HIGH TECHNOLOGY LETTERS | Vol. 30 No. 2 | June 2024 | pp. 109-116

doi:10.3772/j. issn. 1006-6748. 2024. 02. 001

A path planning method for robot patrol inspection in chemical industrial parks[①]

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Abstract

Safety patrol inspection in chemical industrial parks is a complex multi-objective task with multiple degrees of freedom. Traditional pointer instruments with advantages like high reliability and strong adaptability to harsh environment, are widely applied in such parks. However, they rely on manual readings which have problems like heavy patrol workload, high labor cost, high false positives/negatives and poor timeliness. To address the above problems, this study proposes a path planning method for robot patrol in chemical industrial parks, where a path optimization model based on improved iterated local search and random variable neighborhood descent (ILS-RVND) algorithm is established by integrating the actual requirements of patrol tasks in chemical industrial parks. Further, the effectiveness of the model and algorithm is verified by taking real park data as an example. The results show that compared with GA and ILS-RVND, the improved algorithm reduces quantification cost by about 24% and saves patrol time by about 36%. Apart from shortening the patrol time of robots, optimizing their patrol path and reducing their maintenance loss, the proposed algorithm also avoids the untimely patrol of robots and enhances the safety factor of equipment.

Key words: path planning, robot patrol inspection, iterated local search and random variable neighborhood descent (ILS-RVND) algorithm

0 Introduction

There are huge instrument clusters in the chemical industrial parks, whose digital development needs can not be met by simple readings from automatic pointer instruments. To realize digital management of the parks, patrol inspection should be carried out within the designated time window and the instrument readings should be uploaded to the database. This requires task assignment, path control and large-scale real-time data exchange for multiple groups of patrol robots. With the development of 5G technology and the maturity of autonomous mobile robots, large-scale real-time data transmission between robots and background has now been realizable, along with the autonomous inter-point movement of robots. Hence, to a certain extent, the remaining task can be reduced to a path planning problem with a time window[1-5].

Patrol inspection of chemical industrial parks should have time window constraints, and robots need to be subject to multiple constraints like battery energy consumption constraints. Therefore, the inspection is a multi-constraint path optimization problem with economic cost as the optimization objective. The solving methods can be classified into two major categories: one is the exact solution methods, and the other is the heuristic algorithms. Exact solution methods include branch and price, set partitioning and column generation. Heuristic algorithms include tabu search, ant colony, genetic and variable neighborhood descent (VND) algorithms[6-9].

Vehicle routing problem first emerged abroad. In 1956, Flood[10] proposed the traveling salesman problem (TSP), which discussed about a shortest path for salesmen to travel through all locations on a map. Dantzig and Ramser[11] generalized a single TSP to the path optimization problem of multiple tanker trucks filling gas in stations. Since then, many constraints have emerged for different scenarios, such as the vehicle capacity limitations[12] and the time window constraints[13]. Because there should be time window constraints on the patrol inspection of chemical industrial parks, where robots need to be subject to multiple con-

① Supported by the National Key R&D Plan of China (No. 2021YFE0105000), the National Natural Science Foundation of China (No. 52074213), the Shaanxi Key R&D Plan Project (No. 2021SF-472) and the Yulin Science and Technology Plan Project (No. CXY-2020-036).

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Received on Aug. 18, 2023

straints like battery energy consumption constraints, the inspection is a multi-constraint path optimization problem with economic cost as the optimization objective. Laporte et al.[14] used the branch-and-price method to solve the relaxation problem corresponding to the vehicle routing problem. If the solution was an integer, the solving would be stopped; otherwise, the problem would be divided into sub-problems for solving. Marwa et al.[15] adopted the variable neighborhood local search algorithm to solve the capacity-limited vehicle routing problem. By manually setting neighborhood search operators, it implemented alternate search with the utilization of different neighborhood search operators, and evaluated the pros and cons of the solution via objective function.

In summary, although exact solution algorithms can obtain optimal solution to the problem, they are computationally time consuming. With the increasing scale and complexity of problem, the temporal and spatial complexities of computation will increase exponentially. Since the patrol path planning problem in chemical industrial parks is large in scale, the computational time and cost of the exact solution algorithms are demanding. Hence, during the patrol path planning of such parks, a mathematical model of robot patrol path needs to be established according to the actual conditions. Besides, a path planning algorithm that takes due consideration of computational cost, optimization effect and algorithm scale is required as well. In this study, an improved ILS-RVND algorithm is proposed, with a view to better enhancing the robot patrol effect[16-23].

