO algorithm and applied to PID parameter tuning [12]. Tian. et al. proposed an improved particle swarm optimization algorithm (PSO-IBLI) based on the leader-individual interaction mechanism to overcome the shortcomings of the classic PSO algorithm with low optimization accuracy and immaturity. Experimental results show that the accuracy and convergence speed of the PSO-IBLI algorithm is higher than the other three different algorithms [13]. Ren, M. H. et al. also proposed an improved FP-PSO (Fixed-point PSO) algorithm that introduces the simple algorithm (SA) of fixed point theory into the optimization of PSO. The results show that, especially under complex conditions, the convergence accuracy, stability and robustness of the FP-PSO algorithm are significantly better than the existing improvement strategy of optimizing the PSO algorithm by optimizing the initial population [14].

The above-mentioned documents proposed to use ACO and PSO to solve the path optimization problem, and achieved certain optimization results. But they still have a lot of optimization, so there are many authors who think that combining them will have better optimization results.

Ming, L. Y. et al. proposed a fuzzy rule optimization algorithm based on the fusion of adaptive ant colony optimization and particle swarm optimization to generate optimized fuzzy rules. Realize the complex target detection and moving target tracking and the intelligent motion planning of complex operation tasks in the disturbed environment [15]. Wei, P.C. et al. proposed a particle swarm optimization algorithm combined with ant colony optimization algorithm for grid scheduling optimization algorithm, which effectively solves the problem of resource load balancing and task scheduling in the grid. Compared with traditional algorithms, it has comprehensive advantages in terms of time efficiency and solution accuracy [16]. Li, D. H. et al. proposed a particle swarm optimization combined with ant colony optimization (PSO-ACO) algorithm that introduced pseudo-random proportional rules. Alleviate the problem of particle swarm optimization with linearly decreasing weight (LDW-PSO) algorithm falling into the local optimal problem, and speed up the search speed [17]. Elloumi, W. N. et al. proposed a method that combines fuzzy logic with ACO (FACO-Fuzzy Ant Colony Optimization) and PSO (FPSO-

Fuzzy Particle Swarm Optimization) to solve the Traveling Salesman Problem (TSP). The experimental results show that fuzzy logic takes less time to get a better path in solving the TSP problem [18]. Kuo, R.J. et al. proposed a new hybrid meta-heuristic algorithm (ACPSO) that combines ant colony optimization (ACO) and particle swarm optimization (PSO). The problem of job shop scheduling with expiration data time window and release time is solved. The experimental results show that the performance of ACPSO is better than ACO and PSO [19]. Deng, W. C. et al. proposed a new two-stage hybrid swarm intelligent optimization algorithm GA-PSO-ACO algorithm that combines the evolutionary ideas of genetic algorithm, particle swarm optimization and compensation-based ant colony optimization. The calculation efficiency and solution quality are greatly improved, and with the increase of the TSP scale, the convergence speed is faster and better [20]. Xu, Q. M. et al. proposed a fusion algorithm that uses particle swarm optimization algorithm to roughly search the global path based on the improved grid method and eliminates some bad paths according to the pheromone content [21]. Zhao, J. et al. proposed a method to optimize the three parameters α, β, rho by designing two fuzzy controllers. This strategy overcomes the weakness that is easy to fall into local optimization during path optimization and improves the ant colony. The efficient convergence of the optimization algorithm [22]. Qian, H. T. et al. proposed a hybrid algorithm combining ant colony optimization algorithm and particle swarm optimization algorithm (ACO-PSO) for the traveling salesman problem. Use the Max-Min Ant System of PSO to optimize the parameters to solve the problem [23]. Wu, C. Z. et al. proposed an improved ACO that quantifies the length of urban roads, the number of lanes, and the flow of inbound and outbound vehicles, and introduced an improved ACO that replaces the road factor of particle swarm optimization and ACO distance parameters.

