IEEE Access
Multidisciplinary Rapid Review Open Access Journal

Received February 26, 2020, accepted March 10, 2020, date of publication March 24, 2020, date of current version April 8, 2020.
Digital Object Identifier 10.1109/ACCESS.2020.2983082

A Method to Validate Operational Capability Index Model of Heterogeneous Combat Networks Based on Characteristic Topology Analysis

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ABSTRACT In high-tech informative warfare, the combat system-of-systems which become increasingly functional and complex can be abstracted as heterogeneous combat networks (HCNs). The operational capability index (OCI) formula is an important model to evaluate the performance of HCNs. To prevent the error of accepting wrong conclusions when using OCI model, the correctness and accuracy of the model should be substantiated before making critical decisions. Accordingly, this paper presents an integrated methodology of framework named operational capability index model validation based on characteristic topology analysis (OCVCT) for validating and testing the OCI model. In this framework, a concept named characteristic topology, which conforms to military rules and has the highest operational capability assessment, is put forward to replace the compact model as the validation candidate. To search for characteristic topology efficiently, we propose an improved genetic algorithm (GA) with the key-gene oriented crossover operator which considers the prior knowledge of combat networks and takes advantages of both binary and real encoding methods. A case study proves the effectiveness of OCVCT. Moreover, compared with two state-of-the-art and one classical GAs, the improved GA has superiority in convergence speed and reliability. The idea of OCVCT also has a potential application prospect for various evaluation model validations of combat networks.

INDEX TERMS Operational capability index, model validation, characteristic topology, genetic algorithm, heterogeneous combat networks, operational chain.

I. INTRODUCTION

As a force multiplier, information has a profound impact on war [1]. To pursue competitive advantages, the extremely robust networks are constructed by the modern military to connect geographically dispersed forces. Consequently, system-of-systems warfare countermeasures have gradually replaced platform-centric to be the main operational patterns [2]. Being composed of various types of multifunctional entities, the combat system-of-systems can be abstracted as heterogeneous combat networks (HCNs) [3]–[6].

Evaluating the capability of combat networks is of significant military value for improving network performance and for optimizing operational decision making [3], [7]. Recently, the compact mathematical model, to measure the capability of combat networks, named operational capability index (OCI) has been used to investigate the functional robustness [3], network disintegration [4], equipment contribution [5], equipment portfolio [6] and mission planning [8] of combat system-of-systems. Being derived strictly from observe, orient, decide, and act (OODA) cycle theory [9] and the concept of the operational chain (OC) [3], [4], OCI can effectively integrate the different behaviors and capabilities of heterogeneous entities, accurately describe the cooperative relationship among combat forces in joint operations, and fully reflect the characteristics and rules of modern warfare. Many useful insights for the combat system-of-systems construction and operational guidance are provided based on OCI [3]–[6], [8], [10]. It is therefore of significance to guarantee the accuracy and reliability of OCI model to prevent the error of accepting wrong conclusions before making critical decision. Moreover, for military issues, different missions require different operational capabilities. The OCI model should be adjusted constantly to give combat network

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

a suitable evaluation. Model validation is an effective and necessary way to judge the correctness and applicability of OCI model [11], [12].

Unfortunately, no method has been proposed to validate OCI model so far. Finding a suitable validation method for a novel model is always a challenging work and requires creativity [13]. For the compact OCI model, its function is to evaluate the operational capability of complex combat networks. Judging whether the model gives the correct and accurate capability assessment for different combat networks is the most intuitive and effective way to test the model. Obtaining reliable and adequate combat networks with known performance is requisite to realize the above method. However, collecting these data from actual warfare is impractical. First, owing to the deep uncertainty of warfare [4], [14], the information of an observed combat network may contain some missing or erroneous data since the intelligence collection is always incompleteness. Second, adequate number of comparable combat networks cannot be obtained because construction of the combat system-of-systems is tolerably expensive [15]. Therefore, Li *et al.* [16], [17] proposed two combat network generation methods to acquire topology of combat networks. Nevertheless, since these generation methods have strong randomness, the generated topologies, lack of representativeness, have low efficiency for OCI model validation. If a combat network has the highest capability assessment by one OCI model, the characteristics of the model will be inevitably existed in this topology. This topology, named as characteristic topology in this paper, can therefore be a suitable candidate used for OCI model validation.

Mathematically speaking, finding characteristic topology from numerous generated topologies can be regarded as a combinatorial optimization problem belonging to NP Complete. The objective function is OCI model and the optimal solution is the characteristic topology. Due to complexity of the problems, the heuristic algorithms are an effective way to search for the solution [18]. For combat networks, the vertices represent the combat entities, while the edges are directional information links. Therefore, the heterogeneous combat networks can be regarded as information networks. Relying on heuristic algorithm, researchers have done numerous works on topology optimization of information networks [19]–[27]. Genetic algorithm (GA) [19], [21]–[24], ant colony algorithm [20], tabu algorithm [21], [25], greedy algorithm [25] and simulated annealing algorithm [21], [27] are all selected and implemented. In these works, GA is used most frequently. Network topology optimization belongs to combinatorial optimization problem, and GA is suitable in solving this kind of problem. The most suitable binary coding method of genetic algorithm can well represent the adjacent matrix of network [21]–[24]. Moreover, GA has superior convergence ability and strong flexibility [28], [29]. Therefore, GA is also the first choice in this paper.

This paper describes a study on OCI model validation problem to prevent the error of making wrong decisions based on the OCI model evaluation results. The contributions of this paper can be summarized as follows:

(1) An integrated methodology of framework named operational capability index model validation based on characteristic topology analysis (OCVCT) is proposed for validating and testing the evaluation model. OCVCT provides a novel validation idea: the compact mathematical model is transformed into characteristic topology, and then the model is verified by analyzing numerous and meaningful information of this topology. The idea of OCVCT also has a potential application prospect for various evaluation model validations of combat networks.

(2) An improved genetic algorithm is proposed to search for the characteristic topology. The GA takes advantages of both binary and real encoding methods to handle the heterogeneity of combat networks. The crossover operator is further enhanced by the prior knowledge of combat networks. Compared with two state-of-the-art and one classical GAs, the improved GA has superiority in convergence speed and reliability.

(3) The feasibility and effectiveness of OCVCT are tested in a case study, and many useful conclusions are obtained. The specific methods to improve and revise OCI model are given. The validation results can assist commanders when making proper and reasonable decisions.

The remainders of the paper are organized as follows. Section II introduces the basic concepts and background. Section III introduces the OCVCT framework. In Section IV, the improved GA algorithm is described. Section V illustrates the effectiveness of OCVCT with a case study. In section VI, the improved GA is compared with two state-of-the-art and one classical GAs. Finally, conclusions and future work are discussed in section VII.

II. BASIC CONCEPTS AND BACKGROUND

A. MODEL VALIDATION

Anything, such as system, concept, or phenomena, can be abstracted as a model, and researches on model validation cover a comprehensive range of fields [13]. Generally, validation techniques can be classified into four categories: formal, informal, static and dynamic methods [30]. Formal methods are based upon strict mathematical proof [13], [31]. The derivation procedures of OCI models can be regarded as a formal validation procedure. Nevertheless, since every model has a derivation process, this process cannot prove whether the model is sufficiently correct. Informal methods [30], relying on human reasoning, has strong subjectivity. Static methods focus on the structure, assumptions or other inherent characteristics of model [12]. Directly judging the credibility of OCI model from its compact mathematical equation is unrealistic. Dynamic methods are suitable for a variety of models owing to their concise and effective validating idea: executing the model and then evaluating the execution results. When applying the dynamic methods, two approaches are

