IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 22, 2020, accepted March 17, 2020, date of publication March 23, 2020, date of current version April 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2982784

COA Optimized Selection Method of Aviation Swarm Based on DINs and DABC

LUJUN WAN[1,2], YUN ZHONG[3], AND WEN LI[4,5]
[1]Air Traffic Control and Navigation College, Air Force Engineering University, Xi'an 710051, China
[2]State Key Laboratory of Air Traffic Management Systems and Technologies, CETC 28, Nanjing 210007, China
[3]Unit 94062 of PLA, Korla 841000, China
[4]Equipment Management and UAV Engineering College, Air Force Engineering University, Xi'an 710051, China
[5]Unit 95801 of PLA, Beijing 100076, China

Corresponding author: Lujun Wan (pandawlj@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61703425.

ABSTRACT Aiming at the selection problem for course of action (COA) of aviation swarm, this paper proposes an optimized selection method for COA of aviation swarm based on dynamic influence nets (DINs), and discrete artificial bee colony (DABC) algorithm. Firstly, based on the basic concept of the aviation swarm combat plan, static and dynamic modeling and analysis are performed, respectively. Then, the probability propagation mechanism of DINs, which mainly includes key parameter determination and probability propagation algorithm, is established. Subsequently, based on the analysis of the evaluation index, the model is solved by using DABC algorithm with real number coding. Finally, this paper takes the offshore island attack task as an example, and carries out multiple sets of simulation cases to compare DABC algorithm with discrete glowworm swarm optimization (DGSO) algorighm and discrete particle swarm optimization (DPSO) algorithm, through all these cases, the rationality of the model, and the effectiveness and superiority of the algorithm are verified.

INDEX TERMS Aviation swarm, course of action, dynamic influence nets, discrete artificial bee colony algorithm, probability propagation mechanism.

I. INTRODUCTION

With the rapid development of aviation platform technology, information network technology, and artificial intelligence technology, the trend of swarming, networking, as well as intelligentization of air combat has become increasingly apparent. Aviation platforms combat in a swarming mode, i.e., aviation swarm combat, will become an important air combat style in the future [1]. Different from the traditional aerial formation combat style, aviation swarm combat has more balanced platform capability distribution, more diverse formation style, more flexible battlefield command and control (C2), and has significant combat advantages.

The design for course of action (COA) of aviation swarm is that, the optimal or better combat action plan generated by aviation swarm, based on the actual combat environment and the possible hostile behaviors of the enemy. The essence of this problem is a scientific quantitative description and efficient optimization of the causal relationship among dynamic combat action, combat environment, and combat effect, and the pros or cons of designing effect will determine the level of aviation swarm combat capability.

For the analysis and modeling of COA problem, the current research mainly adopts bayesian networks (BNs) and dynamic bayesian networks (DBNs) [2]. As typical probabilistic network models, BNs and DBNs can effectively meet the modeling demands of combat problems with dynamic uncertainty. However, in practical applications, BNs and DBNs have their inherent defects. Firstly, in the process of probability reasoning, BNs and DBNs are highly dependent on the conditional probability table (CPT), and as the number of nodes increases, it will cause difficulties in the construction of CPT. Secondly, the reasoning calculations for a large number of probabilities in CPT, is relatively inefficient in computing time [3]. In order to effectively solve the above problems, through improving the related methods, Chang proposed a novel influence nets (INs) method by introducing causal strength logic (CSAT) parameters [4]. In the modeling process, INs only needs to specify the CAST parameters to characterize the positive and negative effects between a pair

The associate editor coordinating the review of this manuscript and approving it for publication was Rosario Pecora.

of nodes with dependencies, thereby reducing the number of parameter definitions. In addition, because INs adopts the so-called loopy belief propagation (LBP) mechanism to carry out reasoning, it effectively improves the reasoning efficiency [5], [6].

In terms of research details, in the current research, the key parameters are always dependent on expert experience, and the experience of different experts may lack consistency, which makes it difficult for key parameters to reflect comprehensive and accurate expert opinions. Therefore, the corresponding consistency algorithm is needed to gather the similar expert opinions to improve the credibility of key parameters. Besides, due to the limitation of encoding/ decoding method and the algorithm performance itself, the algorithm's solution efficiency is not high, it is necessary to use an efficient algorithm with simple and flexible encoding/ decoding method to solve the model.

To sum up, the research purpose of this paper is to select the best or better COA of aviation swarm, so as to improve the air combat effectiveness. Section II gives the concept of COA, and then a dynamic influence nets (DINs) method is used to systematically model the COA problem of aviation swarm. In Section III, key parameters are determined by using a consistency test method based on Kendall's test of concordance (KTC) [7], and a comprehensive weighted method is used to gather consensus expert opinions, and on this basis, probability propagation mechnism of DINs is put forward. Afterwards, a novle discrete artificial bee colony (DABC) algorithm is used to solve the model in Section IV. Section V provides several groups of simulation experiments to verify the performance of the proposed algorithm, and in Section VI, summary and future research prospects are given.

II. MODELING AND ANALYSIS OF COA

A. BASIC CONCEPT OF COA

Firstly, a few definitions need to be made clear.

Def. 1 (Actions): Actions are defined as feasible combat measures, which are jointly determined by multiple combat experts in accordance with the aviation swarm combat rule and combat resource constraints, and the purpose of actions is to achieve its own combat objectives.

Let the action set as $A = \{a_1, a_2, \cdots, a_{|A|}\}$, and $|A|$ is the number of actions. Considering that the completion of air combat task by aviation swarm is a continuous and dynamic evolution process, it is assumed that the evolution phase can be divided into $T+1$, and the external combat environment at the initial phase $t_0 \sim t_1$, is characterized as $CE(t_0)$.

If at the phase of $t_{k-1} \sim t_k (2 \leq k \leq T+1)$, aviation swarm takes action a_i, then let $P_{k-1}(a_i) = 1, 1 \leq i \leq |A|$. Conversely, if action a_i is not taken, then let $P_{k-1}(a_i) = 0, 1 \leq i \leq |A|$. Therefore, without considering resource and regulatory constraints, the number of optional subaction of a_i in all $T+1$ combat phase is 2^T. And due to the existence of corresponding constraints, the number of feasible subaction strategies of a_i is far less than 2^T.

Assume that the combat subaction set for a_i within all $T+1$ combat phase is $\Psi_i = \{a_i^1, a_i^2, \cdots, a_i^{|a_i|}\}$, $|a_i| < 2^T$. For all $1 \leq j \leq |a_i|$, there must be a_i^j in Ψ_i, is constituted by a sequence $[a_i^j(t_1), a_i^j(t_2), \cdots, a_i^j(t_T)]$ of length T, where $a_i^j(t_k) \in \{0, 1\}$, $1 \leq k \leq T$. Therefore, in $T+1$ combat phase, all combat actions constitute a feasible action space $\Psi_S = \Psi_1 \times \Psi_2 \times \cdots \times \Psi_{|A|}$.

Def. 2 (Hostile Behaviors): Hostile behaviors are defined as actions taken by the enemy to undermine our combat action, and the purpose of hostile behaviors is to hinder the achievement of our combat objectives. Let the possible hostile behavior set as $B = \{b_1, b_2, \cdots, b_{|B|}\}$, where $|B|$ is the number of hostile behaviors.

Due to the uncertainty of hostilities, the occurrence of hostile behaviors has certain random characteristics. However, combat experts can still give the occurrence probability of hostile behaviors in a certain combat phase based on historical combat data and their own combat experience.

At the phase $t_{k-1} \sim t_k (2 \leq k \leq T+1)$, the occurrence probability of $b_l (1 \leq l \leq |B|)$ is generally a probability interval with a range of $[P_{k-1}^{\min}(b_l), P_{k-1}^{\max}(b_l)]$. In this probability interval, this paper assumes that $P_{k-1}(b_l)$ obeys a uniform distribution [8].