Table 1. Comparison of advantages and disadvantages of five algorithms

Algorithm name	Neural network algorithm	Genetic algorithm	Simulated annealing algorithm	PSO	ACO
Advantages	1.Strong ability to process uncertain information	1. Strong global search ability	1. It is not easy to fall into the local optimum	1. The algorithm is simple and easy to understand	1. The algorithm has high accuracy
	2. Strong nonlinear fitting ability	2. Easy to integrate with other algorithms	2. Robust performance	2. Simple programmig 3. Strong robustness	2. Strong global search ability
Shortcoming	1. Convergence is slower	1. Local convergence speed is slower	1. Strong dependence on the initial temperature setting	1. The convergence speed is faster in the initial stage and slower in the later stage.	1. The initial convergence speed is slow
	2. Easy to lose information 3. Easy to fall into local optimum	2. Easy to fall into local optimum	2. The choice of annealing temperature coefficient has a greater impact on the algorithm	2. Easy to premature convergence	2. The selection of parameters is random

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The improved algorithm has obvious path optimization effects, effectively reducing the average congestion rate from 9.73% to 13.63% [24]. Shi, C. et al. proposed a hybrid algorithm that uses particle swarm optimization (PSO) to optimize ACO parameters to solve the path planning problem of mobile robots in a three-dimensional environment. Through 3D simulation experiments, the results show that the effect of the hybrid algorithm is better than PSO and ACO [25].

The above-mentioned literature proposes a combination of PSO and ACO to optimize the parameters, change the pheromone update method and other methods to optimize the path. Compared with a separate PSO or ACO, the combined algorithm has a better optimization effect. By comparing the advantages and disadvantages of traditional and commonly used MetaHeuristic Algorigthm such as neural network algorithm, genetic algorithm, simulated annealing algorithm, PSO, and ACO, as shown in Table 1, we can also find that the advantages of PSO are used to It is indeed a good choice to make up for the shortcomings of ACO. So this paper proposed a hybrid improved algorithm based on PSO optimization ACO(PSO-ACO). This method would use PSO to optimize the parameters of the ACO, and at the same time select the pheromone update method that combines global synchronization and elite strategy to improve the convergence iteration speed and local search ability of the ACO.

This research has made the following contributions:

(1) An inspection model of the petrochemical plant area was established.

(2)The pheromone update method of the ACO is improved, and the relevant parameters of the ACO are optimized.

(3)Established a hybrid model of PSO and ACO. The inspection cost is saved and the inspection efficiency is improved.

The structure of the rest of the article is arranged as follows. The related model established in Chapter 2 and the improved method of ACO based on PSO (PSO-ACO) are introduced. The third chapter is a comparative simulation analysis of the above models and algorithms, finally puts forward a summary.

2. Model Establishment

2.1. Establishment of the Patrol Inspection Model of the Petroleum Plant

The intelligent inspection robot wants to visit m inspection points in the petrochemical plant $a_m(m = 1,2, \dots m)$, each inspection point only inspects once, and finally returns to the initial inspection point to find the shortest inspection path. Its mathematical model is as follows: Suppose the path to visit m inspection points is represented by L, $L = (L_1, L_2, \dots, L_m)$, $L_m = (x_m, y_m)$, then the distance between two inspection points a and b is:

$$d_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \tag{1}$$

The total distance of the inspection path is:

$$D_{ab} = \sum_{\substack{a=1 \\ a=1}}^{\substack{a=m \\ b=m}} d_{ab} \tag{2}$$

Equation (2) is the model that the algorithm designed in this paper needs to be optimized.

2.2. ACO

The problem to be solved in this paper is that the inspection robot starts from the initial inspection point, passes through all inspection points and cannot be repeated, and then obtains a shortest path. $p_{ab}^k(t)$ Represents the probability that ant k chooses to move to inspection point b when it is currently inspecting point a. The formula is as follows:

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$$p_{ab}^{k}(t)=\begin{cases}\frac{\tau_{ab}^{\alpha}(t)\eta_{ab}^{\beta}(t)}{\sum_{s\in allowed_k}\tau_{as}^{\alpha}(t)\eta_{bs}^{\beta}(t)} & s\in allow_k\\ 0 & s\notin allow_k\end{cases} \tag{3}$$

In the formula $\tau_{ab(t)}$ represents the pheromone concentration on the path of inspection point a and inspection point b at time t, $\eta_{ab(t)}$ is the heuristic factor , $\eta_{ab(t)}=\frac{1}{d_{ab}}$, d_{ab} is the distance between inspection point a and inspection point b, $allowed_k$ is the set of next inspection points that ant k can choose. α represents the degree to which the path is valued, β Indicates the degree to which heuristic information is valued.

2.3. PSO

In the iterative process of the PSO, the particles update their position and velocity according to equations (4) and (5):

$$V_a(t+1)=\omega V_a(t)+c_1r_1\left(p_{BEST}\mp x_a(t)\right)+c_2r_2\left(g_{BEST}\mp x_a(t)\right) \tag{4}$$

$$X_a(t+1)=X_a(t)+V_a(t+1) \tag{5}$$

In the formula, $V_a(t)$ and $X_a(t)$ correspond to particle is velocity and position when it is calculated t iterations, ω is the inertia weight, c_1 and c_2 are acceleration factors, r_1 and r_2 are two random numbers, and t represents the algorithm the current number of iterations.