1 Mathematical modeling for robot patrol path in chemical industrial parks

1.1 Description of the park environment

In the chemical industrial parks, pointer-type instruments are mainly used, which can not collect data automatically and over-relies on the manual patrol inspection, easily posing security risks to the parks. Moreover, the cost of manual inspection is rather high. Next, in such parks, the pointer instruments are distributed unevenly. The patrol inspection faces two major difficulties: the first is the large patrol area, which easily leads to missed inspection and reinspection; the second is the restricted patrol (e. g. inapplicability of robot patrol inspection in some towers), which delays timeliness and integrity.

There are two methods for inspecting pointer instruments in the chemical industrial parks. One is the fixed pan/tilt/zoom (PTZ) cameras, which can expand the field of view via PTZ, but are immobile and very expensive. Given their exceptional real-time acquisition of the pointer instrument images, it is unnecessary to consider the real-timeliness problem of these cameras, which can only achieve pointer instrument inspection in a certain area. The second method is the patrol robot-based inspection of pointer instruments, where the robots patrol various areas carrying cameras. Despite its high flexibility, the real-timeliness is a concern due to the large area of the parks. Compared with the former method, this inspection measure greatly reduces the costs.

Hence, during the design of pointer instrument inspection system for chemical industrial parks, fixed PTZ cameras are arranged in places that are hardly reachable by patrol robots (e. g. towers), while the remaining places are inspected by the robots. In this paper, only the path planning problem of patrol robots is discussed.

1.2 Problem description

There are substantial inspection points distributed in the chemical industrial parks, as shown in Fig. 1. The staff formulates inspection requirements on these points according to actual needs, as well as on their timeliness, i. e. the patrol inspection tasks with time windows. After receiving an inspection task, the patrol system deploys the patrol robots from the robot site, plans the path, and implements inspection at the inspection points through the cooperation of various robots. Finally, the robots which have completed inspection return to the robot site for maintenance and standby. Fig. 2 illustrates the task path planning.

To describe the problem more clearly, the following assumptions are added to the above description.

(1) Patrol robots need to return to the starting site after completing the inspection.

(2) Patrol robots have uniform model, constant velocity along the path, as well as homogeneous power consumption.

(3) During each inspection, the time and power consumption at the same inspection points are identical.

(4) At the time of departure, patrol robots are fully charged.

(5) Patrol robots navigate accurately between two points.

(6) At each robot site, the number of patrol robots is full.

(7) Assuming that the navigation path is a straight line between two inspection points.

