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# A Genetic Algorithm-Based Methodology for Analyzing the Characteristics of High-Operational-Capability Combat Networks

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**ABSTRACT** Research on heterogeneous combat networks (HCNs) has attracted considerable interest in the military field since they can provide useful insights into the provision of decision-making assistance. The characteristics of high-operational-capability HCNs are not well studied, which limits the ability to construct a better combat network. To fill this gap, an integrated methodology named genetic algorithm-based high-capability HCN analysis (GAHCA) is presented to elucidate the characteristics of high-operational-capability combat networks. In GAHCA, an improved genetic algorithm is proposed to search more efficiently for high-operational-capability HCNs. Then, the properties of these HCNs are studied by the cartographic picture analysis and contribution analysis of nodes and links. The results unveil the critical topological structures of operational capability generation and quantitatively demonstrate the importance of the military criterion of “concentration of superior forces”. These results further emphasize that blindly increasing military resources may not enhance the operational capability of the HCN and, worse yet, may instead cause a decrease in network capability. These are all meaningful findings for assisting in the construction of a better HCN. Finally, the reliability of the improved genetic algorithm is demonstrated by comparison with two state-of-the-art algorithms and one classical algorithm.

**INDEX TERMS** High operational capability, characteristic analysis, heterogeneous combat network, genetic algorithm.

## I. INTRODUCTION

Heterogenous combat networks (HCNs) have attracted increasing interest in recent years since their study is an effective approach to understand the properties of combat systems [1], [2]. The operational capability of a combat network is a critical index to evaluate the performance of HCNs to win a war [3], [4]. Maximizing the operational capability of the HCN is the ultimate goal for combat forces [5]. Therefore, the characteristics of a high-operational-capability<sup>1</sup> HCN are more valuable to understand than those of an ordinary HCN because we can learn more about success from the best. If we obtain findings about the characteristics of HCNs with high operational capability, the findings would be

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<sup>1</sup>Hereafter, high operational capability will be abbreviated as high capability.

valuable and could serve as useful guidance for building more resilient and robust combat networks. For example, from the topology of high-capability HCNs, we can identify the critical structures of capability generation. By analyzing high-capability HCNs with different scales, we can understand the maximum capabilities produced by different amounts of resources to assist professionals in optimizing the allocation of resources on the battlefield [6]. Therefore, analyzing the characteristics of high-capability HCNs is of significant military value for providing critical information for combat network construction and optimization.

However, previous studies on combat networks were limited to discovering and evaluating the characteristics of HCNs with unknown capability [3], [7]–[10]. These HCNs are abstracted from military maneuvers or constructed based on certain principles [3], [7]. The authors did not clarify whether these HCNs are high-capability, thus the findings may lose some value. For instance, if we mistakenly regard

the inferior network as a high-capability network, then the research results may provide negative guidance for the construction of subsequent HCNs. To some extent, valuable information about the characteristics of HCN is not clearly identified. To solve this problem, a proper methodology for efficiently acquiring and deepening our knowledge of the high-capability combat network should be applied.

In view of these matters, this paper aims to demystify elements of high-capability combat networks, including the properties of their topological structure and their capability generation mechanisms. Accordingly, we propose an integrated methodology called genetic algorithm-based high capability HCN analysis (GAHCA). In this methodology, we first obtain a high-capability HCN by using an improved genetic algorithm. Then, the characteristics of high-capability HCNs are analyzed by multiple methods. The contributions of our work can be summarized as follows.

- 1) An integrated framework called GAHCA is presented to solve high-capability HCN analysis problems. GAHCA integrates multiple algorithms and methods and provides efficient analysis strategies that can help us better understand high-capability combat networks.
- 2) A novel genetic algorithm is proposed to obtain high-capability combat networks. Based on the operational chain, the operators in the genetic algorithm are enhanced by considering the cooperation and critical activities among combat entities. The efficiency of the algorithm is apparently improved.
- 3) Many experiments are conducted based on GAHCA to thoroughly analyze high-capability networks. The results provide critical information on topological structure and resource allocation that can be useful in HCN construction and optimization.

The remainder of this paper is structured as follows. Section II introduces related works about combat networks. A detailed description of GAHCA is provided in Section III. The core algorithm is introduced in Section IV. Section V describes the conduction of numerous experiments and the useful insights these experiments provide. Finally, we draw conclusions and discuss future works in Section VI.

## II. RELATED WORKS

Heterogenous combat networks, as representations of combat systems, are a central topic in the military field to study the properties of military organizations. To the best of our knowledge, studies on HCNs can be classified into four aspects: HCN model establishment, link prediction, performance evaluation and characteristic analysis. Establishing a more accurate and convincing model of HCNs is the basis work of other HCN studies, which provides suitable descriptions for HCNs. Link prediction, focusing on assessing the existence probability of links, aims to identify missing information of acquired combat network topology, which would be helpful to enhance the accuracy of decision-making. Performance evaluation provides various measures to assess the network effectiveness to understand

the ability of HCNs to win a war. Characteristic analysis seeks to explore the properties of HCNs and help us identify their key structures and understand their capability generation mechanisms. Characteristic analysis will deepen our understanding of HCNs and provide inspiring insights for design of a more resilient combat systems. Next, we will introduce these aspects in detail.

### A. MODEL ESTABLISHMENT OF COMBAT NETWORKS

By employing the network science, researchers seek to characterize the complexity of combat systems and build a compact but accurate model of HCNs. Dekker [11] introduced the social network analysis method for combat systems and proposed a combat network model named FINC (Force, Intelligence, Networking and C2), which included force, intelligence, C2 (command and control) nodes and networking edges. Subsequently, Yang *et al.* [12] extended the FINC model and added functional attributes, such as weight for heterogeneous nodes and edges. Jeffrey [13] built an Information Age Combat (IACM) model for combat networks that divided combat entities into sensors, decision points, influencers and targets. Wu *et al.* [14] constructed an awareness combat network based on closed-loop control model considering the real-time data transmission with a dynamic routing protocol mechanism. In the literature [15], a combat network model with three types of meta-functional nodes is presented. Recently, Li *et al.* [8] introduced temporal interaction mechanism into combat network and tried to describe the operation process more accurately. Overall, these HCN network models have one thing in common (except [14]). Specifically, the combat network is heterogeneous and contains at least three types of nodes: sensors, deciders and influencers. The modeling idea of this type of combat networks is widely accepted and used in the follow-up studies [2], [3], [5], [7], [8], [15]–[17]. Thus, this work also chooses HCN model that consists of three entities: sensor, decider and influencer.

### B. LINK PREDICTION OF COMBAT NETWORKS

In addition to building an accurate combat network model, obtaining complete combat network data is also the basis of HCN research. On the battlefield, given the uncertainty and complexity of warfare, collecting complete intelligence about HCNs is a costly task. Researchers tried to find the missing information of network topology by using advanced technology. In the literature [16], a concept of meta-paths was employed to predict the heterogenous links of HCN. Compared with nodes, the links are more difficult to detect when conducting military operations, so the intelligence about links is the main component of missing or erroneous data. Subsequently, using meta-path as input, Li *et al.* [18] proposed a back-propagation neural network-based link prediction methodology to enhance the link prediction efficiency. Then, Chen *et al.* [19] proposed an advanced link prediction method of HCN based on representation learning, which had an advantage when facing sparse HCNs.