2.4. Establishment of PSO-ACO Model

1) Optimize the parameters of the ACO

Ant algorithm is based on the change of pheromone concentration to work out the optimal path. Although the ACO has achieved good results in optimizing the TSP problem, it also has some shortcomings. Because the algorithm is a classic probability algorithm, the initial parameters of the algorithm are randomly given based on people's experience, which leads to poor stability of the algorithm. On the contrary, unlike the ACO, the PSO has a fairly fast approach to the optimal solution, and can quickly and effectively select the optimal parameters of the ACO. Therefore, this paper uses PSO to optimize the ACO parameter α,β to solve the intelligent inspection path optimization problem.

The steps of PSO for ACO parameter α,β are as follows:

Step1: Initialize a certain number of particles $p_0,p_1,\dots,p_m$.

Step2: Feedback the current parameter value corresponding to each particle back to the ACO. A particle corresponds to a set of parameters. Use this set of parameters α,β,ρ to call the ACO once, and then update the pheromone in the environment.

Step3: Judge the pros and cons of the particle position according to the solution result of the ACO, and update P_{best} and G_{best}.

Step4: Update the speed and position of the particles according to the formula (6) and formula (7):

$$V_a(k+1)=\omega V_a(k)+c_1r_1\left(p_a-x_a(k)\right)+c_2r_2\left(p_a-x_a(k)\right) \tag{6}$$

$$X_a(k+1)=X_a(k)+V_a(k+1) \tag{7}$$

In formula (7), ω represents the weight of inertia, c_1,c_2 represents a constant, r_1 and r_2 are random numbers in the interval [0,1]. Represents the current optimal position, and $X_a(k)$ represents the position of the particle a in the kth generation.

Step5: When the particles can no longer produce particles with better performance during evolution, the algorithm will terminate and return to the particle position of the global optimal

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performance. The two optimal combinations in the ACO are the parameter α, β, ρ. When the algorithm is not reached, the algorithm terminates When the condition is met, return to the second step.

2) Improve the pheromone update method

The selection of the pheromone update method has an extremely important impact on the solution quality of the ACO [20-25].

The following is the formula for updating pheromone by traditional ACO:

$$\tau_{ab}(t+1) = (1-\rho)\tau_{ab}(t) + \Delta\tau_{ab}(t) \tag{8}$$

$$\Delta\tau_{ab}(t) = \sum \tau_{ab}^{k}(t) \tag{9}$$

In formulas (8) and (9), ρ represents the degree of pheromone volatilization, the value range of pheromone is [0,1], and $\Delta\tau_{ab}^{k}(t)$ represents the amount of pheromone released by ant K in the path interval at this stage at time t, $\Delta\tau_{ab}$ is the increase in pheromone concentration.

In this paper, the ant week model is used as the updated model of the pheromone volatilization method, so we can get:

$$\Delta\tau_{ab}^{k}(t) = \begin{cases} \frac{Q}{L_k} & \textit{ant k passes though } [a,b] \\ 0 & \textit{otherwise} \end{cases} \tag{10}$$

In formula (10), L_k represents the total distance traveled by the ants in the inspection process, and Q represents the pheromone content.

Aiming at the problem of the traditional ACO pheromone update that cannot accumulate enough pheromone in a short time, this paper uses the pheromone that is continuously updated during the entire algorithm solving process while updating between particles. Global synchronization is similar to the elite strategy. The combined pheromone update method is used to solve the problem.

When the parameter changes, the pheromone is not reinitialized. This method can retain and accumulate enough environmental information in a short period of time to greatly reduce the number of iterations of the called ACO to reduce time consumption. When there is no optimal solution, the pheromone update formula is shown in equations (8) and (9). When a better solution appears, the concentration of the pheromone left by the elite ants is enhanced, and the pheromone is updated according to the formula (11):

$$\tau_{ab}(t+1) = (1-\rho)\tau_{ab}(t) + \Delta\tau_{ab}(t) + \Delta\tau_{ab}(\acute{t}) \tag{11}$$