1.3 Model building

(1) Symbol description

Symbols used for patrol path planning problem are

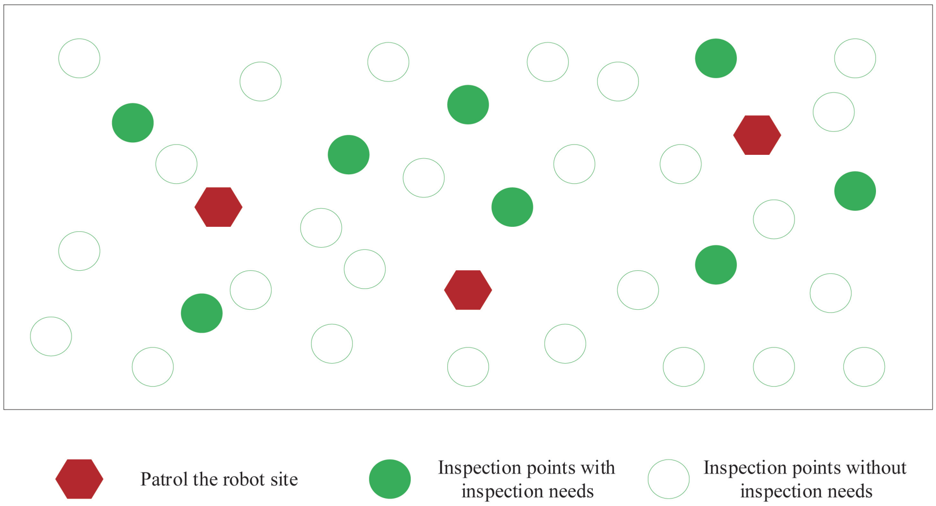


Fig. 1 Inspection need diagram for chemical industrial parks

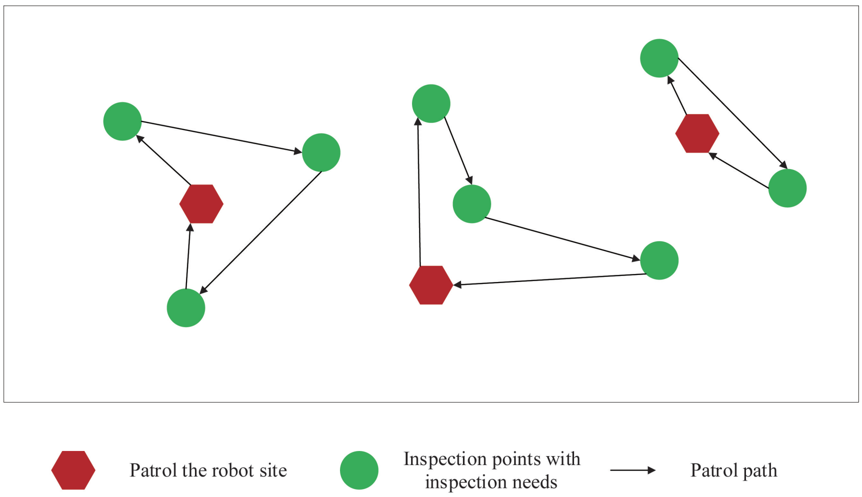


Fig. 2 Patrol inspection schematic for chemical industrial parks

described as follows. The set of patrol robot sites is $F = \{F_1, F_2, \cdots, F_N\}$; the set of inspection points with inspection needs is $K = \{K_1, K_2, \cdots, K_N\}$; the set of patrol robots is $R = \{R_1, R_2, \cdots, R_N\}$; the power consumption required at inspection point i is A_i; the power consumption required for path (i, j) is P_{ij}; the earliest inspection time at inspection points is e_k; the latest inspection time at inspection points is l_k; the timeout cost coefficient is θ; the number of patrol robots at robot site f is d_f; the number of patrol robots used is d_r; the maintenance cost required after single actuation of robots is S; the maintenance cost required for actuating one robot site is m; the maintenance cost required for patrol robots per unit power consumption is w; the risk cost borne by inspection timeout at inspection points is g; the total cost required for one inspection is $Cost$; the robot travel path is x_{ijr}^{f}. When x_{ijr}^{f} is 1, it indicates that the robot r at site f moves from inspection points i to j; when x_{ijr}^{f} is 0, it indicates other conditions.

(2) Penalty function

During the park patrol inspection, some timeouts may occur. For example, the inspection task at point 1 scheduled between 8:00 and 9:00 may be completed at 10:00. Such timeout phenomenon produces completely varying effects on different pointer instruments at different inspection points. For example, in a control process, inspection timeout of 15 min may cause explosion of a key point data due to insufficient variable monitoring. Conversely, the timeout at a certain hydraulic inspection point is insignificant, which produces no impact on the chemical industrial parks.

Thus, the penalty cost should be designed for the corresponding inspection point. Suppose $[e_k, l_k]$ is the time window of inspection point. If the robot arrives at the inspection point within the time window, there will be no risk cost. If the time window constraint of the inspection point is violated, a certain risk cost will be imposed, which is calculated according to Eq. (1).

$$g(i,j) = \begin{cases} 0 & l_k < t < e_k \\ \theta_c \quad \max(\mid t - e_k \mid, \mid t - l_k \mid) \end{cases} \quad (1)$$

where $c(t)$ represents the risk function for patrol inspection at point k within time t; θ denotes the timeout cost coefficient; $g(i,j)$ is the risk cost of the ith patrol robot at inspection point j.

