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Study on Time-Sensitive Targets Strike Path Planning Based on Improved Crayfish Optimization Algorithm

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Abstract

Addressing the challenges of complex solution and low accuracy in time-sensitive targets strike path planning, this paper proposes a novel path planning method which, based on the Open Vehicle Path Problem (OVRP), builds a model and applies the Improved Crayfish Optimization Algorithm (ICOA) to solving it. Relative to the initial Crayfish Optimization Algorithm (COA), the ICOA employs an improved strategy, namely "Chaos Accumulation-Environment Awareness-Lens Imaging" to markedly enhance the optimization efficiency and robustness of the algorithm and, through integer coding and crossover operation, is integrated with a Genetic Algorithm (GA) and innovatively applied to addressing the OVRPs. The experimental results demonstrate that ICOA exhibits better convergence speed and optimization accuracy over the other algorithms in composite optimization, displays enhanced robustness, and is capable of rapidly generating a path planning scheme with a shorter total flight distance in the OVRP model, further verifying the effectiveness of ICOA in solving the OVRPs.

Keywords: Improved crayfish optimization algorithm, Time-sensitive targets, Path planning, Open vehicle path problem, Crossover operation, Global optimization.

1. Introduction

Time-sensitive target (TST) usually refers to a high-value target that appears randomly on the battlefield and the opportunity to strike on it is strictly limited by the time window (Wang et al., 2024). Limited by the time window, the strike path planning of time-sensitive targets requires that, under the premise of considering multiple target points and weapon system capacity, different targets are assigned to multiple task execution units following a certain strike path according to battlefield information and task requirements, so as to achieve the shortest overall moving distance of task execution and thus the fastest strike on the targets. The specific model can be expanded with reference to the Vehicle Routing Problem (VRP), on the basis of which further expanded to Open Vehicle Routing Problem (OVRP) by increasing such conditions as load limit of task execution units and no need to return the weapon system (Vigo and Toth, 2014).

Crayfish Optimization Algorithm (Jia et al., 2023) (COA) is a meta-heuristic algorithm proposed in 2023. Compared with the traditional optimization algorithms, COA introduces variables such as environmental temperature to control the exploration and development of the algorithm, so as to better balance algorithm exploration and development. However, COA still has some limitations in terms of search scope and search efficiency, and individual crayfish are more inclined to conduct local search near caves, which is easy to fall into local optimization. Aiming at this problem, this paper presents an improved crayfish optimization algorithm based on chaotic accumulation and lens imaging.

To solve discrete optimization models such as OVRPs, further modifications are made based on ICOA: the ordering-based crayfish coding and decoding rules are designed, the penalty function for violating constraints is added to the objective function, the summer heat avoidance behavior of crayfish is combined with the crossover operation of GA to update positions of individual crayfish, and the quality of the solution is improved by using two local search operations—reversal and insertion. Finally, the effectiveness of the proposed method is verified by the performance test experiment and the example application experiment.

2. Modelling of time-sensitive targets strike path planning

In this paper, the task execution unit is set as gunship, and builds a mathematical model on the problem of distributed time-sensitive targets attack path planning, and the gunship's total flight distance and flight time, and the risk of it being shot down are minimized by reasonably distributing target attack paths.

2.1. Problem description

Assume that the number of enemy targets is n, and they are randomly distributed in the mission area, while we at most can send K gunships with our weapon system to carry out fire attacks against these targets, and must ensure that each target is struck and wiped out only by one gunship. On the basis of the above conditions, each gunship departs from where the weapon system is located, flies to the target on the planned path, and leaves by itself after hitting the last target on the path (the flying distances of the gunships after they leave are not counted in their total flight distances). See Figure 1 for the combat scenario.

To simplify computing, assume that the gunships carry the same type of ammunition, the maximum ammunition load of each gunship is p, and the amount of ammunition each gunship needed q is also different due to different target destruction and damage requirements, which can be recorded as $q = [q_1, q_2, \ldots, q_n]$, q_i represents the amount of ammunition needed to destroy the ith target.

