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METHODS

A New Method for Multi-UAV Cooperative Mission Planning Under Fault

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ABSTRACT Aiming at the many-to-one mission planning problem in the case of UAV fault, a self-organizing solving method is designed. This method organically combines the situation assessment of single UAV with the collaborative optimization of multiple UAV. On the one hand, the situation assessment of single UAV is carried out based on Bayesian network, and the striking probability of each UAV is obtained. On the other hand, in order to solve the problem of multiple UAV cooperation, the improved discrete particle swarm optimization based mixed strategy (MSDPSO) is proposed. The algorithm has been improved in the following four aspects. Firstly, Sobol sequence is used to initialize the population to improve the coverage of solution space. Then, a nonlinear time-varying strategy is proposed to accelerate the convergence of the algorithm. Cauchy operator is also introduced to enhance the search space of discrete particle swarm optimization. At the same time, an adaptive cross learning strategy is proposed to enrich the diversity of the population, thereby improving the global optimization ability of the algorithm. In addition, the cubic spline interpolation is used to plan trajectory of UAV. Finally, improved discrete particle swarm optimization is used in three-dimensional space for simulation and comparison with both healthy and faulty UAV involved. Results show that the designed algorithm has significant improvement on solution optimality and convergence rate, which provides a theoretical basis for the application of multiple UAV collaborative task planning.

INDEX TERMS Multi-UAV coordination, improved DPSO, Bayesian network, cubic spline interpolation.

I. INTRODUCTION

With the progress of technology, UAVs are widely used in various industries [1]. In complex battlefield, multi-UAV coordinated mission planning is a hot topic [2]. In particular, multi-UAV cooperative execution of striking tasks is an important part of UAV intelligence and diversification [3].

In current developed achievements, the main control methods of UAV task allocation include centralized [4], distributed [5] and hierarchical ways [6]. Peng et al. designed two allocation models to apply to the dynamic task allocation of targets on the ground, and compared with contract net-based algorithm, intelligent optimization algorithm and clustering algorithm, its advantages and disadvantages and research status were analyzed [7]. Due to high-dimensional complex problems, a task allocation method of discrete wolf colony algorithm was proposed and the result proved that the discrete wolf colony algorithm had good convergence [8]. In addition, the mixed integer linear programming (MILP) [9], [10], [11] was used to plan the coordinated tasks of multiple UAVs, which improved the optimization ability. However, its computational complexity also increased with the increasing of tasks, which made the computing time longer, so the method was not suitable for large cluster collaborative task allocation. Besides, by designing a new nonlinear tube-based robust model predictive control (TRMPC) algorithm, a double-loop cascade tracking control framework is established. Chai et al. Conducted a comparative study, the results show that compared with other new development methods in this study, the proposed design

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can achieve better constraint processing and attitude tracking performance [12]. Meanwhile, Chai et al proposed a new integrated real-time trajectory planning and tracking control framework to deal with the parking maneuver problem of autonomous ground vehicles (AGV). By using the cyclic network structure, this method further extends the new idea of using depth neural network (DNN) to approach the optimal parking trajectory. In addition, two transfer learning strategies are applied to make the developed motion planner adapt to all kinds of AGV. Through a number of experimental studies and comparative analysis, the proposed strategy can enable AGV to complete the parking task while enhancing the performance of motion planning and control [13]. Aiming at the problem of cooperative target search of multi-UAV, a cooperative target search algorithm based on cooperative pigeon-inspired optimisation (CPIO) and two continuous parts of each UAV base return algorithm based on artificial potential field (APF) are proposed,the algorithm realizes the search for key areas and prevents UAVs from flying into the no-fly zone, which has a certain reference value for the collaborative planning of multiple UAVs in complex environments. [14]. A system based on embedded hardware and high-level communication protocol was proposed as the basis for identifying, distributing and assigning tasks, and then used by multi-UAV in a simple and decentralized way [15]. Duan et al. proposed a dynamic discrete pigeon swarm optimization algorithm, the algorithm was used to deal with multi-UAV cooperative search-attack task planning, which integrated task allocation and path generation [16], [17]. Aiming at the problem of planning the optimal maneuvering trajectory and guiding the mobile robot to point to the target position in an uncertain environment, Chai et al proposed a hierarchical control framework based on deep learning. This method is based on the recently proposed idea of using depth neural network (DNN) to approximate the optimal motion trajectory so it can significantly reduce the time required for the training process. At the same time, a noise priority experience playback (PER) algorithm is proposed to improve the exploration rate of the control strategy. Through several groups of simulation experiments, it is proved that the proposed strategy can complete the independent exploration task with improved motion planning performance, enhanced anti-collision ability and less training time [18], [19]. To sum up, the current research on multi-UAV cooperative task allocation only considered the improvement of the algorithm and one-to-one target allocation. However, the problem of many-to-one task allocation after the fault of UAV was not fully considered.

In addition, when task assignment is completed, in order to ensure UAVs reach the target, it is also necessary to design and plan the trajectory of UAV. In the current research of UAV trajectory planning, most of achievements only focused on trajectory for single UAV [20]. While the coupling with trajectory planning of multi-UAV and task assignment had not been effectively studied. Some existing researches used graph theory to carry out trajectory planning, such as A$*$ algorithm [21], hungarian algorithm [22], random tree algorithm [23], voronoi graph algorithm [24] and so on. Because these methods were all based on cost map, it was necessary to store the cost map offline, which made these methods more time-consuming. With the development of artificial intelligence technology, biomimetic swarm predation algorithms were widely used in trajectory planning, such as bee swarm algorithm [25], wolf swarm algorithm [26], genetic algorithm [27] and particle swarm optimization [28]. Among them, particle swarm optimization algorithm (PSO) was widely used because of its strong searching ability and easy simulation operation. For example, a particle swarm optimization algorithm for control variables was proposed to carry out the cooperative trajectory planning between UAV and underwater vehicles, the result could reach the theoretical extreme value [29]. Xie et al. proposed a deep reinforcement learning method for 3-D trajectory planning, which used local information and relative distance instead of global information so that the UAV could obtain environmental information in actual battlefield with limited capability, so as to achieve effective obstacle avoidance and feasible trajectory planning of UAV in complex environment [30].

To sum up, for the planning of multi-UAV striking missions, most of the current studies only considered the one-to-one striking planning scenario, namely, a target was hit by a UAV, and only the linear distance of mission assignment was considered, which was not consistent with the trajectory in actual combat environment, causing that the generated paths may not effectively avoid obstacles. Meanwhile, the current researches only involved the unilateral content of task assignment or trajectory planning, and did not consider the coupling of the two. On the other hand, when one of UAVs broke down, the effectiveness of coordinated mission implementation had not been effectively explored.

Based on above analysis, the many-to-one cooperative striking mission planning in the event of UAV fault is studied in this paper, and the mission assignment and trajectory planning are effectively coupled. The main work and innovations are as follows:

1) Considering the coupling of optimal performance of single UAV and cooperative mission planning of multi-UAV, a distributed self-organizing solving strategy is proposed. In this method, the situation assessment of single UAV is firstly carried out by using Bayesian network, and then the result is input into the cooperative mission planning of multi-UAV as a constraint index.
2) In order to solve the problem of multi-UAV cooperative mission planning, an improved DPSO based mixed strategy (MSDPSO) is proposed, which uses Sobol sequence to initialize the population, updates high-quality individuals based on Cauchy operator, and introduces nonlinear time-varying mutation strategy and adaptive cross-learning strategy to enrich the diversity of the population. Comparing with traditional DPSO, the proposed MSDPSO improves solution optimality and convergence rate.

3) Considering the problem of feasible trajectory in mission planning, the algorithm is not based on the distance of straight line between UAVs and targets, but coupled with the actual flighting distance based on trajectory generation.

The rest of the paper is organized as follows: Section II describes the mission planning problem of multi-UAV. Section III presents the solving strategy, the constraints and Bayesian network. In section IV, simulations and comparisons are carried out to verify the effectiveness of the proposed algorithm. Finally, conclusion and future work are given in Section V.

II. PROBLEM DESCRIPSION

It is defined that there are mUAVs and $t$targets, and $m > t$, to carry out many-to-one striking tasks. Bayesian situation assessment and MSDPSO are introduced to complete the task assignment of different targets. If some UAVs malfunction during the mission, healthy UAVs re-coordinate the maneuverability and flighting cost to complete the task assignment under the condition of meeting various constraints. After the completion of task assignment, each UAV uses the method of cubic spline interpolation to carry out trajectory generation according to the given waypoints, and accurately hit the target.

The specific mathematical expressions are as follows:

$$U_{bi}(\sigma_{bj}) \xrightarrow[(x_j, y_j, z_j)]{\prod r_i(q)} U_{ek}(\sigma_{ej}) \tag{1}$$
$$i = 1, 2, 3, \ldots, m, \quad j = 1, 2, 3, \ldots, n, \;\; k = 1, 2, 3, \ldots, t$$

where m represents the total number of UAV, t represents the total number of target, n represents the total number of waypoint, U_{bi} represents starting location of UAVs, U_{ek} represents location of targets, Π represents threatening constraints, $r_i(q)$ represents the trajectory information, (x, y, z) represents the location of waypoints in the flighting process of UAVs, and σ represents the cooperative constraints for task assignment.