### C. PERFORMANCE EVALUATION OF COMBAT NETWORKS

Evaluation of the performance of a combat network is a critical task to understand its ability to win a war, and various measures have been proposed to achieve this goal. Jeffrey [13] noted that the cycle, consisting of links and nodes, of the networks can reflect their dynamic mechanisms and thus generate operational capability for the network. He used the Perron-Frebonius eigenvalue (PFE), which corresponds to the quality of these cycles, to measure the effectiveness of combat networks. Using quantitative analysis, Deller [5] demonstrated that the PFE is related to the connectivity of a network, further supporting the PFE as a valid measurement of the effectiveness of an HCN. Subsequently, Deller *et al.* [20] improved the PFE by adding a measurement value to enhance its utility as a quantifiable metric of network performance. In the literature [15], the concept of natural connectivity was extended, and a measure named directed natural connectivity was introduced to evaluate the structural robustness of combat networks. This measure considers the redundancy and quality of the Observe, Orient, Decide, and Act (OODA) cycle [21] in combat networks. Then, a concept named operational chain, which represents the OODA process in HCNs, is proposed [7]. Based on this chain, a significant measure called the operational capability index is proposed to evaluate the effectiveness of dynamic cooperation among combat entities and the coordination of various capabilities [3]. The operational capability index also concentrates on the significant process to generate capability and is an important model to evaluate the capability of HCNs [2]. Useful insights and suggestions for operational process were obtained by analyzing this index [2], [3], [7]–[9], [22]. Therefore, this paper selects operational capability index to evaluate whether the combat network has a high capability.

### D. CHARACTERISTICS ANALYSIS OF COMBAT NETWORKS

Analyzing the characteristics of combat networks can provide useful information to deepen our knowledge of HCNs. Then, useful guidance for constructing and optimizing the system architecture can be obtained. Therefore, many inspiring studies have been performed to study the properties of HCNs. Dekker [11] analyzed the delay, centrality and intelligence of a combat network, which has a simple and relatively traditional military structure. Yang *et al.* [12] chose scale-free and small-world combat networks and then recognized their critical nodes or links based upon key potential. Li *et al.* [15] generated a combat network with scale-free distributions and also investigated its key equipment and links. In the literature [8], seven entities were randomly chosen to generate a temporal combat network, and the equipment contribution in this network was analyzed by an integrated analysis framework. In another study [7], an HCN was constructed according to a case of military maneuvers. Taking this HCN as an example, the critical role of combat entities in military engagements was studied. To evaluated the disintegration

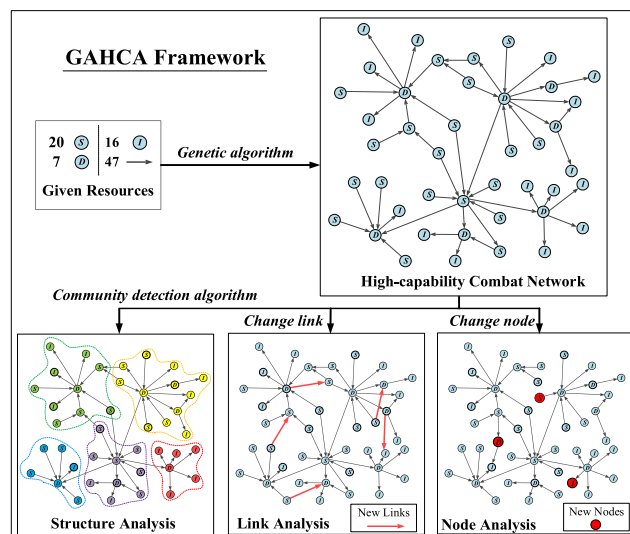


FIGURE 1. GAHCA framework.

efficiency of operational capability, Li *et al.* applied an united framework to an HCN, which is constructed by the operation process [3]. In one study [10], taking a special HCN as a case, the importance of each meta-path was studied in the weapon-target recommendation mission. In addition, Yang *et al.* constructed an HCN according to the connection probability and identified the critical nodes by community structure [23]. In Tab. 1, we summarize the studied combat networks and network characteristics in the above literatures. As noted, these studied HCNs were abstracted from military maneuvers or constructed based on certain principles, and the authors did not clarify whether these HCNs have high capabilities. The characteristics of high-capability combat networks remain unclear. Our work aims to fill this gap and to provide valuable information for assistance in HCN construction and optimization.

### III. GENETIC ALGORITHM-BASED HIGH-CAPABILITY HCN ANALYSIS (GAHCA)

This section will introduce the integrated framework named GAHCA, which aims to find high-capability HCNs and then analyze their characteristics. The GAHCA procedures are shown in Fig. 1. The high-capability topologies, namely, the optimized topologies, of combat networks, obtained by an improved genetic algorithm (GA), form the core of GAHCA. Then, the high-capability HCNs are analyzed from three perspectives: first, by employing a community detection algorithm, a cartographic picture of the topology is obtained, which provides significant topological information and the structural properties of combat networks; second, using a genetic algorithm multiple times by increasing and decreasing the number of links, the capability contribution of information links is analyzed; finally, we study the capability contribution of combat entities by running a genetic algorithm with different numbers of nodes. In the following sections, we illustrate GAHCA in detail.

TABLE 1. Related works on characteristics analysis of combat networks.

References	The studied characteristics	The studied combat networks
[11]	Delay, centrality and intelligence	The simple & traditional military structure
[12]	Critical nodes or links	Scale-free and small-world HCNs
[15]	Key equipment and links	Scale-free HCN
[8]	The equipment contribution	HCN generated randomly with 7 nodes
[7]	The critical role of combat entities	HCN from military maneuvers
[3]	Capability disintegration efficiency	HCN constructed by the operation process
[10]	Importance of HCN meta-path	A special HCN case
[23]	The critical nodes	HCN constructed by the connection probability

TABLE 2. Notations.

	Notation
$G$	A combat network
$V$	Set of combat entities in $G$
$E$	Set of information links in $G$
$S, D, I$	Sensor, decider and influential entities
$n_s, n_d, n_i$	Total number of $S, D, I$
$n$	$n = n_s + n_d + n_i$
$m$	Total number of information links
$v_i^S, v_i^D, v_i^I$	Combat entity $i$ in $V$ (entity types are $S, D$ and $I$ respectively)
$e_i$	Information link $i$ in $E$
$P(G)$	Operational capability index of $G$
$l_j$	Operational chain $j$ in $G$
$v_{S,j}, v_{D,j}, v_{I,j}$	Combat entity $j$ in $l_j$ (entity types are $S, D$ and $I$ respectively)
$P_S(v_{S,j}), P_D(v_{D,j}), P_I(v_{I,j})$	Operational capability of $v_{S,j}, v_{D,j}, v_{I,j}$

The notations in the problem formulation and equations are summarized in Tab.2.