In the current combat scenario, the coordinates of each time-sensitive target have been accurately localized through preliminary reconnaissance, so the strike paths need to be rationally planned to make the total flight route of the gunships the shortest.

2.2. OVRP model

The Vehicle Routing Problem (VRP) is a classical combinatorial optimization problem. The problem described in this paper is a common derivative of VRP, that is, the capacitated vehicle routing problem (OVRP). In order to facilitate the establishment of the OVRP model, the parameters and decision variables are defined and shown in Table 1.

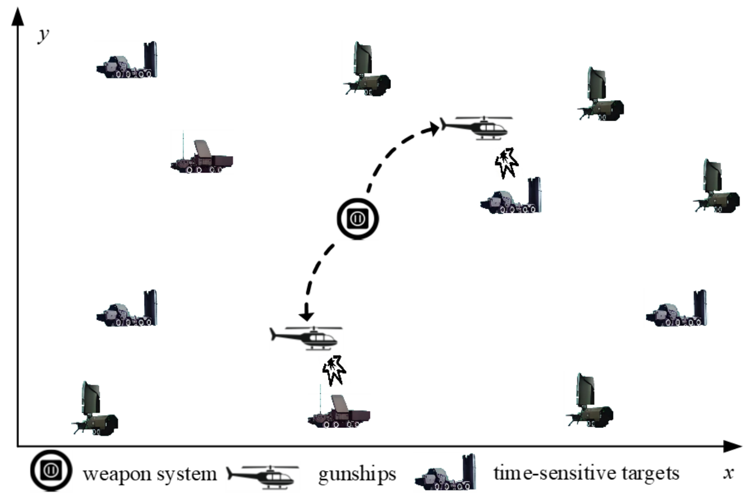

Figure 1: Schematic diagram of combat scenarios.

Table 1: Model parameters and decision variables.

Parameters/variable symbols	Implication
n	number of targets
$v = 0, 1, 2, \ldots, n$	a collection of nodes, where 0 represents the weapon system
q_i	the amount of ammunition needed to destroy target i
K	the number of gunships in the weapon system
d_{ij}	the distance between node i and node j
p	maximum charge per gunship
x_{ij}^k	whether gunship k visits node j immediately after visiting node i. If so, x_{ij}^k =1, otherwise x_{ij}^k=0

The mathematical model of OVRP can be established as follows according to problem description:

$$\min \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} \left(d_{ij} \times x_{ij}^k \right) \tag{1}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{n} x_{ij}^k = 1, \quad \forall i, j = 1, 2, \cdots, n \tag{2}$$

$$\sum_{i=0}^{n} x_{iu}^k - \sum_{j=1}^{n} x_{uj}^k = 0, \ \forall k = 1, 2, \cdots, \ K; \forall u = 1, 2, \cdots, n \tag{3}$$

$$\sum_{i \in S} \sum_{j \in S} x_{ij}^k \leq |S| - 1, \quad \forall S \subseteq V \setminus \{0\} \tag{4}$$

$$\sum_{j=1}^{n} q_j \left(\sum_{i=0}^{n} x_{ij}^k \right) \leq Q, \quad \forall k = 1, 2, \cdots, K \tag{5}$$

$$\sum_{j=1}^{n} x_{0j}^{k} \leq 1, \quad \sum_{i=1}^{n} x_{i0}^{k} = 0, \quad \forall k = 1, 2, \cdots, K \tag{6}$$

$$x_{ij}^{k} \in \{0, 1\}, \quad \forall k = 1, 2, \cdots, K; \quad \forall i, j = 1, 2, \cdots, n \tag{7}$$

Formula (1) is the objective function, representing the total distance flown by the gunship. Formulas (2) to (7) are constraints. Formulas (2) ensure that every target can be hit. Formula (3) ensures the continuity of flight of each gunship. Formula (4) indicates the elimination of any strike route that does not include a weapon system. Formula (5) indicates that the ammunition load of each gunship in the weapon system before departure cannot be greater than the maximum load of the gunship. Formula (6) indicates that the weapon system uses up to K gunships to destroy all targets. Constraint (6) indicates that no gunship flows back to the weapon system. Constraint (7) indicates that x_{ij}^{k} is a variable whose value ranges from 0 to 1.