$\tau_{ab}(t)$ in formula (11) is obtained by formula (9), $\Delta\tau_{ab}(\acute{t})$ is the optimal pheromone concentration left by the ant on the path $[a,b]$ duri1ng the iterative solution process of this path, and has:

$$\Delta\tau_{ab}(t) = \begin{cases} \frac{Q}{G_k} & [a,b] \textit{ in the best path} \\ 0 & \textit{otherwise} \end{cases} \tag{12}$$

In formula (12), G_k is the length of the shortest path. Therefore, step 2 can be changed to: return the parameter value corresponding to each initial particle to the ACO. A particle corresponds to a set of parameters. α, β, ρ uses this set of parameters to calculate the ACO once. When the parameters change, the pheromone is not renewed. initialization. If no better path planning solution appears, the pheromone update formula is shown in equations (8) and (9). When there is a better planning path result, it starts to enhance and update the pheromone concentration left by the elite ants according to formula (11).

The flowchart of the hybrid algorithm solving process is shown in Fig 1.

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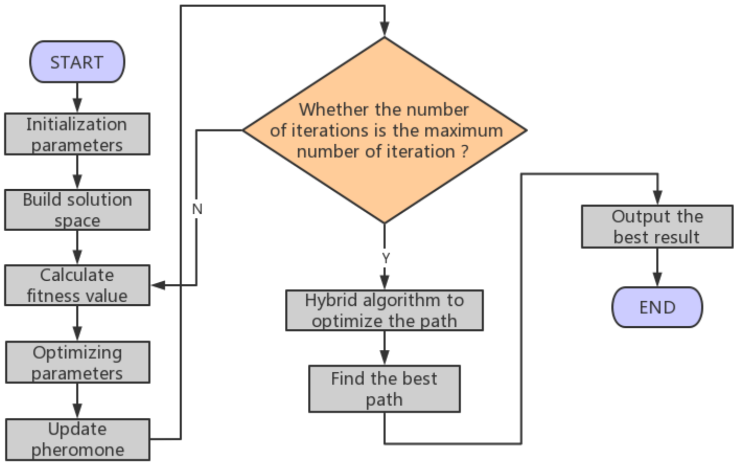

Fig 1. PSO-ACO hybrid algorithm solution flow chart

3. Simulation and Analysis

In order to verify the performance of the PSO-ACO, this experiment uses an example of 30 inspection points in the petrochemical plant area to use PSO, ACO, and PSO-ACO to conduct simulation experiments to verify the algorithms proposed in this paper are superior to the other two algorithms. The coordinates of 30 inspection points are shown in Table 2.

Table 2. The coordinates of 30 inspection points

Inspection point	X axis coordinate	Y axis coordinate	Inspection point	X axis coordinate	Y axis coordinate
1	101	200	16	371	137
2	263	142	17	454	161
3	400	203	18	426	257
4	346	126	19	388	211
5	260	169	20	365	253
6	321	159	21	403	279
7	310	99	22	429	299
8	409	111	23	340	188
9	416	89	24	360	216
10	448	87	25	319	268
11	286	207	26	334	314
12	175	125	27	277	337
13	289	145	28	324	355
14	234	176	29	288	288
15	133	69	30	216	286

3.1. Simulation Analysis of ACO

In this algorithm, the number of ants is 50, the number of iterations is 200, the pheromone importance factor is 1, the heuristic function importance factor is 5, and the pheromone volatilization factor is 0.1. The shortest distance and average distance obtained in each iteration are shown in Fig 2, and the ACO path plan is shown in Fig 3.