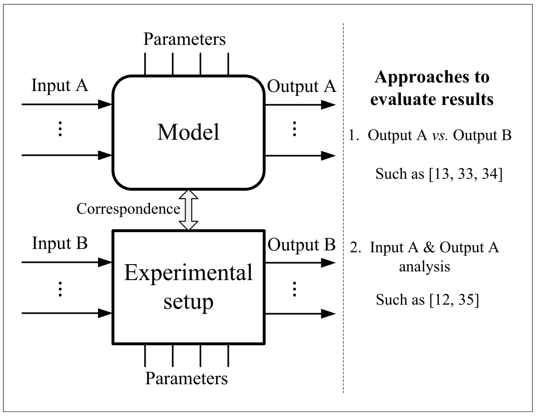

FIGURE 1. Two approaches to evaluate execution results in the dynamic validation method.

employed most commonly to evaluate the execution results. As shown in Fig. 1, the experimental setups represent the real system, credible models and anything to generate trusted data. The first and most effective approach is to validate the model by comparing the output with experimental setup. For example, Green and Ranga [32] described two types of tests for emulator and simulation environment, and then compared output of the two tests. Marušić and Lončar [33] presented an experimental setup to produce available data which was contrasted with model results. Zhang *et al.* [34] verified the calculated results with the commercially available simulation data. However, when difficulties exist in creating experimental setup, validating execution results is concentrated on analyzing the I/O (input and output) data based on assumptions and related theories, which is the second approach. For example, Hajnoroozi *et al.* [35] employed ''measurement units'' to create input data for the simulation model and then the obtained response data were analyzed to calibrate the model. Poropudas and Virtanen [36] put forward an output data analysis approach which converted output data into games and then estimate games to validate air combat models. OCI, as an evaluation model and derived from an abstract concept, cannot find credible experimental setup. When applying dynamic validation methods, OCI model is more suitable for the second approach. In addition, since inputs of OCI model are complex combat network topologies which contain meaningful information, the emphasis of analysis should focus on input data.

B. HETEROGENEOUS COMBAT NETWORKS

Since research on heterogeneous combat networks will facilitate the combat system-of-systems construction and operational guidance, many researchers try to construct a more persuasive HCN. The widely-used models of HCN based on network science can be divided into two categories: IACM (information age combat model) [37] and FINC (Force, Intelligence, Networking and C2) [38]. In IACM, the entities are divided into four categories, namely sensors, decision points, influencers, and targets. FINC contains three types of entities, namely force, intelligence and C2 nodes. Except for the unique entity (i.e., target nodes) in the IACM, the other three nodes of two models have similar meanings. For example, both sensors in IACM and intelligence nodes in FINC represent the combat forces that execute reconnaissance, monitoring, and early warning missions; both decision points in IACM and C2 nodes in FINC represent the combat forces that execute commands and control missions; both influencers and force nodes represent entities that execute fire attacks and electromagnetic interference missions. Therefore, the two models are basically the same in essence, and the modeling idea of this combat networks is widely accepted and used [3]–[6], [8], [16], [39]–[42]. In the follow-up researches of HCN, the main difference is to determine whether there is a target node or not. Since all entities of the enemy can be regarded as target nodes, the target nodes are not considered independently in many researches [3], [4], [39], [40]. Based on this idea, the target nodes will not be introduced in our work. Moreover, when applying dynamic validation method to analyze the input and output data of OCI model, different combat networks should be generated and compared. The edges between sensor, decider and influencer entities are information links, whereas the edges between influencer entities and target entities are usually energy flows [5], [6], [16], [41]. Comparison between energy flows and information links is not feasible since the physic properties of them are generally different. Thus, the HCNs studied in this work consist of three entities: sensor, decider and influencer.

C. OPERATIONAL CHAIN

The theory of Observation, Orientation, Decision and Action Cycle is well known to describe the operational process needed to win a war [43]. In combat networks, sensor is the executor of Observation; decider undertakes the tasks of Orientation and Decision; and influencer completes Action. To represent operational process in combat network, the concept of operational chain is employed in many researches [3]–[6], [16], [17], [44]. Operational chain is an information link chain that different entities in the chain cooperate with each other to complete the OODA cycle. The basic operational process of operational chain can be described as follows: sensor detects the intelligence from enemy target and transmits it to decider; After fusing and analyzing the data, decider makes decisions, and gives attack orders to influencer; Then, influencer attacks enemy targets. The specific definition of operational chain slightly changes in different works. For example, in references [3], [4], no target entity exists in operational chain; in references [5], [6], [16], [17], [44], the chain includes target entity. Since the combat networks we will study only consist of sensor, decider and influencer, the operational chain excludes the target entity in this paper. According to references [3], [4], the chain containing only one sensor, decider and influencer is defined as basic operational chain (OC_{Basic} in Fig. 2). Generalized operational chains (OC_A, OC_B and OC_C in Fig. 2) contain intelligence sharing between sensors,

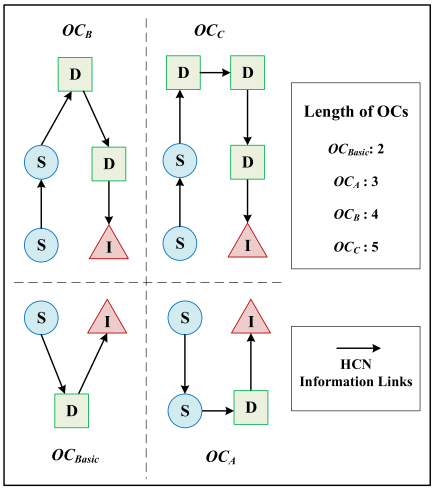

FIGURE 2. Operational chains in HCN.

information communicating between deciders and reconnaissance commanding from deciders to sensors, which means there are multiple sensors and deciders in one operational chain. In Fig. 2, The black arrows represent the information links. The length of OCs is defined as the number of information links existing in the chain. Therefore, the length of OC_{Basic} is 2 and OC_A, OC_B and OC_C are generalized operational chains with lengths of 3, 4 and 5 respectively.

III. OPERATIONAL CAPABILITY INDEX MODEL VALIDATION BASED ON CHARACTERISTIC TOPOLOGY ANALYSIS

In this section, we will introduce the integrated methodology of framework named OCVCT to validate the correctness and accuracy of the OCI model. From Fig. 3, we can see that the OCVCT contains two steps. Frist, based on an improved genetic algorithm, the characteristic topology of the OCI model is obtained. Second, according to the assumptions and theories which were used to derive the model, the correctness and accuracy of OCI model can be evaluated by analyzing characteristic topology. In the following sections, the framework will be illustrated in detail.

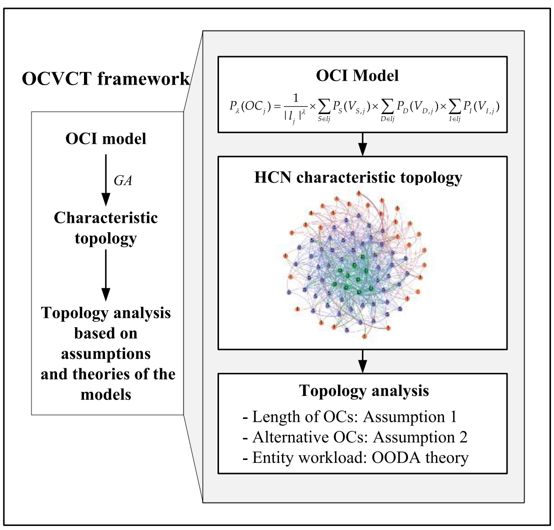

FIGURE 3. OCVCT framework.

The OCVCT is not only suitable for OCI model validation. It also has an application prospect for other network evaluation models. The network evaluation models, used for evaluating the quality of the network, have been constructed in various forms. The common network evaluation models include network connectivity measures [45], spectrum measures [46], and functional measures [3], [4] and they are usually derived strictly from some credible theories and assumptions with compact mathematical forms.

A. OCI MODELS AND THEIR ASSUMPTIONS

OCI models and their assumptions will be introduced first. In reference [3], to derive the operational capability index model, two assumptions are given:

Assumption 1: Operational chain with shorter length will be more reliable for information transmission quality, leading to a faster OODA cycle.

