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Adaptive dynamic reconfiguration mechanism of unmanned swarm topology based on an evolutionary game

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Abstract: Autonomous cooperation of unmanned swarms is the research focus on "new combat forces" and "disruptive technologies" in military fields. The mechanism design is the fundamental way to realize autonomous cooperation. Facing the realistic requirements of a swarm network dynamic adjustment under the background of high dynamics and strong confrontation and aiming at the optimization of the coordination level, an adaptive dynamic reconfiguration mechanism of unmanned swarm topology based on an evolutionary game is designed. This paper analyzes military requirements and proposes the basic framework of autonomous cooperation of unmanned swarms, including the emergence of swarm intelligence, information network construction and collaborative mechanism design. Then, based on the framework, the adaptive dynamic reconfiguration mechanism is discussed in detail from two aspects: topology dynamics and strategy dynamics. Next, the unmanned swarms' community network is designed, and the network characteristics are analyzed. Moreover, the mechanism characteristics are analyzed by numerical simulation, focusing on the impact of key parameters, such as cost, benefit coefficient and adjustment rate on the level of swarm cooperation. Finally, the conclusion is made, which is expected to provide a theoretical reference and decision support for cooperative mode design and combat effectiveness generation of unmanned swarm operations.

Keywords: unmanned swarm operation, autonomous collaboration, topology reconstruction, evolutionary game.

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1. Introduction

The intelligent collaboration of unmanned swarm operations is an important operational style for future wars [1,2]. The battlefield situation is changing rapidly, and the operational tasks and operational environment of the unmanned system are changing all the time, which also determines that the unmanned swarms must have a high degree of autonomy and adaptability and can realize self-organization and self-coordination according to the battlefield situation, while continuously carrying out the established operational tasks.

A swarm information network is not only the "neural system" of information communication but also the basic guarantee of achieving swarm cooperability. However, in high dynamic, high uncertainty and strong confrontation scenarios, electromagnetic interference and environmental barriers may affect the network topology, and some nodes may even be damaged or captured, which directly leads to node failure. Traditional fixed network planning and passive network adjustment cannot adapt to a strong confrontation environment. Realizing adaptive and intelligent network reconfiguration to ensure that the whole swarm has a high level of autonomous collaboration is not only a scientific and technical problem but also an engineering application problem.

In recent years, many scholars have performed constructive research on swarm autonomous collaboration and network adaptive reconstruction. Among them, the evolutionary game [3–5] is a new method to solve the above problems in the intelligent background. The evolutionary game combines the "equilibrium view" of economics with the "adaptability" concept of biology. It depicts the process of the group adapting to the external environment through learning, imitation and trial and error under the condition of incomplete rationality and asymmetric information. It provides a basic theoretical framework for analyzing the unity of opposites among

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multiple individuals and revealing the group cooperation mechanism. Among them, when solving the problem of network adaptive reconstruction, the optimization goal is usually to maximize the level of swarm cooperation, and the network nodes adaptively adjust the topology based on the game pay-off. However, in evolutionary games, cooperation often benefits defectors, while cooperators bear costs. This undoubtedly leads to the extinction of altruism in evolutionary competition with selfishness [6]. As a result, explaining cooperative evolution has become a very challenging core issue in evolutionary game theory.

Currently, Harvard University has performed many pioneering works in the field of cooperative evolution and introduced the concept of the spatial dimension into evolutionary games for the first time, which opened a precedent in the research of spatial evolutionary games [7,8]. A spatial evolutionary game uses a network to describe the interaction between individuals and emphasizes the network structure's influence on the dynamic swarm evolution and the level of cooperation. As long as the structure is appropriate, relying on simple strategies can also maintain the collaborators' survival. Since then, Nowak's team studied regular lattices, circular graphs, Erdos-Renyi (ER) random graphs, and small world networks and has creatively proposed the relationship between the cost-effectiveness ratio of the game and the average degree of the network and pointed out that the smaller the network connectivity is, the better the cooperation in natural selection [9,10]. After that, they theoretically deduced the cooperation phenomenon on the regular lattice and obtained the boundary conditions for the generation and expansion of cooperation [11]. On the basis of the above work, the differences between homogeneous and heterogeneous networks in promoting collaborative behavior are further compared and analyzed. Simulation results show that weak connections can promote the generation of collaborative behavior in heterogeneous networks [12]. During the same period, other researchers studied the dynamic process of multiplayer games on graphs and found that spatially structured swarms could promote cooperation more than unstructured swarms [13]. In the past two years, the team has applied the dynamic evolution of cooperation in spatial structure to social networks and analyzed the critical conditions for human society to produce collaborative behavior [14]. As a result of the contradiction between the evolutionary convergence probability and the evolutionary convergence time, the tradeoff of the spatial structure between the two is preliminarily explored [15], and the cooperative evolution on the structural swarm is further extended to the weighted graph [16]. Santos takes the lead in the field of evolutionary game research on scale-free networks. Due to the complexity of the scale-free network, previous research on collaborative behavior mainly adopts the method of statistical simulation, knowing its input and output but not its process mechanism. Santos creatively abstracted, simplified and approximated the scale-free network and theoretically deduced the internal mechanism of cooperative evolution [17]. This also revealed that the scale-free characteristics (heterogeneity) of the network and the direct connection between large degree nodes are the core factors for the emergence of cooperative phenomena. In addition, the scale-free network based on the growth and preferential attachment mechanism provides a unified framework for the emergence of cooperation [18−21]. In the domestic research field of cooperative evolution mechanisms on complex networks, representative teams include the Wang Long team of Peking University [22−27], Zheng Dafang team of Zhejiang University [28−30], and Lv Jinhu team of Beijing University of Aeronautics and Astronautics [31]. They conducted long-term and systematic research on various evolutionary game models, such as the prisoner's dilemma, public goods, snowdrift and stag hunt, as well as evolution dynamics and cooperative emergence mechanisms on various complex networks, such as random graph, small-world and scale-free networks.

In recent years, research on the impact of linking dynamics on cooperation has become a trending topic in the spatial evolutionary game [32−35]. If the popular connection (i.e., the edge connecting the collaborators) can be retained in the game, and the unpopular connection (i.e., the edge connecting the collaborators and the defectors) can be quickly disconnected, then the dynamic network will be better than the static network in promoting the emergence of swarm cooperation. In previous studies on edge dynamics, researchers often distinguished the edges according to the strategic attributes of the individuals connected by the edges, specifically divided into the c-c edge, that is, the edge connecting two collaborators. Similarly, there are the c-d edge (the edge connecting collaborator and defector) and the d-d edge (the edge connecting two defectors). During the topological adjustment of the evolution process, different edge dynamics occur for different types of edges to promote cooperation. For example, the c-c edge is given certain preferential treatment, or the collaborators are given the privilege to escape the betrayers so that the c-c edge is permanently retained in the evolution or lasts longer than other edges in the evolution. In contrast, the c-d edge, which is considered to be unwelcome in evolution, is easily disconnected. Through this mechanism, cooperation can be promoted, and betrayal can be suppressed.

However, the preconditions of the above mechanism are too harsh. In reality, the relationship between individuals is maintained by various social and nonsocial factors, such as spatial location, reputation selection, and network reciprocity (refer to the famous 'Five Rules' proposed by Nowak [5]), and it is often adjusted in a softer way. Moreover, the topology adjustment in unmanned swarm operation has its special military laws and business logic. Therefore, it is necessary to build a flexible and adaptive topology reconstruction mechanism under the premise of clarifying military requirements to meet the realistic challenges of unmanned battlefields.

In the early stage, we made a preliminary exploration of the cooperative evolution and autonomous collaborative mechanism of unmanned swarms. Based on evolutionary game theory, we derive the strategy abundance function and strategy dominance condition of unmanned swarms [36] and simulate and analyze the cooperative evolution characteristics of mixed uniform structures [37], scale-free networks [38], and community networks [39–42]. However, the above achievements are based on the assumption of a static network, without considering the dynamic adjustment and adaptive reconfiguration requirements. Based on the existing achievements, this research proposes an unmanned swarm adaptive dynamic reconfiguration mechanism. Specifically, if a network node, whether a collaborator or a defector, encounters a collaborator (defector), the individual will be satisfied (dissatisfied) with this type of interaction and will unilaterally expect to extend (shorten) the duration of the connection. In this way, the duration of each connection will be adjusted reasonably and adaptively instead of being manually specified. Each individual will behave more rationally in this process and finally achieve the adaptive reconfiguration of network topology.