Def. 3 (Desired Effects): Desired Effects are defined as the ultimate combat objectives to be achieved by aviation swarm. For different tasks performed, the type and number of desired effects are different. The goal of selecting an effective COA is to maximize the probability of achieving the desired effect. Let the desired effect set of aviation swarm combat as $D = \{d_1, d_2, \cdots, d_{|D|}\}$, where $|D|$ is the number of desired effects.

Def. 4 (Intermediate Effects): Intermediate Effects are defined as the phased combat effects achieved by aviation swarm in order to achieve the ultimate combat objective. Intermediate effects are the link between actions, hostile behaviors and desired effects. When aviation swarm performs complex tasks, it is difficult to directly establish the causal relationships among a large number of actions, hostile behaviors and desired effects.

Therefore, the classification and association of each causal relationship is generally achieved through intermediate effects, thereby effectively reducing the difficulty of characterizing all causal relationships in the combat process. Let the intermediate effect set of aviation swarm combat as $C = \{c_1, c_2, \cdots, c_{|C|}\}$, where $|C|$ is the number of intermediate effects.

B. STATIC MODEL OF COA BASED ON INs

The causal relationship modeling of COA based on INs is to use the CAST parameter to express the relationship strength between actions, hostile behaviors, desired effects and intermediate effects, and generate the probability of achieving desired effect through the probability propagation from the root node to the leaf node. As shown in Figure 1, it is a static model of COA based on INs.

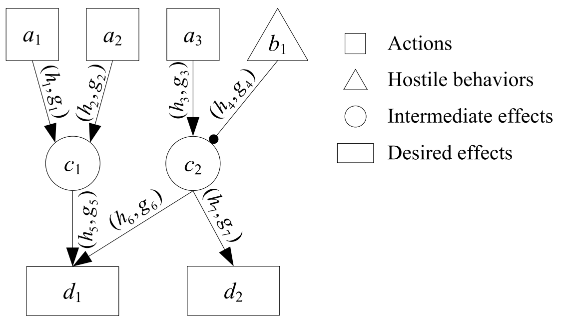

FIGURE 1. Static model of COA based on INs.

The static model of COA based on INs can be characterized as a quaternion array $IN = \{V, E, CAST, BP\}$, where $V = \{A, B, C, D\}$ represents the node set in influence nets, including actions, hostile behaviors, desired effects and intermediate effects. The value of the node is binary, i.e., the value is 0 or 1.

$E = \{(A, C), (B, C), (C, D)\}$ represents the causal relationship of all nodes in influence nets, and it is described by a directed edge with an arrow or a round head.

CAST represents the influence strength value in influence nets, for direct edge (A, C), the influence strength value is $CAST_{A,C} \in \{(h, g)|h \geq -1, g \leq 1\}$, where h represents the influence level of parent node equals 1 on child node equals 1, and g represents the influence level of parent node equals 0 on child node equals 1. Generally, according to the value of h and g, the causal relationship can be divided into two types, i.e., promotion relationship and inhibition relationship. For direct edge (A, C), when $h > 0$, $g \leq 0$, it indicates that A has a promoting effect on C, and the corresponding $e \in E$ is a directed edge with an arrow head, while when $h \leq 0$, $g > 0$, it indicates that A has an inhibitory effect on C, and the corresponding $e \in E$ is a directed edge with a round head.

BP represents the prior probability or benchmark probability of the corresponding node value is 1, i.e., the probability that the specific node value equals 1 without the external causality. Among them, the root node corresponds to the prior probability, and the leaf node corresponds to the benchmark probability. In an actual COA problem, there may be multiple events that affect an event. Taking event c_n affected by event set $A = \{a_1, a_2, \cdots, a_{|A|}\}$ as an example, suppose $\boldsymbol{X}_{|A|}$ is a binary random vector with $|A|$ dimensions, the value of the i-th component in $\boldsymbol{X}_{|A|}$ is x_i. If event a_i occurs, then $x_i = 1$, on the contrary, $x_i = 0$.

In order to measure the influence of the value of x_i on event c_n, Equation (1) is used to define the influence strength value of event a_i on event c_n from a qualitative perspective.

$$h(a_i) = \begin{cases} 1, & \text{Given } a_i\text{, event } c_n \text{ must occur} \\ -1, & \text{Given } a_i\text{, event } c_n \text{ must not occur} \\ 0, & \text{Occurence of } c_n \text{ is independent to } a_i \end{cases} \tag{1}$$

If a_i is given, the conditional probability that event c_n to be true is $P(c_n|A_i)$, then Equation (2) represents the influence strength value $h(a_i)$ defined from a quantitative perspective.

$$P(c_n|a_i) = \begin{cases} 1, & h(a_i) = 1 \\ 0, & h(a_i) = -1 \\ P(c_n), & h(a_i) = 0 \end{cases} \tag{2}$$

where $P(c_n)$ is the benchmark probability that event c_n occurs.

Let $h(a_i) \in [-1, 1]$, and use linear interpolation to expand the definition space of $P(c_n|A_i)$. If a_i is given, then the conditional probability that event c_n occurs, i.e., $P(c_n|A_i)$, can be defined as follows.

$$P(c_n\,|a_i\,) = \begin{cases} P(c_n) + h(a_i) \cdot [1 - P(c_n)], & h(a_i) \in [0, 1] \\ P(c_n) + h(a_i) \cdot P(c_n), & h(a_i) \in [-1, 0) \end{cases} \tag{3}$$

C. DYNAMIC MODEL OF COA BASED ON DINs

Through Equation (1), (2) and (3) in above, the mapping relationship between *CAST* value and conditional probability $P(c_n|A_i)$ is established, so that the causal relationship among actions, hostile behaviors, desired effects, and intermediate effects is linked with the influence strength value to generate the influence nets accordingly.

However, aviation swarm combat process is continuous and dynamic, combat actions and hostile behaviors will continuously evolve as the battlefield situation changes. As a result, the static model of COA based on INs cannot effectively represent the dynamic evolution of parameter variables [9].

In order to overcome the shortcomings of non-dynamic characteristics of INs during the modeling process, this paper uses DINs to dynamically model the COA problem of aviation swarm combat, and introduces a self-loop (SL) mechanism in the calculation of the influence strength value. It means that the desired effect and intermediate effect realization probability of a certain combat phase are not only related to the combat action sequence of current combat phase, but also are related to the desired effect and intermediate effect realization probability of previous combat phase, thus effectively describing the Markov characteristic of the state transition of the desired effect and intermediate effect.

For the evaluation index of selecting the best COA for aviation swarm combat, a single or a combination indicator can be used. The evaluation indicators generally include that, (i) the desired effect realization probability $P\{d_m(t_k)\}$ in $t_{k-1} \sim t_k$ phase, (ii) the desired effect realization probability $P\{d_m(t_{T+1})\}$ in the final combat phase, and (iii) the average desired effect realization probability $P\{\underline{d}_m\}$ in all combat phase. Considering that the optimal purpose of aviation swarm combat is to effectively complete tasks, the desired effect realization probability $P\{d_m(t_{T+1})\}$ in the final combat phase is selected as the evaluation index.

Therefore, with the aviation swarm combat resources as the constraints, and the desired effect realization probability under a specific sequence of actions as the optimization goal, the optimization model of COA selection based on DINs is defined as Equation (4).

$$\max F(S) = {}_{m=1}^{|D|} f(P\{d_m(t_{T+1})|CE(t_0), \Psi_S\})$$
$$s.t. \begin{cases} R(t_k) \leq R_0, \quad 1 \leq k \leq T+1 \\ S \subseteq \Psi_S \end{cases} \tag{4}$$

where $R(t_k)$ is the combat resource consumption in combat phase $t_{k-1} \sim t_k$, and R_0 is the combat resource threshold.