Assumption 2: A larger number of alternative operational chains will improve the robustness of combat networks and enhance the operational efficiency.

Based upon these assumptions and OODA theory, Li [3] derived the operational capability index model, i.e.,

$$P(G_{HCN}) = \sum_{lj} P(OC_j) \tag{1}$$

where the $P(G_{HCN})$ is the operational capability of whole heterogeneous combat networks. $P(OC_j)$ is the operational capability of one operational chain l_j and it can be expressed as:

$$P(OC_j) = \frac{1}{|l_j|} \times \sum_{v^S \in lj} P_S(v^S) \times \sum_{v^D \in lj} P_D(v^D) \times \sum_{v^I \in lj} P_I(v^I) \tag{2}$$

where v^S, v^D, v^I are the sensor, decider, influencer entities in the j-th operational chain l_j. $P_S(v^S)$ is the detection capability of sensor entities, $P_D(v^D)$ is the decision capability of decider entities, and $P_I(v^I)$ is the attack capability of the influencer entities. $|l_j|$ is the length of operational chain. According to assumption 2, the operational capability is inversely proportional to $|l_j|$.

In order to provide comparison models, in this paper, a parameter λ named length attenuation factor is added into equation (2). In equation (2), though $|l_j|$ has been introduced to satisfy the requirement of assumption 1, the impact of the length may not be described properly. Boyd, the founder of OODA theory, repeatedly emphasized the crucial position of the speed of the OODA cycle. The U.S. military, especially the Navy, even holds the following view: "warfare is necessarily a function of decision making and, whoever can make and implement decisions consistently faster gains a tremendous, often decisive advantage" [47]. Therefore, to reflect the dominant position of shorter chain, we define that with the increasing of $|l_j|$, the operational capability of operational chain decreases by λ power of $|l_j|$. And equation (2) can be rewritten as

$$P_\lambda(OC_j) = \frac{1}{|l_j|^\lambda} \times \sum_{v^S \in lj} P_S(v^S) \times \sum_{v^D \in lj} P_D(v^D) \times \sum_{v^I \in lj} P_I(v^I). \tag{3}$$

Thus, the whole operational capability of heterogeneous combat networks can be expressed as

$$P_\lambda(G_{HCN}) = \sum_{lj} P_\lambda(OC_j). \tag{4}$$

When the value of λ varies, different and comparable OCI models can be obtained.

B. CHARACTERISTIC TOPOLOGY

The topology of combat network can be expressed as $G = (V, E)$, where V represents the node set and E represents the link set. In this paper, node set is composed of sensor entities (S), decider entities (D) and influencer entities (I) [3], [4]: $V = V_S \cup V_D \cup V_I$. $V_S = (v_1^S, \cdots, v_i^S, \cdots, v_{ns}^S)$ represents sensor entity set. $V_D = (v_1^D, \cdots, v_i^D, \cdots, v_{nd}^D)$ represents decider entity set. $V_I = (v_1^I, \cdots, v_i^I, \cdots, v_{ni}^I)$ represents influencer entity set. n_S, n_D, n_I are total number of S, D, I entities respectively. Link set, $E = (e_1, \cdots, e_i, \cdots, e_M)$, represents the set of information links between two entities in combat networks. The links are directed edges and M is the total number of links. This paper divides the information link set into five categories: intelligence sharing link ($S \to S$), intelligence upload link ($S \to D$), reconnaissance command link ($D \to S$), fire control information link ($D \to I$) and communicating link ($D \to D$) [4]. Since the links, being all information links, have identical physical carriers, it is assumed that different links can be substituted for each other.

Because heterogeneous combat networks are abstracted from actual combat system-of-systems, the topologies should satisfy the following military constraints.

Constraint 1: In a mission, due to the limitation of resources, the devices and weapons cannot be arbitrarily increased or reduced and they are considered as fixed values [4], [19]. Thus, the number of nodes (n_S, n_D, n_I) and edges (M) cannot be changed.

Constraint 2: In modern warfare, low bandwidth services are the main services and the overall network invulnerability is more important than link bandwidth. Thus, no duplicate edges are permitted in the network.

Constraint 3: Each combat entity, playing a certain role in a combat mission and probably becoming the dominant entity because of the military uncertainty, should not be isolated so that the distribution of information links must ensure the full connectivity of the network.

As discussed in section II, the feasible way to validate OCI models is the analysis of input data, i.e., combat networks. We think that the most suitable network for OCI model validation is called characteristic topology and its definition is:

Definition 1: Characteristic topology. In a specific operational mission, an OCI model evaluates the operational capability of all possible heterogeneous combat networks which satisfies the military constraints. Among these networks, the one with the highest operational capability is defined as the characteristic topology of this OCI model.

Using characteristic topology to represent OCI model to accomplish validation work is an effective idea. Characteristic topology has the highest capability evaluated by the corresponding model. The relationship between characteristic topology and corresponding OCI model is the same as the relationship between objective function and optimal solution of heuristic algorithms. In heuristic algorithms, the fact that objective function determines the characteristic of the optimal solution is accepted by everyone. Hence, analyzing the optimal solution (characteristic topology) can provide insights into objective function (OCI model). In this paper, an improved genetic algorithm will be proposed to search for the characteristic topology.

Moreover, using characteristic topology would have many advantages. First, different from compact mathematical equation of OCI model, enough and meaningful information could be acquired from complicated topology structures. Second, compared with other random topologies, the characteristic topology can fully reflect the characteristic of OCI model and will therefore improve the validation efficiency. Third, characteristic topology is easy to visualize, and the strength and weakness of the OCI model can be seen intuitively.

C. TOPOLOGY ANALYSIS BASED ON ASSUMPTIONS AND THEORIES

To judge whether the OCI models meet the requirements of the assumptions and theories, three aspects of characteristic topology will be analyzed to validate the model.

(1) Length of operational chains. According to assumption 1, shorter length leads to a fast and reliable OODA cycle. Thus, for each characteristic topology, the average length of operational chains will be calculated and the longest chain in combat network will be detected. If those lengths are shorter, the combat network will have a higher operational capability.

(2) Alternative operational chains. Depending on assumption 2, a larger number of alternative operational chains will improve the invulnerability of combat networks. In other words, this assumption means that if one operational chain is destroyed, there are many other chains can be used to replace it. However, some military engagement is time sensitive. The commander strives to use as little time as possible to improve decision speed and achieve decisive advantage [47]. The quality of alternative chains also has significant military value. Thus, the number of all operational chains and high-quality chains should be considered simultaneously. Moreover, we also should investigate that when one chain is destroyed, whether other alternative chains still exist or not. Hence, for characteristic topology, some damage strategy should be employed.

(3) Entity workload. From OODA theory, we know that the founder, Boyd, repeatedly emphasized the crucial position of the speed of OODA cycle [47]. Since the OCI models take advantage of this theory, we should investigate the tempo of OODA cycle from multiple perspectives, not just from the length. If one combat entity undertakes too many operational tasks in one military mission, the entity bears a heavy workload which leads to low operational efficiency. As a result, the OODA tempo declines. In combat networks, every combat entity is abstracted as a node. Since operational chain is the carrier of an operational task, the number of chains passing through one entity can be used to estimate the workload of each node. Thus, the workload of the i-th node can be defined as:

$$W_i = N_i^{oc}/N_{HCN}^{oc} \tag{5}$$

where N_i^{oc} is the number of operational chains passing through the i-th node and N_{HCN}^{oc} is the number of all operational chains in combat network. If W_i is too large, the i-th node will have a high probability to handle many operational tasks simultaneously, which decrease the speed of OODA cycle.

IV. KEY-GENE ORIENTED CODING TRANSITION GENETIC ALGORITHM (KCTGA)

According to the definition, the characteristic topology can be obtained by genetic algorithm. Finding characteristic topology of OCI model accurately and quickly is the prerequisite to ensure the reliability and efficiently of OCVCT. Accordingly, this paper proposes an improved genetic algorithm.