3. ICOA algorithm

3.1. COA algorithml

Crayfish Optimization Algorithm (COA) is a kind of meta-heuristic optimization algorithm that takes the behaviors of freshwater crayfish in foraging, summer heat avoidance and competition. Compared with the other meta-heuristic algorithms or intelligent optimization algorithms, the COA features simple computation, good robustness, strong search ability and fast convergence speed in solving OVRP problems. The standard COA can be divided into four stages during execution: initialization stage, stage of summer heat avoidance, stage of competition for caves and foraging stage. The summer heat avoidance stage belongs to the exploration stage of the algorithm, and the stage of competition for caves and foraging stage represent the development stages of COA.

3.2. Algorithm improvement strategy

The original COA has the defects of degraded diversity, insufficient exploration ability, being easy to fall into local optimization and low optimization precision, which greatly limits the practical application of it. The improved ICOA mainly enhances the global exploration ability and avoids the algorithm from falling into local optimal through the following three strategies.

Piecewise chaotic mapping initializes the population. ICOA presents more obvious advantages with using Piecewise chaotic mapping to initialize the population (Li et al., 2024). First, the sequences it produces are highly unpredictable and complex, which help the algorithm explore more solutions. Secondly, it can generate sequences with inherent randomness, which helps to avoid premature convergence of the algorithm to the local optimal solution, and improves the global search ability. Finally, it can provide more abundant distribution points, which helps to enhance the robustness of the algorithm.

Perception-based aquatic environment change strategy. ICOA introduces the aquatic environment perception renewal strategy (Heming et al., 2024) to guide crayfish to find a better aquatic environment through water quality factors. The value of water quality factor V, randomly between [0, 5], stands for the quality of the aquatic environment at the current location. Crayfish use the forefoot perception R and adaptive flow factor B to perceive the quality of the current aquatic environment, and R takes a random value between [0, 1]. Since crayfish have different levels of perception, a random position X_2 is found between the candidate position and the current position, i.e.,

$$X_2 = \left(X_{opt} - X_{ij}^t\right) \times r \tag{8}$$

Where X_{opt} stands for the candidate optimal position.

When $V \geq 3$, the crayfish would perceive the current aquatic environment as poor and not suitable for survival, and then judge the flowing direction of water according to the adaptive water flow factor B and forefoot perception R before crawling backwards to find a better aquatic environment. The position change formula is as follows:

$$X_{ij}^{t+1} = X_2 + \left(X_1 - X_{ij}^t\right) \times \cos\left(\theta\right) \times B \times V \times rand + X_1 \times \sin\left(\theta\right) \times B \times rand \tag{9}$$

Where X_1 is a random position within the population, and θ is randomly from 0 degree to 360 degrees.

When $V < 3$, it means that crayfish perceives the current aquatic environment as good and it is unnecessary to update the environment.

Lens imaging reverse learning strategy. ICOA introduces the lens imaging reverse learning strategy, aiming to improve the solution search process in a “reverse” way. This strategy simulates the physical phenomenon of lens imaging and enhances the diversity and effectiveness of search by changing the spatial distribution of solutions. The lens imaging reverse learning strategy needs to first define the lens coefficient l, which can be adjusted according to the number of iterations or some rules. Here, we define the formula l as follows:

$$l = \left(1 + \sqrt{\left(\frac{t}{T}\right)}\right)^{10} \tag{10}$$

Secondly, the reverse mapping of the current position is obtained according to the lens coefficient l, and the formula is as follows:

$$X_{ij}^{t+1} = \frac{ub_j + lb_j}{2} + \frac{ub_j + lb_j}{2l} - \frac{X_{ij}^t}{l} \tag{11}$$

Finally, it makes sure that the new position after the reverse mapping is still in the solution space and, after comparing the new position with the original one, the optimal position can be selected and updated.