The objective function indicates that when it takes the initial external combat environment as the starting point, the model is to maximize the aggregate function of all final desired effect probabilities by selecting the corresponding combat sequence in the feasible action space. The first constraint indicates that the combat resource consumption in any combat phase cannot exceed the combat resource threshold. The second constraint indicates that the combat sequence must be selected in the feasible space.

As shown in Figure 2, it is a dynamic model of COA based on DINs, where the dashed line indicates the backward influence relationship of desired effects and intermediate effects, and parameter $P_k(V_i^0)$, $1 \leq k \leq T, V_i \in \{C, D\}$ indicates the probability value of the corresponding node is 1, which is passed from combat phase t_{k-1} to combat phase t_k, i.e., $P_k(V_i^0) = P_{k-1}(V_i)$ holds.

III. PROBABILITY PROPAGATION MECHANISM OF DINs

Like INs, the probability propagation of DINs is an approximate reasoning under the condition that the parent and child node are independent. The core elements of probability reasoning, CAST parameters, are given by combat experts based on combat experience. Unlike INs, DINs has dynamic characteristics, i.e., the probability of the parent node will change over time, and the child node will change accordingly.

The probability propagation mechanism of DIN mainly includes two aspects, i.e., key parameter determination and probability propagation algorithm. Among them, the key parameters mainly include CAST parameters, prior probability and benchmark probability.

A. KEY PARAMETER DETERMINATION

The key parameters in DINs are generally determined by the knowledge fusion method of multiple experts. In the specific representation method, a key parameter can be characterized by a two-dimensional coordinate system, which is also called belief graph, with the abscissa as the authority Q and the ordinate as the influence strength *CAST*.

Specifically, Q and *CAST* adopts fuzzy language type classification method, the mapping from comments to quantitative expression is established.

The evaluation of authority Q is divided into five levels, which are very high (VH), relatively high (RH), average (AV), relatively low (RL) and very low (VL), the corresponding quantified values are 1, 0.75, 0.5, 0.25, 0 respectively.

The evaluation of influence strength *CAST* is divided into seven levels, which are absolutely strong (AS), very strong (VS), relatively strong (RS), average (AV), relatively weak (RW), very weak (VW) and absolutely weak (AW),

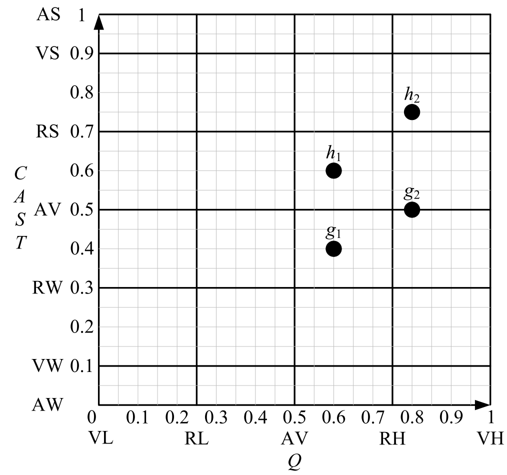

FIGURE 3. ***CAST* representation method based on belief graph.**

the corresponding quantified values are 1, 0.9, 0.7, 0.5, 0.3, 0.1, 0 respectively.

As shown in Figure 3, it is *CAST* representation method based on belief graph.

The measurement points $h_2(0.8,0.75)$ and $g_2(0.8,0.5)$ respectively indicate that, without considering the positive and negative signs, the h value given by an expert with authority of 0.8 is 0.75, and the g value is 0.5.

Generally, corresponding methods are used to generate the influence strength values directly. However, the current research lacks a consistency test of expert opinions, which causes some expert opinions that are inconsistent with other expert opinions to affect the final influence strength value generation. Therefore, the KTC method is used to test the consistency of expert opinions, and then the final results are generated by the fusion of expert opinions passing the consistency test.

(i) Consistency test based on KTC method

Let the combat expert set as $Z = \{z_1, z_2, \cdots, z_{|Z|}\}$, where $|Z|$ is the number of experts, and the consistency test steps for expert opinions in set Z are as follows.

Step 1 For expert $z_o \in Z(1 \leq o \leq |Z|)$, let the given influence strength value as $h_o(Qh_o, Ch_o)$ and $g_o(Qg_o, Cg_o)$, where Qh_o as well as Qg_o is the authority of expert z_o, generally $Qh_o = Qg_o$ holds, and Ch_o and Cg_o are h and g value given by expert z_o respectively. Taking h value as an example, the constructed ascending vector according to the vector $H_o = (Ch_{o,1}, Ch_{o,2}, \cdots, Ch_{o,|V|})$ given by expert z_o is as follows.

$$R_o = (r_{o,1}, r_{o,2}, \cdots, r_{o,|V|}) \tag{5}$$

where $r_{o,v}(1 \leq v \leq |V|)$ is the sort number of $Ch_{o,v}$ with ascending order in H_o.

Step 2 Establish hypothesis J_0, i.e., the combat expert opinions in set Z are inconsistent on the evaluation of the influence strength value, and alternative hypothesis J_1 is that, the combat expert opinions in set Z are consistent on the

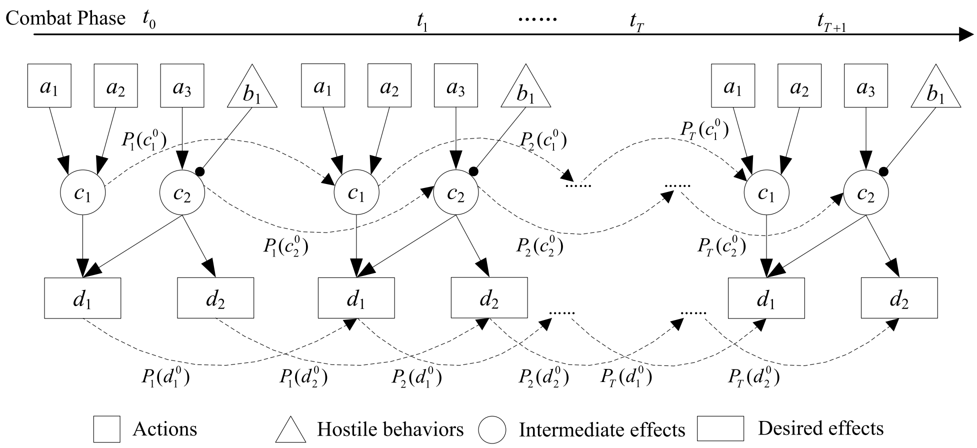

FIGURE 2. **Dynamic model of COA based on DINs.**

evaluation of the influence strength value. Let the significance level $\alpha = 0.05$.

Step 3 According to Equtation (6), calculate the KTC value of expert set Z, i.e., Kendall(Z).

$$\text{Kendall}(Z) = \frac{12\sum_{v=1}^{|V|}\left(\sum_{o=1}^{|O|} r_{o,v} - \frac{1}{|V|}\sum_{v'=1}^{|V|}\sum_{o=1}^{|O|} r_{o,v'}\right)^2}{|O|^2 \cdot |V| \cdot (|V|^2 - 1)} \tag{6}$$

Step 4 Compare the size of Kendall(Z) and the test threshold K_α, which is determined by the value of significance level α and $|V|$. If Kendall(Z) $< K_\alpha$, then hypothesis J_0 holds, otherwise, hypothesis J_1 holds.