A. CHROMOSOME ENCODING

The adjacent matrix is used as the chromosome to represent an heterogeneous combat network topology $G = (V, E)$. The chromosome G can be expressed as

$$G = (e_{ij})_{n\times n} = \begin{pmatrix} e_{11} & \cdots & e_{1n} \\ \vdots & \ddots & \vdots \\ e_{n1} & \cdots & e_{nn} \end{pmatrix} \tag{6}$$

where e_{ij}, being a Boolean number, represents the information links from the i-th node to the j-th node in combat networks. Adjacent matrix, as a special binary encoding solution, can describe the heterogeneity of the network effectively by using the following definitions: when $i \in [1, n_s]$, v_i is a S node; when $i \in (n_s, n_s + n_d]$, v_i is a D node and when $i \in (n_s + n_d, n_s + n_d + n_i]$ v_i is an I node. For example, when $i \in (n_s, n_s + n_d]$ and $j \in [1, n_s]$, e_{ij} represents reconnaissance command link (D→S). Fig. 4 is the illustration of the chromosome encoding. The valid edges are only allowed in colored parts in Fig.4.

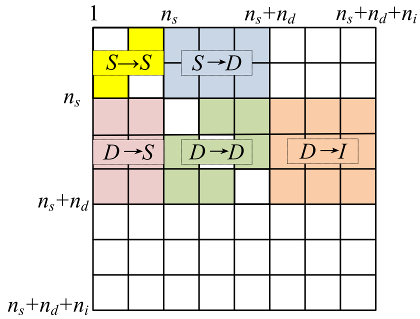

FIGURE 4. The illustration of the chromosome encoding.

B. FITNESS CALCULATION

The fitness of each chromosome is the operational capability index $P_\lambda(G_{HCN})$. To calculate $P_\lambda(G_{HCN})$, we should first find all the operational chains which could be searched by two methods.

The first method takes advantages of depth-first algorithm (DFS) [48]. The process of DFS is to go deep into every possible branch path of the tree until cannot go any further, and each node can only access once. To exploit DFS, the adjacent matrix should be converted to adjacent list. Then, from each initial node S, the following steps are applied to calculate operational chains:

Step1 for an initial node S, visit the adjacent unvisited nodes. Mark the unvisited nodes as visited and record the walks (In graph theory, the walk is a sequence of vertices and edges $v_1e_1v_2\cdots e_iv_{i+1}$ and the length of a walk is the number of edges in the sequence.) from the S node to them.

Step2 for the newest visited node of each walk, visit its adjacent unvisited nodes. If the unvisited node is not an I node, mark it as visited and record the walk from the S node to this visited node. If the unvisited node is an I node, the walk is recorded as an operational chain. Repeat Step2 until no adjacent node is found for the newest visited node of each walk.

The algorithm can accurately find every operational chain, which means we can not only know the number of chains, but also know the distribution of links and nodes in detail. However, the method has a high time complexity.

The second method can obtain the number of chains with a fast calculating speed. As shown in Fig. 4, since no edge exists between S nodes and I nodes, the walk from S to I must pass through D nodes. Thus, the operational chain can be regarded as a special walk starting at v_i^S and ending at v_j^I. Let G^k be the kth power of equation (6) and $e_{ij}^{(k)}$ is the ijth element in G^k. The number of operational chains with length k can be expressed as

$$n_{ij}^{(k)} = \sum_{ij} e_{ij}^{(k)} \tag{7}$$

where $i \in [1, n_s]$ and $j \in [n_s + n_d + 1, n_s + n_d + n_i]$. With k increasing, the $n_{ij}^{(k)}$ will become extremely large because the walks contain repeated edges [16]. Therefore, equation (7) can only be used to acquire the number of chains approximately. However, when $k = 2$, the calculation results is accurate. The second method, though it's not always reliable, has an extremely low time complexity and has been used to study the performance of combat networks by some researchers [16], [17].

C. SELECTION AND MUTATION OPERATORS

Tournament operator is employed to execute selection. The strategy of this operator is to choose a certain number of chromosomes from the population at a time, and then the one with the largest fitness value will be selected to enter the next generation.

The single point mutation method is used to mutate chromosomes. In this operator, a gene with the value of "1" is randomly selected in adjacent matrix. Then another gene with the value of "0" is chosen in colored part of Fig. 4. Finally, the values of these two genes are exchanged. The single point mutation method does not produce self-loop, and can ensure that the total number of nodes and links in combat network cannot be changed.

D. KEY-GENE ORIENTED CODING TRANSITION CROSSOVER OPERATOR

The crossover operator makes offspring inherit genes of their parents and concentrates the large searching area into a relatively superior local area. To improve the convergence efficiency of GA, the crossover operator which makes more changes should be utilized [49]. These operators often collect and mix the genes of parents and then distribute them to their offspring randomly. However, as a binary encoding solution, the chromosome of Fig. 4 only contains "1" and "0". Mixing and distributing genes will lead to the loss of parent's characteristics. Recently, Chen *et al.* [19] has proposed a dual-encoding genetic algorithm (DMGA) which converts adjacent matrix into adjacent list. Since adjacent list is a real number encoding solution, destructive operator can be utilized without the concern of losing characteristics of parents. However, since the mix and distribution of genes are random in DMGA, there is plenty of room for the performance improvement of this algorithm.

In this paper, based upon the EX operator in reference [29], the "good" genes are selected and preserved to enhance DMGA. The process of crossover operator proposed in this paper is illustrated in Fig. 5. First, the encoding form of two parents is changed from adjacent matrix into adjacent list. The genes existing in both parents are selected and preserved as "good" genes. Then, the remaining genes are mixed. The D nodes coordinate and co-operate various operational capabilities and they are of great significance in combat networks [3]. Therefore, we define that the edges containing D nodes are key-genes which can be regarded as another kind of "good" gene. Then, we can generate two offspring and the good child consists of more key-genes. Consequently, the convergence speed is enhanced. Considering that the crossover operator is the main contribution of our work, the proposed GA can be named as key-gene oriented coding transition genetic algorithm (KCTGA).

E. GA PROCESS

The GA process to obtain characteristic topology of an OCI model is shown in Fig. 6. The OCI model is introduced into GA as the objective function. The random combat network topologies are the initial population. Calculating the operational capability of each topology by using OCI model, the combat network with higher fitness is selected to retain. Through the operators of crossover and mutation, new combat networks are generated. Repeating the above steps until the iteration is end. The best solution of GA (i.e., the characteristic topology of OCI model) is obtained. During iterations, all combat networks should satisfy the military constraints. The formulation to calculate characteristic topology can be described as (8), as shown at the bottom of the next page.

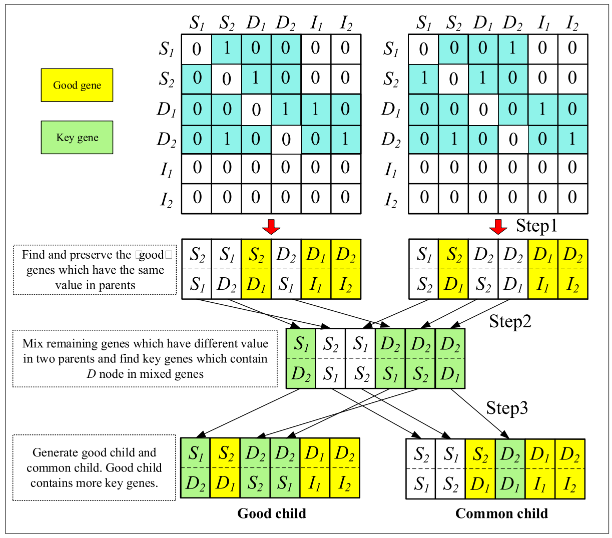

FIGURE 5. Improved crossover operator.