4. OVRP computing based on ICOA

ICOA is used in the function optimization process with continuous changes, while OVRP problem is a discrete optimization problem under constraints OVRP thus cannot be solved directly by ICOA, so ICOA needs to be modified accordingly.

4.1. Encoding and decoding

All the paths that gunships can choose when attacking targets are realized by integer coding . Assuming that there are 5 targets and they are numbered from 1 to 5, and the weapon system (numbered 0) has 3 gunships, the coding adopted by ICOA when solving OVRP is shown in the figure 2.

1	5	6	2	7	3	4

Figure 2: Way of coding of individual crayfish.

As can be seen from Figure 2, the individual crayfish contain a total of seven integers, with 1 to 5 standing for the targets and 6 and 7 for the weapon system. The positions of the 7 integers can be arbitrarily changed to be encoded in different ways. The coding can be decoded into different attack schemes. For example, if the coding shown in Fig. 22 is decoded, the strike plan thus produced contains the following three strike paths:

The first strike path: 0→1→5.

The second strike path: 0→2.

The third strike path: 0→3→4.

If the number of targets is known to be n, and the weapon system allows at most K gunships to strike against the targets, the individual crayfish is represented as a random arrangement of $1 \sim (n + K - 1)$.

4.2. Objective function

As can be seen from the above encoding methods, the strike schemes decoded from individual crayfish cannot guarantee that each strike path meets the load constraint. Therefore, it is necessary to impose penalties on the strike path violating the constraint so as to make strike schemes decoded by the algorithm in the search process quickly meet the load constraint. The specific computing formulas are as follows:

$$f(s) = c(s) + \beta \times q(s) \tag{12}$$

$$q(s) = \sum_{k=1}^{K} \max\left\{ \left(\sum_{j=1}^{n} q_j \left(\sum_{i=0}^{n} x_{ij}^{k} \right) - Q \right), 0 \right\} \tag{13}$$

Where s is the attack plan decoded by the individual crayfish at present; $f(s)$ is the total cost of the current scheme; $c(s)$ is the total distance flown by the gunship; $q(s)$ is the sum of the ammunition quantity of gunships along each strike path that goes beyond the load constraint; β is the weight that violates the load constraint.

4.3. Individual crayfish location update

The mathematical formula for updating the position of crayfish can't be applied directly to OVRP. Therefore, this paper fully considers the characteristics of OVRP and individual crayfish position updating, and integrates the crossover operation of genetic algorithm (GA) to complete the update of crayfish position.

Assuming that the current location of the cave isX_{shade}^{t} and the current random individual crayfish is X_j^t, the update formula is:

$$X_j^{t+1} = \begin{cases} Cross_1\left(X_j^t, X_{shade}^t\right) & rand < 0.5 \\ Cross_2\left(X_j^t, X_{shade}^t\right) & rand \geq 0.5 \end{cases} \tag{14}$$

Where $Cross_1$ and $Cross_2$ represent two types of crossover operations on individual crayfish. Suppose that individual crayfish X_1 and X_2 are encoded as follows:

$X_1 = 1, 2, 7, 5, 4, 6, 3$; $X_2 = 7, 5, 1, 6, 3, 2, 4$.

The sixth element is randomly selected from X_1 for $Cross_1$ operation with X_2, and then new individual crayfish $X'_1$and X'_2 are generated as shown in Figure 3.