Its mathematical model is expressed as follows.

$$Cost = \sum_{i \in F \cup K j \in F \cup K} \sum_{r \in R} \sum_{f \in F} x^f_{j \in F} p_{ij} w + \sum_{i \in K} A_i w + \sum_{i \in R} \sum_{j \in K} g(i,j) + d_j m + d_r S \quad (2)$$

Constraints:

$$\sum_{r \in Rs} \sum_{i \in F \cup K, j \neq i} x_{jr} = 1 \qquad j \in K \quad (3)$$

$$\sum_{i \in F \cup K} \sum_{j \in F \cup K} \sum_{r \in R} x_{jr} < d_f \quad f \in F \quad (4)$$

$$\sum_{i \in F \cup K} \sum_{j \in F \cup K} p_{ij} < 1 \quad (5)$$

Eq. (2), which is objective function, represents the total cost of patrol inspection. Eqs (3) – (5) represent the constraints. Eq. (3) indicates that each inspection point must be inspected; Eq. (4) indicates that the number of robots dispatched from the robot site must be within the carrying capacity; Eq. (5) indicates that the patrol robots must have enough power to return to the robot site.

2 Design based on the improved ILS-RVND algorithm

With the hybrid heuristic algorithms based on iterated local search and random variable neighborhood descent (ILS-RVND), the constrained vehicle path planning problems can be solved. On this basis, a simulated annealing mechanism is added in this paper to ensure the global optimum, while on the other hand, a rewarming perturbation mechanism is added to allow free splitting or merging of paths under adaptive threshold conditions, thereby ensuring the path degree of freedom. Additionally, robot electric quantity and time window constraint mechanisms are added for solving the problem herein.

(1) Initial solution construction

Path construction of initial solution is carried out in a random way. Although this method requires continuous elimination of the initial solution that is not in line with reality, the initial solution can be very stochastic and has a huge range, which is thus suitable for the initial solution construction for the algorithm in this paper.

(2) Local search operator

Local search is an operation to improve the solution in neighborhood, whose operators include 2-opt, 2-opt*, swap and move. These operators are used separately to switch, split and reverse order between two points in the path. To facilitate the operator execution, all paths of a robot site are encoded, which are later decoded after completion of operator operation, as shown in Fig. 3.

(3) Perturbation operators

Perturbation operators function to destroy the solution that is trapped in the local optimum. The degree of freedom of patrol robot number existing in the path planning problem also needs to be solved with perturbation operators. On the one hand, this study satisfies the robot number degree of freedom problem by adding path merging and splitting operators, which are illustrated in Fig. 4. On the other hand, maximum unupdating threshold is set to force the existing solution to break the local optimum.

(4) Iteration mechanism

On the basis of ILS-RVND algorithm, simulated annealing and perturbation failure mechanisms are added to the algorithm. On the one hand, the simulated annealing mechanism is used to solve the local optimum problem existing in algorithmic optimization; on the other hand, the perturbation failure mechanism is used to improve the search range and quality of global optimum solution. Iterations of the algorithm are divided into two layers: inner and outer iterations. The inner layer carries out local search and perturbation, while the outer layer carries out cooling of simulated annealing.

As shown in Eq. (6), the algorithm accepts non-optimal solution according to the probability of Boltzmann equation. The outer layer performs cooling. With the decrease of temperature, the probability of accepting the non-optimal solution becomes lower and lower. A threshold is set in the algorithm. When the solution is not updated under a certain threshold, it is forced to break out the local optimum solution.

$$P = \begin{cases} 1 & f(\text{new}) < f(x) \\ e^{-(f(\text{new}) - f(x))/kT} & f(x) > f(\text{new}) \end{cases} \quad (6)$$

where P denotes the probability of accepting non-optimal solution; $f(x)$ stands for the solution; $f(\text{new})$ stands for the new solution; k is the constant; and T is the temperature. The proposed algorithm is described in Table 1.