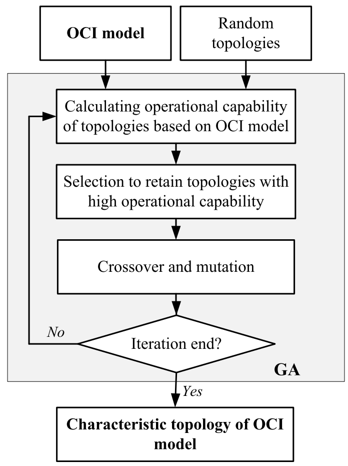

FIGURE 6. GA process to generate characteristic topology.

V. CASE STUDY

To illustrate the feasibility and effectiveness of OCVCT in solving OCI model validation problem, extensive experiments are conducted on combat networks.

A. CASE DESCRIPTION

In a military mission, there are 12 nodes in heterogeneous combat networks, including 5 S nodes, 3 D nodes and

4 I nodes. Due to the limitation of communication devices, it is assumed that 30 effective information links can be provided. In equation (3), we take λ from 1 to 15 to obtain 15 OCI models. For each OCI model, a characteristic topology is generated. The characteristic topology obtained at $\lambda = 1$ is CT_1, at $\lambda = 2$ is CT_2, at $\lambda = 3$ is CT_3, etc.

The operational capability of 12 nodes, ranging from 1 to 10, are shown in Tab. 1. The crossover probability of genetic algorithm is 0.8, the mutation probability is 0.2, the number of iterations is 100, and the population size is 20. To guarantee the accuracy of OCI calculation, the depth-first algorithm is applied to search for operational chains.

TABLE 1. The operational capability of each nodes in HCN.

Nodes	S_1	S_2	S_3	S_4	S_5	D_1	D_2	D_3
Capability	8	6	3	9	5	2	5	8

Nodes	I_1	I_2	I_3	I_4
Capability	2	5	6	9

B. TOPOLOGY ANALYSIS

In every case of λ, the GA runs 100 times and generates 50 topology results. The result with the highest operational capability is selected to analyze. Fig. 5 is characteristic topologies of OCI models at $\lambda = 1$, $\lambda = 5$, $\lambda = 10$ and $\lambda = 15$ respectively. The four topologies are apparently different which means that four OCI models have different evaluation criteria on combat networks.

As we can see intuitively from Fig. 7(a) and Fig. 7(b), when D_3 is destroyed, all operational chains in the network will be broken. With the increasing of λ, part of the operational chains no longer passes through D_3. In Fig. 7(c), only both node D_2 and node D_3 are destroyed simultaneously, the whole combat network will disintegrate completely. In Fig. 7(d), three D nodes are backup to each other. If any D node is reserved, combat network can still work effectively. Therefore, Fig. 7(d) has the best robustness if all combat entities have identical protection ability. According to the above analysis, D_3 node is critical in the combat networks because it has the largest capability compared with other D nodes. However, for I nodes, the algorithm is not sensitive to their capability. From all the subgraphs in Fig. 7(except Fig. 7(b)), four I nodes have the same degree. As the middle node of the combat chain, decider entities have a huge impact on the operational chains. I nodes, as the end of the operational chain, can only be connected with D. Its capability difference

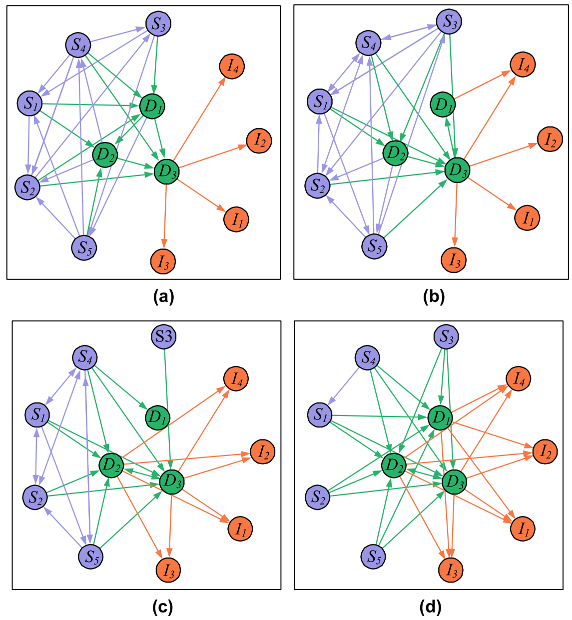

FIGURE 7. The characteristic topologies of OCI models with different λ. (a) $\lambda = 1$; (b) $\lambda = 5$; (c) $\lambda = 10$; (d) $\lambda = 15$.

is relatively unimportant. In modern warfare, it is therefore more valuable to improve the capability of deciders than that of influencers. For S nodes, judging the influence of node capability on network topology directly is difficult. However, when λ is small, the links are mainly concentrated between S nodes. At this time, the OCI model pays more attention to the number of operational chains, indicating that the links between S nodes are the keys to increase the number of chains.

Besides, as shown in Fig. 7(c), only one intelligence upload link ($S \rightarrow D$) is connected to D_1, which means that this combat entity cannot conduct any operational task since no operational chain passes through this node. In this topology, the resource of decider entity is underutilized. Therefore, intuitively analyzing the characteristic topology will also bring insights into OCI models. Next, to compare 15 OCI models more profoundly, we will analyze the characteristic topologies according to the analysis methods discussed in Section III.

1) LENGTH OF OPERATIONAL CHAINS

To investigate the reliability and speed of OODA cycle, the longest and average length of the chains will be studied. Three scenarios with different numbers of effective

$$
\begin{cases}
\max P_\lambda(G_{HCN}) \\
s.t.\ \begin{cases}
\sum e_{i,j} = M \\
e_{i,j} = 0, \quad i \in [1, n_S],\ j \in (n_S + n_D + 1, n_S + n_D + n_I] \\
e_{i,j} = 0, \quad i \in (n_S + n_D + 1, n_S + n_D + n_I],\ j \in [1, n_S + n_D + n_I] \\
e_{i,j} = 0, \quad i = j
\end{cases}
\end{cases}
\tag{8}
$$

information links were considered: 24 links, 30 links and 36 links. Fig. 8(a) shows the average length and Fig. 8(b) shows the longest length for each characteristic topology. As shown in these figures, both the average and the longest length decrease as λ increases. When conducting military missions, the characteristic topology derived from higher λ OCI model has the apparent superiority in reliability and tempo of OODA cycle. Thus, the OCI model with higher λ can satisfy the requirement of assumption 1 better.

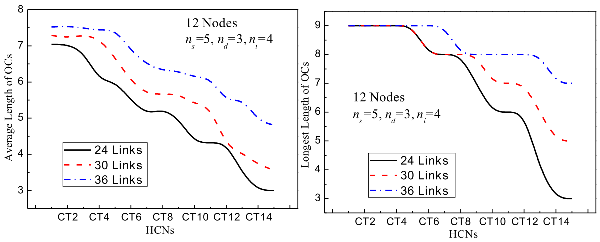

FIGURE 8. The length of operational chains in each characteristic topology. (a) average length; (b) longest length.

2) ALTERNATIVE OPERATIONAL CHAINS

Two scenarios will be considered to assess the quantity and quality of operational chains. In the first scenario, the combat networks are undamaged without any attack and the number of overall and basic chains will be counted for each topology. As we can see in Fig. 9(a), the overall number of the chains reduces when λ increases. Though the quantity of the chain has an overwhelming advantage at lower λ, the quality is not optimistic. In Fig. 9(b), larger λ results in characteristic topology containing more basic chains which is of far more value to military engagement than generalized chains since basic chain means fast and reliable OODA cycle. Therefore, if the quality of operational chain is the main concerns of the military commander, when evaluating the combat network, taking a larger λ is a relatively wiser choice for OCI model construction.

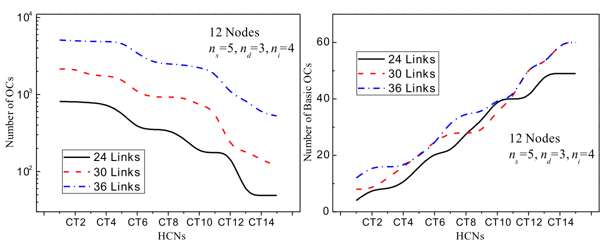

FIGURE 9. The number of operational chains in each characteristic topology. (a) number of overall operational chains; (b) number of basic operational chains.