III. SOLVING STRATEGY

In order to solve the problem of cooperative mission planning of multi-UAV under fault, a distributed self-organizing solving strategy is proposed in this paper. Bayesian network is firstly used to evaluate the situation of single UAV, and the probability of each UAV hitting each target is given. Then, an improved discrete particle swarm optimization algorithm based on mixed strategy (MSDPSO) is proposed for multi-UAV cooperative mission planning. The evaluation of single UAV is effectively coupled with the planning of multi-UAV. PSO is used for trajectory pre-planning, and cubic spline interpolation is introduced to smooth the trajectory. Finally, the actual range of trajectory is introduced back to mission planning to verify the effectiveness of the proposed algorithm.

The algorithm structure diagram is shown in Fig. 1.

TABLE 1. Definition of input nodes.

Variate	Interpretation	State set
Distance	Distance between the UAVs	Far Near
Speed	UAV moving speed	Fast Slow
Height	UAV altitude	High Low
Engine	Engine damage degree	No fault Fault
Wing	Damage degree	No fault Fault
Residual fuel	Fuel status of UAV	Sufficient Deficiency
Ammunition	Status of surplus ammunition	Sufficient Deficiency
Communication	Information anti-jamming ability of UAV	Strong Weak

TABLE 2. Definition of output nodes.

Variate	Interpretation	State set
$DE_{i,k}$,($i=1,2,$L m $k=1,2,$L t)	Possibility of the UAV hitting target	Target k ($k=1,2,$L t)

A. SITUATION ASSESSMENT BASED ON BAYESIAN NETWORK

Bayesian network is used to evaluate the status of each UAV, and the probability is added to multi-UAV cooperative mission planning as an evaluation index.

The model of Bayesian network consists of input layer and decision layer, a detailed description of each node is as follows:

The input layer is composed of evidence nodes to detect the battlefield environment in real time and provide evidence for network input.

The evidence node is mainly composed of the following aspects: distance, speed, height, engine, wing, residual fuel, ammunition and communication. These nodes' information can be directly obtained by sensors and other detectable equipment carried on UAV. In order to reduce the amount of computation and improve the speed of decision-making, the information is discretized and transmitted to Bayesian network as node evidence, which is shown in Table 1.

The input nodes are analyzed concretely according to the simulation scene, and the decision-making nodes of the network is to provide guidance for actions of UAVs, as is shown in Table 2.

As Bayesian situation assessment is an input of mission planning, the corresponding cost function can be given as follows

$$\begin{cases} f_B = \displaystyle\sum_{i=1}^{m} \sum_{k=1}^{t} D_{ik} \\ D_{ik} = \begin{cases} DE_{i,k} & if\ DE_{i,k} \geq DE_{\hat{i},k} \quad and\ i \neq \hat{i} \\ DE_{\hat{i},k} & if\ DE_{i,k} < DE_{\hat{i},k} \quad and\ i \neq \hat{i} \end{cases} \end{cases} \tag{2}$$

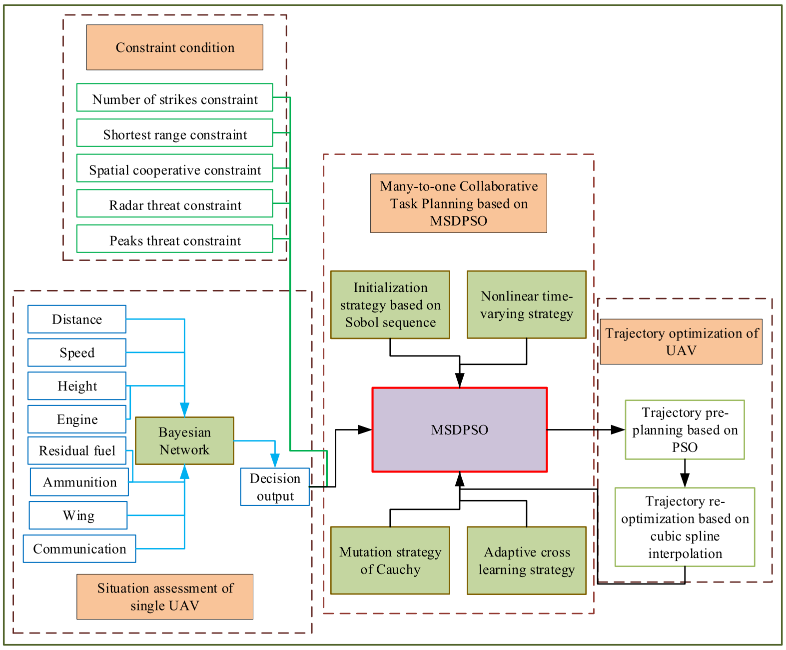

FIGURE 1. Algorithm structure diagram.

where m represents the number of UAV and t represents the number of target, DE is a decision variable, which represents the probability of the ith UAV hitting the kth target, through the comparison of the striking probability of different UAVs hitting the same target, the maximum striking probability is obtained, which is represented by D_{ik} and brought into the function of assessable index as a substitute value, which is denoted by f_B.

In addition, the multi-UAV cooperative mission planning is an optimization problem under a variety of constraints. In order to facilitate the modeling and solving of the algorithm, some constraints are set in the following.

B. CONSTRAINT CONDITION

1) STRIKING NUMBER CONSTRAINT

Assuming that when UAV performs task assignment, the number of striking on a certain target k is expressed as $M_{Attack}(k), k \in t$. The striking number constraint can be expressed as

$$M_{Attack}(k) = \begin{cases} A_1 & k = even\ number \\ A_2 & k\text{=odd}\ number \end{cases} \tag{3}$$

when the target label is even number, the UAV will strike A_1 sorties, when the target label is odd number, A_2 sorties will be hit. The specific number of strikes will be set according to the simulation.

The corresponding cost function of this constraint is

$$\begin{cases} f_2 = \sum_{i=1}^{m} \sum_{k=1}^{t} B_{ik} \\ B_{ik} = \begin{cases} p_{ik}^{b} & if\ M_{Attack}\ (k) \neq A_1 or A_2 \\ 0 & if\ M_{Attack}\ (k) = A_1 or A_2 \end{cases} \end{cases} \tag{4}$$

where f_2 is the punitive value of the striking number, p_{ik}^{b} represents the cost value of the corresponding striking times when the ith UAV carries out the striking mission for the kth target, and the specific value is set according to the simulation, the B_{ik} is the value of the price after judgment and comparison.

2) SPATIAL COOPERATIVE CONSTRAINT

When multiple UAVs cooperate to carry out a mission, if a UAV fails to perform the mission or there are obstacles in performing the task, other UAVs can quickly make adjustments to replace or help the malfunctioning UAV to complete the task. Therefore, the constraint with spatial cooperative ability is established, it is assumed that the distance between UAVs is set to d. In order to avoid collision, d should meet

$$d > d_{\min} \tag{5}$$

where $d_{\min}$ represents the minimum safe distance between UAVs.

The corresponding cost function is

$$\begin{cases} f_3 = \sum_{j=1}^{n} C_j \\ C_j = \begin{cases} p_j^c & if\ d \leq \mathrm{d}_{\min} \\ 0 & if\ d > d_{\min} \end{cases} \end{cases} \tag{6}$$

where f_3 is the punitive value of the spatial cooperative constraint, p_j^c is expressed as the punitive value of distance after comparison between waypoint and the set minimum safe distance, the specific value is set according to the simulation, and C_j is the value of generation after judgment and comparison.

3) SHORTEST RANGE CONSTRAINT

In the current research on mission assignment of multi-UAV, the constraint of range is only based on the planning of straight-line distance, which is not consistent with the actual flighting trajectory of UAVs, that is, the task assignment based on straight-line distance does not necessarily meet the optimal allocation results in the flighting environment with obstacles. Therefore, the proposed constraint of the shortest voyage takes the actual flighting ranges of UAVs into account.

Supposing that S_1 represents the cost that the UAV has to pay from the starting point to the target. In order to more intuitively show the change of fitness of objective function, the normalized cost function for voyage is given as follows

$$\min S_1 = \left(\sum_{j=1}^{n-1} l_i\right) / l_{str} \tag{7}$$

$$l_i = sqrt\left[\left(x_{j+1} - x_j\right)^2 + \left(y_{j+1} - y_j\right)^2 + \left(z_{j+1} - z_j\right)^2\right] \tag{8}$$

where n represents the total number of waypoint, j represents a certain waypoint and (x, y, z) separately represents the coordinates on the horizontal plane and the vertical height of the waypoint, and l_{str} represents the straight distance between the starting point and the target. The result of trajectory planning is that in the mission space, by searching a series of waypoints, these waypoints that meet the total constraints of the shortest range are obtained by iterative optimization, so as to form a flighting trajectory.