3 Case analysis

3.1 Example data and parameter settings

The data used in this paper comes from a chemical industrial park, where there are hundreds of points

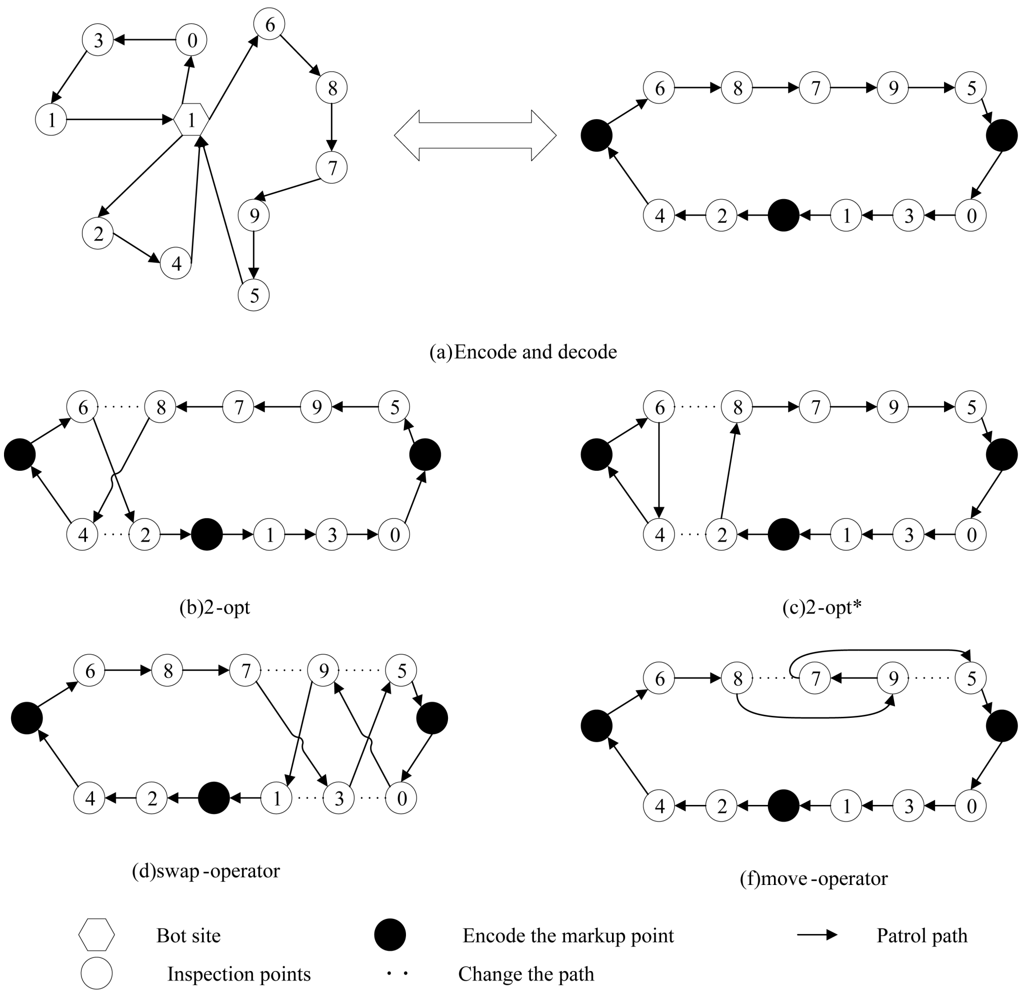


Fig. 3 Schematics of local search

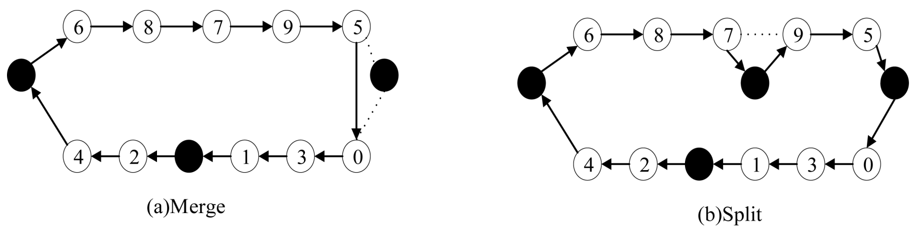


Fig. 4 Perturbation operators

with inspection needs. In this study, 30 points are randomly selected from them. Table 2 displays their coordinates.

The coordinates in the table are denoted separately by X and Y. The robot site coordinates are set as shown in Table 3.