**A. DEFINITION OF A HIGH-CAPABILITY HCN**

An HCN consists of combat entities (nodes) and directional information links (edges). The combat network can be expressed as  $G = (V, E)$ , where  $V = (v_1, \dots, v_i, \dots, v_n)$  represents the set of combat entities, and  $n$  is the total number of combat entities.  $E = (e_1, \dots, e_k, \dots, e_m)$  is the set of information links and  $e_k = (v_i, v_j)$ .  $m$  is the total number of information links. In this paper, combat entities are divided into three categories: sensor entities ( $S$ ), such as radars or scout planes; decider entities ( $D$ ), such as command vehicles or operational centers; and influential entities ( $I$ ), such as artillery or fighters. The edges are grouped into five types: sharing intelligence links ( $v_i^S, v_j^S$ ), uploading intelligence links ( $v_i^S, v_j^D$ ), commanding reconnaissance links ( $v_i^D, v_j^S$ ), controlling fire links ( $v_i^D, v_j^I$ ) and communicating information links ( $v_i^D, v_j^D$ ).

As discussed in Section II.C, this paper chooses operational capability index to evaluate whether the combat network has a high-capability. The operational capability index of a combat network can be expressed as follows [9]:

$$P(G) = \sum_{l_j \in G} P(l_j) \tag{1}$$

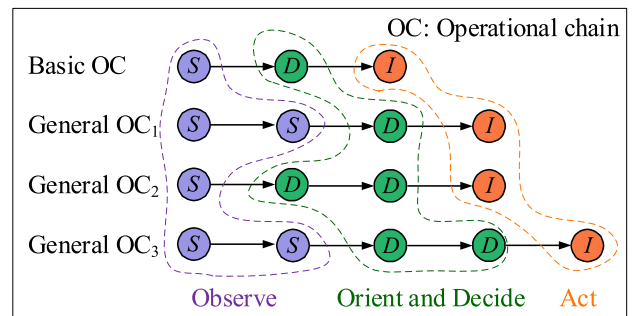


FIGURE 2. Operational chains.

where  $l_j$  is an operational chain (OC) in combat network [3], [7], [17], and  $P(l_j)$  is operational capability of  $l_j$ . OC is a special chain in combat networks, which consists of a sequence of combat entities and information links. As shown in Fig. 2, the operational chain carries the OODA loop [21] and suggests the procedures to accomplish a specific mission. In an OC, sensor entities detect the enemy information and then transfer the intelligence to the decider entities; the decider entities analyze the information and give an attack order to the influential entities; the influential entities respond to the order and accomplish the attack task. The OCs can be divided into basic OC and general OCs. A basic OC consists of one sensor, one decider and one influential entity. General OCs have multiple sensors and deciders. The operational capability of one operational chain  $l_j$  can be expressed as [3]:

$$P(l_j) = \frac{1}{|l_j|} \times \max P_S(v_{S,j}) \times \max P_D(v_{D,j}) \times \max P_I(v_{I,j}) \tag{2}$$

where  $P_S(v_{S,j}), P_D(v_{D,j})$  and  $P_I(v_{I,j})$  are the capabilities of the combat entities in operational chain  $l_j$ , and  $|l_j|$  is the length of this chain. Equation (2) suggests that shorter chains and many alternative chains in an HCN lead to higher operational efficiency [2], [3], [7].

Therefore, to calculate the operational capability of a combat network, the operational chains in this combat network should be identified. Then, the capability of each operational chain is calculated according to (2).

The operational capability of HCN is obtained by integrating all operational capability of OCs (see (1)).

According to the above theories, the high-capability combat network in this paper is defined as follows:

**Definition 1:** High-capability combat network. In all heterogeneous combat network topologies that meet military constraints, the network with the highest operational capability index (Eq. (1)) is defined as the high-capability combat network.

There are two military constraints these HCNs should be satisfied.

**Constraint 1:** The three types of nodes cannot be converted to each other because of their unique functions. However, the edges, which are composed of information links, can be replaced with each other.

**Constraint 2:** No isolated node is permitted since each combat entity has its own strategic value.

### B. ALGORITHM TO SEARCH HIGH-CAPABILITY HCNS

Topology optimization is a crucial design stage in the search for the best connections among and distribution of network components and thus is an appropriate strategy to find the high-capability topology of an HCN [24]. The heuristic algorithms used in topology optimization can creditably find the network with the expected performance under a given set of constraints [25]. If properly revised, these heuristic algorithms can effectively handle the heterogeneity [2] and the large scale of the selected network [26]. Compared with other heuristic algorithms, genetic algorithms are more commonly used to solve information network optimization problems [2], [6], [27]–[31]. This is because GAs have superior convergence capability and flexibility in solving combinatorial optimization problems [32]. Therefore, this paper also chooses a GA for obtaining a high-capability combat network.

Specifically, a depth-first search algorithm is applied to search for operational chains and enables us to calculate the value of (1). Then, with (1) as the objective function and satisfying constraints 1 and 2, an improved genetic algorithm is introduced to optimize the HCN. As a result, a high-capability combat network is obtained. The details of these algorithms are illustrated in Section IV.

### C. HIGH-CAPABILITY HCN ANALYSIS METHODS

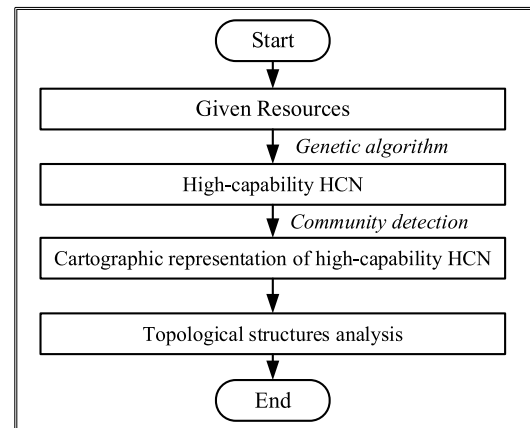
It is challenging to intuitively obtain valuable information from high-capability HCNs given their complexity and size. Valid techniques and strategies should be employed to illustrate and investigate the structure and functional properties of high-capability HCNs.

#### 1) TOPOLOGICAL STRUCTURE ANALYSIS METHOD

Here, as shown in Fig. 1, we first apply the community detection algorithm [33] to obtain a cartographic representation of the high-capability network to analyze its topological structure [34]. The cartographic representation, consisting of community modules, provides a simplified description of

the HCN and thus can conveniently summarize information about the nodes and links. This representation enables us to obtain scale-specific information at a glance, similar to reading a geographic map [35]. Consequently, we can easily obtain deep insights into the topological properties of combat networks. Identifying communities is the first, critical step in generating cartographic pictures. In recent decades, numerous algorithms have been proposed for community detection [36]–[38]. The modularity-based algorithm is the classical method, whose detected results are usually regarded as the evaluation criteria for community division owing to their reliability and accuracy [39], [40]. Therefore, the modularity-based method is chosen in this paper to detect the communities of high-capability HCNs. Then, we can intuitively acquire and comprehend the topological structure of the network, providing useful guidance for HCN construction.

The detailed procedures to analyze the topological structure are as follows (See Fig. 3):



**FIGURE 3.** Procedures to analyze a topological structure.

*Step 1:* the high-capability HCN is obtained by the genetic algorithm;

*Step 2:* the cartographic representation of this high-capability HCN is generated by a modularity-based community detection algorithm;

*Step 3:* the topological structures of HCN are analyzed.