In addition, there are threats of radars and peaks in the actual environment, when UAVs perform trajectory planning, these threats need to be taken into account, so the following constraints will be introduced.

4) THREATENING CONSTRAINTS OF RADARS

When multi-UAV is on the mission, it is necessary to avoid being detected by radars. Assuming that the areas detected by radars are expressed as a hemispherical sphere and will not be covered by the surrounding terrain, then in the course of trajectory planning for the mission, the model of radar is set as

$$L_{radar} = (x_r, y_r, z_r, r_r) \tag{9}$$

where (x_r, y_r, z_r) indicate the central position of the radar, and r_r indicates its monitoring radius, the distance between each waypoint and the radar is calculated as

$$d_{jr}^R = \sqrt{(x_j - x_r)^2 + (y_j - y_r)^2 + (z_j - z_r)^2}. \tag{10}$$

The corresponding cost function for this constraint is

$$\begin{cases} f_R = \sum_{j=1}^{n} \sum_{L=1}^{L} B_{jr} \\ B_{jr} = \begin{cases} p_{jr}^r & if\ d_{jr}^R \le r_r \\ 0 & if\ d_{jr}^R > r_r \end{cases} \end{cases} \tag{11}$$

where (x_j, y_j, z_j) indicate the coordinate of the waypoint $j(j = 1, 2, \ldots, n)$.p_{jr}^r is the punitive value of the $j(j = 1, 2, \ldots, n)$ at the $L(L = 1, 2, \ldots, L)$ radar, and B_{jr} is the cost of threats after comparison, d_{jr}^R is the distance between the waypoint and the center of radars, f_R is the total punitive value of threats of radars.

5) THREATENING CONSTRAINTS OF PEAKS

In the actual environment, when multi-UAV cooperate to carry out task, it is also necessary to avoid peaks in the flighting area. Therefore, the UAV fleet should maintain a certain distance from peaks, the modeling of peaks are as follows

$$\begin{cases} x_u = a + u \\ y_u = b + u \\ z_u = c * \exp[(a - x)/d]^2 - [(b - y/d)]^2 \end{cases} \tag{12}$$

where x_u, y_u and z_u represent the 3D coordinate positions of peaks, a and b represent the starting position of the peak, c represents the height of the peak, d represents the adjustable coefficient, and u represents the span of the peak.

The cost function of this constraint is

$$\begin{cases} f_M = \sum_{j=1}^{n} \sum_{e=1}^{E} C_{je} \\ C_{je} = \begin{cases} p_{je}^m & if\ z_j \le z_u, \quad y_j \le y_u,\ x_j \le x_u \\ 0 & if\ z_j > z_u, \quad y_j \le y_u,\ x_j \le x_u \end{cases} \end{cases} \tag{13}$$

where (x_j, y_j, z_j) is the positional coordinate of waypoint, and f_M is the total punitive value of the constraints of peaks, p_{je}^m is the threatening value of the $e(e = 1, 2, \ldots, E)$ of peaks corresponding to the $j(j = 1, 2, \ldots, n)$ waypoint, and C_{je} is the threatening cost after comparison.

C. FUNCTION OF THE EVALUATION INDEX

The cooperative mission planning of multi-UAV needs to meet above constraints to optimize the performance of each UAV. Therefore, the objective function is expressed as

$$S = c_1 S_1 + c_2 f_2 + c_3 f_3 + c_4 f_R + c_5 f_M + c_6 f_B \tag{14}$$

where S represents the total cost value, S_1 represents the cost value of the shortest voyage, f_2 represents the cost value of the number of striking, f_3 represents the cost value of spatial cooperative constraint, f_R represents the cost value of the threat of radars, f_M represents the cost value of the threat of peaks, f_B represents the cost value of situation assessment of Bayesian networks. In addition, c represents the weighted value of each constraint, which meets the following conditions:

$$c_1 + c_2 + c_3 + c_4 + c_5 + c_6 = 1 \tag{15}$$

The sum of the weighted values of all constraints is 1, which indicates that when the algorithm is used for optimization, the solution is the optimal value of balancing each index. Considering that all kinds of constraints in the actual environment are accidental, and in order to get a more convincing optimal solution, the average values of all weights are taken in this study.

D. IMPROVED DISCRETE PARTICLE SWARM OPTIMIZATION BASED ON MIXED STRATEGY (MSDPSO)

Based on the idea of genetic algorithm (GA), discrete particle swarm optimization algorithm (DPSO) designs crossover and mutation strategies in discrete space, and redefines the update rules of particle position, as shown below.

$$X_\partial(te+1) = \gamma_2 \otimes F_3(\gamma_1 \otimes F_2(\omega \otimes F_1(X_\partial(te), P_p(te)), P_g(te))) \quad (16)$$

where te represents the number of iteration in the current stage, and ω represents mutation factor, γ_1 and γ_2 represent crossover factors. $X_\partial(te)$ represents position of the ∂ th particle in teth iteration, $P_p(te)$ represents the individual extreme value in teth iteration, $P_g(te)$ represents the global extreme value.

Due to slow solving efficiency and poor applicability of DPSO, the improved discrete particle swarm optimization algorithm based on mixed strategy (MSDPSO) is proposed, which effectively improves the optimality and convergence speed of the algorithm. The specific improvements are shown below.

1) INITIALIZATION STRATEGY BASED ON SOBOL SEQUENCE

Because DPSO initializes the population by generating pseudo-random number between 0 and 1, the organization and ergodicity are poor, and the individual distribution is uneven, which leads to low optimization. Thus, the Sobol sequence is proposed for initialization, which makes the distribution of population more standardized and the space of solution covers higher, so the optimization accuracy is promoted. Fig.2 shows a comparison between initialization by pseudo-random and Sobol sequence.

From the comparison of Fig. 2, it shows that spatial coverage of solution with the Sobol sequence is higher than that of traditional initialization, and the distribution is more standardized. The convergence speed for mission planning under Sobol sequence would be improved.

2) NONLINEAR TIME-VARYING STRATEGY

Drawing lessons from the idea of genetic algorithm (GA), DPSO discretized the position and speed of PSO and updated it into strategy of crossover and mutation, but its mutation cannot be adjusted in time according to the change of position, which led to deterioration of optimization. In order to solve this problem, a nonlinear time-varying strategy is introduced.

$$\begin{cases} \omega = 1 + \cos\left(\pi \times \dfrac{te}{Te}\right) & te \le \alpha Te \\ \omega = \cos\left(\pi \times \dfrac{te - 0.5Te}{Te}\right) & \alpha Te < te \le \beta Te \\ \omega = 0.9 - 0.5 \times \left(\dfrac{te}{Te}\right) & te \ge \beta Te \end{cases} \quad (17)$$

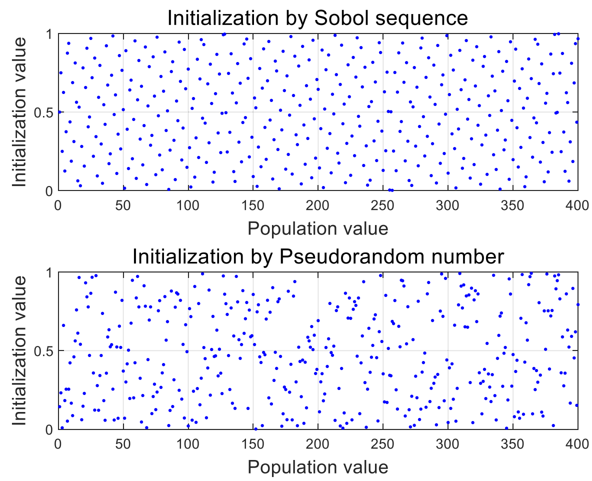

FIGURE 2. Comparison of initialization methods.

As shown in Equation (17), the mutation is divided into three stages, in which Te represents the maximum number of iteration and te represents the number of iteration in the current stage. When the mutation is in the later stage, the optimality of the solution is poor. Therefore, the first two stages of designing a nonlinear and time-varying mutation factor can enhance the mutated ability of particles, so as to get rid of local search in time and improve the optimization ability of the solution. The value of fitness tends to be optimal, and the factor of mutation adds to the linear link of the third stage, so as to accelerate the convergence speed of the algorithm. α and β represent the coefficient factors of different stages respectively, and the specific values are set according to simulation. In addition, the factors of crossover γ_1 and γ_2 also affect the regenerative speed and optimization ability of particles. In order to further improve the convergence speed and global optimization ability of the algorithm, the factor of crossover is linearly improved, as shown below:

$$\gamma_1 = 0.25 + 0.8 \times (te/Te) \quad (18)$$

$$\gamma_2 = 0.75 - 0.8 \times (te/Te) \quad (19)$$

where the cross factor γ_1 increases with the progress of the iteration, and γ_2 decreases with the accumulation of the iteration. This makes the algorithm actively carry out global search at the beginning of the iteration, and then improves the convergence speed. At the end of the iteration, the strengthening of individual learning ability makes it difficult for the population to fall into local optimum. Meanwhile, the sum of γ_1 and γ_2 is 1, indicating that the particles take into account both optimization ability and convergence speed.