The departure time of patrol robots is 8:00 am. The robots have an average velocity of 25 km · h^{-1} and a power consumption per kilometer of 1%. The time windows $[e_k, l_k]$ of inspection points are evenly distributed in [8,12], [9,13] and [10,14], while the inspection power consumptions at inspection points are homogeneously distributed within 1% – 5%. The inspection durations at inspection points are homogeneously distributed within 3 – 15 min. The capacity of each robot site is 3 patrol robots. The risk function is set as shown in Eq. (7), and θ is set to 5.

$$c(t) = \max(|t - e_k|, |t - l_k|) \tag{7}$$

3.2 ILS-RVND algorithm solving based on multi-mechanism simulated annealing

K-means clustering is adopted in the initial solution, which assigns clusters to the nearest robot site and randomly generates patrol paths. Fig. 5(a) illustrates the

Table 1 Improved ILS-RVND algorithm

Inputs: Inspection point coordinates, robot site coordinates, robot site capacity
Output: Optimal solution

1. Set the initial temperature T_0, end temperature T_{end}, cooling coefficient α and number of inner iterations n
2. Set the threshold γ, perturbance probability β, counter count = 0 and rewarming coefficient δ
3. Generate an initial solution S_0, store its cost in bestcost, and assign it to solution S
4. While ($T_k < T_{end}$)
5. For i in n
6. Perform local search to obtain the new solution S^*, and calculate its cost S^* (cost)
7. Calculate the power consumed by robots in each path for the new solution
8. Enter the perturbation mechanism with probability β, and update the new solution S^*
9. If (power > 1): Give up the new solution
10. Elseif (S(cost) > S^*(cost)): Accept the new solution with probability P, $S \leftarrow S^*$
11. Else: Accept the new solution, $S \leftarrow S^*$
12. If (count > γ): Enter the perturbation mechanism and update solution S, $T_{k+1} = \delta T_k$
13. Count = count + 1
14. $T_{k+1} = \alpha T_k$
15. End for
16. If (S(cost) < bestcost): bestcost = S(cost)
17. End while
18. Output the optimal solution S

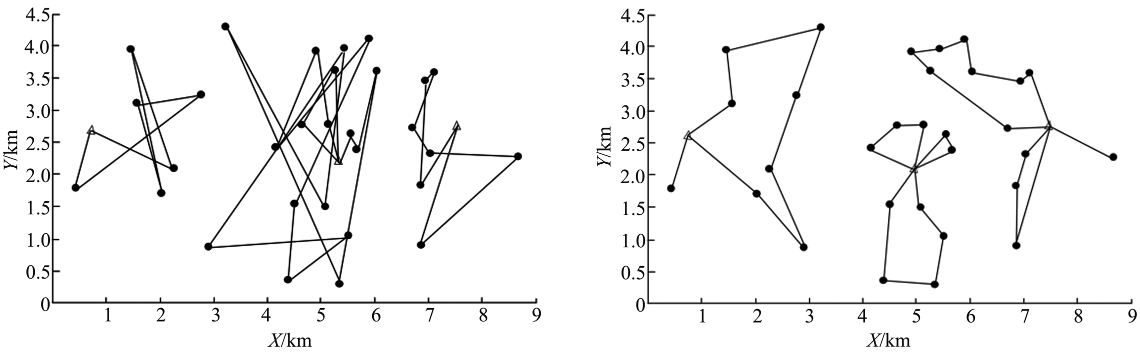
Table 2 Coordinates of inspection points

No.	0	1	2	3	4	5	6	7	8	9
X	6.11	5.59	5.61	4.33	3.82	4.27	5.45	2.89	4.72	5.92
Y	5.91	7.09	6.05	7.05	6.85	8.67	6.91	6.87	6.67	4.93
No.	10	11	12	13	14	15	16	17	18	19
X	5.97	5.63	4.77	4.79	4.64	4.41	4.41	3.53	3.51	3.05
Y	5.44	5.28	4.67	5.15	5.56	4.14	5.68	4.52	5.08	5.51
No.	20	21	22	23	24	25	26	27	28	29
X	2.32	2.36	6.32	5.24	5.12	4.09	5.94	3.69	3.80	2.89
Y	5.36	4.41	3.22	2.78	1.58	2.26	1.45	2.05	0.45	2.91