Subsequent chapters are as follows: In Section 2, the military requirements are analyzed, and the behavior analysis framework of unmanned swarm autonomous collaboration is given, which is the basis for establishing the topology adaptive dynamic reconfiguration mechanism. Section 3 builds the topology adaptive dynamic reconfiguration mechanism from topology dynamics and strategy dynamics. On this basis, the construction method of the swarm community network is given, and the characteristics of the network are analyzed. Next, the mechanism characteristics are analyzed using a numerical simulation, focusing on the impact of key parameters, such as benefit coefficient, cost and adjustment rate on the cooperation level. Finally, a conclusion is given based on the simulation results. In this paper, evolutionary game theory and complex network theory are creatively introduced into the design of unmanned swarm coordination mechanisms. The framework, mechanism and method provide a new perspective and technical approach for solving the network topology reconstruction problem in unmanned swarm operations.

2. Framework for autonomous collaborative behavior in unmanned swarms

The behavior analysis of unmanned swarm autonomous collaboration involves three key issues: the emergence of swarm intelligence, the construction of an information network, and the design of a collaborative mechanism. Together, the three build a basic framework for the behavioral analysis of unmanned swarm autonomous collaboration. Among them, the emergence of intelligence from the individual to the swarm is the internal driving force for swarm autonomous collaborative behavior. The information network is the topological space where information interaction occurs and the spatial carrier of autonomous collaboration. The collaborative mechanism is the fundamental way to realize swarm autonomous collaboration.

According to the classical system engineering theory "relationship structure determines function", the information network with a certain topological structure is the basis for the emergence of intelligence at the swarm level. The result of intelligent emergence in turn drives the dynamic reconfiguration of network topology. At the same time, intelligent emergence is a time-space game based on pay-off, and intelligence is the basic premise of rational individual interactive games in coordination. Emergent intelligence is the outward appearance of collaborative mechanism. Collaborative behavior adjustment and strategy updating are closely related to the spatial network structure. Therefore, network topology is an important basis for individual behavior (strategy) updates in the collaborative mechanism. In turn, coordination mechanism changes network topology and information flow. The relationship among the three is shown in Fig. 1.

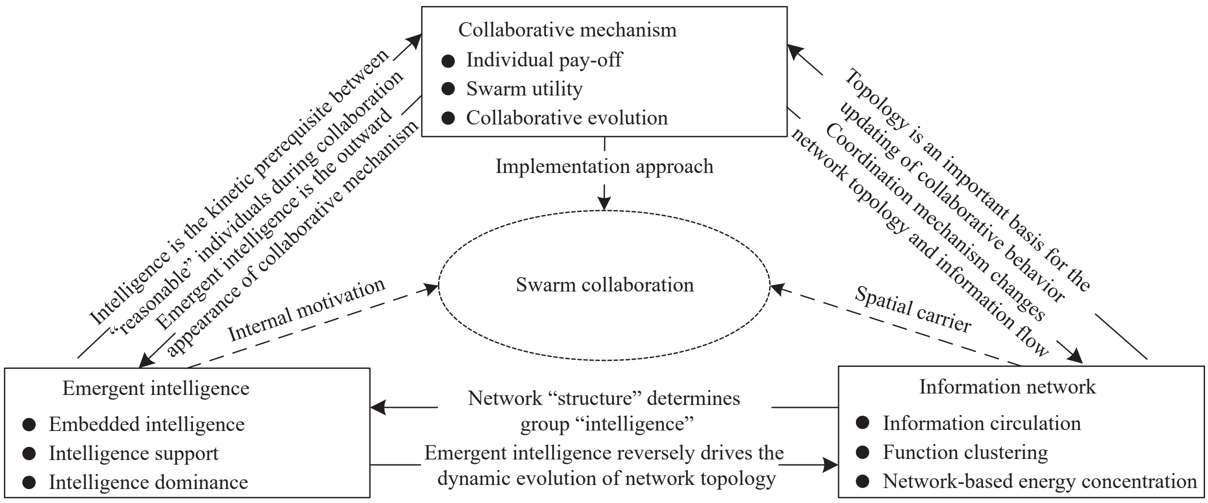


Fig. 1 Framework for autonomous collaborative behavior in unmanned swarms

2.1 Emergent intelligence

The swarm emergent intelligence, as against individual intelligence, is achieved through collaborative mechanism, and emergent intelligence is the outward appearance of collaborative mechanism. In an unmanned swarm, units with 'intelligence' not only passively accept preset instructions, but most importantly, in their interaction with other individuals, they emerge higher-level intelligence beyond individual intelligence at the swarm level through optimal coordination and organization of their own resources, costs and other factors. Finally, the overall utility of the swarm is optimized.

The development of unmanned combat force started from the remote-control stage of human-machine interaction, experienced the cooperative stage of human-machine combination, and is developing toward the autonomous direction of human-machine integration [43]. It can be predicted that the intelligent emergence of unmanned swarms will also undergo evolution from 'intelligent embedding' with manned systems as the main and unmanned systems as the auxiliary, to 'intelligent support' with manned systems as the auxiliary and unmanned systems as the independent, and then to 'intelligent leading' with bionic autonomy and swarm attack and defense.

In the future, unmanned swarm operation systems will have higher awareness, analysis, planning, decision-making and execution capabilities and will move toward independent battlefield situation awareness, independent operational task planning, independent implementation of operational actions, independent links of operational coordination, and independent evaluation of operational effects [44].

2.2 Information network

A common task can only be completed through the coordination of units with different functions. When dealing with such coordination problems, an important task is how to build an information interaction network between individuals. Different functional units conduct information interaction based on the network, thus emerging the ability and intelligence beyond each unit at a higher level, so as to complete tasks that cannot be completed by any single unit.

On the one hand, from the perspective of scale, future swarm operations can be divided into three levels (taking air force as an example). The first level is the follow type with the number of less than 30 or 50. The second level is the cluster type with the number ranging from 30 to 50 to 100; and the third level is the swarm type with the number of more than 100 or even more than 1 000. On the other hand, from the perspective of intelligence, once the unmanned swarm develops to the 'intelligent leading' stage, the scale of the swarm will naturally be extremely large. The expansion of the scale refers to the exponential growth of the complexity of the interaction relationship. Building the swarm network quickly based on the information intractability and combined with the business logic of the swarm operation is a difficult problem that the operation planners must solve.

A representative idea of information network construction in unmanned swarm operations is to integrate the characteristics of random networks [45] and community networks [46,47] on the basis of traditional tree networks to construct a network topology matching the combat task.

For example, in the typical combat style of an unmanned aerial vehicle (UAV) swarm [48], a UAV swarm can be divided into several sub swarms, such as intelligence reconnaissance, electromagnetic interference, and fire strike. The sub swarms are tightly coupled inside and loosely coupled between them, presenting the topological organization structure of a ‘community network’. The operational relationship is shown in Fig. 2. Among them, information needs to be highly effectively transmitted. Establishing the mapping relationship between military requirements, such as information flow and network energy gathering and complex network characteristics, such as scale-free and small world, is the most important task in network form design.