In the second scenario, the number of operational chains will be studied when combat network has been attacked and part of the network has been destroyed. The motivation for this section is to investigate whether there are enough replaceable operational chains when one of them has been broken. Two choices can be selected to realize it: removing one node or removing one edge in one chain. However, since the distribution of heterogeneous edges are changed in different topologies, choosing comparable edges to destroy is unrealistic. Fortunately, the category and number of nodes are identical in each network. Thus, we remove one node in topologies and the remaining operational chains will be analyzed.

Fig. 10 is the remaining operational chains when destroying one kind of node. As shown in these figures, as λ increases, the number of remaining operational chains will decrease in most cases. However, some exceptions exist when S_3, D_1, D_2 and D_3 are removed. Decider entities, like the brain of the human body, play a critical role in military engagements, which could be the prime target for enemies [3]. Investigating the number of remaining chains after D nodes being damaged is of greater value for combat network robustness study than other nodes. Thus, we should pay more attention on Fig. 10(b). In Fig. 10(b), when λ is too low or too high, the number of remaining chains is very limited especially for D_3 who has the highest node capability as shown in Tab. 1. In CT_1 to CT_4, though the original number of the chains is considerably large as shown in Fig. 9(a), the removal of D_3 will lead to drastic decline of operational chains. This is because when λ is lower, to find combat network with higher operational capability, the OCI models focus on the number of the chains other than the length. Therefore, the information links are distributed among S nodes and D nodes in these characteristic topologies. As a result, only D_3 has the capacity to command and control I nodes directly such as combat networks in Fig. 7(a) and (b). When D_3 is destroyed, all chains in the network will be interrupted since D_3 participates in all operational tasks. In CT_{10} to CT_{15}, the number of remaining chains is also limited. This is because the original number of chains is scarce. Therefore, to persist considerable number of operational chains after D_3 is removed, the optimal characteristic topologies are CT_5 to CT_{10}.

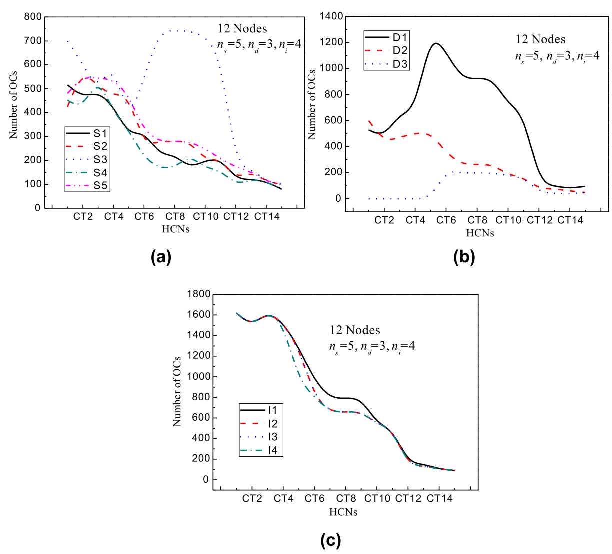

FIGURE 10. Remaining operational chains when removing one node in characteristic topologies (a) removing S nodes; (b) removing D nodes; (c) removing I nodes.

In Fig. 11, the remaining number of basic operational chains increases as λ rises. Therefore, when taking the emphasis on quality, the lower λ is not a good choice for OCI models. Considering Fig. 10 and Fig. 11 simultaneously, if we want OCI model to have an accurate evaluation for combat network who has excellent robustness when one D node damaged, the λ should not be too low or too high.

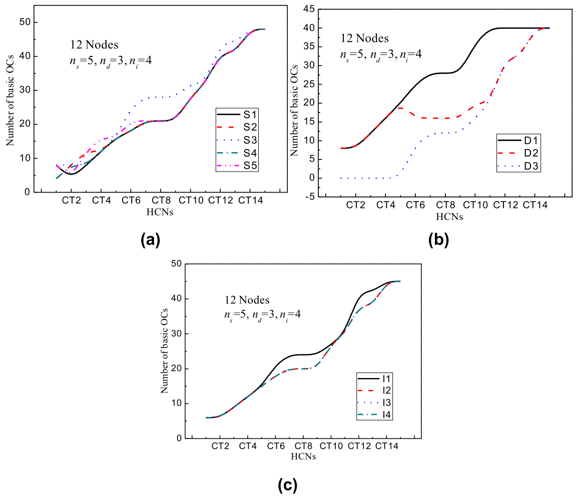

FIGURE 11. **Remaining basic operational chains when removing one node in characteristic topologies (a) removing S nodes; (b) removing D nodes; (c) removing I nodes.**

3) ENTITY WORKLOAD

Fig. 12 shows the workload W_i of each node in characteristic topologies. We can see that if the operational capability of a node is higher, the node will undertake more tasks such as S_4, D_3 and I_4, i.e., combat entities with great capability come great responsibility. However, except S_3, the W_i of other sensor entities is close to 0.75 in CT_1 to CT_{10}, which means that these sensor nodes have a 75% probability to participate in any operational tasks. Worse still, in CT_1 to CT_4, the W_i of D_3 is equal to 1, which means that D_3 involves in every operational task in a military mission. When λ increases, in corresponding characteristic topologies, the W_i of high capability nodes declines and W_i of low capability nodes rises. Division of labor reduces the workload of whole combat network, leading to a high operational efficiency. If we want to give a high capability estimation for combat networks which have low workload for each entity, the higher λ should be taken for OCI models. However, too large λ will make OCI model pay more attention on shorter operational chains, which will make allocation of tasks too average and the competent entities cannot play the critical role in the war.

C. RESULTS OF MODEL VALIDATION FROM CHARACTERISTIC TOPLOGY ANALYSIS

Directly analyzing the mathematical formula of equation (3), the intuitive conclusion can be drawn that when λ is lower, the corresponding characteristic topology will have lager number of alternative chains. However, after analysis of characteristic topology, we find that though the number of the chain is the most at the lowest λ, the destruction of one decider entity will cause most of the chains to fail. In other words, there is a high correlation between these "fake" alternative chains. And just when λ is relatively higher, the characteristic topology can provide the "real" alternative chains when some decider entities are destroyed. Moreover, these chains have superior quality.

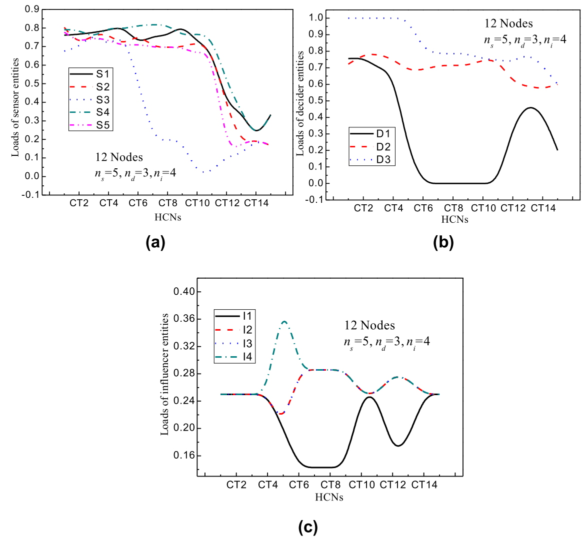

FIGURE 12. **Entity workload of each node. (a) sensor entities; (b) decider entities; (c) influencer entities.**

Therefore, analyzing characteristic topology can provide us directions to revise the OCI models. For example, in this case, if we want to provide high operational capability estimation for combat networks in which the decider entities have a backup to each other, the λ should be assigned higher. If centralized command is the priority of the mission, the λ should be assigned lower. In a word, the characteristic topology analysis could afford us insights into OCI models which could not observe directly from the model itself.