Table 3 Coordinates of robot sites

No.	0	1	2
X	2.778 76	2.247 52	2.659 63
Y	7.525 50	5.251 94	0.722 60

initial solution. The simulated annealing mechanism is adopted in the iterations, whose parameters are as follows: initial temperature $T_0 = 100.0$; cooling coefficient $\alpha = 0.98$; rewarming coefficient $\delta = 1.58$; end temperature $T_{end} = 0.1$. The solution unupdating threshold is set to 500. When the solution is not updated for more than 500 times, forced perturbation is implemented, and Fig. 5(b) displays the relevant optimized path. The optimization results are detailed in Table 4. As is clear, the cost is reduced by 24.15%, the inspection time shortens by 35.70%, and the number of timeout inspection points decreases by 12. The experiment results prove that using the ILS-RVND algorithm based on multi-mechanism simulated annealing, the optimal path with low cost and timeliness at inspection points can be planned.



(a) Initial path (b) Optimized path

Fig. 5 Path changes before and after iterations

Table 4 Comparison before and after optimization

Path	Cost/yuan	Timeout points (quantity)	Total path length/km	Total time/h
Initial path	484.43	12	125.14	6.36
Optimized path	367.96	0	83.42	4.09

3.3 Discussion and analysis of results

In this paper, two heuristic solution algorithms are selected for comparative analysis with the proposed algorithm. The running time, cost, timeout points and total path length are analyzed for each algorithm. Under fixed initial solution, iterative experiments are conducted separately on the standard GA, ILS-RVND and the proposed algorithm, and the comparison results are displayed in Fig. 6. Each algorithm is tested for 30 iterations, and the relevant optimization results are detailed in Table 5.

Table 5 Results of 30 iterations for various algorithms

Item / Algorithm	Average cost /yuan	Timeout points (quantity)	Average path length /km	Average running time /s
GA	386.47	6-16	99.56	135.8
ILS-RVND	379.63	3-12	93.34	586.4
Proposed algorithm	365.43	0-5	84.86	886.3

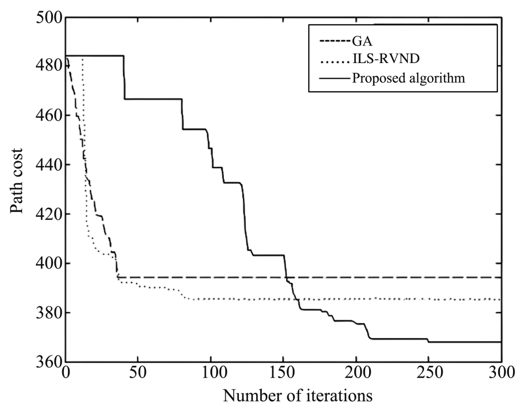


Fig. 6 Iteration curves for three algorithms

4 Conclusions

(1) On the basis of analyzing the patrol inspection task needs in chemical industrial parks, this study proposes a patrol path optimization model for such parks, and designs an ILS-RVND algorithm based on the multi-mechanism simulated annealing. In the case of an actual industrial park, the effectiveness of the model and algorithm is verified, which reduces the inspection time, patrol path and maintenance loss of patrol robots, lowers the probability of untimely patrol inspection and enhances the safety factor of equipment.

(2) On the basis of ILS-RVND, the perturbation and simulated annealing mechanisms are incorporated to improve the path degree of freedom and accept non-optimal solution, thus enabling very large search scope in the early stage. In the later stage, rewarming perturbation mechanism is used to expand the search scope again, in order to obtain the optimal solution, so that the optimal cost is reduced and the number of iterations is large. Under the aforementioned mechanisms, the

proposed algorithm jumps out of the local optimum to seek the global optimum. On the other hand, it elevates the path degree of freedom to expand the search scope, which thus yields the highest quality result.

(3) Compared with the GA and ILS-RVND algorithms, optimization with the algorithm reduces the cost by 20.3%, 21.7% and 24.5%, respectively, while shortens the total length of patrol paths by 20.5%, 25.4% and 32.2%, respectively. Besides, the timeout points are also significantly optimized. The running times for the three algorithms are 2.26, 9.77 and 14.77 min, respectively. In conclusion, the proposed algorithm obviously outperforms the other two regarding cost, total path length and timeout data, and its running time is also within the acceptable range, which is thus suitable for solving the problem described herein.

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