3) MUTABLE STRATEGY OF CAUCHY

In view of the fact that DPSO is easy to fall into local optimization, the introduction of Cauchy operator can effectively improve the ability of global optimization and enhance the searchable space. Because the step size of Cauchy is smaller at the midpoint and larger at both ends, it has a greater disturbance to the individual particles, so that the particles can adjust their positions in time to avoid falling into local optimization. At the same time, the peak of Cauchy distribution decreases slowly and the peak is smaller, so that the particles spend less time on searching after mutation, and then spend more time on global optimization, so the convergence speed of the improved algorithm is improved.

The discretized algorithm uses the following improved Cauchy mutated formula to update the optimal position of the current individual and improve the global optimization ability.

$$\dot{X}_{new}(te) = ceil(\dot{X}_{new}(te) \times (1 + cauchy(-1, 0))) \quad (20)$$

where $\dot{X}_{new}(te)$ represents the optimal value updated by Cauchy mutation, $cauchy(-1, 0)$ represents the Cauchy operator, and the integer instruction is used to discretize the optimal position. As a result, the global optimization ability is enhanced and the convergence speed is also improved.

4) ADAPTIVE CROSS LEARNING STRATEGY

In view of the poor global optimization of DPSO, an adaptive cross-learning strategy is added in the early and later stage of the iteration to fit the cross-replacement between particles into a way of communication and learning between people. Particles continue to search for individual optimization in order to improve their own states, as shown below.

$$X_{new} = \begin{cases} \text{ceil}(x + \text{rand} \times (x - x_p)) & f(x_p) < f(x) \\ \text{ceil}(x + \text{rand} \times (x_p - x)) & f(x_p) \geq f(x) \end{cases} \quad (21)$$

where x represents random particles, x_p represents adjacent particles, and $rand$ indicates the random number between 0 and 1, which is used to enlarge the learning process between individuals, individual optimization is updated through continuous iteration, enriching the diversity of the population, and improving the global optimization of the improved algorithm.

E. UAV TRAJECTORY PLANNING

1) PARTICLE SWARM OPTIMIZATION ALGORITHM (PSO)

In order to ensure the rationality of mission assignment, it is necessary to make a reasonable flighting trajectory for UAVs to reach targets. Therefore, the trajectory planning is carried out based on basic particle swarm optimization algorithm (PSO). Its mathematical model is shown in the following formula.

$$v_i^{te+1} = \lambda v_i^{te} + \varepsilon_1 rand_1(p_b^{te} - x_i^{te}) + \varepsilon_2 rand_2(p_g^{te} - x_i^{te}) \quad (22)$$

$$x_i^{te+1} = x_i^{te} + v_i^{te+1} \quad (23)$$

whereλ represents inertia weighted coefficient, ε_1 and ε_2 are learning factors, P_b and P_g are individual optimal value and global optimal value respectively, $rand$ is a random number between 0 and 1, te is the current number of iterations.

2) CUBIC SPLINE INTERPOLATION

Compared with the task assignment based on straight-line distance, feasible trajectory generation can ensure better rationality of mission, but the trajectory obtained by PSO is a series of relatively rough waypoints, which lead to unsmooth trajectory of UAV. Therefore, the cubic spline interpolation is used to smooth the pre-planned trajectory of PSO, so as to get a smoother trajectory.

Supposing that $\tau = n_0 < n_1 < \cdots < n_n = \upsilon$, where n denotes total waypoint, the segmented function $p(n)$ on the interval $[n_{j-1}, n_j]$ is a polynomial less than or equal to cubic and second-order derivable. The details are as follows:

$$p(n) = \{p_j(n), n \in [n_{j-1}, n_j], \quad j = 1, \ldots, n\} \quad (24)$$

$$p_j(n) = \phi_j \cdot n^3 + \varphi_j \cdot n^2 + o_j \cdot n + \varsigma_j \cdot n^3 \quad (25)$$

where $\phi_j, \varphi_j, o_j, \varsigma_j$ represents the undetermined coefficient, and its sum is $4n$. In general, in order to obtain the undetermined coefficient of cubic spline interpolation function $p(x)$, the natural boundary condition is adopted, that is:

$$p_j''(x_j) = p_j''(x_n) = 0 \quad (26)$$

To sum up, a set of simultaneous equations is used to determine the value of undetermined coefficient.

F. PROCEDURE OF MULTI-UAV COOPERATIVE TASK PLANNING

Till now, the overall procedure of solving the task planning for multi-UAV is shown in Algorithm 1. The detailed procedures are introduced as follows:

IV. SIMULATIONS AND COMPARISONS

In this section, a variety of simulative experiments are carried out to verify the effectiveness and feasibility of the MSDPSO. These experiments are carried out in the environment of MATLAB and run on a computer configured with intel 5, 1.19GHz.

A. PARAMETER SETTING

The number of iteration $Te = 200$, the number of population $N = 400$, the number of waypoint $n = 10$, the number of striking $A_1 = 3, A_2 = 2$, the safe distance of UAV $d_{\min} = 20m$, and the nonlinear time-varying value $\alpha = 0.3$, $\beta = 0.6$.

The simulative environment of 3D is set as $250 \times 250 \times 70$ km, including 5 monitoring areas of radars and 2 areas of peaks. Radars are drawn by hemispheres and peaks are drawn by curved surfaces with different ups and downs. The parameter settings are shown in Table 3.

UAVs are modeled as particles and the relevant dynamic models are ignored. Assuming that in the initial situation, there is no faulty UAVs, the simulative experiment is carried out with 12 UAVs hitting 5 targets, the coordinate positions are shown in Table 4, the locations of targets are shown in Table 5.

In order to verify the optimization performance of the proposed algorithm, several groups of simulation experiments

Algorithm 1 Pseudo Code of the Proposed Method

```
Set starting position for UAV and destination position.
Set the swarm parameters, N, Te, n, A_1, A_2, d_min, α, β.
Set the penalty values of constraint conditions.
Set a relative large value for fitness value.
Calculate particle fitness value and select Gbest and Pbest.
//Main Loop
Initialize particles using Sobol sequence.
For i = 1 : Te
    the situation assessment of single UAV is carried
    out by using Bayesian network according to (2).
    Implement adaptive cross learning strategies
     according to (21);
     if i = i + 1 = i + 2 = · · · = i + 10
        Execute Cauchy mutation strategy by (20);
      else if
                    Execute nonlinear time varying
strategies according to (17)∼(19).
      end;
        Generate new particle in the group by (21).
   end;
   Sort fitness value of all particles.
   Trajectory pre-planning of based on PSO by
    (22)∼(23).
   Trajectory generation of with cubic spline
    interpolation by (24)∼(26).
End
Output the planned trajectory for UAVs.
```

TABLE 3. Parameters of the threat.

Obstacle type	Parameter setting
Radar 1	$x_1 = 120, y_1 = 217, z_1 = 0, r_1 = 31$
Radar 2	$x_2 = 150, y_2 = 162, z_2 = 0, r_2 = 32$
Radar 3	$x_3 = 150, y_3 = 100, z_3 = 0, r_3 = 30$
Radar 4	$x_4 = 95, y_4 = 96, z_4 = 0, r_4 = 29$
Radar 5	$x_5 = 125, y_5 = 42, z_5 = 0, r_5 = 27$
Peak 1	$a_1 = 70, b_1 = 60, c_1 = 40, d_1 = 19, k_1 = 12$
Peak 2	$a_2 = 80, b_2 = 150, c_2 = 50, d_2 = 19, k_2 = 19$

are carried out between MSDPSO and DPSO with each improved strategy. Then, in order to verify the application effectiveness of the improved algorithm, the scenarios of cooperative mission planning of multi-UAV in health state, severe faulty state and minor faulty state are compared and simulated respectively.

B. ANALYSIS OF SIMULATION RESULTS

1) RESULTS AND COMPARISONS IN 3-D ENVIRONMENT

In previous research, the mission planning of multi-UAV only considers mission assignment based on linear distance,

TABLE 4. Starting position of UAVs.

UAV label	Position coordinate
U1	(30,245,25)
U2	(30,220,35)
U3	(40,195,30)
U4	(35,170,35)
U5	(20,145,30)
U6	(30,135,30)
U7	(20,125,35)
U8	(35,115,30)
U9	(35,100,35)
U10	(40,75,25)
U11	(35,50,30)
U12	(20,25,25)

TABLE 5. Locations of targets.

Target label	Position coordinate
T1	(180,215,0)
T2	(180,147,0)
T3	(200,115,0)
T4	(181,59,0)
T5	(140,25,0)

which does not meet the mission requirements of multi-UAV in actual flighting. MSDPSO takes the actual trajectory into account, which improves the applicable effectiveness of the algorithm. Therefore, in order to obtain convincing experimental results, the task assignment based on straight line and actual trajectory are simulated and compared respectively, the result is shown in Fig. 3.