(ii) Gather consensus expert opinions based on comprehensive weighted method

Through the consistency test of expert opinions, the consensus degree of expert set Z can be obtained as η_Z.

$$\eta_Z = \begin{cases} 0, & \text{Kendall}(Z) < K_\alpha \\ 1, & \text{Kendall}(Z) \geq K_\alpha \end{cases} \tag{7}$$

Next, it needs to find an expert group Z', so that the experts in Z' have the similiar opinion and Z' has the highest group authority.

$$\max \mu_{Z'} \quad s.t. \begin{cases} \eta_{Z'} = 1 \\ Z' \subseteq Z \end{cases} \tag{8}$$

where the first constraint indicates that the expert opinions in Z' must be consistent, and $\eta_{Z'}$ is the group authority of Z', the calculation method is as follows.

$$\mu_{Z'} = \sum_{z_o \in Z'} Qh_o \tag{9}$$

To solve Equation (8), comprehensive weighted method should be used to gather expert opinions to obtain the fused influence strength value, and the specific steps are as follows.

Step 1 Initialize expert set $Y = \emptyset$, and let the counting flag $count = 1$.

Step 2 Judge whether the consensus degree η_Z of expert set Z is equal to 1, if not, move the expert with the least opinion similarity in Z to set Y, and repeat step 2 until there is only one expert left in Z or $\eta_Z = 1$. The calculation method of opinion similarity is shown in Equation (10).

$$\delta_o = \frac{\sum_{1 \leq o' \leq |O|, o \neq o'} \text{Kendall}(\{z_o, z_{o'}\})}{|O| - 1} \tag{10}$$

Step 3 Let $Z_{count} = Z$, $count = count + 1$, and let $Z = Y$.

Step 4 Compare the group authority of $Z_1, Z_2, \cdots$, and let $Z' = \text{argmax}\{\mu_Z^1, \mu_Z^2, \cdots\}$.

Step 5 Through step 1 to step 4, the expert group that conforms to the consistency principle and has the largest group authority is determined, and Equation (11) is used to calculate the result of h value that combines the knowledge of multiple experts.

$$H = \sum_{z_o \in Z'} \frac{Qh_o}{\mu_{Z'}} H_o \tag{11}$$

Similarly, the g value, prior probability, and benchmark probability can be calculated through the above steps.

B. PROBABILITY PROPAGATION ALGORITHM

In any combat phase, the realization probability of the child node depends on the realization probability of the parent node. Therefore, as the combat process continues to progress, it is necessary to update the child nodes' realization probability from top to bottom according to the change of the parent nodes' realization probability. The specific probability propagation algorithm is as follows.

Step 1 For a specific combat phase, nodes can be divided into different levels based on the current out-degree and in-degree conditions of all nodes in the network. Among them, the root node level is highest, the middle node level is middle, and the leaf node level is lowest.

Step 2 Judge whether to enter the next combat phase, and if so, update the level of all nodes and the prior probability of the root node.

Step 3 Normally, the conditional probability of a child node is calculated based on the influence strength value and parent node value. Let the parent node set as A, the child node as c_n, the influence strength value of a_i is $h(a_i)$, then the conditional probability calculation process of c_n is as follows.

(i) Aggregate all positive influence strength values to generate M_{pos}.

$$M_{pos} = 1 - \prod_{h(a_i)\geq 0} (1 - h(a_i)) \tag{12}$$

(ii) Aggregate all negtive influence strength values to generate M_{neg}.

$$M_{neg} = 1 - \prod_{h(a_i)<0} (1 + h(a_i)) \tag{13}$$

(iii) Combine M_{pos} and M_{neg} to generate M.

$$M = \begin{cases} \dfrac{M_{pos} - M_{neg}}{1 - M_{neg}}, & M_{pos} \geq M_{neg} \\ \dfrac{M_{neg} - M_{pos}}{1 - M_{pos}}, & M_{pos} < M_{neg} \end{cases} \tag{14}$$

(iv) Calculate the corresponding conditional probability $P(c_n|A_1, a_2, \cdots, a_{|A|})$.

$$P(c_n|a_1, a_2, \cdots, a_{|A|}) = \begin{cases} P(c_n) + M \cdot [1 - P(c_n)], M_{pos} \geq M_{neg} \\ P(c_n) + M \cdot P(c_n), M_{pos} < M_{neg} \end{cases} \tag{15}$$

Step 4 According to the full probability equation, calculate the realization probability of the child node. Similarly, take the parent node event occurrence in step 3 as an example, the calculation method of $P(c_n)$ is defined as Equation (16).

$$\begin{aligned} P(c_n) = & P(c_n|a_1, a_2, \cdots, a_{|A|}) \times P(a_1, a_2, \cdots, a_{|A|}) \\ & + P(c_n|\neg a_1, a_2, \cdots, a_{|A|}) \\ & \times P(\neg a_1, a_2, \cdots, a_{|A|}) \\ & + P(c_n|a_1, \neg a_2, \cdots, a_{|A|}) \\ & \times P(a_1, \neg a_2, \cdots, a_{|A|}) + \cdots \\ & + P(c_n|\neg a_1, \neg a_2, \cdots, \neg a_{|A|}) \\ & \times P(\neg a_1, \neg a_2, \cdots, \neg a_{|A|}) \end{aligned} \tag{16}$$

Step 5 Follow the above steps to update the probabilities of all nodes at all levels.

Considering the dynamic characteristics of aviation swarm combat, the realization probability of target nodes, i.e., the desired effects and intermediate effects, need to be calculated phase by phase. The specific steps are as follows.

Step 1 Initialize the state of all target nodes, and input the parameter values gathered by the consensus expert opinions.

Step 2 Select feasible actions in phase $t_{k-1}{\sim}t_k$, and then generate the occurrence probability of hostile behaviors in this phase.

Step 3 Probability propagation, i.e., the generation of desired effect and intermediate effect realization probability, is performed according to Equation (12) to Equation (16) in this combat phase.

Step 4 Propagate the desired effect and intermediate effect realization probability to the next combat phase, and calculate the desired effect and intermediate effect realization probability in the next combat phase according to Equation (12) to Equation (16).

Step 5 If the combat task ends, then calculate the objective function value $F(S)$.

IV. MODEL SOLVING

The COA selection problem of aviation swarm is a typical combination optimization problem, and its essence is to select the combination of actions that maximize the realization probability of the desired effects.

It mainly includes three key parts, first, it gathers expert opinions to generate all influence strength values based on the KTC method, and the second is to calculate the desired effect realization probability based on DINs, the third is to adopt the optimization algorithm to select the best action plan.

Considering the occurrence characteristics of hostile behaviors, we can adopt Monte Carlo method to determine the probability of hostile behaviors, adopt DINs method to calculate the desired effect realization probability, and use DABC algorithm to select the best action plan.

As shown in Figure 4, it is the basic framework of selecting the best COA for aviation swarm combat.

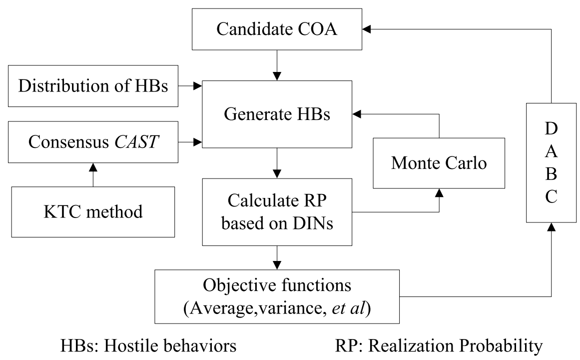

FIGURE 4. Basic framework of selecting the best COA for aviation swarm combat.

A. ENCODING AND DECODING METHOD

For combat action a_i in all $T + 1$ combat phase, the feasible action set, i.e., $\Psi_i = \{a_i^1, a_i^2, \cdots, a_i^{|a_i|}\}$, is determined by combat experts, and multiple combat subactions constitute an overall action strategy.

Taking into account the iterative characteristics of DABC algorithm, a $|A|$-dimentional real number encoding method is adopted. For individual elements at different positions in a vector, the value ranges are different. For the i-th individual element, the value range is $(1, |a_i| + 1)$, where $|a_i|$ is the number of subactions of combat action a_i.