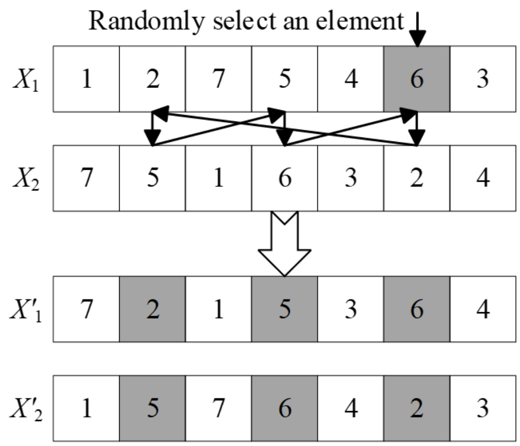

Figure 3: Schematic diagram of Cross1 crossover operation.

A set of elements are randomly selected from X_1 and $Cross_2$ with X_2 to generate new individual crayfish X'_1 and X'_2, as shown in Figure 4.

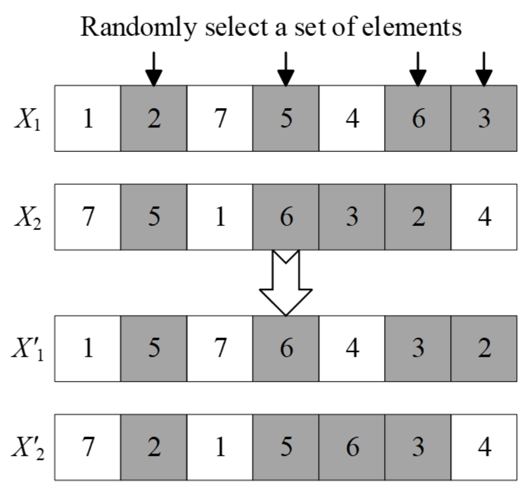

Figure 4: Schematic diagram of Cross2 crossover operation.

4.4. Local search function

The purpose of local search is to improve the quality of the solution, which corresponds to the crayfish's behavior during the foraging stage. For OVRP, this paper adopts two methods of reverse operation and insert operation to carry out local search.

The reverse operation reverses the ordering of all elements between two positions of the individual crayfish, and the insert operation inserts the element in the first position of the individual crayfish behind the selected element in the second position.

After the reverse and insertion operations are performed, the objective function values of the newly generated code and the original individual code are compared, and the code with smaller function value is selected as the new code for the next generation of individual crayfish.

4.5. OVRP computing process based on ICOA

The specific steps of ICOA solving are as follows:

Step 1 To initialize the crayfish population number NIND, individual crayfish length N, iteration number t and maximum iteration number T, and randomly encode the crayfish population to form the initial position X_i.

Step 2 To calculate the objective function values of each individual crayfish according to the location of the crayfish population and store them.

Step 3 To compare the current iteration number t and the maximum iteration number T. If $t \leq T$, continue with Step 4, otherwise jump to Step 7.

Step 4 To update the location of the crayfish population, so that the locations of the current individual crayfish and the optimal burrows are crossed in the first crossover mode with a 50% probability, and the second crossover mode with a 50% probability.

Step 5 To update the objective function value of each individual crayfish, and conduct local search operations to make the crayfish population update in the direction of procuding better objective function values.

Step 6 To update the number of iterations so that $t = t + 1$, and jump to Step 3.

Step 7 To output the globally optimal objective function values and the corresponding individual crayfish position codes, and decode the position codes into the optimal strike scheme.

5. Simulation experiment and analysis

All experiments in this paper are performed in a computer configured as AMD 7840HS CPU@3.80GHz, with 16.0 GB memory and using Matlab2021b software, under Windows11 operating system.