Through the comparison of simulation, Fig. 3(a) shows that the task assignment of multi-UAV based on straight line cannot effectively avoid collision in 3D space, this will cause damage to UAVs and be detected by radars, thus leading to failure of the task. And the result of optimization is not optimal by comparing the simulative result. While MSDPSO considers the actual trajectory of UAVs, and the flyable trajectory can avoid obstacles, as is shown in Figs. 3(b)-(c).

Through the comparison of Fig. 3(b) and Fig. 3(c), it can be seen that the trajectory obtained based on PSO is discrete waypoints, but the trajectory of UAV optimized by cubic spline interpolation is smoother, which proves that the

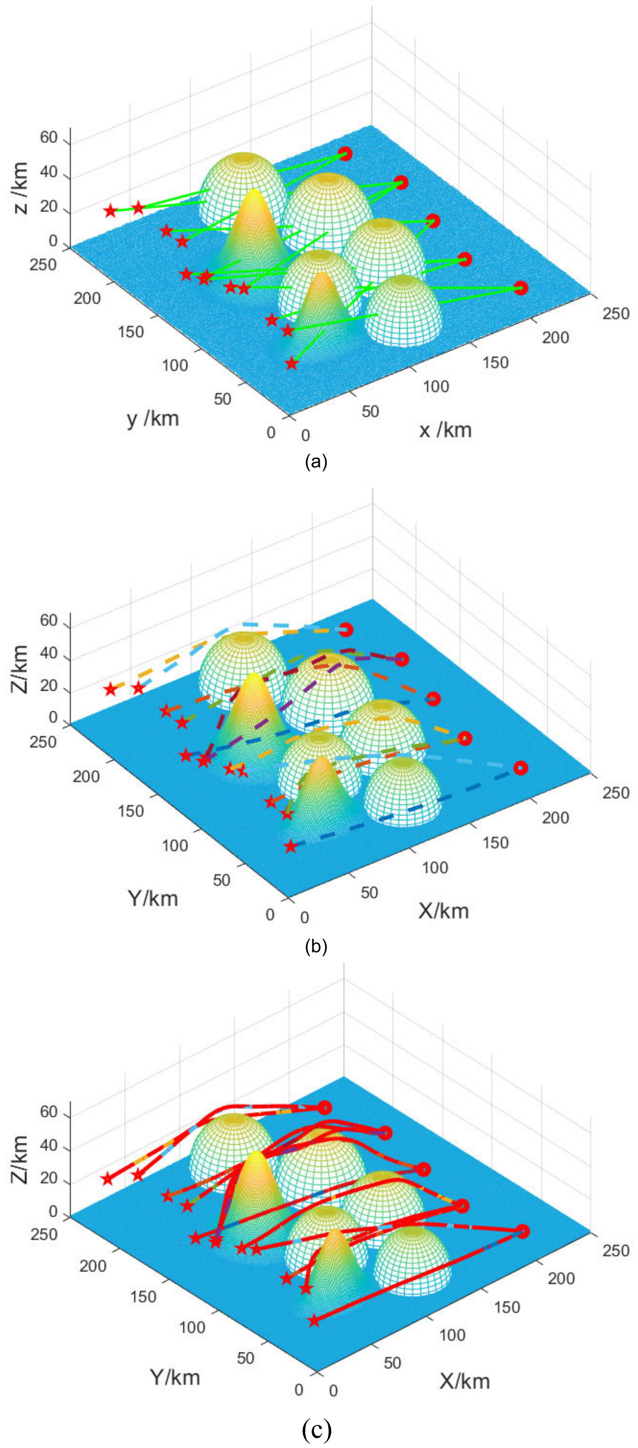

FIGURE 3. (a) Task assignment based on straight line. (b) Task assignment considering actual trajectory. (c) Trajectory smooth based on cubic spline interpolation.

trajectory using cubic spline interpolation is more in line with the actual flighting of UAV.

2) THE PERFORMANCE OF MSDPSO SIMULATION

According to the improved methods under different strategies, DPSO is improved and optimized respectively, and the following four kinds of improved DPSO with single strategy are obtained: improved discrete particle swarm optimization algorithm based on Sobol sequence initialization (SDPSO), improved discrete particle swarm optimization algorithm based on nonlinear time-varying mutation factor (NDPSO), improved discrete particle swarm optimization algorithm based on Cauchy mutation strategy (CDPSO), and improved discrete particle swarm optimization algorithm based on adaptive cross learning strategy (RDPSO).

In order to verify the effectiveness of the improved algorithm, MSDPSO is compared with SDPSO, NDPSO, CDPSO, RDPSO and DPSO. Meanwhile, Monte Carlo simulations of 10 times, 30 times, 50 times and 100 times are carried out separately, and the average value of various algorithms are calculated to get the contrasting diagrams of the fitness values of algorithms, as is shown in Fig. 4.

After several groups of Monte Carlo experiments are carried out to calculate the average value, it can be seen that MSDPSO is superior to DPSO and other single strategy improved algorithms in all iterations, and the effectiveness of optimization is better.

The comparison of average running time of each algorithm is shown in Fig. 5. It is verified that MSDPSO has shorter running time, which shows the improvement on convergence speed of the algorithm.

In addition, in order to verify that the optimization stability and effectiveness of MSDPSO are better than that of DPSO, the specific fitness curves under 100 Monte Carlo simulations are given, the results are shown in Fig. 6.

The results show that the fitness curves based on MSDPSO are more stable and convergent than DPSO, indicating that MSDPSO is more stable, and the optimal value is better than DPSO, which verifies that MSDPSO has higher global optimization ability and faster convergence speed.

3) MISSION PLANNING OF MULTIPLE UAVS IN HEALTHY STATE

In order to compare with the results of mission planning after fault. First of all, the situation assessment of each UAV is carried out by using Bayesian network, and the probability of each UAV hitting each target is obtained, as shown in Fig. 7, which is added to the index of multi-UAV mission planning as part of objective function.

Secondly, the cooperative task allocation of multiple UAVs in healthy state is carried out based on MSDPSO, and then the trajectory optimization of UAV is carried out by using cubic spline interpolation. Under various constraints and combined with relevant parameters, the simulations are shown in Fig. 8.

According to Figs.7-8, the cooperative mission planning of multi-UAV in the simulation scene basically accords with the law of striking distribution under the situation assessment of Bayesian network. It is verified that Bayesian network as an evaluation index has a certain guiding effectiveness to the objective function of mission planning.