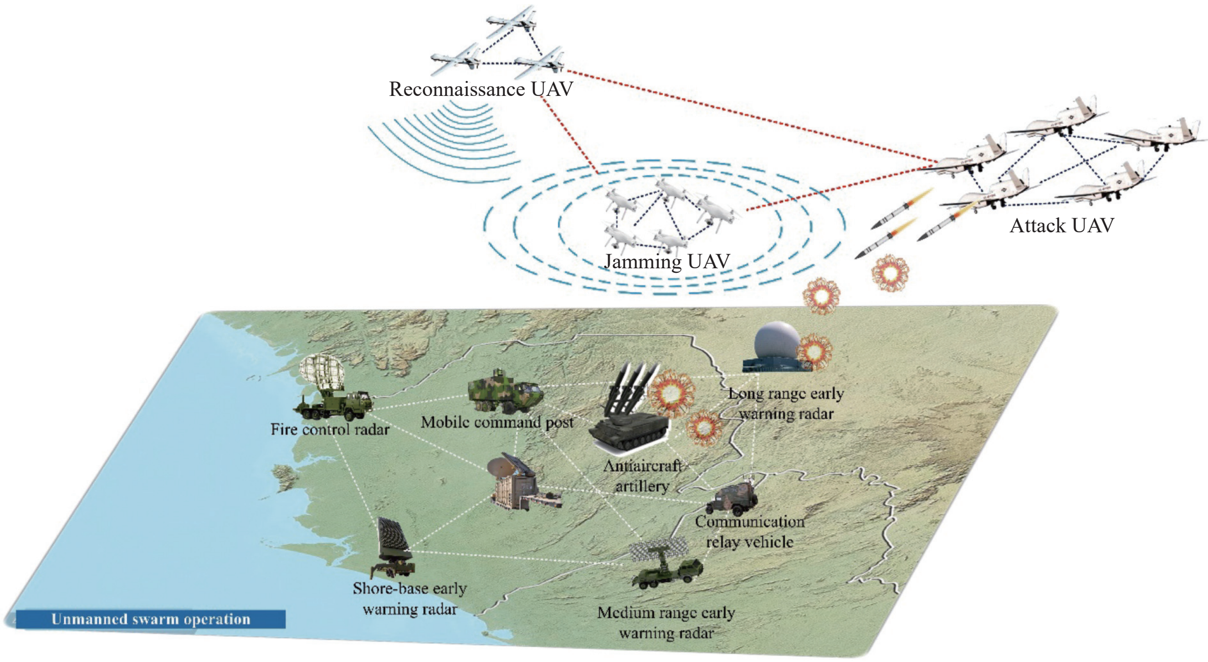


Fig. 2 Diagram of unmanned swarms attacking a ground force

2.3 Collaborative mechanism

An unmanned swarm operation system has the characteristics of regional distribution, intelligent autonomy and decentralization. The swarm must build orderly coordination and cooperation based on the information network to ensure battlefield survivability and mission completion ability. In addition, according to system theory, the elements of unmanned clusters and battlefield environments constitute a complex giant system, and the elements are interdependent, influence and restrict each other. The ultimate essence of a multi-unmanned platform cooperative operation is to find the best control strategy of the whole large-scale system. Therefore, the design of a collaborative mechanism is very important.

In the collaborative interaction, the unmanned platform with intelligence needs to calculate and evaluate its own energy, loss, cost, behavioral cost and other factors to maximize its own pay-off. This process is inevitably accompanied by competition among individuals, resulting in the deviation between the individual pay-off and the total utility in the optimization. Therefore, one of the key problems in the design of collaborative mechanisms is maintaining the consistency between individual pay-off and swarm utility.

For example, in the cluster fire strike task, the intelligent combat platform with decision-making ability will carefully control the fire resource launch amount to maintain its own combat effectiveness. From the cluster level, the more firepower resources each combat unit contributes to the cluster, the higher the overall survival rate and the greater the operational efficiency. The contradiction between the two will lead to “the tragedy of the commons” [49]. This mechanism may lead to the delay of fighters or give the enemy an opportunity to counter attack.

A good collaborative mechanism design is the key to solving the contradiction between individual benefits and the total utility. At present, under the framework of the classic multi-agent system (MAS) theory [50], complex adaptive systems (CAS) theory [51] and complex network theory, the competition and conflict between individuals and swarms in their respective optimization directions need to be studied further.

Above, the framework for autonomous collaborative behavior in unmanned swarms is discussed from the three aspects of emerging intelligence, information networks and collaborative mechanisms. The research in this paper is carried out under this framework, focusing on information networks and collaborative mechanisms. This paper attempts to design a topology adaptive dynamic reconfiguration mechanism for information networks to promote the emergence of swarm cooperation.

3. Topology adaptive dynamic reconfiguration mechanism

This section builds the topology adaptive dynamic reconfiguration mechanism from the two processes of topology dynamics and strategy dynamics. Topological dynamics describes the principle and process of adjusting and reconstructing the edges between nodes; strategy dynamics describes the selection of game models, the calculation of node benefits, and the way to implement strategy transformation based on benefits. They complement each other and support each other. They also alternate in the topology reconstruction process. Topology is the spatial carrier of strategy adjustment, and the strategy is the basis of topology reconstruction.

3.1 Topological dynamic process of swarm evolution

The core of the topological dynamics process of swarm evolution is to clarify three questions: Who will initiate the topology adjustment? According to what principles are adjustments made? How can the new topological relationship be reconstructed after adjustment? Based on military needs, the following three rules will be presented to answer the above three questions.

The maximum scale of unmanned swarm operation can reach hundreds or even thousands [44]. For such a large-scale node, it is neither realistic nor necessary to adjust the topology simultaneously. Therefore, the first question to be answered in topology reconstruction is: Which nodes need to adjust the corresponding edges? In system operations, it is emphasized to carry out key attacks against key nodes, such as the enemy command and control center and communication center to achieve the goal of destroying the enemy's operational system. Therefore, in topology reconstruction, we should also focus on the key nodes that affect the overall operational effectiveness of the swarm and take the corresponding edges as the key adjustment objects. From the point of view of network science, a node with a larger degree is often the hub of the whole network, which plays a decisive role and can act as the initiator of topology adjustment. Therefore, the first rule for swarm topology adjustment is given.

Adjustment initiator rule (R_1): All nodes in the swarm network with a degree greater than 5 ($\text{hub} - \text{degree} > 5$) are selected as initiators of topology adjustment. All the edges connected to this node will be adjusted according to certain rules, such as increasing the connection probability, decreasing the connection probability, and breaking.

In the swarm network, once the edge l_{ij} with i and j as nodes is generated, node i will be given an α_{ij}. α_{ij} obeys the uniform distribution in interval [0, 0.9] and represents the probability that edge l_{ij} remains unchanged during the topology adjustment initiated by node i. In general, $\alpha_{ij} \neq \alpha_{ji}$ and the interval is set as [0, 0.9] instead of [0, 1], mainly considering the fact that there are few permanent connections in the real situation. Based on the above settings, the second rule for swarm topology adjustment is given.

Connection expectation adjustment rule (R_2): Each topology adjustment initiator in the swarm adjusts the edge connection probability according to the current strategy of its neighbors. The specific adjustment principles are as follows:

$$\begin{cases} \alpha_{ij} = \alpha_{ij} + \tau, \ S_j = C \\ \alpha_{ij} = \alpha_{ij} - \tau, \ S_j = D \\ \alpha_{ji} = \alpha_{ji} + \tau, \ S_i = C \\ \alpha_{ji} = \alpha_{ji} - \tau, \ S_i = D \end{cases} \tag{1}$$

where τ describes the adjustment frequency. The larger τ corresponds to the faster adjustment frequency, and the smaller τ corresponds to the slower adjustment frequency. When α reaches the extreme value (i.e., 0 or 0.9), α will only be allowed to change in the opposite direction. C and D represent two strategies (i.e., collaboration and defection, respectively), and S_j stands for strategy adopted by i's neighbors (i.e., j).

It should be noted that while the topology adjustment initiator i adjusts its edge connection probability, its neighbor j will also synchronously adjust its edge connection probability. After i and j adjust their edge connection probabilities α, it will be decided whether to continue to maintain the connection relationship between i and j, that is, whether edge l_{ij} continues to exist or breaks to build a new connection. Therefore, the third rule for swarm topology adjustment is given.

Connection reconfiguration rule (R_3): In the edge adjustment initiated by i, l_{ij} will be disconnected with probability $1-\alpha_{ij}$. Once i removes j from its neighbors, i will randomly select one of its non-neighbor nodes to establish a new connection. There are two criteria for selection:

(i) It must be the same type of node. For example, the command and control node still selects the command and control node. Corresponding to the swarm network, it selects the node in the same community.

(ii) The distance d between i and the selected node (i.e., the network hops) should be moderate. The distance should not be too large. The network hops reflect the actual communication distance of the battlefield, and practical problems, such as communication loss and interference must be considered. The distance should not be too small. Information exchange can be realized between nodes with small distances through other nodes as relays, and there is no need to establish direct links. Generally, $3 \leqslant d \leqslant 4$.

In R_2, the node adjusts its edge probability according to its neighbors' current policy. However, the strategy of each node in the network is not unchanged. It is updated from time to time based on its benefit. The next section describes the dynamic process of node policy updates in the swarm within the framework of evolutionary game theory.