When decoding, the subaction numbers are mainly determined based on the integer information of the individual elements. If the second individual element value is 3.0837, it means that the third subaction of a_2 is actually taken, i.e., a_3^2.

Through this encoding and decoding method, an effective mapping of the coding space to the decoding space can be achieved, and the decoding information can uniquely and conflict-freely represent the corresponding feasible solution, thereby greatly improving the search efficiency.

B. OBJECTIVE FUNCTION

Due to the uncertainty of hostile behaviors in actual combat, the desired effect realization probability may not be a fixed value, but a random value corresponding to the specific hostile behavior. In order to better reflect the random influence in the combat process, the Monte Carlo method is used to randomly generate the probability of hostile behaviors. By setting the random number to be R, the mean value μ and variance value σ^2 of all $P\{d_m(t_{T+1})|CE(t_0), \Psi_S\}$ are calculated. Based on μ and σ^2, the signal-to-noise ratio (SNR) value can be obtained according to Equation (17).

$$\mathrm{SNR} = -10 \cdot \lg[1/\mu^2 \cdot (1 + 3\sigma^2/\mu^2)] \tag{17}$$

This paper selects the mean value μ as the objective function.

C. DABC ALGORITHM PROCESS

Traditional artificial bee colony (ABC) algorithm simulates the foraging activities of bees to solve the combinatorial optimization problem, and it has the advantages of simple parameter setting and strong optimization ability [10]. The DABC algorithm proposed in this paper can be adopted to solve the discrete optimization problem shown in Equation (4), and the specific process of DABC algorithm is as follows.

Like the classic ABC algorithm, the process of DABC algorithm mainly includes four phases, i.e., the initialization phase, employed bee phase, onlooker bee phase, and scout bee phase. The number of initialized food sources, employed bees, and onlooker bees, are N_{fs}, N_{eb}, N_{ob}, respectively, there is an unevolved counter *trial* for each food source, and the initial value of *trial* is 0.

(i) Initialization phase

The element values in the initial food source matrix $\boldsymbol{X}$ are randomly generated within a feasible interval, and the number of rows in $\boldsymbol{X}$ equals the number of food sources N_{fs}, the number of columns in $\boldsymbol{X}$ equals the number of optional actions $|A|$. As shown in Equation (18), it is a randomly generated equation for the element in m-th row and s-th column, i.e., x_{ms}, in matrix $\boldsymbol{X}$.

$$x_{ms} = x_s^{\min} + rand_1 \times (x_s^{\max} - x_s^{\min}) \tag{18}$$

where $x_s^{\min}$ and $x_s^{\max}$ respectively represent the upper and lower bounds of the element in the s-th column in matrix $\boldsymbol{X}$, and $rand_1$ represents a random number in the range (0,1).

(ii) Employed bee phase

After the initial food source matrix $\boldsymbol{X}$ is generated, the employed bee searches for a better food source nearby according to the current location, and the update equation is as follows.

$$x'_{ms} = x_{ms} + rand_2 \times (x_{ms} - x_{m's}) \tag{19}$$

where x'_{ms} is an element in the newly generated food source matrix, $x_{m's}$ is a corresponding element in any other food source matrix, and $rand_2$ represents a random number in the range (0,1). If x'_{ms} is outside the range of [$x_s^{\min}$, $x_s^{\max}$], then take x'_{ms} as the nearest boundary value.

$$x'_{ms} = \begin{cases} x_s^{\min}, & \text{if } x'_{ms} < x_s^{\min} \\ x_s^{\max}, & \text{if } x'_{ms} > x_s^{\max} \end{cases} \tag{20}$$

Calculate the fitness value of the new food source. If it is better than that of the old one, then replace, and if it is inferior to that of the old one, the old one is kept unchanged, and the corresponding *trial* value is increased by 1.

(iii) Onlooker bee phase

After all the employed bees have completed the search, they exchange food source location information with the onlooker bees, and the onlooker bees calculate the following probability according to the corresponding food source location information.

$$p_m = 0.9 \times \frac{fit_m}{\max_{m=1,2,\cdots,N_{fs}} fit_m} + 0.1 \tag{21}$$

If p_m is greater than the randomly generated number $rand_3$ in the range (0,1), the onlooker bee will update the location of the food source according to Equation (19).

Similarly, it is necessary to compare the fitness values of the new food source and the old food source. If the former one is better, the old one is replaced, while if the latter one is better, the old one is kept unchanged, and the unevolution counter *trial* value is increased by 1.

(iv) Scout bee phase

If the solution quality of a certain food source has not evolved in $trial_{\max}$ iterations, then the employed bee correspondence to the food source will become a scout bee, the original food source is abandoned, and a new food source is randomly generated according to Equation (18). Besides, the corresponding *trial* value is set to be 0.

Repeat the above steps until the predetermined number of iterations, i.e., $iter_{\max}$, is reached or the desired optimization effect is achieved, and output the final result.

V. SIMULATION EXPERIMENT ANALYSIS

A. SIMULATION CASE DESIGN

There are many types of aviation swarm combat tasks, and this paper takes the offshore island attack task as an example. It is assumed that the enemy builds a complete combat defense system on an offshore island, and there are lots of important enemy targets, which include combat command centers, radar positions, ammunition depots, ports, and airports.

Our combat expectation is to concentrate all kinds of combat forces to destroy the enemy's key targets, so that it is easy to seize the control of the island in the next step.

(i) In terms of combat actions, the aviation swarm can take actions as follows.

a_1: Air-to-air attack on enemy air combat formations

a_2: Air-to-sea attack on enemy surface ships

a_3: Air-to-ground attack on fixed targets of the enemy

a_4: Air-to-ground attack on pre-fixed targets of the enemy

a_5: Air-to-ground attack on moving targets of the enemy

a_6: Air-to-ground attack on pre-moving targets of the enemy

a_7: Combat information support

a_8: Air intercept

a_9: Electronic interference

a_{10}: Aerial refueling

(ii) In terms of hostile behaviors, the types of behaviors are given by experts based on their experience or historical data, and the possible hostile behaviors are as follows.

b_1: Enemy air combat formations lauch air interception

b_2: Enemy surface ship formations launch air attack

b_3: Enemy air defense system lauches air defense combat

b_4: Enemy lauches electronic interference

b_5: Off-island reinforcement air combat formations participate in combat

(iii) In terms of desired effects, there are mainly two types.

d_1: Aviation swarm successfully completes all tasks

d_2: Damage of aviation swarm during task execution

(iv) In terms of intermediate effects, our combat actions and hostile behaviors work together to generate corresponding intermediate effects.

c_1: Execution effect of air-to-air attack

c_2: Execution effect of air-to-sea attack

c_3: Execution effect of pre-targets attack

c_4: Swarm builds up before attacking fixed/moving targets

c_5: Execution effect of fixed/moving targets attack

c_6: Aviation swarm returns to base

As shown in Figure 5, it is a DINs model of aviation swarm combat based on certain expert knowledge.

According to the analysis of experts, aviation swarm performing the attack task can be divided into six phases.

Phase $t_0 \sim t_1$, intercept the enemy's air interception formation. Phase $t_1 \sim t_2$, suppress the enemy's surface ships. Phase $t_2 \sim t_3$, attack the enemy's pre-fixed or pre-moving targets. Phase $t_3 \sim t_4$, after aerial refueling and before attacking fixed or moving targets, swarm builds up. Phase $t_4 \sim t_5$, attack the enemy's fixed or moving target. Phase $t_5 \sim t_6$, after intercepting the enemy's off-island reinforcement air combat formation, aviation swarm returns to base.

As shown in Table 1, it is the type and occurrence probability of hostile behaviors in each combat phase.

Based on experts' experience, considering combat resource and rule constraints, alternative strategies for different actions in all combat phase are given [11], which is shown in Table 2.