#### 2) LINK CONTRIBUTION ANALYSIS METHOD

Then, we analyze the link contributions to the operational capability of a high-capability HCN. The purpose of this method is to investigate the change in capability with different node-to-link ratios. A previous study demonstrated that this strategy enables us to understand the maximum capability produced by different amounts of battlefield resources and the optimal allocation of military resources; thus, it deepens our knowledge of the relationship between nodes and links in high-capability HCNs [6].

The detailed strategy to study the link contribution to operational capability is as follows (See Fig. 4):

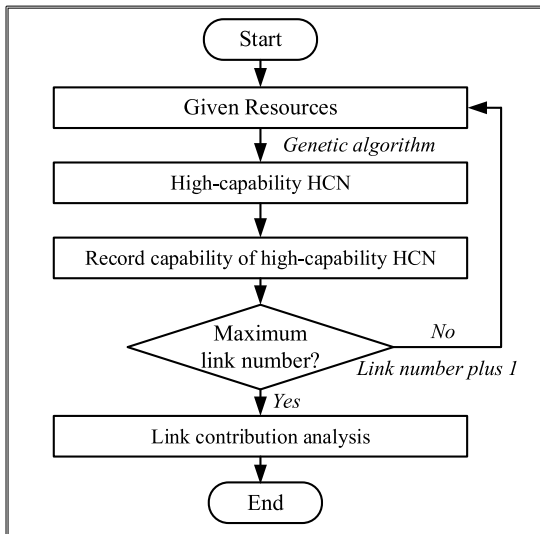


FIGURE 4. Procedures to analyze the link contribution.

*Step 1:* obtain one high-capability HCN using the genetic algorithm;

*Step 2:* record the operational capability of this high-capability HCN;

*Step 3:* if the number of links does not reach the maximum, add 1 to the number of links and return to Step 1. Else, go to Step 4.

*Step 4:* analyze the relationship between operational capability and number of links.

### 3) NODE CONTRIBUTION ANALYSIS METHOD

The detailed strategy to study node contribution to operational capability is similar to the link strategy. The difference is that we change the number of nodes, rather than the links, in this strategy.

## IV. OPERATIONAL CAPABILITY ORIENTED GENETIC ALGORITHM (OCOGA)

In this section, we will detail the improved genetic algorithm, named the operational capability-oriented genetic algorithm, which considers the generation mechanism of the operational capability and consequently permits enhancement of the convergence efficiency of the algorithm.

### A. DEPTH-FIRST SEARCH ALGORITHM FOR OPERATIONAL CAPABILITY CALCULATION

In genetic algorithms, the chromosome represents a combat network topology  $G = (V, E)$ . To select the best chromosome of the genetic algorithm in each iteration, the fitness, namely, the operational capability, of the network should be calculated by (1). In this equation, the operational capability of the HCN is the accumulation of the capabilities of its operational chains. Therefore, the operational chains, as the foundation of the capability calculation, should be first searched. In our previous work, two techniques were

employed to accomplish this task: the matrix power-based method and the depth-first search algorithm [2]. The matrix power-based method has a fast calculation speed; however, it cannot search specific information about each chain and is typically used to acquire only the total number of chains in the network. In contrast, the depth-first search (DFS) algorithm can accurately identify each operational chain despite its high time complexity. For a very large network, however, the time consumption of the DFS algorithm is unacceptable. Fortunately, however, most operational chains have a low contribution to operational capability; in other words, they are useless in military missions [2], [3]. Thus, some constraints can be added to the DFS algorithm so that we can only search the truly valuable chains and thus decrease the calculation time. In OODA theory, the tempo of the OODA loop is crucial because combat forces who make decisions faster can gain a tremendous advantage [41]. Since the OODA loop in a shorter operational chain is faster and more reliable than that in a longer chain, the most valuable operational chain is the one that has the shortest length.

Therefore, we introduce a new parameter  $\alpha$ , known as the chain length threshold, which determines the maximum length of the valuable operational chain. The DFS algorithm is constrained to search only for operational chains shorter than  $\alpha$ . By neglecting long and useless operational chains, the DFS algorithm with  $\alpha$  has a low time consumption. For additional details regarding this DFS algorithm, please refer to [2]. Based on the valuable operational chains obtained by the DFS algorithm, we can calculate the operational capability of the HCN according to (1).

### B. CAPABILITY-ORIENTED CROSSOVER OPERATOR

In this section, we propose a new crossover operator for HCNs that considers the mechanism for generating operational capability and thus improves the iteration efficiency. According to equation (1), the quality and quantity of operational chains determines the capability of the combat network. After crossover, if the number of operational chains in the new HCN is increased and their quality is enhanced, this HCN, compared with its parents, will have a higher operational capability. The most remarkable feature of high-quality operational chains is a short length. The basic operational chain ( $OC_1$  in Fig. 2) has the shortest length and consists of two kinds of links: intelligent upload links ( $v_i^S, v_j^D$ ) and controlling fire links ( $v_i^D, v_j^I$ ). The second shortest general operational chains ( $OC_2$  and  $OC_3$  in Fig. 2), in addition to ( $v_i^S, v_j^D$ ) and ( $v_i^D, v_j^I$ ), also contain an intelligence sharing link ( $v_i^S, v_j^S$ ) or an information communicating link ( $v_i^D, v_j^D$ ). Therefore, the information links ( $v_i^S, v_j^D$ ), ( $v_i^D, v_j^I$ ), ( $v_i^S, v_j^S$ ) and ( $v_i^D, v_j^D$ ) contribute to a high-quality operational chain, whereas the reconnaissance command link ( $v_i^D, v_j^S$ ), if it exists, will lead to longer and inferior operational chains, containing at least 4 links since the operational chain is initiated by the sensor entity [3], [7]. Given these observations, the procedures of the improved

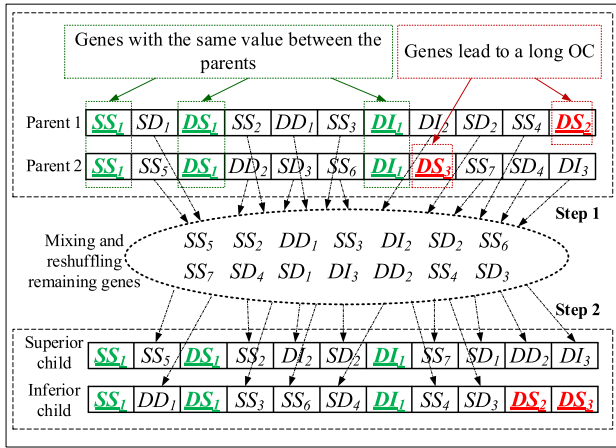


FIGURE 5. Improved crossover operator.

crossover operator are shown in Fig. 5. First, referring to the EX operator [32], the genes that are present in both parents are identified and preserved in the offspring. Then, the reconnaissance command links ( $v_i^D, v_j^S$ ) are assigned in the inferior child since they result in a low-quality operational chain. To increase the differences between the offspring and their parents, the remaining genes were mixed and reshuffled and then distributed to the two children. Then, two HCNs, i.e., the superior child and the inferior child, are obtained. The superior child contains more high-quality operational chains and thus has a higher operational capability.