5.1. Comparative test analysis

The comparative test compares the convergence speed and calculation accuracy of ICOA with other algorithms. In order to better verify the effectiveness and robustness of ICOA algorithm, this paper selects CEC2020 test function set to test it. ICOA is compared with other six algorithms (Heidari et al., 2019; Abdollahzadeh et al., 2021a,b; Zhao et al., 2023), its effectiveness can be better demonstrated in this paper.

In order to ensure the fairness and objectivity of the experiment, the population size was uniformly set to be 100, the dimension to be 10, and the maximum number of iterations to be 500. Each algorithm was run independently on each test function for 30 times, and its average fitness value was taken to draw the corresponding convergence curve, as shown in Figure 5.

According to Figure 5, ICOA ranks top in other test functions than functions F1 in terms of the convergence speed, indicating that the convergence speed of ICOA is effectively improved by Piecewise initialization strategy. In addition, ICOA shows good optimization accuracy in all functions,

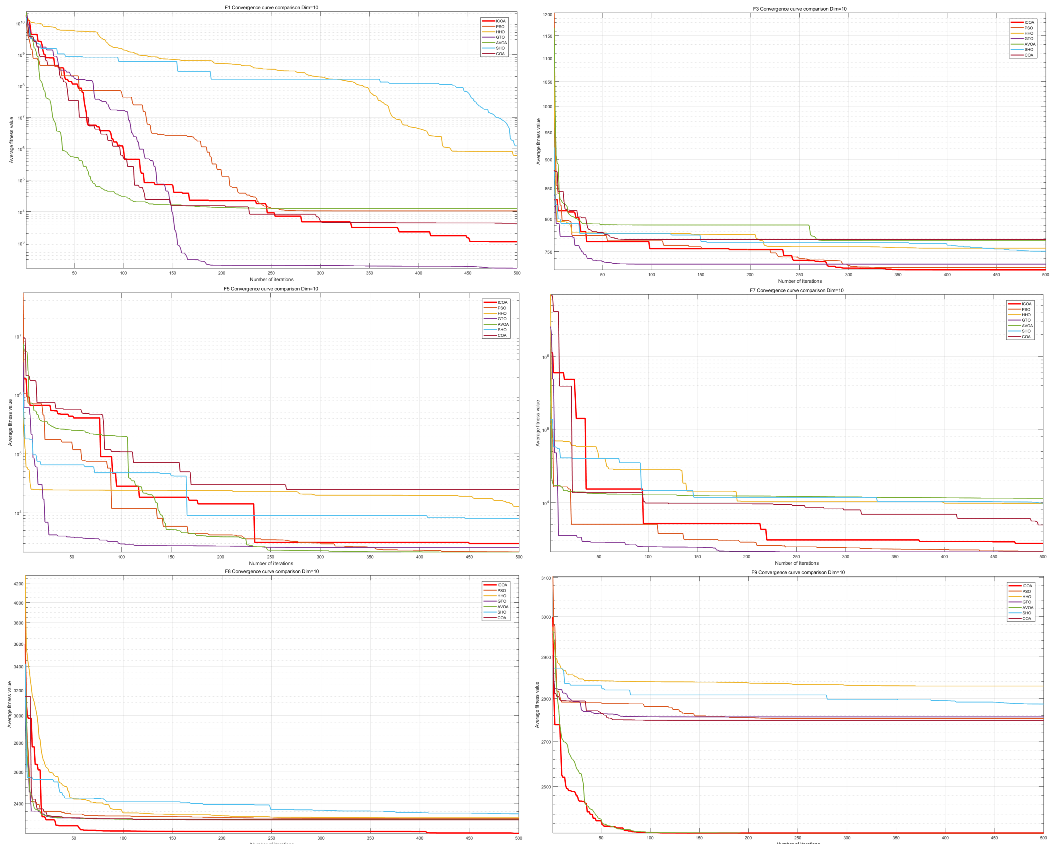

Figure 5: Mean convergence curve.

basically ranking the top two. Especially in function F5, ICOA is far ahead of the other algorithms, indicating its greatly enhanced ability to jump out of local optimization and global search ability after the introduction of environment perception strategy and lens imaging reverse learning strategy, as well as its higher robustness for combinatorial optimization problems.