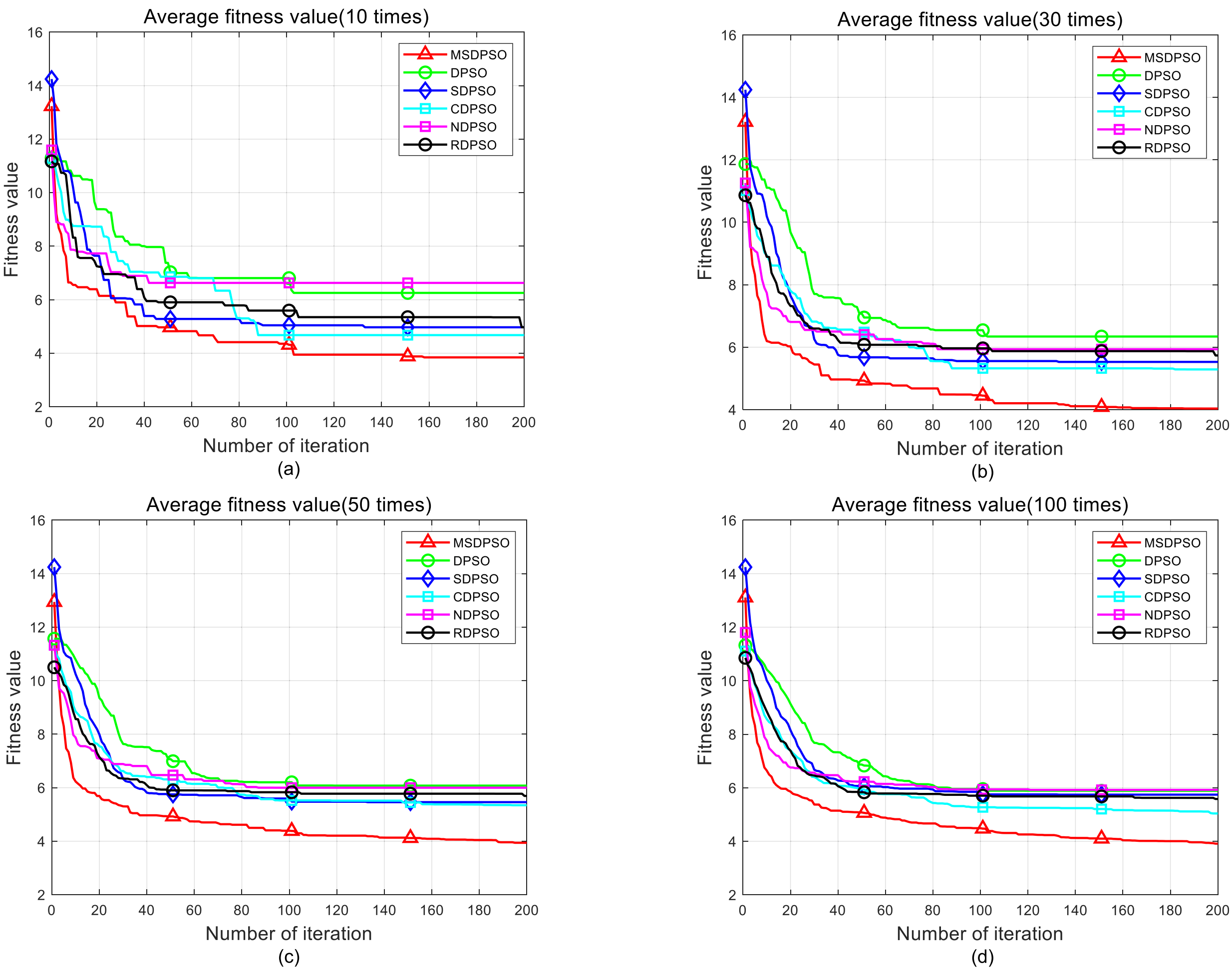

FIGURE 4. **(a) Comparing diagrams with 10 monte carlo simulations. (b) Comparing diagrams with 30 monte carlo simulations. (c) Comparing diagrams with 50 monte carlo simulations. (d) Comparing diagrams with 100 monte carlo simulations.**

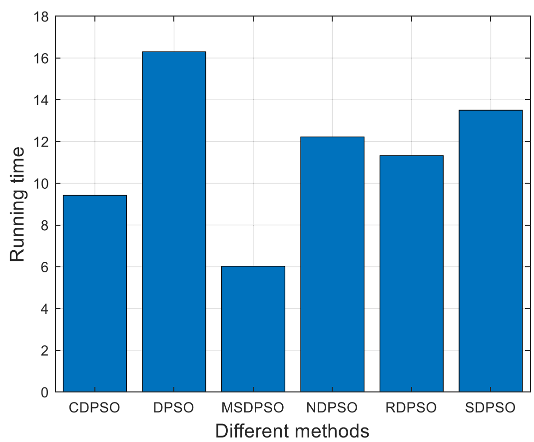

FIGURE 5. **Comparison of running time.**

4) COOPERATIVE MISSION PLANNING OF MULTIPLE UAVS UNDER SEVERE FAULT

It is assumed that during the striking mission of the 12 UAVs, UAV No. 2 and No. 8 have a severe fault at the third waypoint of the original trajectory planning, losing all striking capability and cannot continue to carry out the mission, so it is necessary to integrate each UAV to reassign tasks.

As the two malfunctioning UAVs withdraw from the combat sequence, in order to ensure the optimality of the mission, it is necessary to readjust the number of striking for healthy UAVs, so it is set that $A_1 = A_2 = 2$. Other constraints remain unchanged, and each UAV takes the position at the faulty moment as a new starting point to re-carry out mission planning. Meanwhile, based on Bayesian network, the situation assessment of the remaining 10 UAVs is carried out under the condition of meeting various constraints, as is shown in Fig. 9.

Taking the probability of situation assessment of after the fault as a reference, the cooperative mission planning of multi-UAV is carried out after the withdrawal of severe faulty UAVs, as is shown in Fig. 10. The red stars represent the starting locations of UAVs, the black stars indicate the locations of the waypoints when UAVs break down.

Taking the locations of UAVs at the faulty moment as new starting points, the remaining 10 UAVs re-execute the mission planning, the specific simulative results are shown in Fig. 11.

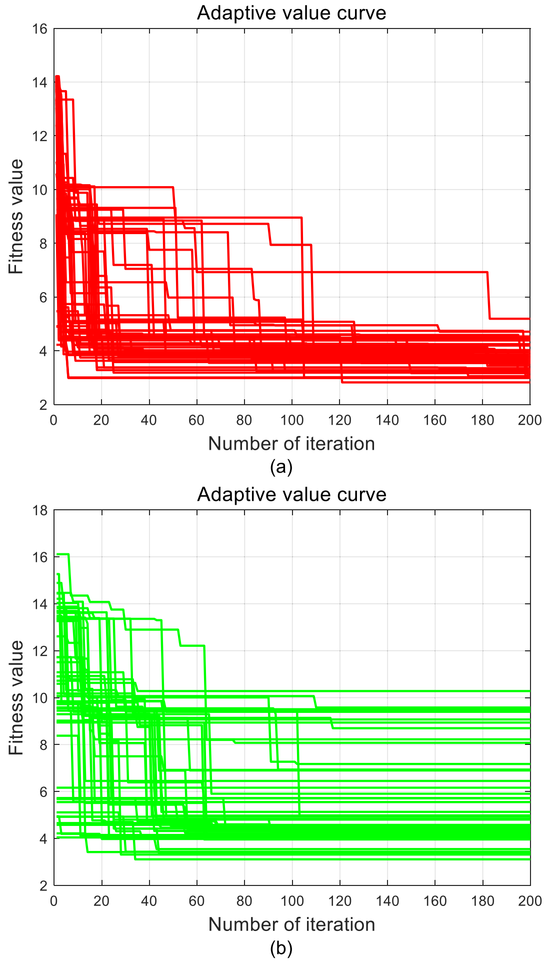

FIGURE 6. (a) Fitness value of MSDPSO. (b) Fitness value of DPSO.

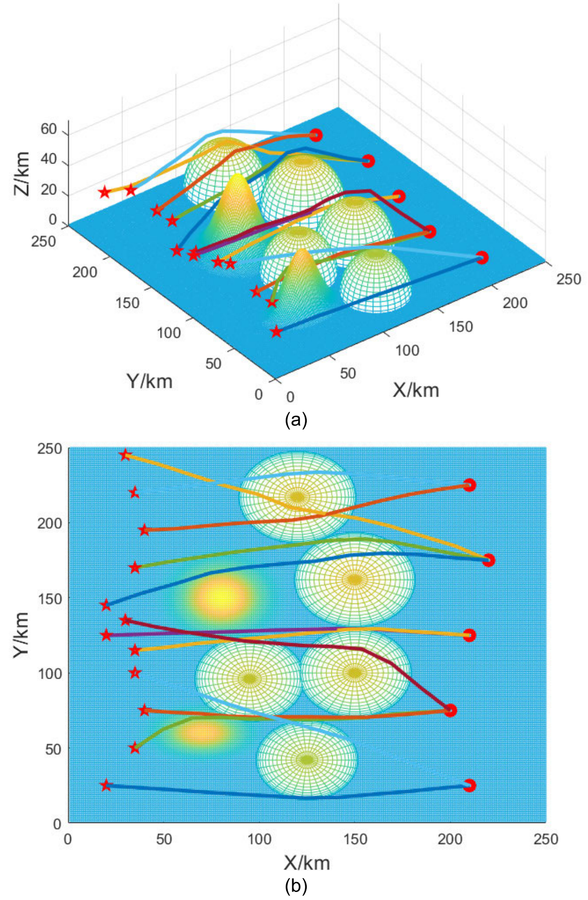

FIGURE 8. (a) 3D view of UAV cooperative mission planning in healthy state. (b) X-Y view of UAV cooperative mission planning in healthy state.

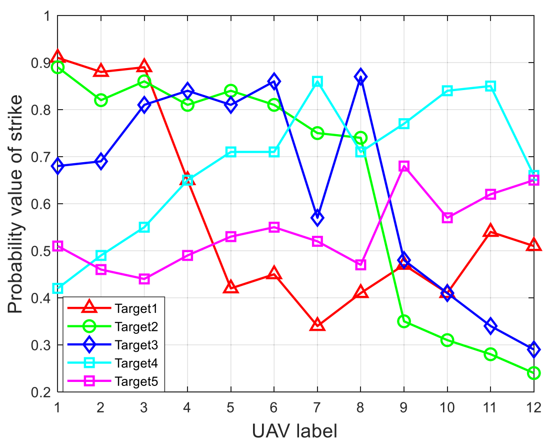

FIGURE 7. Evaluation of bayesian network in healthy state.

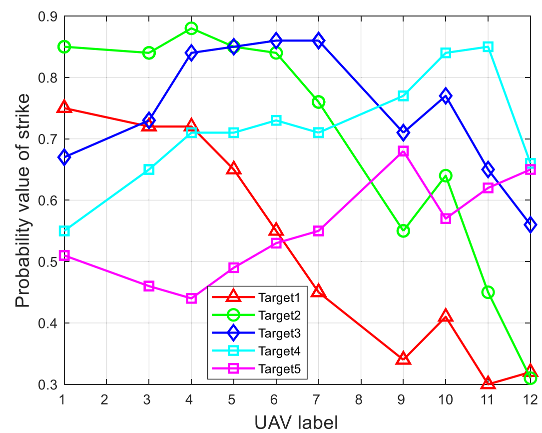

FIGURE 9. Evaluation of bayesian network under severe fault.