### C. CAPABILITY-ORIENTED MUTATION OPERATOR

Similar to the crossover operator, to produce HCNs containing high-quality operational chains, the mutation operator is also revised. The calculation rule of this operator is shown in Fig. 6. First, the chromosome is transformed into an adjacency matrix. Then, the single point mutation method, converting one “1” to “0” or one “0” to “1”, is employed for gene mutation [2]. In our operator, not all genes can be selected and changed in the adjacency matrix. As shown in Fig. 6, a mutation can only occur in the colored (blue and red) parts, which represent the five types of information links in an HCN. Remarkably, after a mutation in the red part, gene “0” cannot be mutated to “1”, decreasing the number of reconnaissance command links ( $v_i^D, v_j^S$ ). Consequently, the inferior operational chains in offspring are decreased, and the operational capability of the new HCN is enhanced.

### D. CALCULATION PROCEDURES OF HIGH-CAPABILITY HCNs

The calculation procedures of high-capability HCN are shown in Fig. 7. First, a set of random combat networks that are subject to battlefield resource constraints as well as the heterogeneity requirements of the HCN are generated as the initial population. Then, taking (1) as the objective function, the higher-capability combat networks are selected

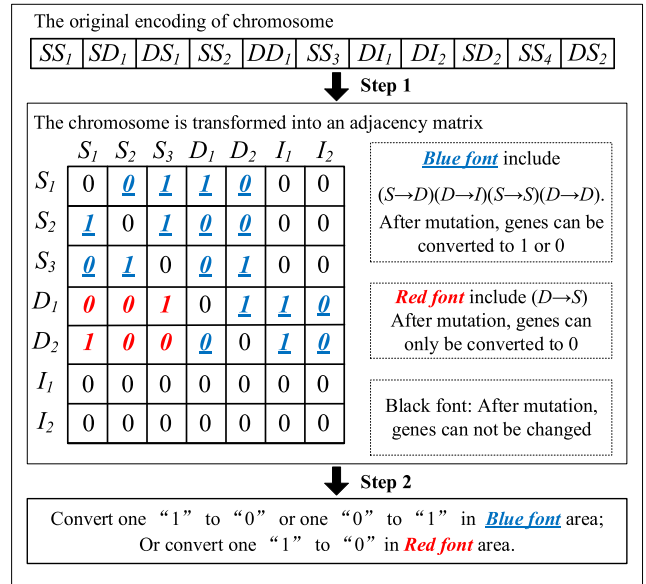


FIGURE 6. Improved mutation operator.

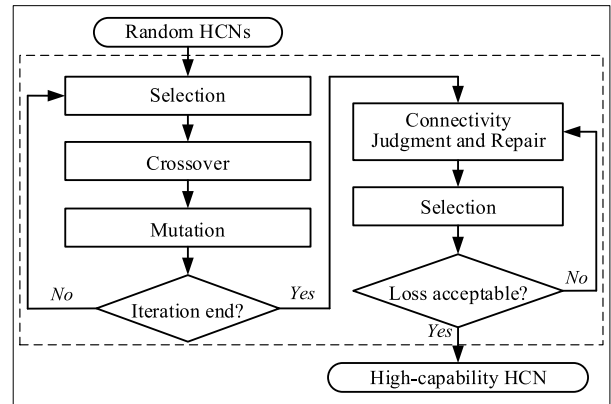


FIGURE 7. Calculation procedures of a high-capability HCN.

and reserved. Through capability-oriented crossover and mutation, new offspring are reproduced to replace their parents and form the new population. These procedures are repeated until the iteration ends, and the formulation of this calculation process is described as:

$$\begin{cases} \max P(G) \\ s.t. \begin{cases} e_i \in ((v_i^S, v_j^S), (v_i^S, v_j^D), (v_i^D, v_j^S), (v_i^D, v_j^D), (v_i^D, v_j^I)) \\ e_i \notin (v_i, v_i) \\ \forall e_i \neq \forall e_j \end{cases} \end{cases} \quad (3)$$

Because combat networks are usually large with hundreds of nodes and links, it is worth noting that to improve the calculation speed, the connectivity of the network is not checked by each operator; instead, we judge and repair the network connectivity after the iteration ends. After the iterations, we first transform link set  $E$  of the high-capability

topology into an adjacency matrix. Then, the below formula is used to determine its connectivity:

$$I + E + E^2 + \dots + E^{n-1} > 0 \quad (4)$$

For topologies with isolated nodes, we randomly select a certain number of existing links to connect them to the main network. This connectivity repair process, in which the connection relationship among a small number of nodes is changed, will inevitably decrease the fitness of the optimal solution. Therefore, we define a threshold for fitness loss: when the fitness loss of the network is less than the threshold after connectivity repair, the corresponding network is selected as the final optimized combat network. This repair strategy provides the algorithm with the ability to optimize the large combat network and will significantly reduce the computational time.

Finally, we analyze the time complexity of the critical steps of OCOGA. In the fitness calculation, the DFS algorithm is employed to identify the valuable operational chains of combat networks. For each source vertex (sensor entity), we run DFS once. Thus, the time complexity of the fitness calculation is  $O(n_s \cdot (n + m))$ . The meanings of  $n_s$ ,  $n$  and  $m$  are shown in Tab. 1. The capability-oriented mutation operator, which converts one “1” to “0” or one “0” to “1”, is independent of the network scale, so its time complexity is  $O(1)$ . The capability-oriented crossover operator mixes and reshuffles each gene of the chromosome, so the time complexity is  $O(n)$ .

## V. CASE STUDY

To prove the effectiveness of GAHCA and obtain useful insights into high-capability combat networks, we conduct numerous network optimization and high-capability HCN analysis experiments. The topological structure of a high-capability network is analyzed in section V.A. The operational capability contributions of the information links and combat entities of the network are analyzed in section V.B and V.C.

### A. TOPOLOGICAL STRUCTURE ANALYSIS

To investigate the topological structure of a high-capability network, we set the parameters of the combat network based on those of an actual combat mission [3], [7]. Leveraging OCOGA and the community detection algorithm, we generate a cartographic picture of the high-capability topology of the network, enabling a thorough analysis of the topological structure. Tab. 3 details the specific information of the network, which includes 66 sensor entities, 15 decider entities, 39 influential entities and 260 information links that can be allocated.  $\alpha$  is set to 2 and 3 when running the genetic algorithm. The number of iterations for termination is 5000. The network connectivity of optimized results is repaired after the iterations; after 3000 repairs, the result with the lowest capability loss is taken as the final network. The heuristic method based on modularity optimization is applied to detect the community of high-capability combat networks [42].

TABLE 3. Network information.