3.2 Dynamic process of the swarm evolution strategy

Autonomous collaboration in swarm warfare has two characteristics: 'evolution' and 'game'. On the one hand, although the individuals are intelligent, the achievement of the overall utility optimization at the swarm level is not achieved overnight but an iterative and self-organized evolution process. Individuals must conduct a large number of repeated interactions and improve strategies through learning, imitation and trial and error to constantly adapt to the external environment and finally achieve the optimal overall utility. On the other hand, autonomous collaboration of unmanned swarms is the multiple interaction and coordination optimization of multiple combat units based on factors such as loss, cost and behavioral cost. The collaborative process is not only related to its own strategy selection but also depends on the strategies of other units in the swarm, which is manifested as a multiplayer game.

Among many evolutionary game models, the public goods game (PGG) provides a basic theoretical framework for revealing the cooperative evolution mechanism. This game model takes the public goods investment as the background and depicts that the cooperators and defectors (free-riding) play a strategic game over time based on parameters such as cost, benefit coefficient and selection intensity, which makes the proportion of cooperators and defectors change dynamically and finally tend to evolve into a steady state. In PGG, balancing individual benefits and overall utility and improving the proportion of collaborators are important prerequisites for solving the 'tragedy of the commons' and realizing unmanned swarm autonomous collaboration.

For multiplayer games, one way is to regard it as the superposition of multiple two-player games. The other is to expand the traditional two-player game and embed the 'multiplayer interaction' into the pay-off [17]. According to the second way, in a network of scale N, let the degree of i be $k_i = k_i^C + k_i^D$, where k_i^C and k_i^D are the number of individuals holding strategies C and D in the neighborhood of i in a certain round of the game.

(i) If i chooses strategy C, then the total contribution of all players in the multiplayer public goods game composed of i and its neighbors is $k_i^C c_o + c_o$(where c_o is the cost contributed by a single collaborator). After multiplying the benefit coefficient r, the total utility is $r(k_i^C c_o + c_o)$. Then, the benefit of each individual is $r(k_i^C c_o + c_o)/(k_i+1)$. Since the cost of i is c_o, the pay-off of i is $r(k_i^C c_o + c_o)/(k_i+1) - c_o$.

(ii) If i chooses strategy D, then the total contribution of all players in the multiplayer public goods game composed of i and its neighbors is $k_i^C c_o$. The total utility is $rk_i^C c_o$, and the benefit of each individual is $rk_i^C c_o/(k_i+1)$. Since i has no cost, the pay-off of i is $rk_i^C c_o/(k_i+1)$. If $a_{k_i^C}$ and $b_{k_i^C}$ are the pay-offs of i with strategies C and D, then

$$a_{k_i^C} = \frac{r(k_i^C c_o + c_o)}{k_i+1} - c_o, \tag{2}$$

$$b_{k_i^C} = \frac{rk_i^C c_o}{k_i+1}. \tag{3}$$

The pay-off matrix is shown in Table 1.

Table 1 Pay-off of multiplayer public goods evolutionary game

Strategy of i	Number of collaborators in i's neighbors					
	k_i	$\cdots$	k_i^C	$\cdots$	1	0
C	$rc_o - c_o$	$\cdots$	$r\left(k_i^C c_o + c_o\right)/(k_i+1) - c_o$	$\cdots$	$2rc_o/(k_i+1) - c_o$	$rc_o/(k_i+1) - c_o$
D	$rk_i c_o/(k_i+1)$	$\cdots$	$rk_i^C c_o/(k_i+1)$	$\cdots$	$rc_o/(k_i+1)$	0

At each complete time step, node i plays games with all its neighbors. According to (2) and (3), the pay-off is calculated within the framework of the multiplayer public goods evolutionary game, and then the strategy is switched with probability according to the strategy update rule. At present, there are several typical strategy update rules in evolutionary games, such as unconditional imitation [52], replicator dynamics [53], and the Fermi rule [54]. The Fermi rule emphasizes the comparison of player pay-off and neighbor pay-off. Driven by this rule, the probability of i switching its strategy in the strategy space $\{C, D\}$ is

$$P_{S_i \in \{C,\, D\}} = \frac{1}{1 + \mathrm{e}^{\omega(F_i - \bar{F}_{k_i})}} \tag{4}$$

where $\omega \in [0,\ 1]$ is the selection intensity, which can amplify or reduce the influence of $F_i - \bar{F}_{k_i}$ on the strategy update probability. Through the reality test, the weak selection intensity ($\omega << 1$) can promote cooperation. Let $F_i \in \{a_{k_i^C},\ b_{k_i^C}\}$ be the pay-off of i and $\bar{F}_{k_i}$ be the average pay-off of its k_i neighbors. Let $\Delta = F_i - \bar{F}_{k_i}$. If Δ=0, then $P_{S_i \in \{C,\ D\}} = 1/2$, and the unmanned platform has the same preference for strategies C and D. If Δ>0 (the individual pay-off F_i is higher than the average pay-off of neighbors $\bar{F}_{k_i}$), then $P_{S_i \in \{C,\ D\}} < 1/2$. At this time, the unmanned platform prefers to maintain the current strategy. If Δ<0 (the individual pay-off F_i is lower than the average pay-off of neighbors $\bar{F}_{k_i}$), then $P_{S_i \in \{C,\ D\}} > 1/2$. At this time, the individual prefers to update the current strategy to another strategy in the strategy space $\{C,\ D\}$.

The dynamic process of the swarm evolution strategy is abstracted into three steps:

(i) According to the network generation algorithm, an unmanned swarm network with a scale of N is generated. Implement a random policy distribution for N network nodes (C and D strategy holders each account for approximately 50%).

(ii) An individual i forms a game group G with all its neighbors who have direct network connections. According to the multiplayer public goods evolutionary game, the pay-off F_i and $\bar{F}_{k_i}$ can be calculated separately.

(iii) After the end of each round of the game, the individual i evaluates the pay-off and updates the strategy according to the Fermi rule.

It should be noted that while i unilaterally updates its strategy, each neighbor j in G will also synchronously update the strategy according to the above process.

In specific application scenarios, a single unmanned platform in the swarm acts as an individual player in the game. Swarms composed of multiple unmanned platforms have common missions, such as fire attacks on the same position and intelligence reconnaissance on the same area. The individual has optional different behavior modes as a game strategy. At every moment, the individual interacts with its ‘neighbors’ (other individual with physical connection based on geographical location and logical connection based on information communication). The individual obtains a certain combat effectiveness and a certain pay-off according to his or her own and neighbor strategies. An intelligent unmanned platform with independent decision-making capability can change its behavior (strategy update) by assessing its combat effectiveness (pay-off). Through multiple rounds of games and repeated strategy updates, a high degree of coordination has emerged at the swarm level, making the swarm control finally reach the evolutionary stable state (such as consistency and synchronization). In the above process, the selection of the game type, the design of the revenue calculation method and the determination of the strategy update rules are of great importance. The above factors are the key to realize the objective of swarm autonomous collaboration.

Whether it is topology dynamics or strategy dynamics, the premise of topology reconstruction and policy updating is based on the ‘information network’ of a specific structure. Therefore, the next section focuses on the swarm network generation algorithm.

4. Swarm network construction

The unmanned swarm information network must be able to reflect the rules of the battlefield combat system. First, it should be able to reflect the correct flow of material, energy, and especially information. Second, it can reflect the information cohesion of homogeneous (functional) combat units and the information loose coupling characteristics between heterogeneous units. In addition, if the operational command relationship is considered, the network hierarchy must also be considered. According to the requirements for information network construction, this section proposes a method for building an unmanned swarm community network and analyzes its degree distribution. A community network is the spatial basis for topology reconstruction and strategy update behavior of unmanned swarms.

4.1 Community network generation

A community network is a special complex network that is closely coupled internally and loosely connected externally. It exists widely in natural biological communities, social groups, scientific research teams and military swarms.

In a certain military operation, there are four types of unmanned swarms with command and control, investigation, firepower and support, which are required to cooperate to complete the combat task, that is, the number of communities, $M = 4$. The community network generation algorithm of inner-community preferential attachment and inter-community preferential attachment is adopted to generate a multi-community unmanned swarm network with a scale of N and a community number of M. The generation process is as follows.