Fig. 11 shows that after malfunctioning UAVs withdraw from the current locations, the healthy UAVs successfully carried out mission planning, which verifies MSDPSO has good effectiveness of optimization.

In addition, from the simulative results of UAV striking allocation before and after the fault in Fig. 12, the red triangles represent the task assignment result of the UAV in the normal state, and the green circles indicate the task assignment result of the UAV in the event of a severe fault. it can be seen that MSDPSO can effectively adjust the change of the constraint of the number of striking after fault, and successfully complete the task. And the distance between each UAV also satisfies the minimum safe distance, as shown in Fig. 13.

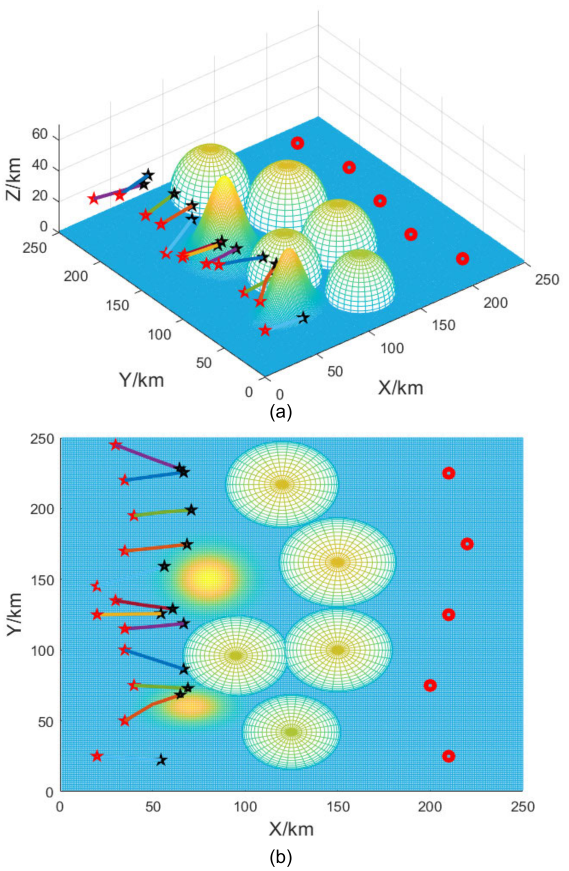

FIGURE 10. (a) 3D view of faulty location of UAVs. (b) X-Y view of faulty location of UAVs.

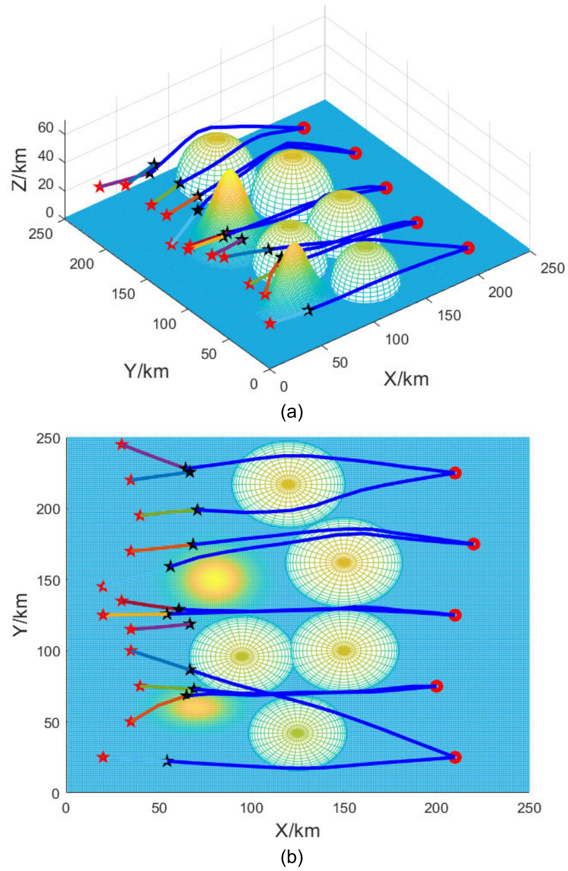

FIGURE 11. (a) 3D view of UAV cooperative mission planning under severe fault. (b) X-Y view of UAV cooperative mission planning under severe fault.

5) COOPERATIVE MISSION PLANNING OF MULTIPLE UAVS UNDER MINOR FAULT

It is assumed that during the striking mission of 12 UAVs, UAV No. 2 and No. 8 have a minor fault at the third waypoint of the original trajectory planning, losing part of striking capability and cannot strike in accordance with the original mission. Thus, it is necessary to integrate each UAV to replan the mission.

Due to minor fault of two UAVs, in the case of not withdrawing from the combat sequence, the flighting ability of the UAV under the fault is limited, so it can only strike the targets within the local range. In order to complete the original mission planning, the healthy UAVs adjust their status to assist the malfunctioning UAVs to re-complete the task of hitting new targets. Therefore, in order to optimize the results of mission planning, each UAV completes tasks at the lowest cost under the preset constraints. At the same time, based on Bayesian network, the situation assessment of UAVs under minor fault is carried out, as shown in Fig. 14.

Similarly, with reference of the probability of Bayesian network, cooperative mission planning is carried out for multi-UAV under minor faulty scenario, as is shown in Fig. 15. The red stars represent starting points of UAVs, and the black stars indicate locations of waypoints when the second and eighth UAV break down. The blue lines represent the trajectories of UAV No.2 and No.8 before fault.

TABLE 6. Comparison of voyages before and after fault.

Faulty UAV label	Voyage before fault (km)	Voyage after fault (km)
U2	187.54	187.54
U8	186.73	152.26

According to the simulative information, before the fault, the UAV No.2 and No.8 separately attacks the target No.1 and No.3, after the fault, the UAV No.2 and No.8 still retain part of the striking capability, and the states of the healthy UAVs are not affected. Therefore, by reducing the shortest ranges on the faulty UAVs, the malfunctioning UAVs are allowed to strike the nearest target first within the ranges of its action, meanwhile, other constraints remain unchanged, and based on MSDPSO, UAVs continue to complete the striking mission, the results of simulation are shown in Fig. 16.

According to results of allocation, the comparison of voyages before and after the fault of malfunctioning UAVs is shown in Table 6, it can be seen that the malfunctioning UAVs complete the striking mission with reduced voyages

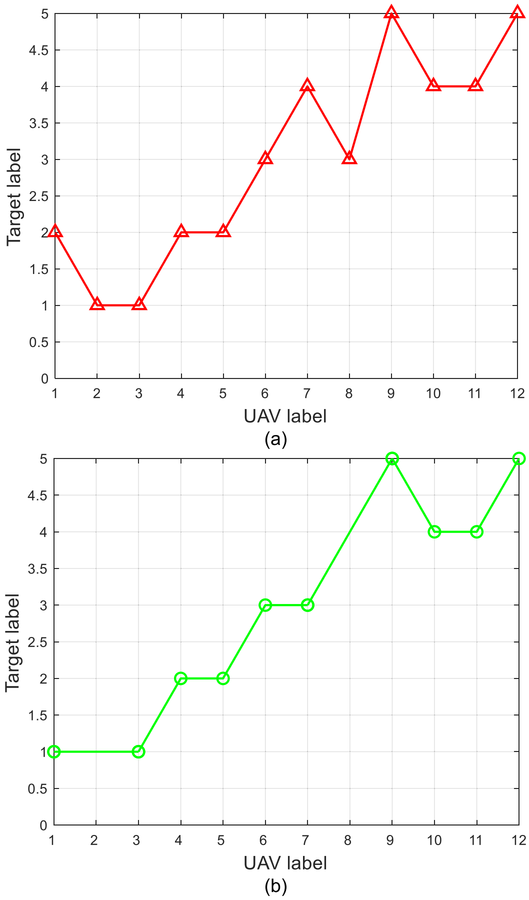

FIGURE 12. **(a) Striking distribution under healthy state. (b) Striking distribution under severe state.**