Type	Sensor nodes	Decider nodes	Influencer nodes	Links
Number	66	15	39	260

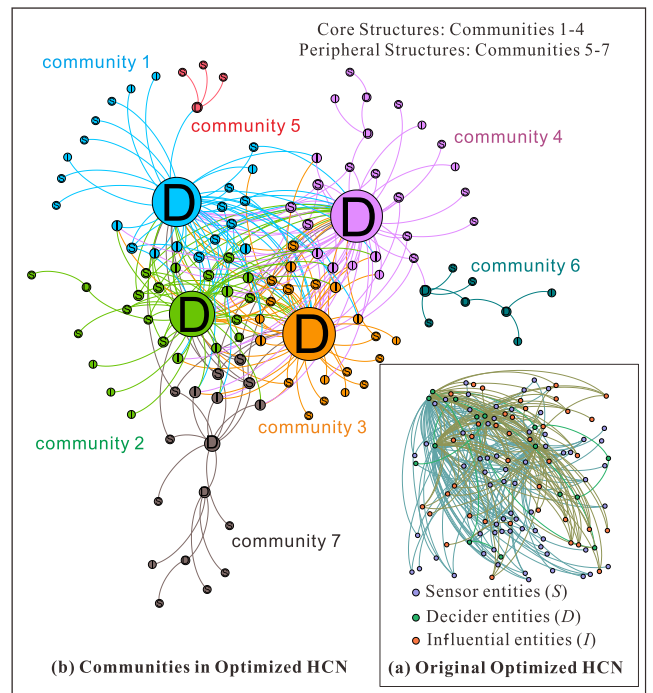


FIGURE 8. High-capability topology of the HCN at  $\alpha = 2$ .

The modularity-based algorithm is the most commonly used algorithm for functional cartography [34], [35] and has high calculation stability. Because this method is embedded into Gephi software [43], we directly use Gephi to obtain cartographic pictures of the combat network.

When  $\alpha$  is set to 2, Fig. 8(a) shows the random layout of the high-capability HCN topology, whereas Fig. 8(b) is the cartographic representation of the topology. In Fig. 8(b), the size of the node represents its degree, and nodes with the same color belong to the same community. Compared with the random layout, the cartographic picture disentangles the complexity of the topological structure of the network. Fig. 8(b) indicates that the high-capability HCN consists of 7 communities, 4 large communities (communities 1-4) and 3 small communities (communities 5-7). A large-degree decider entity, which connects almost all the other nodes in the community, is present in each of the 4 large communities. This decider entity can directly connect sensors and influential entities, resulting in a typical topological structure that can yield an enormous number of basic operational chains. The basic operational chain, with a length of 2, is the main contributor to operational capability when the value of  $\alpha$  is set to 2. Therefore, in the optimization process, the genetic algorithm prefers retaining topological structures consisting of a large number of basic chains. The 3 smaller



communities contain a series structure of decider nodes. Compared with the structure of the 4 large communities, these structures have relatively more difficulty generating the basic chain. However, they effectively connect multiple decider nodes and ensure the full connectivity of the combat network.

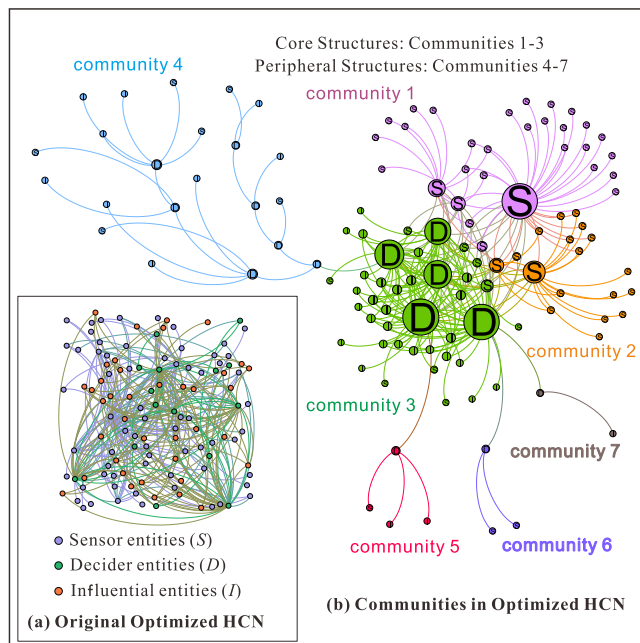


FIGURE 9. High-capability topology of the HCN at  $\alpha = 3$ .

When  $\alpha$  is set to 3, the resulting random layout and cartographic picture of the high-capability topology take the forms shown in Fig. 9(a) and Fig. 9(b), respectively. The high-capability HCN again consists of 7 communities. Communities 1 and 2 are composed purely of sensor entities, which means that the function of these two communities is intelligent collection. Community 3 contains only decider and influential entities, and its function is to make decisions and then execute striking assignments. Community 3 cooperates with communities 1 and 2 to form a large number of operational chains with a length of 3. Compared with the basic operational chain, these chains contain one more sensor entity. Although the operational chains of lengths 2 and 3 are all valid contributors to operational capability at  $\alpha = 3$ , the optimizing algorithm is inclined to choose the longer chains. The low capability and large number of operational chains of length 3 leads to higher capability accumulation than for shorter chains, resulting in a better capability value for the entire network. Therefore, communities 1 to 3 form the core structure in the combat network for the generation of operational capability. Communities 4 to 7 form the peripheral structure of the combat network, the result of a compromise between network connectivity requirements and operational capability requirements.

From Fig. 8 and Fig. 9, we can see that certain sensor or decider entities have a high degree. These entities, whose main function is information processing, form the core

structure for capability generation. Therefore, to obtain a combat network with high operational capability, network builders should provide more information support for stronger decider entities and sensor entities, which will help generate more valid operational chains and consequently enhance the operational capability of the HCN.

### B. LINK CONTRIBUTION ANALYSIS

This section will study the contribution and influence of information links to operational capability in a combat network. In an HCN, the number of information links usually corresponds to the network resources; for example, the number of links in a microwave relay network is related to the number of optical terminals [6]. Link contribution analysis can provide useful insights into resource allocation, thus improving the network construction efficiency.

To ensure that the genetic algorithm converges to the optimal value, three small-scale HCNs are selected to investigate the link contribution. For different  $\alpha$  values and the number of links  $M$  of the network while fixing the number of combat entities, the differences in operational capability among the resulting high-capability topologies are studied. The parameters of the genetic algorithm are mutation probability 0.2, crossover probability 0.8, iterations 150, and repair loss threshold 0. For each combination of parameters, the genetic algorithm executes 20 runs, and the optimal operational capability (OOC) is recorded and plotted. The dependence of the OOC on the number of information links  $M$  is shown in Fig. 10. As  $M$  increases, the OOC first increases and then slows and tends to plateau. A similar situation occurs when  $\alpha$  is 3 or 4. This analysis indicates that when the number of combat entities is fixed, a continuous increase in the number of information links cannot always improve the operational capability. To enhance the efficiency of HCN construction, the total number of pieces of communication equipment must be calculated in strict accordance with the number of combat entities.

### C. NODE CONTRIBUTION ANALYSIS

This section studies the contributions of nodes (combat entities) to and their influences on the operational capability of combat networks. When building a combat network, the number of decider entities corresponds to the command-and-control organization, which is strictly affected by the military mission and the organizational structure of the associated combat forces; therefore, it is difficult to increase or decrease this number. Sensor and influential entities are usually composed of weapons and equipment, and their number is relatively easy to change by allocating battlefield resources.