B. ANALYSIS OF SIMULATION RESULTS

In order to verify the correctness of the model, and the effectiveness and superiority of the algorithm, multiple sets of simulation experiments are carried out on a computer configured with Intel (R) Core i3 2.27GHz CPU, based on MATLAB R2010a simulation platform.

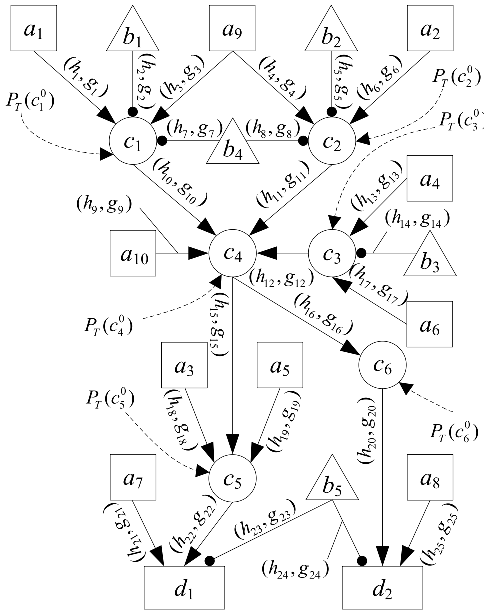

FIGURE 5. DINs model of aviation swarm combat.

TABLE 1. Type and occurrence probability of hostile behaviors.

Phase	Type and occurrence probability of hostile behaviors				
	b_1	b_2	b_3	b_4	b_5
$t_0 \sim t_1$	[0.8,0.9]	[0.3,0.4]	0	[0.4,0.6]	0
$t_1 \sim t_2$	0	[0.7,0.9]	0	[0.5,0.7]	0
$t_2 \sim t_3$	[0.3,0.4]	0	[0.5,0.7]	0	0
$t_3 \sim t_4$	0	0	[0.3,0.4]	0	[0.1,0.2]
$t_4 \sim t_5$	0	0	0	0	[0.3,0.5]
$t_5 \sim t_6$	0	0	0	0	[0.7,0.9]

Through these simulation experiments, DABC algorithm, discrete glowworm swarm optimization (DGSO) algorighm [12], and discrete particle swarm optimization (DPSO) algorithm [13], are compared.

In terms of DABC algorithm parameter settings, let $N_{fs} = N_{eb} = N_{ob} = 10$, $trial_{\max} = 10$, $iter_{\max} = 50$.

Experiment 1: Firstly, based on the KTC method, generate influence strength values by integrating multi-expert knowledge. Let the number of experts as $|Z| = 6$, after checking the table, it can be known that when the significance level $\alpha = 0.05$ and $|V| = 25$, the threshold $K_\alpha = 36.4151$. And it is assumed that the normalized expert authority vector is (0.25,0.15,0.10,0.15,0.20,0.15).

According to the analysis of experts, the h and g values without consistency test are given in Table 3 and Table 4, respectively.

When KTC method is used to generate the consistency h value, the expert group set with the highest authority is $\{z_2, z_4, z_5, z_6\}$, and all the final h values generated are 0.38,

TABLE 2. Alternative strategies for different actions.

Pha\Strat	a_1			a_2			a_3			
	a_1^1	a_1^2	a_1^3	a_2^1	a_2^2	a_2^3	a_3^1	a_3^2	a_3^3	a_3^4
$t_0 \sim t_1$	1	0	0	1	0	0	0	0	0	0
$t_1 \sim t_2$	0	1	0	0	1	0	0	0	0	0
$t_2 \sim t_3$	0	0	1	0	0	1	0	0	0	0
$t_3 \sim t_4$	0	0	0	0	0	0	1	0	0	0
$t_4 \sim t_5$	0	0	0	0	0	0	0	1	0	1
$t_5 \sim t_6$	0	0	0	0	0	0	0	0	1	1
Pha\Strat	a_4			a_5				a_6		
	a_4^1	a_4^2	a_4^3	a_5^1	a_5^2	a_5^3	a_5^4	a_6^1	a_6^2	a_6^3
$t_0 \sim t_1$	0	0	0	0	0	0	0	0	0	0
$t_1 \sim t_2$	1	0	0	0	0	0	0	1	0	0
$t_2 \sim t_3$	0	1	1	0	0	0	0	0	1	1
$t_3 \sim t_4$	0	0	1	1	0	0	0	0	0	1
$t_4 \sim t_5$	0	0	0	0	1	0	1	0	0	0
$t_5 \sim t_6$	0	0	0	0	0	1	1	0	0	0
Pha\Strat	a_7								a_8	
	a_7^1	a_7^2	a_7^3	a_7^4	a_7^5	a_7^6	a_7^7	a_7^8	a_8^1	a_8^2
$t_0 \sim t_1$	1	1	1	1	1	1	1	1	0	0
$t_1 \sim t_2$	0	1	1	1	1	1	1	1	0	0
$t_2 \sim t_3$	0	0	1	1	1	1	0	1	0	0
$t_3 \sim t_4$	0	0	0	1	1	1	0	0	1	0
$t_4 \sim t_5$	0	0	0	0	1	1	1	1	0	1
$t_5 \sim t_6$	0	0	0	0	0	1	1	0	0	0
Pha\Strat	a_8		a_9						a_{10}	
	a_8^3	a_8^4	a_9^1	a_9^2	a_9^3	a_9^4	a_9^5	a_9^6	a_{10}^1	a_{10}^2
$t_0 \sim t_1$	0	0	1	1	1	1	1	1	0	0
$t_1 \sim t_2$	0	0	0	1	1	1	1	1	0	0
$t_2 \sim t_3$	0	0	0	0	1	1	1	1	1	1
$t_3 \sim t_4$	0	0	0	0	0	1	1	1	0	1
$t_4 \sim t_5$	0	1	0	0	0	0	1	1	0	0
$t_5 \sim t_6$	1	1	0	0	0	0	0	1	0	0

−0.28, 0.65, 0.71, −0.30, 0.79, −0.05, −0.31, 0.63, 0.50, 0.56, 0.67, 0.69, −0.62, 0.23, 0.58, 0.44, 0.49, 0.35, 0.68, 0.52, 0.59, −0.51, −0.56, 0.35.

When generating the consistency g value, the expert group set with the highest authority is $\{z_2, z_3, z_5, z_6\}$, and all the final g values generated are -0.72, 0.51, −0.66, −0.85, 0.73, −0.55, 0.35, 0.20, −0.67, −0.77, −0.14, −0.57, −0.27, 0.23, −0.62, −0.40, −0.45, −0.93, −0.48, −0.48, −0.74, −0.59, 0.74, 0.65, -0.47.

Experiment 2: Let the occurence probability of histile behavior b_l as $(P_{k-1}^{\min}(b_l) + P_{k-1}^{\max}(b_l))/2$, adopt DABC algorithm to solve the model. Under the randomly generated COA $S_1 = (a_1^2, a_2^2, a_3^2, a_4^1, a_5^1, a_6^2, a_7^2, a_8^2, a_9^4, a_{10}^1)$ and the optimal COA $S_2 = (a_1^1, a_2^1, a_3^3, a_4^2, a_5^3, a_6^2, a_7^6, a_8^1, a_9^5, a_{10}^1)$ generated by DABC algori- thm, it analyzes three kinds of objective functions, $F_1(S) = P\{d_1(t_{T+1}) = 1|CE(t_0), \Psi_S\}$, $F_2(S) = P\{d_2(t_{T+1}) = 1|CE(t_0), \Psi_S\}$, and $F_3(S) = P\{d_1(t_{T+1}) = 1, d_2(t_{T+1}) = 0|CE(t_0), \Psi_S\}$.

As shown in Figure 6 and Figure 7, they are the changes of three objective functions at different combat phase under S_1 and S_2 respectively.

TABLE 3. Positive influence strength values without consistency test.