4.1.1 Initialization

Each community is initially composed of $m_0 (m_0 > 1)$ fully connected nodes. A fixed node is randomly selected in each community, and C_M^2 edges are used to connect each community with the other $M-1$ communities to ensure that there is one edge between every two communities.

An initial network of $M = 4$, $m_0 = 3$ is shown in Fig. 3.

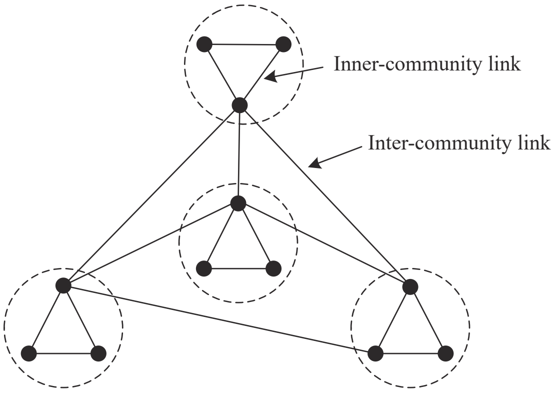


Fig. 3 Initial network of M=4, m_0=3

4.1.2 Increase

In each time step, a new node is added to a random community. The new node is connected to the existing $m(1 \leqslant m \leqslant m_0)$ nodes in the community through m edges; $n(0 \leqslant n < m)$ nodes are connected to other $M-1$ communities through n edges.

4.1.3 Priority connection

The preferential connection occurs at both the internal node and the external node.

(i) Inner-community preferential attachment

When a new node is internally connected with a randomly selected community (such as j), the probability $\prod_{s_{ij}}$ that node i in community j is selected is proportional to its internal degree s_{ij}.

$$\prod_{s_{ij}} = \frac{s_{ij}}{\sum_k s_{kj}} \tag{5}$$

(ii) Inter-community preferential attachment

When a new node has an external connection with node i of the other $k(k \neq j)$ community, the probability $\prod_{l_{ik}}$ that i is selected is proportional to its external degree l_{ik}.

$$\prod_{l_{ik}} = \frac{l_{ik}}{\sum_{i,k\neq j} l_{ik}} \tag{6}$$

The above steps are repeated, and a community network containing M communities, Mm_0+t nodes and $(MC_{m_0}^2+C_M^2)+(m+n)t$ edges is generated after t time steps.

With the Netlogo simulation platform, the final generated network is shown in Fig. 4.

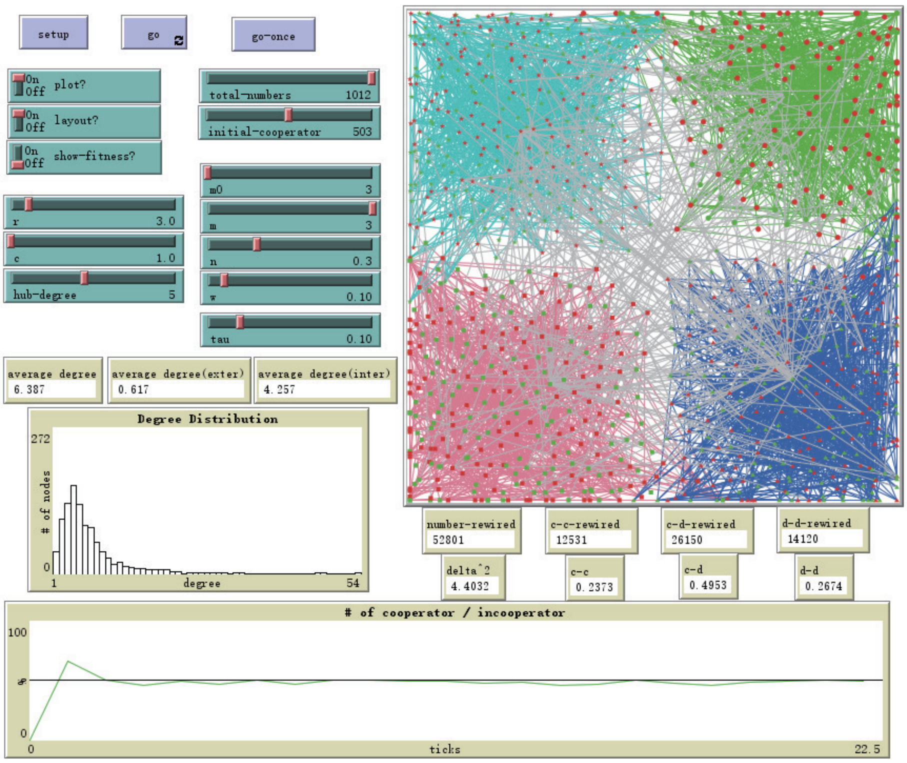


Fig. 4 Simulation interface and generated final network

The upper left panel of the figure shows the initial parameter settings of the network generation, such as the total number, the initial number of nodes m_0 in each community, the new connections m in each time step, and edge adjustment frequency τ. The upper right panel shows the network connection and node classification. The round point is the command-and-control node, the square point is the investigation node, the triangle point is the fire node, and the star point is the support node. In addition, there are current network parameters, such as the number of reconnections of various types of edges (number-rewired, c-c-rewired, c-d-rewired, d-d-rewired) and the current proportion of various types of edges in the network (c-c, c-d, d-d). The lower left panel shows the degree distribution of the network, including average degree, internal degree and external degree. The network presents typical scale-free characteristics. The lower panel of the figure shows the overall cooperation level of the swarm after the network is generated based on topology dynamics and evolves with strategy dynamics.

4.2 Network characteristics analysis

Close to the actual combat network, we hope the network model constructed in Subsection 4.1 has scale-free characteristics, as well as community characteristics. Therefore, in this part, we will verify whether the above model have these characteristics through mathematical inference.

Let s_{ij} be continuous. According to the mean field theory [55], $\prod_{s_{ij}} = s_{ij} \Big/ \sum_k s_{kj}$ can be approximately expressed as the continuous rate of change of s_{ij}. Therefore, for node i in community j,

$$\frac{\partial_{s_{ij}}}{\partial_t} = A\frac{s_{ij}}{\sum_k s_{kj}}. \tag{7}$$

For community j, $\Delta s_j = m/M$ and $s_{ij} = \sum_k s_{kj} = 2mt\frac{1}{M} + m_0(m_0-1)$. Therefore,

$$\frac{\partial_{s_{ij}}}{\partial_t} = \frac{m}{M}\frac{s_{ij}}{\sum_k s_{kj}}. \tag{8}$$

For larger time t, since $\sum_k s_{kj} = 2mt\frac{1}{M} + m_0(m_0-1) \approx 2mt\frac{1}{M}$, therefore,

$$\frac{\partial_{s_{ij}}}{\partial_t} \approx \frac{s_{ij}}{2t} \Rightarrow \frac{\partial_{s_{ij}}}{s_{ij}} \approx \frac{\partial_t}{2t},$$

that is,

$$s_{ij}(t) \approx c(t)^{0.5}. \tag{9}$$

In one time step (interval) t_i, the new node i is added to the swarm j, thus satisfying the initial condition of $s_{ij}(t_i) = m$. We substitute $s_{ij}(t_i) = m$ into the above equation:

$$s_{ij}(t) \approx m\left(\frac{t}{t_i}\right)^{0.5}. \tag{10}$$

Then, the probability that the node degree is less than k is

$$P(s_{ij}(t) < k) = P\left(t_i > \frac{m^2 t}{k^2}\right). \tag{11}$$

Assuming that all nodes (including the initial nodes) are added to the network at the same time step (interval), then the time step t_i is a random variable subject to uniform distribution. The probability density is

$$P_i(t_i) = \frac{1}{Mm_0 + t}. \tag{12}$$

If (12) is brought into (11), then

$$P\left(t_i > \frac{m^2 t}{k^2}\right) = 1 - P\left(t_i \leqslant \frac{m^2 t}{k^2}\right) = 1 - \frac{m^2 t}{k^2(Mm_0 + t)}. \tag{13}$$

After deriving (13), the probability density $P(k)$ is obtained as

$$P(k) = \frac{\partial P(s_{ij}(t) < k)}{\partial k} = \frac{2m^2 t}{Mm_0 + t}k^{-3}. \tag{14}$$

$P(k)$ obeys the power-law distribution of $\gamma = 3$, $P(k) \sim k^{-\gamma}$.