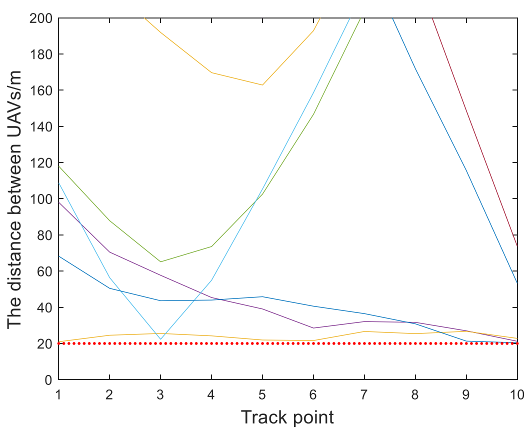

FIGURE 13. **UAV distance under severe state.**

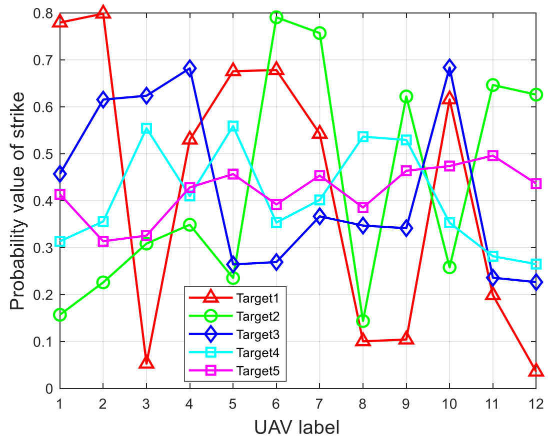

FIGURE 14. **Evaluation of bayesian network under minor fault.**

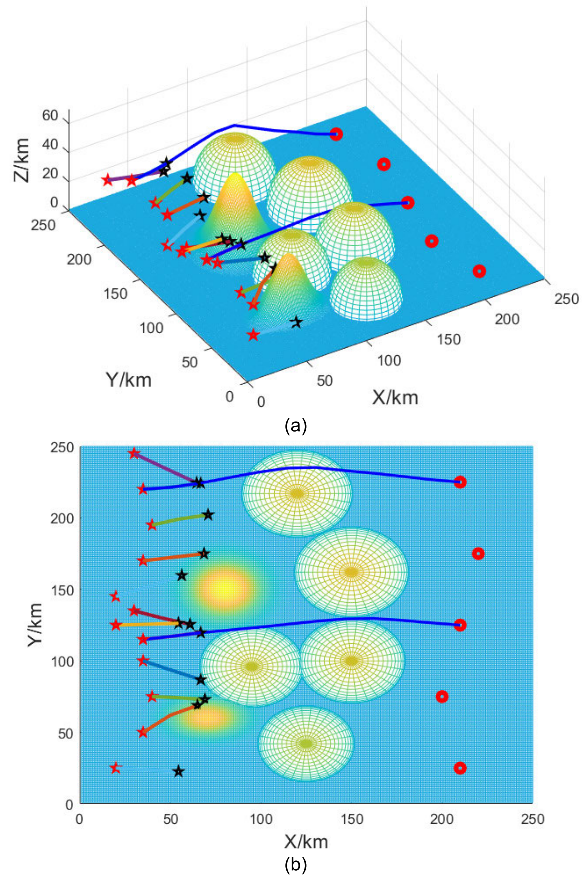

FIGURE 15. **(a) 3D view of the positions and original trajectories of the malfunctioning UAVs. (b) X-Y view of the positions and original trajectories of the malfunctioning UAVs.**

In Fig. 16, the rose lines represent the trajectory plannings of the healthy UAVs, and the black lines represent trajectories of faulty UAVs after mission rescheduling. Meanwhile, in order to make an effective comparison, the trajectories of malfunctioning UAVs before the fault are retained, as shown by blue lines. And combined with Fig. 17, it can be seen that before the fault, the UAV No.2 and No.8 hit the target No.1 and No.3 respectively. After the fault, UAV No.2 still strike the target No.1, indicating that the target is still within the limited voyage, the target No.1 is closest to the location of faulty UAV No.2, but the UAV No.8 is converted to strike the target No.4, indicating that healthy UAVs can give priority to malfunctioning UAVs, so that malfunctioning UAVs can first choose the target to strike according to the state of fault.

Similarly, as is shown in Fig. 18. The distance between each UAV under minor fault also satisfies the minimum safe distance. it can be seen that the minimum safety distance

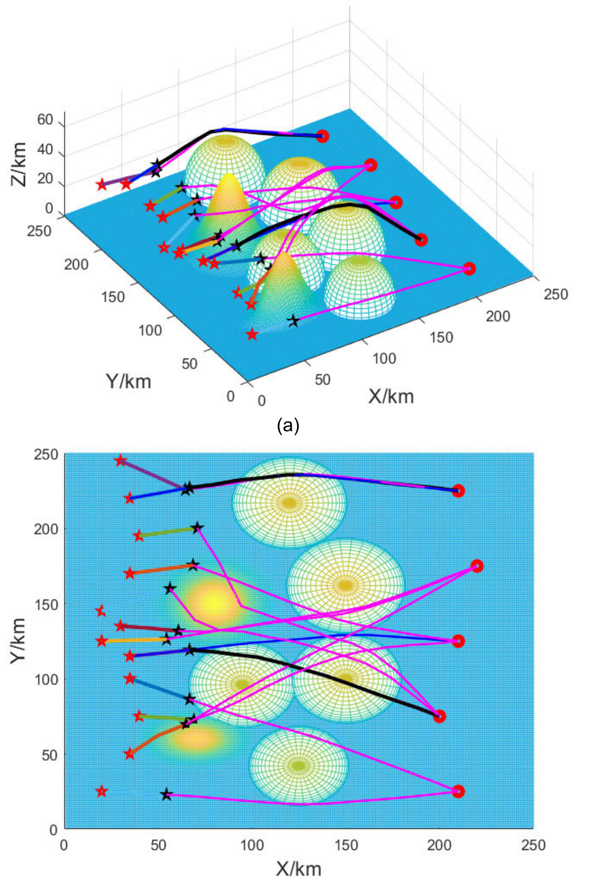

FIGURE 16. **(a) 3D view of multi-UAV cooperative mission planning under minor fault. (b) X-Y view of multi-UAV cooperative mission planning under minor fault.**

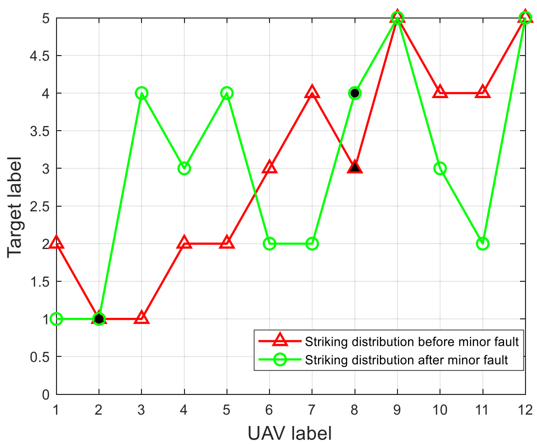

FIGURE 17. **Striking distribution before and after minor fault.**

between each UAV is set to 20km, and in the process of iterative optimization, each UAV keeps no less than the minimum safe distance in the trajectory planning of 10 track points. Because all UAVs meet the spatial cooperative constraints, the UAV with relatively close distance is intercepted as the final simulation diagram. The distance information of UAV with relatively large distance is ignored.

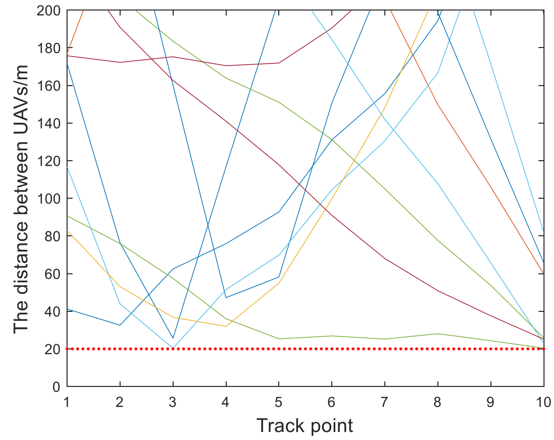

FIGURE 18. **UAV distance under minor fault.**

V. CONCLUSION

In order to solve the problem of cooperative mission planning of multiple UAV under fault, the paper proposed a self-organizing solving strategy. Firstly, the Bayesian network is introduced to evaluate the situation of single UAV. Then, an improved discrete particle swarm optimization based mixed strategy (MSDPSO) is proposed to solve the problem of multi-UAV cooperation, and four improvement strategies are introduced in detail. Finally, according to different faulty scenarios, several groups of simulative experiments are carried out, the results verify that the proposed algorithm has certain engineering applicability. The main results are summarized as follows:

1) The situation assessment of single UAV based on Bayesian network can be effectively coupled with the cooperative mission planning of multi-UAV.
2) The improved discrete particle swarm optimization based mixed strategy can obtain better optimal solution than traditional discrete particle swarm optimization and four single Strategy improved discrete particle swarm optimization.
3) The convergence rate of improved discrete particle swarm optimization based mixed strategy is faster than that of each DPSO.
4) The MSDPSO can optimize to get a better allocation scheme, thus reducing the cost of task planning, which verifies the effectiveness of the proposed method.

In the future, the problem of one-to-many mission planning of UAV under fault will be explored in depth.

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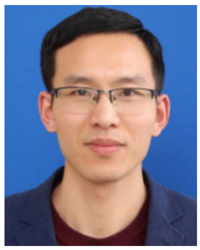

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