Z\V	h_1	h_2*	h_3	h_4	h_5*	h_6	h_7*	h_8*	h_9
z_1	0.95	0.98	0.04	0.06	0.98	0.13	0.22	0.40	0.65
z_2	0.72	0.22	0.66	0.53	0.07	0.76	0.01	0.72	0.75
z_3	0.63	0.97	0.12	0.58	0.17	0.04	0.70	0.94	0.21
z_4	0.31	0.06	0.92	0.89	0.74	0.83	0.08	0.40	0.48
z_5	0.02	0.50	0.39	0.55	0.04	0.86	0.06	0.03	0.75
z_6	0.57	0.26	0.71	0.94	0.43	0.69	0.06	0.17	0.51
Z\V	h_{10}	h_{11}	h_{12}	h_{13}	h_{14}*	h_{15}	h_{16}	h_{17}	h_{18}
z_1	0.62	0.44	0.36	0.84	0.39	0.09	0.02	0.18	0.75
z_2	0.26	0.87	0.07	0.86	0.48	0.08	0.89	0.91	0.86
z_3	0.40	0.53	0.35	0.95	0.13	0.78	0.98	0.16	0.69
z_4	0.85	0.69	0.98	0.77	0.07	0.35	0.08	0.09	0.74
z_5	0.49	0.41	0.74	0.96	0.96	0.06	0.53	0.06	0.10
z_6	0.38	0.33	0.87	0.09	0.87	0.48	0.85	0.85	0.37
Z\V	h_{19}	h_{20}	h_{21}	h_{22}	h_{23}*	h_{24}*	h_{25}	/	/
z_1	0.16	0.08	0.09	0.05	0.18	0.05	0.43	/	/
z_2	0.48	0.97	0.82	0.98	0.85	0.56	0.04	/	/
z_3	0.95	0.13	0.46	0.36	0.92	0.92	0.26	/	/
z_4	0.26	0.70	0.92	0.01	0.29	0.07	0.31	/	/
z_5	0.55	0.41	0.14	0.73	0.50	0.97	0.56	/	/
z_6	0.07	0.73	0.32	0.60	0.41	0.51	0.43	/	/

* indicates negative number.

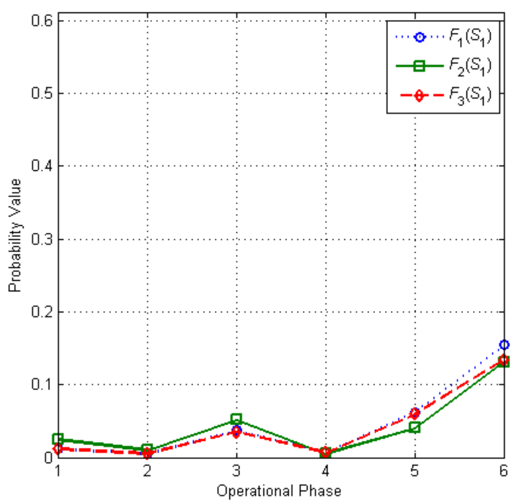

FIGURE 6. Changes of objective functions under S_1.

It can be seen from Figure 6 and Figure 7 that, $F_3(S_1) = 0.1340$, $F_3(S_2) = 0.3416$. Therefore, the combat effect of S_2 is better than that of S_1. Through the above simulation, it can be found that, the algorithm can effectively perform optimal search, and better solutions can be found by iterative optimization i.e., the effectiveness of proposed DABC algorithm is proved.

TABLE 4. Negative influence strength values without consistency test.

$Z\backslash V$	g_1*	g_2	g_3*	g_4*	g_5	g_6*	g_7	g_8	g_9*
z_1	0.70	0.05	0.07	0.61	0.02	0.30	0.97	0.65	0.08
z_2	0.91	0.31	0.93	0.64	0.96	0.66	0.30	0.35	0.94
z_3	0.76	0.22	0.97	0.86	0.96	0.82	0.65	0.04	0.53
z_4	0.44	0.66	0.48	0.02	0.08	0.61	0.93	0.85	0.91
z_5	0.61	0.93	0.19	0.94	0.59	0.65	0.23	0.04	0.36
z_6	0.66	0.36	0.78	0.95	0.55	0.11	0.36	0.39	0.91
$Z\backslash V$	g_{10}*	g_{11}*	g_{12}*	g_{13}*	g_{14}	g_{15}*	g_{16}*	g_{17}*	g_{18}*
z_1	0.12	0.99	0.55	0.80	0.92	0.20	0.17	0.21	0.09
z_2	0.98	0.11	0.12	0.02	0.11	0.58	0.32	0.35	0.94
z_3	0.91	0.10	0.83	0.58	0.17	0.62	0.47	0.84	0.99
z_4	0.45	0.97	0.99	0.76	0.97	0.17	0.82	0.82	0.58
z_5	0.64	0.18	0.95	0.01	0.48	0.51	0.03	0.09	0.89
z_6	0.65	0.13	0.33	0.67	0.06	0.80	0.90	0.78	0.93
$Z\backslash V$	g_{19}*	g_{20}*	g_{21}*	g_{22}*	g_{23}	g_{24}	g_{25}*	/	/
z_1	0.10	0.07	0.38	0.05	0.08	0.75	0.10	/	/
z_2	0.74	0.25	0.52	0.75	0.09	0.93	0.85	/	/
z_3	0.78	0.06	0.98	0.37	0.95	0.19	0.01	/	/
z_4	0.81	0.30	0.96	0.26	0.80	0.99	0.76	/	/
z_5	0.23	0.60	0.64	0.78	0.98	0.95	0.31	/	/
z_6	0.36	0.84	0.92	0.34	0.94	0.27	0.62	/	/

* indicates negative number.

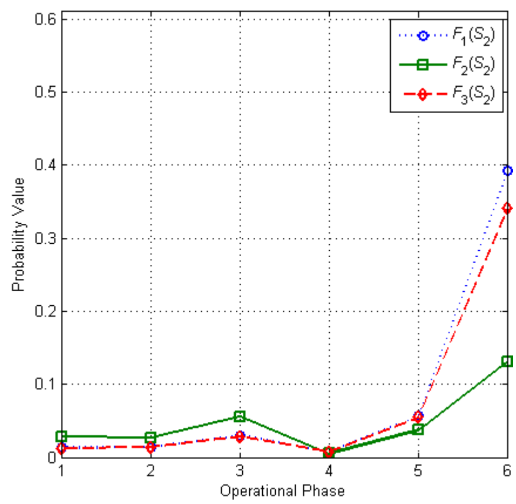

FIGURE 7. Changes of objective functions under S_2.

Experiment 3: Firstly, take the occurrence probability of hostile behaviors as a random value within a certain interval, and determine H groups of hostile behavior occurrence probability by H-times Monte Carlo simulations. Then, respectively run DABC algorithm, DGSO algorithm, and DPSO algorithm for G-times, and take the mean value of all $F_3(S)$ as the objective function, let $H = G = 20$. Afterwards, take the occurrence probability of hostile behavior to be a certain value, run DABC algorithm (Algorithm I), DGSO algorithm (Algorithm II), and DPSO algorithm (Algorithm III) for G-times, and compare the solution distribution of each algorithm. As shown in Figure 8, it is the mean fitness values of three algorithms under 20 groups of probability values. As shown in Figure 9, it is solution distribution of three algorithms under 20 groups of experiments with a certain hostile behavior probability.

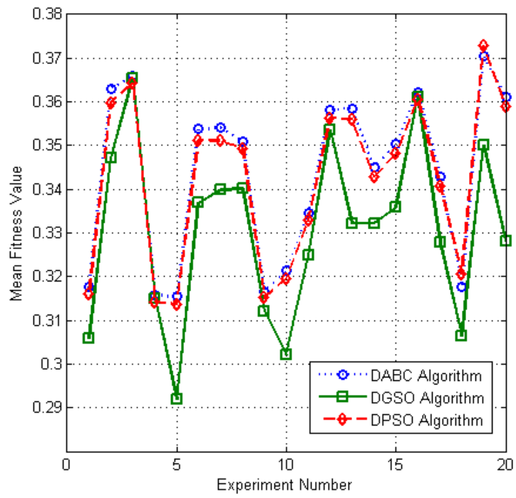

FIGURE 8. Mean fitness values of three algorithms.