Similarly, for the degree of the externality distribution of nodes, the following conditions are satisfied:

$$\frac{\partial_{l_{ik}}}{\partial_t} = \frac{M-1}{M}n\frac{l_{ik}}{\sum_{m,n,n\neq j} l_{mn}} \tag{15}$$

where

$$\sum_{m,n,n\neq j} l_{mn} = 2\frac{M-1}{M}nt + [M(M-1)-(M-1)],$$

and the solution of the above equation can be approximated as

$$l_{ik}(t) = n\left(\frac{t+\beta}{t_j+\beta}\right)^{0.5} \tag{16}$$

where

$$\beta = \frac{[M(M-1)-(M-1)]M}{2n(M-1)},$$

when t is large, $2\dfrac{M-1}{M}nt \gg [M(M-1)-(M-1)]$ holds, so $\partial_{l_{ik}}/\partial_t \approx l_{ik}/2t$, that is,

$$l_{ik}(t) \approx n\left(\frac{t}{t_j}\right)^{0.5}. \tag{17}$$

Therefore, the degree distribution of the external connection can be expressed as

$$P(k) = \frac{2n^2 t}{Mm_0+t}k^{-3}. \tag{18}$$

$P(k)$ obeys the power-law distribution of $\gamma = 3$, $P(k) \sim k^{-\gamma}$.

Combined with the above conclusions, the degree of node i in community j is

$$k_{ij}(t) = s_{ij}(t)+l_{ij}(t) \approx (m+n)\left(\frac{t}{t_i}\right)^{0.5}. \tag{19}$$

Then, the degree distribution of the community network is

$$P(k) = \frac{2(m+n)^2 t}{Mm_0+t}k^{-3}. \tag{20}$$

The whole community network also follows the power-law distribution of $\gamma = 3$.

In addition, since $n < m$, it can be seen from (10) and (17) that the external degree of the node is always smaller than the internal degree. Therefore, the characteristics of ‘internal tight coupling and external loose connection’ of community networks are also confirmed.

5. Mechanism characteristic analysis

Based on the topology dynamics and strategy dynamics process in Section 3 and the community network construction algorithm in Section 4, this section analyzes the characteristics of the topology adaptive dynamic reconfiguration mechanism from three aspects. First, we compare and analyze the cluster cooperation level generated by the classical pure strategy dynamic process and the dynamic reconfiguration mechanism proposed in this study. Then, we simulate and analyze the relationship between the cooperation level and cost c and benefit coefficient r under a dynamic reconfiguration mechanism. Third, the change law of the cluster cooperation level under the coherent effect of cost, benefit coefficient and adjustment rate is simulated and analyzed.

5.1 Coevolutionary process of group strategy dynamics and topological dynamics

The literature on pure strategy dynamics process can be divided into two categories: one is to model the space of strategy games as a well-mixed one (which can be considered as a fully-connected network) [22,56,57]; the other is static network (strategic dynamic process occurs on a network that is always constant), such as lattices, ring, ER random graphs, small world networks, and scale-free networks. Nowak of Harvard University has done a lot of pioneering work in this field [3−5,7,8,11,12,16], and introduced the concept of spatial dimensions into evolutionary games, opening a precedent in the study of spatial evolutionary games.

To investigate the effect of the topology adaptive dynamic reconfiguration mechanism on the level of swarm cooperation, a group of comparative experiments are conducted. The swarm cooperation level under the pure strategy dynamics mechanism (red broken line in Fig. 5) and the swarm cooperation level after adding the topology adaptive dynamic reconfiguration mechanism (blue broken line in Fig. 5) are simulated and compared. Parameter values are set as follows: Swarm scale N= 1 012, benefit coefficient $r = 1.2$, cost $c_o = 1.0$, selection intensity $\omega = 0.1$, and adjustment rate $\tau = 0.1$. $f_c(k)$ is used to characterize the collaboration level of the swarm. The simulation settings are as follows: Each data point is run 100 times (10 network topology implementations correspond to 10 initial policy distributions) and then averaged. For each operation, the cooperators and defectors are randomly distributed in equal proportion on the network, and after 10 000 steps of evolution, the results of 2 000 steps are averaged. Unless otherwise specified, the subsequent simulation settings are the same.

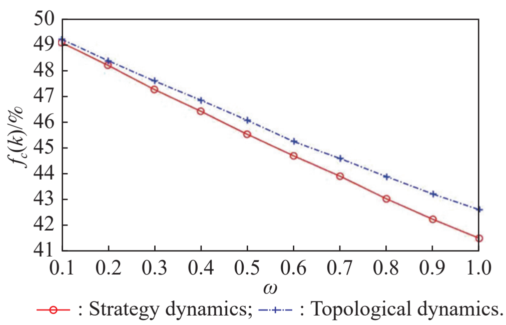
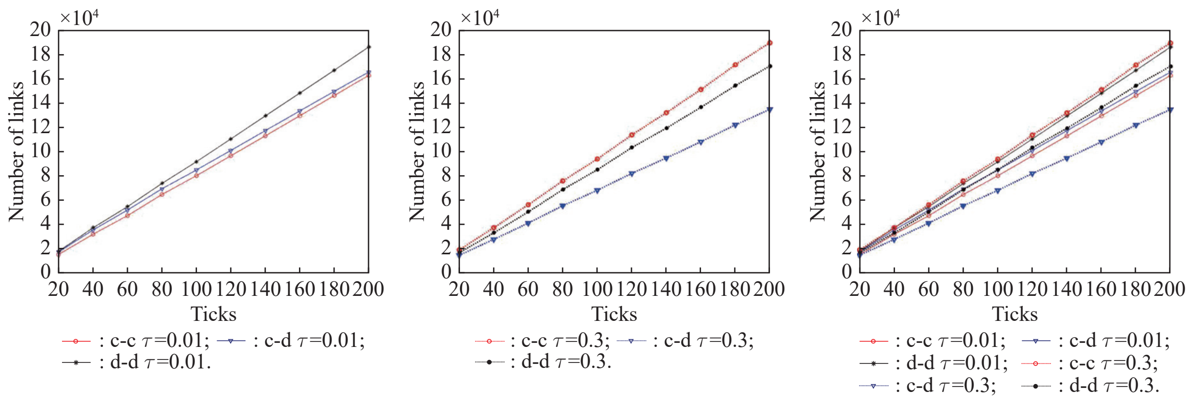


Fig. 5 Comparison of the swarm cooperation level between strategy dynamics and topological dynamics

It can be seen in Fig. 5 that the cooperation level of the cluster is maintained below 50%, that is, $f_c(k) < 0.5$, and this equilibrium is a noncooperative dominant equilibrium. Comparing the two broken lines, it is not difficult to find that when topological dynamics are added, individuals can adaptively adjust the interaction relationship according to the strategy of the interaction object, which greatly improves the level of cooperation. Especially with the increase of selection intensity ω, topological dynamics can promote swarm cooperation more obviously than single strategy dynamics (If $\Delta f_c(k)$ represents the difference between the two in the level of cooperation, then $\Delta f_c(k)|_{\omega=0.9} = 0.01 > \Delta f_c(k)|_{\omega=0.1} = 0.001$ holds). An adaptive dynamic reconfiguration mechanism can resist the inhibition of cooperation by the increase of selection intensity, and the collaborators will be more competitive in the process of swarm evolution.

Furthermore, in the coevolution process of group strategy dynamics and topological dynamics (adaptive dynamic reconfiguration mechanism), the evolution trend of the connection number n of different types of edges with time is investigated. The statistical results are shown in Fig. 6.



(a) τ=0.1 (b) τ=0.3 (c) τ=0.01, τ=0.3

Fig. 6 Evolution of the number of different types of edges

Fig. 6 shows that with the evolution of time, the number of all types of connected edges in the network shows an upward trend, including the concerned edges, c-c, indicating that the edges connected with the partners will be more stable.