5.2. Application of ICOA in OVRP

In order to verify the performance of the proposed algorithm in solving the OVRP model, the input data of the model are set as follows: the number of targets is 25 and they are numbered consecutively from 1 to 25, the number of the weapon system is 0, and there are 3 gunships, each of which has the maximum loading capacity of 16kg. The rest data are shown in Table 2.

See Table 3 for the setting of parameters of ICOA.

After calculation, the optimal strike path obtained is shown in Figure 6.

As can be seen from Figure 6, the attack scheme with the shortest total flight distance of armed helicopters includes three attack paths:

First strike path: 0, 12, 5, 11, 1, 3, 20, 21, 16 ,9, 10.

Second strike path: 0, 18, 14, 25, 13, 19, 4, 17, 150.

Third strike path: 0, 6, 24, 23, 7, 8, 22, 2.

By computing, the total flight distance of the gunship is 28.4836 km.

Table 2: Data information on weapon systems and targets struck

Serial number	x coordinates/km	y coordinates/km	Ammunition needed/kg
0	3.0	4.0	0
1	3.7	5.2	0.7
2	4.9	4.9	3.0
3	5.2	6.4	1.6
...	...	...	...
24	0.8	5.2	1.0
25	0.7	3.8	2.8

Table 3: ICOA parameter setting

Parameter name	Parameter value
Number of crayfish population	100
Maximum number of iterations	300
Penalty function coefficient for violating ammunition load constraints	10

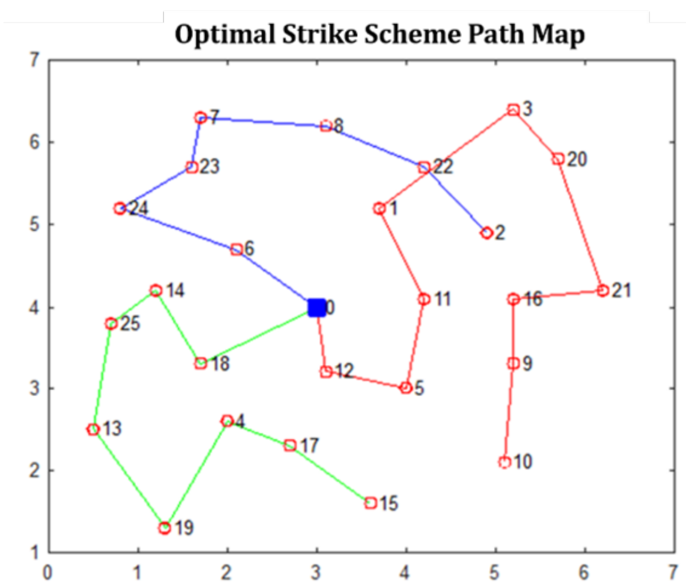

Figure 6: Optimal Strike Scheme Path Map.

Therefore, solving the OVRP model using ICOA is feasible for solving the strike path planning problem for time-sensitive targets in warfare.

6. Conclusion

In this paper, an OVRP model is established to solve the problem of path planning for attacks on time-sensitive targets by gunships. On this basis, ICOA is used to determine the path configuration scheme to reduce the total flight distance and strike risks of gunships. The main conclusions are as follows:

1) Compared with the original COA, the ICOA using the improved strategy of "chaos accumulation - environment perception - lens imaging" has been significantly improved in terms of optimization efficiency and robustness.

2) When modified appropriately, the mode of encoding, objective function, update mode and local search of ICOA can be used to solve the OVRP model.

3) Through comparative test experiments of it with another 6 algorithms, it is proved that ICOA has great advantages in computing accuracy and convergence speed.

In conclusion, ICOA can solve large-scale path planning problem stably and efficiently.

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