Moreover, the OCI model can be further improved by adding some parameters to avoid problems discovered by characteristic topology analysis. For example, to average the workload of each entity, equation (3) can be revised as

$$P_\lambda(OC_j)=\frac{1}{|l_j|^\lambda}\frac{\sum\limits_{v^S\in lj}P_S(v^S)\times\sum\limits_{v^D\in lj}P_D(v^D)\times\sum\limits_{v^I\in lj}P_I(v^I)}{\max\limits_{v^S\in lj}W_S(v^S)\times\max\limits_{v^D\in lj}W_D(v^D)\times\max\limits_{v^I\in lj}W_I(v^I)} \tag{9}$$

where $W_S(v^S)$, $W_D(v^D)$ and $W_I(v^I)$ are the workload of each entity defined by equation (5). However, the correctness of equation (9) should be tested by OCVCT and this is our future work.

VI. PERFORMANCE STUDY OF PROPOSED KCTGA

A. COMPARATION ALGORITHMS

In this section, the performance of improved GA named KCTGA will be studied and its convergence efficiency will be compared with two state-of-the-art genetic algorithms,

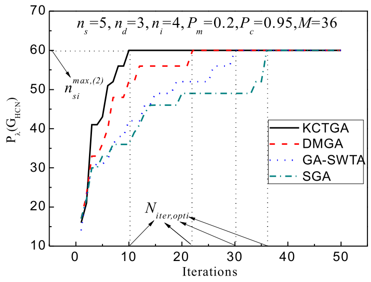

FIGURE 13. Convergence speed of 4 GAs at one run.

named DMGA and GA-SWTA, and one classical genetic algorithm, named single-point crossover genetic algorithm (SGA).

The DMGA proposed by authors of [19] is applied to optimize the mobile microwave relay networks which belong to military communication networks and can be regarded as the physic carrier of combat networks. Moreover, the constraints of two problems are the same such as the resources are a fixed value and no duplicate edges are allowed in the network. Therefore, the problem solved by [19] and this paper has a high similarity. The DMGA has an excellent convergence speed in dealing with such constraint problems.

The GA-SWTA [29] is used to handle the sensor-weapon–target assignment (S-WTA) problem. Like KCTGA, the chromosome encoding technique in GA-SWTA should consider heterogeneous genes. Furthermore, as the military problems, both S-WTA and combat network exist strict constraints. Thus, GA-SWTA can be transplanted into the problem of this paper smoothly.

SGA [22] is a classical genetic algorithm whose performance is well known and can therefore be applied as the standard with which other GA can be compared.

B. EXPERIMENTAL SETTINGS

In our experiment, the parameters of OCI model are selected as: $\lambda = 15$ and $P_S(V_{S,j}) = P_D(V_{D,j}) = P_I(V_{I,j}) = 32$. With the above parameter combination, the operational capability of one basic operational chain is

$$P_\lambda(OC_j) = \frac{1}{|2|^{15}} \times 32 \times 32 \times 32 = 1. \tag{10}$$

And the operational capability of a generalized chain with the length of 3 is

$$P_\lambda(OC_j) = \frac{1}{|3|^{15}} \times 32 \times 32 \times 32 = 0.0023. \tag{11}$$

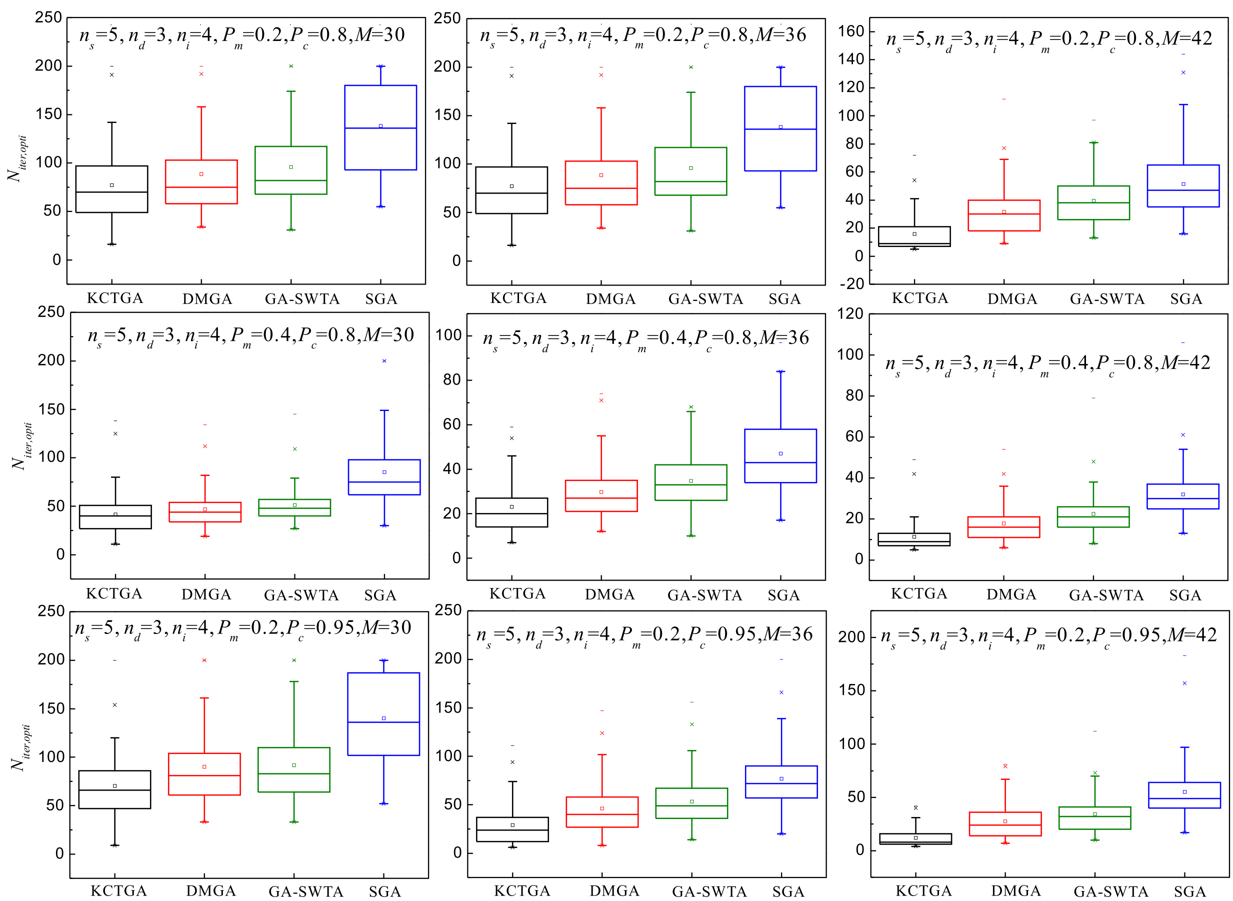

FIGURE 14. $N_{iter,opti}$ of 4 GAs at $n_s = 5$, $n_d = 3$ and $n_i = 4$ with different parameters.