In Fig. 6(a), when the adjustment frequency τ of the edge connection probability is low（$\tau = 0.01$）, the size of edge d-d in the swarm will be dominant, while the size of edge c-c is at the lowest level of the three types of edge connections. However, when τ is increased (τ is increased from 0.01 to 0.3), the number of c-c edges in the swarm will overwhelm the number of d-d edges and c-d edges to occupy an advantage (as shown in Fig. 6(b)). However, we make a horizontal comparison of the number of various connected edges under different τ and find that the direct impact of the τ increase is the increase in the number of c-c edges and the decrease in the number of d-d edges and c-d edges. If the number of links is represented by nol, then $\text{nol}_{\text{cc}}|_{\tau=0.3} > \text{nol}_{\text{cc}}|_{\tau=0.01}$, $\text{nol}_{\text{cd}}|_{\tau=0.3} < \text{nol}_{\text{cd}}|_{\tau=0.01}$, and $\text{nol}_{\text{dd}}|_{\tau=0.3} < \text{nol}_{\text{dd}}|_{\tau=0.01}$ hold simultaneously (as shown in Fig. 6(c)). Therefore, as the core parameter of the topology adaptive dynamic reconfiguration mechanism, the adjustment frequency τ can greatly enhance the interaction between collaborators.

5.2 Relationship between the cooperation level and the cost and benefit coefficient

It is of great practical significance to investigate the impact of operational costs c (such as communications, intelligence, and firepower) and benefit effectiveness on swarm cooperation. In real operations, it seeks to exchange the lowest cost input for the optimal swarm cooperation effect and ultimately achieve the maximum operational efficiency. In contrast, if the cost is too high, even if the combat goal is finally achieved, the gain will outweigh the loss. Benefit coefficient r determines the appreciation rate of individual resources. The appreciation of resources comes from the improvement of the "1 + 1 > 2" capability brought about by the internal swarm cooperation, which is manifested in the overall operational effectiveness of the swarm's attack and defense beyond a single combat platform. Too small a benefit coefficient cannot promote the transformation of unmanned platforms to a cooperative strategy, and too large a benefit coefficient has no practical significance. It is of great importance to study the influence of the benefit coefficient on the level of swarm cooperation to reasonably set the size of the benefit coefficient and improve the overall level of swarm cooperation.

The value range of c is generally set as $c \in [1.0,\ 3.0]$. $c = 1$ represents the total amount of basic combat resources; if $c > 3$, from a practical point of view, the cost of input resources is too high and has lost its operational significance. Here, let $c \in [1.0,\ 5.0]$, which not only covers the general value space but also considers the unexpected situation. In addition, as the core parameter of topology dynamics, the degree of hub nodes will have a direct impact on the level of swarm cooperation. Therefore, this section takes the cost and benefit coefficients as independent variables to investigate their impact on the level of swarm cooperation under different hub degrees.

Fig. 7(a) shows the change curve of cooperation level $f_C(k)$ with the cost under different adjustment rates. Let $r \in [1,\ 10]$, hub−degree $\in [2,\ 10]$, $\tau = 0.1$, and $c = 1$. Fig. 7(b) shows the change curve of cooperation level $f_C(k)$ with the benefit coefficient under different adjustment rates.

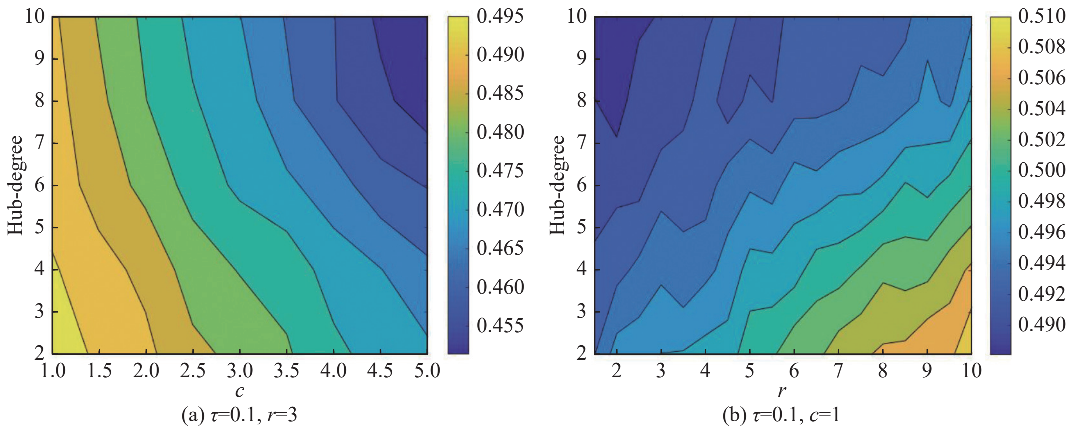


Fig. 7 Relationship between the cooperation level and the cost and benefit coefficient

The results show that the level of cooperation is negatively related to the cost, that is, an increase in cost will reduce the level of cooperation. With the increase of benefit coefficient r, $f_C(k)$ shows a single increasing trend. This indicates that due to the increase of benefit coefficient, a large number of cooperation phenomena appear in the swarm, and the ‘free riding’ behavior is suppressed. The above conclusions are consistent with our previous conclusions in hybrid homogeneous networks and static community networks [36,38]. In addition, the larger the hub−degree, the lower the level of swarm cooperation, while the smaller the hub−degree, the higher the level of swarm cooperation.

In the actual control, we should try our best to improve the benefit coefficient of the unmanned combat swarm. For example, with the help of management, for each combat unit of the cluster, the ‘investment’ cost (such as the total amount of bombs) of its previous combat operations can be accumulated. In subsequent combat operations, the higher the investment cost, the more materials and ammunition will be supplied or the higher the priority of materials and ammunition supply. The cost of a single operation should be reduced and maintained as much as possible. For example, we can improve the reliability and survivability of the combat platform and we improve the strike accuracy and damage power of the unit ammunition with the help of advanced technical means. In addition, since the hub node often acts as the key node of the swarm command, the control center and the communication center and is also the initiator of topology adaptive reconstruction, an excessively small hub−degree will lose its practical significance, and an excessively large hub−degree will inhibit cooperation. Therefore, when designing the topology adaptive dynamic reconfiguration mechanism, the selection of hub−degree should be comprehensively considered in combination with the actual background to ensure the effective emergence of swarm cooperation behavior.

5.3 Coherent effects of cost, benefit coefficient and adjustment rate on the level of cooperation

In reality, it is too idealistic to regulate the overall behavior of the cluster by adjusting a single parameter. In more cases, it is necessary to comprehensively regulate multiple parameters. In this section, we comprehensively consider the coherent effects of three key parameters, benefit coefficient r, cost c_o, and adjustment rate τ, on the level of cooperation. Fig. 8 depicts the dependence of the cooperation level on the parameters c_o, r, and τ in the public goods game when the system is in the equilibrium state. Fig. 8(a)−Fig. 8(d) correspond to the results with τ values of 0.01, 0.05, 0.1 and 0.3, respectively.