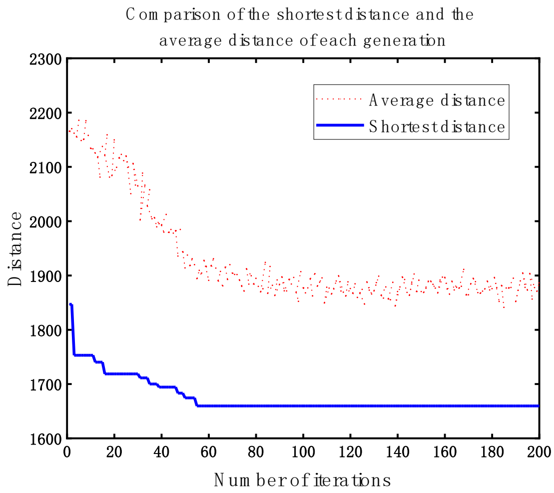

Fig 2. ACO iteration result graph

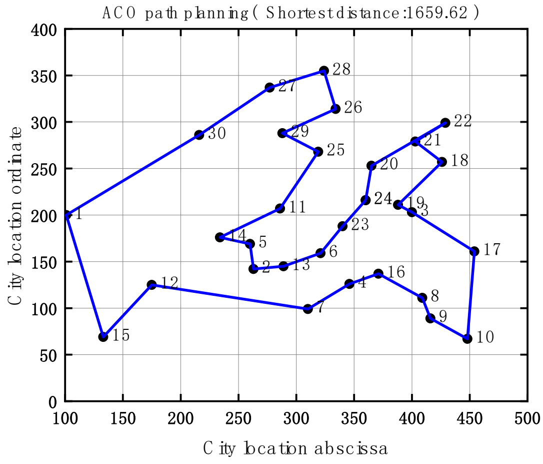

Fig 3. ACO path planning

It can be seen from Fig 2 that the ACO has excellent performance in solving this path optimization problem, and the algorithm has a relatively fast convergence speed. It converged in 55 iterations, and the shortest distance was 1659.62m. Since the small example form and structure of the 30-node TSP problem is relatively simple, the ACO adopts a positive feedback mechanism and has a certain global optimization capability, so the mature ACO can quickly and effectively find the optimal solution.

3.2. Simulation Analysis of PSO

PSO is a commonly used algorithm to solve TSP problems, and it is often used to optimize and solve various problems. So this article first uses PSO to solve the problem. In this simulation experiment, the number of particles is 500, the number of iterations is 2000, and the inertia weight is 1. The iterative result of the PSO optimization process is shown in Fig 4. The path planning of the PSO is shown in Fig 5.

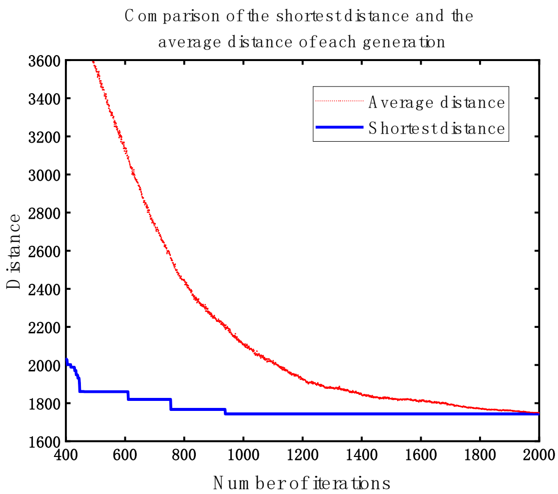

Fig 4. PSO iteration result graph

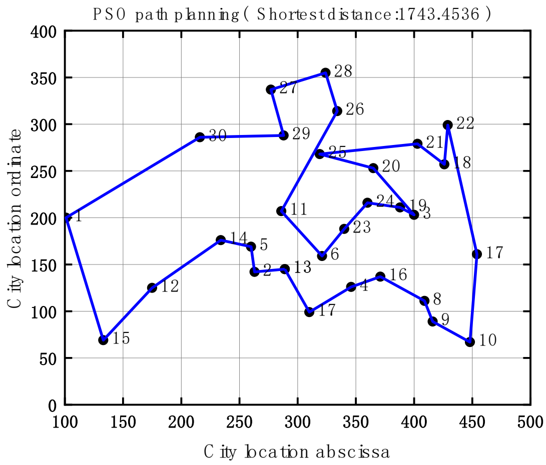

Fig 5. PSO path planning

It can be seen from Fig 4 that the performance of the PSO is average. Due to the fast convergence speed in the initial stage of the algorithm and the slow convergence speed in the later stage, the overall convergence time is longer. It takes 939 iterations to converge, that is much greater than the 55 iterations of the ACO. The shortest distance is 1743.4536m. Compared with the ACO, the PSO has a shorter time for each iteration, but relatively speaking, the number of iterations increases. Generally speaking, the performance of PSO is not as good as ACO in solving small-scale TSP problems.

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3.3. Simulation Analysis of PSO-ACO

Through the simulation analysis of the previous two sections, it is concluded that the performance of the ACO is better than that of the PSO, but the simulation results of the improved algorithm are shown below. In this algorithm, the number of ants is 50, the number of iterations is 200, and the pheromone volatilization factor is 0.1. The iterative result of the PSO-ACO is shown in Fig 6. The path planning after the particle swarm optimization ACO is shown in Fig 7.