To ensure that the genetic algorithm converges to the optimal value, two small-scale HCNs are selected to investigate the node contributions. Under different  $\alpha$  values, by fixing the number of information links and changing the number of sensors or influential entities of the network,

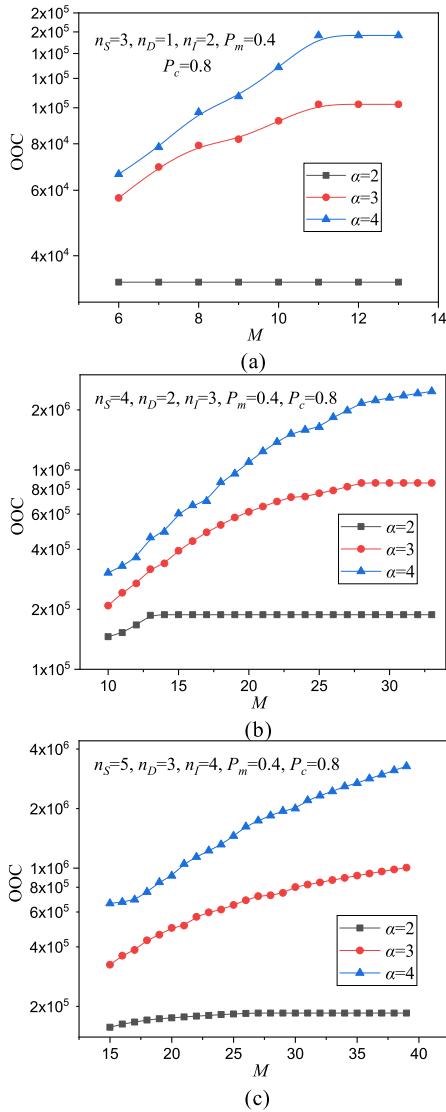


FIGURE 10. Optimal operational capability versus the number of information links with different  $\alpha$ .

the differences in operational capability among different high-capability topologies are studied. The proportion of the number of different combat entities refers to the actual combat network [3]. The parameters of the genetic algorithm are: mutation probability: 0.2; crossover probability: 0.8; number of iterations: 150; and repair loss threshold: 0. For each combination of parameters, the genetic algorithm is executed for 20 runs, and the optimal operational capability is recorded and plotted. The dependence of the OOC on the number of sensor entities ( $n_s$ ) is shown in Figs. 11(a)-(b). When  $n_s$  increases, the OOC first increases, subsequently tends to a plateau, and finally shows a decreasing trend. The reason is that when there are too many sensor entities, to ensure the connectivity of the whole network, the information links are forced to form a peripheral structure that cannot produce a sufficient number of high-value operational chains, which decreases the operational capability for the

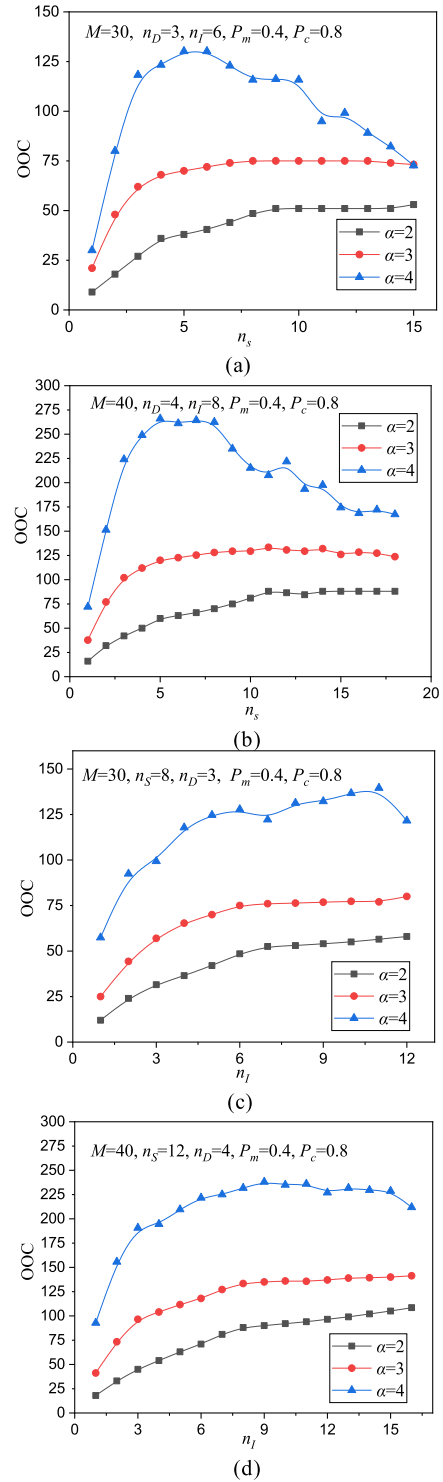


FIGURE 11. Optimal operational capability versus number of combat entities with different  $\alpha$ .

HCN. The situation is slightly improved when  $\alpha$  is 2 or 3; for these values, there is not a considerable difference between the peripheral structure and the core structure of the combat network, and the decrease in capability with increasing  $n_s$  is not as obvious as for  $\alpha = 4$ .