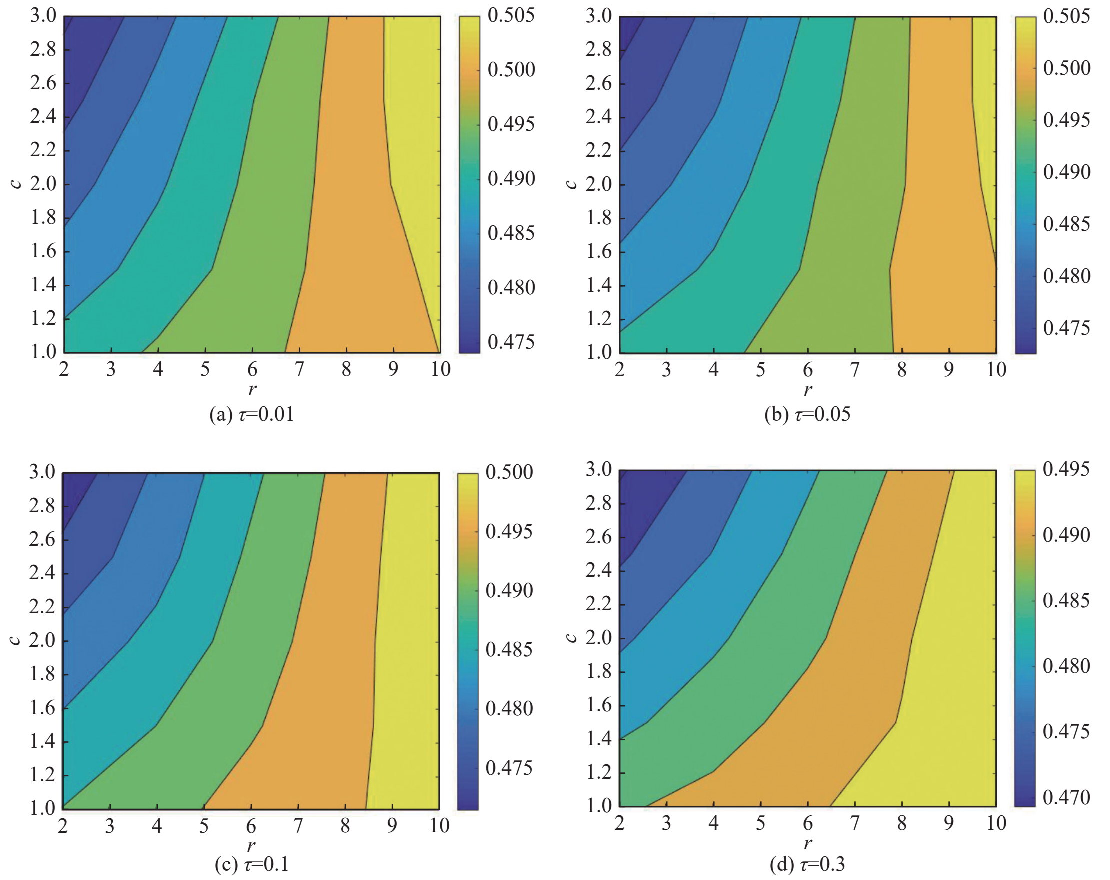


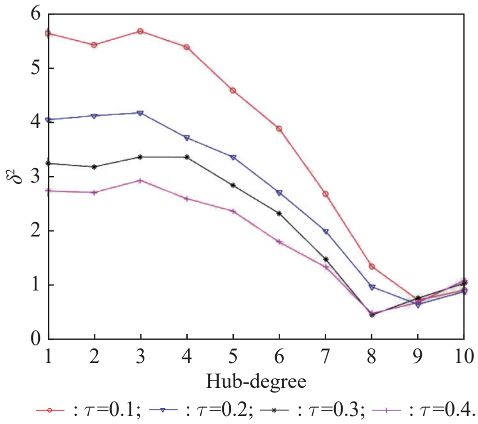
Fig. 8 Coherent effects of cost, benefit coefficient and adjustment rate on the level of cooperation

As shown in Fig. 8, regardless of the τ value, the cooperation level of swarm evolution equilibrium will decrease with the increase of c_o/r. Moreover, the coupling evolution between strategy and network structure does pave the way for the propagation of collaborative behavior in the space public goods game. Moreover, a larger adjustment rate τ often corresponds to a larger threshold c_o/r(once these thresholds are exceeded, collaborative behavior will disappear). It is shown that the promotion effect of the adaptive dynamic reconfiguration mechanism on cooperation will monotonically increase with an increasing τ. The cluster more easily maintains a high level of cooperation over a wide range of r and c_o; that is, the faster the adjustment of the topology is, the more successful the cooperation will evolve.

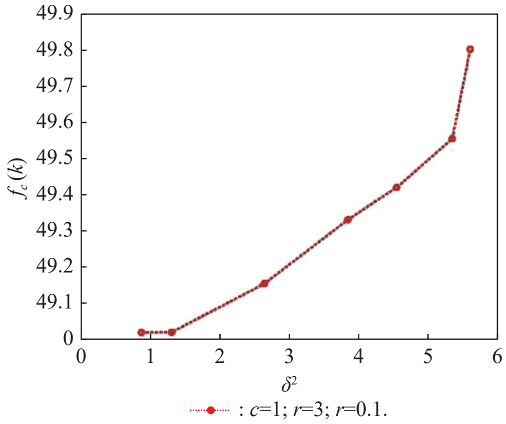
In addition to examining the impact of key parameters on the level of cluster cooperation, such as c_o, r, τ and hub-degree, another interesting issue is the way that the network topology evolves with time under the topology adaptive dynamic reconfiguration mechanism. Generally, the variance of the normalized degree distribution given by (21) is used to quantify the structural change of the network.

$$\delta^2 = \frac{\bar{k}_i^2 - \bar{k}_i^2}{\bar{k}_i} \tag{21}$$

where k_i is the degree of i. With $\tau = 0.1, 0.2, 0.3, 0.4$, the network degree distribution variance corresponding to different hub-degree values is plotted, as shown in Fig. 9(a).



(a) δ^2-hub-degree



(b) $f_c(k)$-δ^2

Fig. 9 Normalized degree distribution variance of swarm networks

Fig. 9(a) shows that for a large range hub-degree, the degree distribution of the network is substantially different from that of the static network (Poisson distribution, $\delta^2 \approx 1.087$); that is, the topological structure of the cluster shows heterogeneity under the effect of topological dynamics. The heterogeneity represented by δ^2 shown in Fig. 9(b) can considerably promote cooperation. In fact, this conclusion has also been proven in the [18,19]. In addition, Fig. 9(a) also shows that the larger the adjustment rate τ is, the smaller δ^2 is. However, we confirm that 'the promotion effect of the adaptive dynamic reconfiguration mechanism on cooperation is monotonously enhanced with the increase of τ' in Fig. 8. The two conclusions contradict each other; that is, it is impossible to directly form a logically consistent chain with the parameters τ, δ^2, and $f_c(k)$.

Furthermore, it can be seen from (1) that the increase of τ makes the network connection between collaborators tighter and the connection with defectors looser, which directly promotes the improvement of the level of swarm cooperation. At the same time, τ can also indirectly affect the level of swarm cooperation by affecting δ^2; the larger τ is, the smaller δ^2 is. The above two forces compete with each other on the parameter of "swarm cooperation level", but the overall performance shows that τ promotes the cluster cooperation level.

In this part, we embed the topological dynamics process into the classical strategy dynamics process and simulate the influence of relevant parameters on the cooperation evolution under the dynamic reconfiguration mechanism. Under this mechanism, individuals adjust the interaction relationship in a softer, adaptive and more realistic way. The results show that the topology adaptive dynamic reconfiguration mechanism can considerably promote the generation of swarm cooperation behavior, and the level of swarm cooperation is closely related to cost, benefit coefficient, and adjustment rate. The lower the cost and benefit coefficient, the smaller the degree of the hub node, and the faster the adjustment rate, the more successful the cooperation will evolve in the swarms.

6. Conclusions

Autonomous cooperation of unmanned swarms is the research focus on 'new combat forces' and 'disruptive technologies' in the military fields. A key issue in autonomous collaboration is designing a reasonable mechanism to improve the cooperation level of the operational swarms to ensure the overall operational efficiency of the swarms. This paper designs an adaptive dynamic reconstruction mechanism of unmanned swarm topology based on an evolutionary game to meet the real needs of dynamic adjustment of swarm networks under highly dynamic and strong confrontation scenarios and simulates and analyzes the impact of the cost, benefit coefficient and adjustment rate on the level of swarm autonomous collaboration under this mechanism. This paper creatively introduces evolutionary game theory and complex network theory into the collaborative mechanism design of unmanned swarms. The framework, mechanism and method provide a new perspective and technical approach for solving the network topology reconstruction problem in unmanned swarm operations.

Some parameters in this paper are set by subjective research and judgment of experts in the field and are all simulation data. In fact, the values of parameters such as network degree k in the 'adjustment initiator rule' and network hop d in the 'connection reconfiguration rule' are very important for operational decision-making. Reasonably determining the value range for specific combat tasks and battlefield situations will directly determine the benefits of evolutionary games and the level of swarm cooperation. In addition, this research just focuses on the binary strategy of this research just focuses on the binary strategy of collaboration and defection, and the diversity of strategies is also the content that we will study in the next step. The difficulty lies in the determination of the strategy set and the calculation of the game pay-off. Next, we propose to implement simulation analysis based on real data, further optimize the model algorithm, and provide methods and means to assist scientific and accurate battlefield decision-making.

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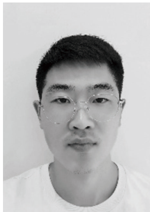

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