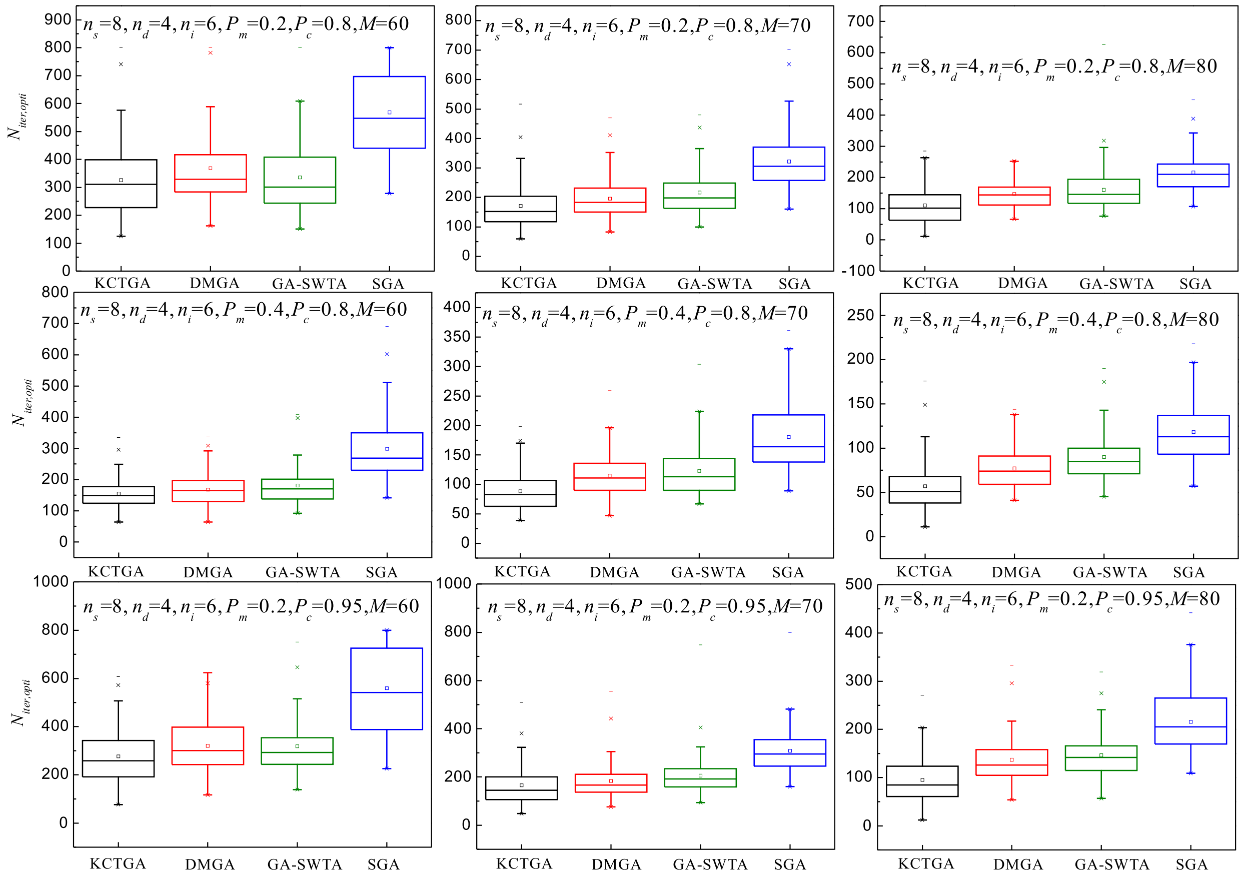

FIGURE 15. $N_{iter,opti}$ of 4 GAs at $n_s = 8$, $n_d = 4$ and $n_i = 6$ with different parameters.

Since longer chains serve extremely low contribution of operational capability for combat networks, ignoring the operational capability contributed by generalized chains is reasonable. Accordingly, the equation (4) can be approximately written as

$$P_\lambda(G_{HCN}) = \sum_{lj} P_\lambda(OC_j) = n_{si}^{(2)} \times \frac{1}{|2|^{15}} \times 32^3 = n_{si}^{(2)}, \quad (12)$$

where $n_{si}^{(2)}$ is the number of basic operational chains and it can be calculated by equation (7). Therefore, these parameters allow us to obtain operational capability extremely fast. The accuracy of calculation result is also acceptable. Consequently, numerous results can be obtained efficiently to compare the algorithms.

Moreover, when the number of information links is larger than $N_{oc} = n_s \times n_d + n_d \times n_i$, the maximum $n_{si}^{(2)}$ is a fixed value and it can be expressed as

$$n_{si,\max}^{(2)} = n_s \times n_d \times n_i. \quad (13)$$

Since equations (12) and (13) mean that the optimal value of $P_\lambda(G_{HCN})$ is a known parameter, it is convenient and persuasive to use $N_{iter,opti}$, which is the iteration number when $P_\lambda(G_{HCN})$ reaches $n_{si,\max}^{(2)}$, to judge the convergence speed of the algorithms. All algorithms are implemented in MATLAB and the experiments are performed on a (TM) i5-8300 CPU @ 2.30 GHz personal computer with 16 GB memory.

C. RESULTS AND DISCUSSIONS

Fig. 13 shows the $P_\lambda(G_{HCN})$ against iterations when four genetic algorithms execute only once. Substituting $n_s = 5$, $n_d = 3$, $n_i = 4$ and $M = 36$ into equation (13), the $n_{si,\max}^{(2)}$ is equal to 60. We can see that KCTGA outperforms other three GAs, and its $N_{iter,opti}$ is only 10. The SGA has the worst convergence performance and $P_\lambda(G_{HCN})$ needs 36 iterations to reach $n_{si,\max}^{(2)}$. lower $N_{iter,opti}$ also means that the corresponding algorithm has more chance to obtain an optimal solution when the total number of iterations is not enough. For example, with the increasing of the network scale, the GA may easily get trapped in a local optimum and hence more iterations are required.

However, since genetic algorithm is a stochastic search technique, the superiority of KCTGA cannot be demonstrated credibly by only one run. Therefore, the four algorithms are executed 100 runs at each combination of parameters. The results of $N_{iter,opti}$ among 100 runs are depicted as the box chart in Fig. 14 and Fig. 15. The boxes are determined by the 25th and 75th percentiles. The medians and means are shown as a line and a square respectively in the center of the boxes. The top of whiskers extends to the largest data less than or equal to 1.5 times the quartile range (IQR), and the bottom extends to the smallest data larger than 1.5 times the IQR. As shown in two figures, the boxes of KCTGA are lower than the boxes derived by other three GAs in 94.4% cases. This indicates that KCTGA exhibits a better convergence speed. Moreover, when the number of information links increases, the box of KCTGA is becoming comparatively much lower and shorter, which means the convergence stability is also improved. This is because larger number of links will provide more key-genes for good child in crossover operator. Consequently, the good child will be closer to optimal solution and hence the convergence performance is enhanced.

VII. CONCLUSION

The OCI formula is an important model to measure the performance of heterogeneous combat networks. Validating the correctness and accuracy of OCI model is of significant military value to prevent the acceptation of the wrong conclusions in combat network studies. Based on the characteristic topology, this paper provides a method named OCVCT to validate OCI models.

Based upon OCVCT, many meaningful validation results have been drawn, which are helpful to the derivation of reliable OCI models. For example, the OCI model with lower λ may give high operational capability evaluation for the wrong combat networks which have a larger number of "fake" alternative operational chains. However, too large λ will make OCI model incline to the combat networks which almost only contain the shortest operational chains, rendering allocation of tasks too uniform and the competent entities have no chance to play the critical role in the combat system-of-systems. These results can provide us orientations to change the value of λ to satisfy the requirements of the specific missions, making OCI model adaptive for different warfare. Moreover, the OCI model can be further improved by adding some parameters to avoid problems discovered by characteristic topology analysis.

To search for characteristic topology accurately and efficiently, we proposed a novel genetic algorithm named KCTGA. Considering the prior knowledge of combat networks and taking advantages of both binary and real encoding methods, an improved crossover operator is introduced. Compared with two state-of-the-art and one classical GAs, the KCTGA has a better convergence speed and reliability.

However, this paper only provides a basic idea required in solving operational capability index model validation problems. Plenty of work remains to be done in the future, for example, when the scale of combat network is extremely large, the limitation of GA will lead to high time complexity of KCTGA. Therefore, the faster characteristic topology generation method which is not based on the heuristic algorithm should be investigated. The idea of OCVCT can be exploited for other evaluation model validations, but how to transplant the method properly needs to be studied.

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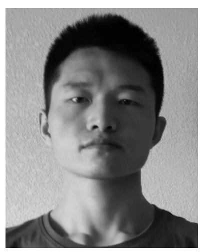

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