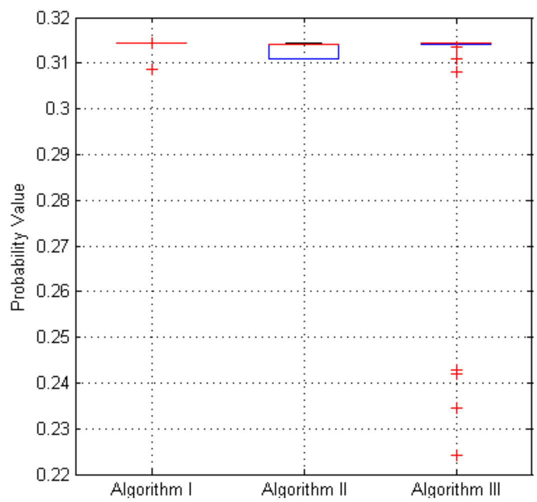

FIGURE 9. Solution distribution of three algorithms.

It can be seen from Figure 8 that, compared with the comparison algorithms, DABC algorithm can obtain the optimal solution 17 times, in all Monte Carlo simulations with better results. Since the parameters are set randomly, the algorithm can be considered to be statistically better.

As can be seen from Figure 9, compared with the DGSO and DPSO algorithm, the probability values obtained by the DABC algorithm are larger, besides, the DGSO algorithm is significantly inferior to the other two algorithms. In tems of the value distribution, the DABC algorithm optimizes the value distribution more centrally, and has fewer bad values.

Through the above simulation, the superiority of proposed DABC algorithm is verified.

VI. CONCLUSION

Aiming at the COA selection problem of aviation swarm combat, a novel COA optimized selection model and algorithm of aviation swarm based on DINs and DABC is constructed. The consistency test method based on KTC method is used to obtain key parameters such as h value and g value in accordance with the opinion of the most authoritative expert group. Based on this, an optimization model based on DINs is constructed, and finally, DABC algorithm is adopted to solve the model. Simulation experiments show that, the model constructed in this paper is reasonable, and the proposed algorithm is effective and superior. Through the research in this paper, it is possible to efficiently generate the optimal or better COA of aviation swarm, thereby improving the combat efficiency of aviation swarm in performing a variety of air combat tasks.

The future research work can address the uncertainty in air combat [14], i.e., an interval optimization model needs to be established due to the uncertainty nature of parameters [15], such as the prior probability, benchmark probability and influence strength value, and an interval optimization algorithm should be used to solve it.

ACKNOWLEDGMENT

The authors would like to thank the research sites and materials provided by the State Key Laboratory of Air Traffic Management Systems and Technologies. They also like to thank Researchers at Air Force Engineering University, including Jieyong Zhang and Zhiqiang Jiao for their contributions to this article.

REFERENCES

[1] X. L. Liang, Q. Sun, Z. H. Yin, and Y. Wang, "A study of aviation swarm convoy and transportation mission," in *Proc. Int. Conf. Swarm Intell., Adv. Swarm Intell.*, Harbin, China, 2013, pp. 368–375.

[2] H. Y. Tu, Y. N. Levchuk, and K. R. Pattipati, "Robust action strategies of organizational processes: Analysis and solutions of case," *J. Syst. Simul.*, vol. 17, no. 7, pp. 1648–1654, Nov. 2005.

[3] A. K. Zaidi, F. Mansoor, and P. Papantoni-Kazakos, "Theory of influence networks," *J. Intell. Robot. Syst.*, vol. 60, nos. 3–4, pp. 457–491, Dec. 2010.

[4] K. C. Chang, P. E. Lehner, A. H. Levis, A. K. Zaidi, and X. Zhao, "On causal influence logic," George Mason Univ., Fairfax, VA, USA, Tech. Rep., Nov. 1994.

[5] S. Haider and A. H. Levis, "Finding effective courses of action using particle swarm optimization," in *Proc. IEEE Congr. Evol. Comput.*, Hongkong, Jun. 2008, pp. 1135–1150.

[6] Y. G. Zhu, "Study on joint fire strike plan optimization problem based on stochastic timed influence net," Ph.D. dissertation, Dept. Syst Engin, Nat. Univ. Defense Technol., Changsha, China, 2011.

[7] W. W. Turechek, "Nonparametric tests in plant disease epidemiology: Characterizing disease associations," *Phytopathology*, vol. 94, no. 9, pp. 1018–1021, Sep. 2004.

[8] Z. Wang, M. Zheng, J. Guo, and H. Huang, "Uncertain UAV ISR mission planning problem with multiple correlated objectives," *J. Intell. Fuzzy Syst.*, vol. 32, no. 1, pp. 321–335, Jan. 2017.

[9] S. Haider and A. H. Levis, "A heuristic approach for belief updating in timed influence nets," in *Proc. Command Control Res. Technol. Symp.*, Washington, DC, USA, 2004, pp. 1–13.

[10] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: Artificial bee colony (ABC) algorithm and applications," *Artif. Intell. Rev.*, vol. 42, no. 1, pp. 21–57, Jun. 2014.

[11] P. Y. Yao, L. J. Wan, F. F. Ma, and D.-D. Shui, "Optimized action policy selection in task coalition evolution based on dynamic influence nets," *Syst. Eng. Electron.*, vol. 36, no. 8, pp. 1527–1536, Aug. 2014.

[12] W. Dong, K. Zhou, Q. Fu, and Y. Duan, "The discrete glowworm swarm optimization algorithm with an adaptive neighborhood search," *J. Comput. Theor. Nanosci.*, vol. 13, no. 6, pp. 3824–3834, Jun. 2016.

[13] G. Na, Q. Zhi-Hong, and L. Xiang-Jun, "On modeling and discrete particle swarm optimization for task assignment of cooperating UAVs," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Mianyang, China, May 2011, pp. 1044–1049.

[14] L. W. Wagenhals, I. Shin, and A. H. Levis, "Creating executable models of influence nets with coloured Petri Nets," *Int. J. Softw. Tools Technol. Transf.*, vol. 2, no. 2, pp. 168–181, Dec. 1998.

[15] H. Liu, M. Lin, and L. Deng, "UAV route planning for aerial photography under interval uncertainties," *Optik*, vol. 127, no. 20, pp. 9695–9700, Oct. 2016.

LUJUN WAN was born in Lianyungang, Jiangsu, China, in 1986. He received the B.S., M.S., and Ph.D. degrees in command information system from Air Force Engineering University, in 2007, 2009, and 2013, respectively. He is currently an Associate Professor with Air Force Engineering University and a Postdoctoral Researcher with the State Key Laboratory of Air Traffic Management Systems and Technologies. His research interests include air traffic control and aviation swarm combat.

YUN ZHONG was born in Jintan, Jiangsu, China, in 1990. He received the B.S. degree in network engineering, the M.S. degree in communication and information system, and the Ph.D. degree in command information system from Air Force Engineering University, in 2012, 2014, and 2018, respectively. He is currently an Assistant Engineer with the Unit 94062 of PLA. His research interest is decision support systems.

WEN LI was born in Xinyang, Henan, China, in 1981. She received the B.S. and M.S. degrees in command information system from Air Force Engineering University, in 2006 and 2008, respectively, where she is currently pursuing the Ph.D. degree with the Equipment Management and UAV Engineering College. She is currently an Engineer with the Unit 95081 of PLA. Her research interest is air traffic control.