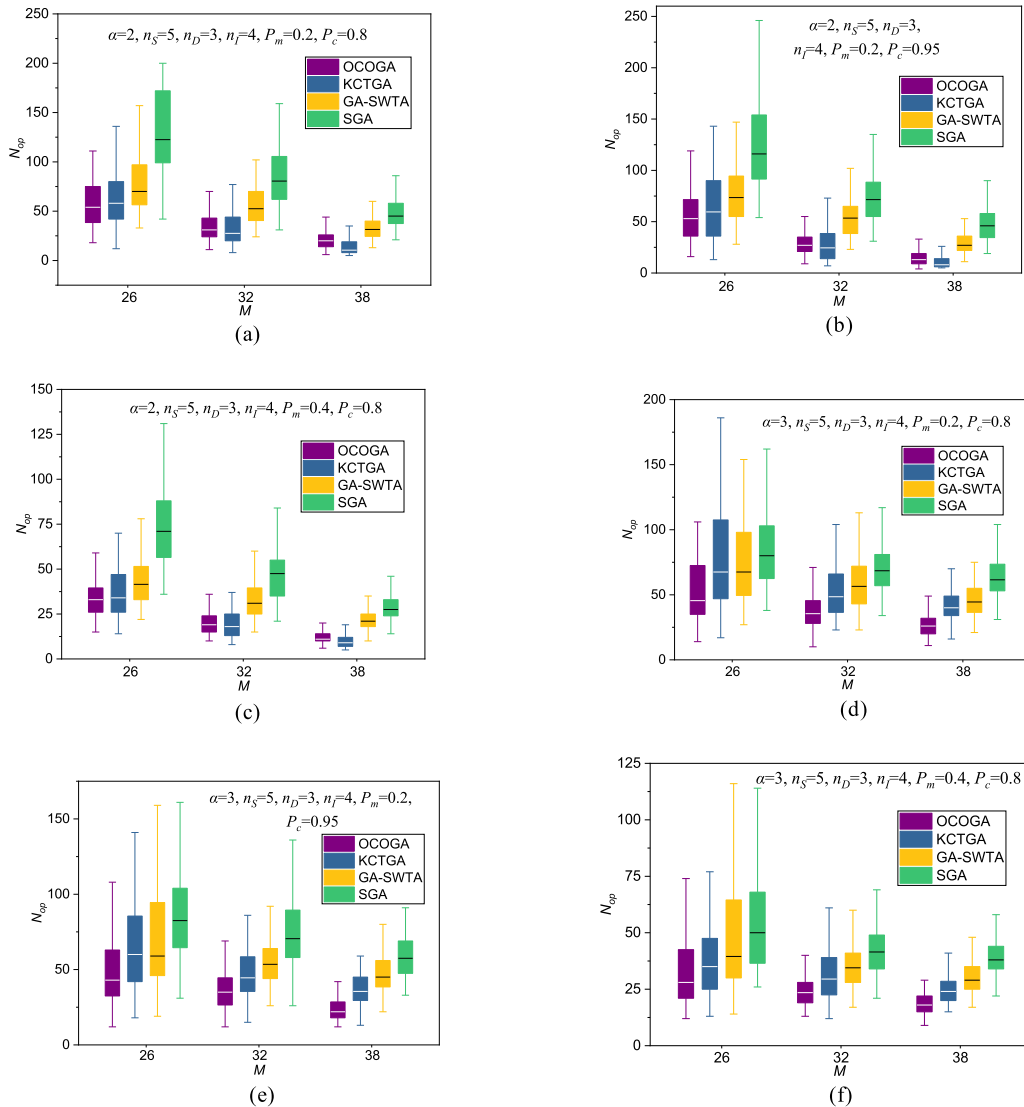


FIGURE 12.  $N_{op}$  of 4 genetic algorithms with different parameters.

Figs. 11(c-d) show the curve of the OOC changing with the number of influential entities ( $n_i$ ). Similar to the trends observed for  $n_s$ , when  $n_i$  increases, the OOC first increases, subsequently slows down, and finally declines. Therefore, if communication resources (*i.e.*, information links) are limited, a continuous increase in number of sensors or influential entities will not always improve the operational capability of the HCN. Even worse, an excessive increase in number of combat entities will exhaust information and communication equipment, make it difficult to form the core structure and decrease the operational capability of the HCN.

#### D. RESULTS AND DISCUSSION

Based on the above analysis, some critical characteristics can be found for high-capability combat networks.

First, high-capability HCNs are composed of two kinds of structures: core structures and peripheral structures. Core

structures, which centralize information links and high-performance combat entities, are the main participants in operational capability generation. In contrast, peripheral structures ensure the connectivity of the network and employ fewer communication resources. The presence of core structures in a high-capability HCN quantitatively demonstrates the importance of the military criterion of “concentration of superior forces”. If we want to construct a high-capability HCN, we should concentrate superior forces and form the core structure.

Second, to construct a high-capability combat network, we must find the optimal allocation point of various resources to guarantee the coordinated distribution of weapons and equipment. Blindly increasing the number of combat entities or information links may not enhance the operational capability of the HCN and, worse yet, may instead lead to a decrease in network capability. Therefore, high-capability

HCNs should have a reasonable proportion of nodes and links.

## VI. PERFORMANCE EVALUATION OF OCOGA

### A. COMPARISON ALGORITHMS

To prove the reliability and efficiency of the improved genetic algorithm (OCOGA) in HCN optimization, its convergence speed is compared with that of three other genetic algorithms in this section. The three comparison algorithms are:

- 1) The key-gene oriented coding transition genetic algorithm (KCTGA) [2] was recently proposed to handle the capability model validation problem for combat networks. KCTGA can fully account for the heterogeneity of combat networks and has excellent convergence for HCN optimization.
- 2) The genetic algorithm for sensor-weapon-target assignment (GA-SWTA) [32] was proposed to solve the SWTA problem by Li *et al.*. The optimization problems of both SWTAs and HCNs have strict constraints and heterogeneous genes; GA-SWTA is therefore a proper benchmark to test the OCOGA.
- 3) The single-point crossover genetic algorithm (SGA) [28], a classical genetic algorithm, can be considered a standard for evaluating the convergence capability of new genetic algorithms.

### B. EXPERIMENTAL SETTINGS

The following methods are used to test the convergence speeds of the four algorithms. First, the optimal fitness  $OC_{op}^{SGA}$  is obtained by the SGA. As a classical algorithm, SGA has a known performance and a wide range of search spaces [28]. When the number of runs and corresponding iterations is sufficient, the optimal fitness calculated by the SGA can be used as the test standard for the other algorithms. Next, the four algorithms are employed to optimize the combat network. When the network fitness reaches 95% of  $OC_{op}^{SGA}$ , the iteration number  $N_{op}$  is recorded. Since the best algorithm can achieve the optimal value in fewer iterations, the genetic algorithm with the smallest  $N_{op}$  has the best convergence ability in optimizing the combat network.

### C. RESULTS AND DISCUSSION

Fig. 12 shows the convergence speeds of the four algorithms. Due to the inherent stochastic property of genetic algorithms, their performance cannot be illustrated by one run. For each parameter combination, the algorithms execute 100 runs, the results of which are depicted by a box plot. The lower and upper ends of the boxes signify the first and third quartiles, respectively, of the number of iterations, and the median is shown as a line in the center of the box.

Fig. 12 shows that OCOGA outperforms the other three genetic algorithms with only one exception: when  $\alpha$  is 2 and the number of links is large, the convergence rate of KCTGA is slightly better than that of OCOGA (Fig. 12(a-c),  $M = 38$ ). However, for this combination of parameters, the number of information links is approximately triple the number of

combat entities, which is not common in real combat forces due to the limited communication resources [3], [6], [7]. Moreover, the repair strategy of OCOGA provides it with the ability to address a large-scale combat network with hundreds of nodes and links, whereas KCTGA does not have this ability [2]. Therefore, it can be claimed that our algorithm, OCOGA, has better convergence efficiency than the other three algorithms and thus enables us to obtain a better solution in HCN optimization, resulting in a more reliable analysis for high-capability combat networks.

## VII. CONCLUSION

In recent years, researchers have published many studies on combat networks to provide insights into improving the survivability of combat systems and enhancing the efficiency of operational processes. However, the properties of high-capability HCNs are still poorly understood, thus limiting our ability to construct a better combat network. To fill this gap, an integrated methodology named GAHCA is proposed in this paper.

Based on the GAHCA, many critical characteristics of high-capability HCNs have been found, providing meaningful guidance for HCN construction and optimization. For example, high-capability combat networks are mainly composed of two kinds of communities: core structures and peripheral structures. Core structures generate most of the capability in an HCN, quantitatively demonstrating the importance of the military criterion of “concentration of superior forces”. Peripheral structures ensure the full connectivity of the combat network. Second, blindly increasing the number of combat entities or information links may not enhance the operational capability of the HCN and, worse yet, may instead decrease the network capability. This is a counterintuitive but significant characteristic for high-capability HCNs. We must find the optimal allocation point of the various resources on the battlefield, guaranteeing the coordinated distribution of weapons and equipment.

To ensure the credibility and reliability of characteristic analysis, we propose a novel genetic algorithm named OCOGA to search for high-capability combat networks. The OCOGA takes into consideration the generation mechanism of operational capability and then improves the convergence efficiency. A comparison with two state-of-the-art and one classical genetic algorithm demonstrates the reliability of the OCOGA.

However, much work remains to be done to improve the reliability and effectiveness of high-capability combat network analysis. For example, developing a novel community detection algorithm that can address the heterogeneity of HCNs may improve the accuracy of topological structure analysis. Moreover, this paper only discusses some characteristics of high-capability HCNs, and more work should be done in the future to deepen our knowledge of the properties of combat networks.

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