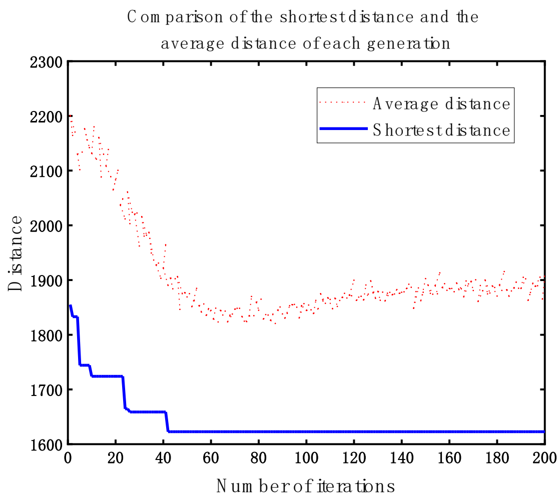

Fig 6. PSO-ACO process iteration results

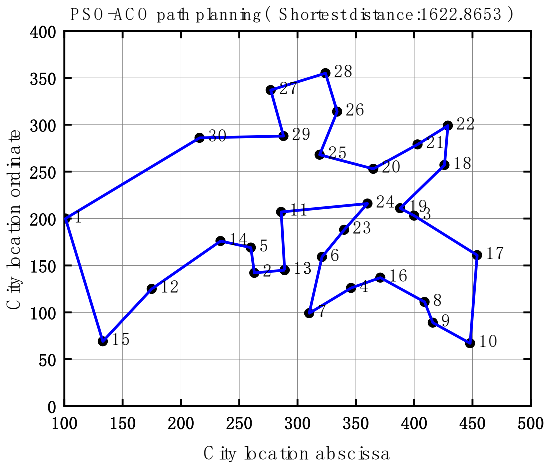

Fig 7. PSO-ACO path planning

It can be seen from Fig 6 that the PSO-ACO had converged after 42 iterations. Compared with the previous two algorithms, the number of iterations is significantly better than the 939 times of the PSO and the 55 times of the ACO. And the shortest distance is 1622.87m, which is 120.58m shorter than the PSO's 1743.45m, and 36.75m shorter than the ACO's 1659.62m. It can be explained that the pheromone update method of optimizing the parameters of the ACO through the PSO and the combination of global synchronization and the elite strategy has higher accuracy and better optimization effect than the PSO and ACO. The iterative result is closer to the optimal solution of the test function, and the volatility of the data is relatively small. In summary, the improved ACO has better performance than the PSO and the most primitive ACO. The optimal paths of the three algorithms for path optimization are shown in Table 3.

Table 3. Comparison of the results of the three algorithms

Algorithm name	Shortest distance	Optimal path
PSO	1743.4536m	1→15→12→14→5→2→13→7→4→16→8→9→10→17→22→18→21→25→20→3→19→24→23→6→11→26→28→27→29→30→1
ACO	1659.62m	1→15→12→7→4→16→8→9→10→17→3→19→18→21 →22→20→24→23→6→13→2→5→14→11→25→29→26→28→27→30→1
PSO-ACO	1622.8653m	1→30→29→27→28→26→25→20→21→22→18→19→3→17→10→9→8→16→4→7→6→23→24→11→13→2→5→14→12→15→1

It can be seen from Table 3 that the shortest distance of the PSO is 1743.45m, the shortest path of the ACO is 1659.62m, and the shortest path of the PSO-ACO is 1622.87m. It can be seen from the analysis that the PSO-ACO Compared with the ACO path reduced by 2.21%, compared with the PSO path reduced by 6.91%, the PSO-ACO had achieved better path optimization results.

4. Conclusion

In the actual production and operation of the petrochemical plant area, the early warning and elimination of risks is a very important part. Aiming at the problems of path overlap and time-consuming in the inspection process of intelligent robots in petrochemical plant areas, an improved path optimization algorithm based on particle swarm optimization ACO is proposed

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to improve inspection efficiency and reduce inspection costs. . Through computer simulation analysis, the results show that the PSO converges after 939 iterations, and the shortest path is 1743.45m; the ACO converges after 55 iterations, and the shortest path is 1659.62m; the PSO-ACO has passed Convergence after 42 iterations, the shortest path is 1622.87m. The PSO-ACO reduces the path of 2.21% compared with the ACO, and reduces the path of 6.91% compared with the PSO. It can be seen that the PSO-ACO has achieved better results than the ACO and PSO in the process of optimizing the closed curved inspection path.

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