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Importance-based Resilience Assessment and Optimization of Unmanned Ship Swarm System

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Abstract
Based on the unmanned ship swarm system, a resilience model for unmanned ship swarms is proposed by comprehensively considering the preventive indicators, robustness indicators, recoverability indicators, and reconfigurability indicators of the swarm system. Firstly, preventive and robust indicators are proposed based on the characteristics of the unmanned ship swarm system, and the improvement of system performance efficiency by redundant unmanned ships is established as a recoverability indicator. Then, reconfigurable indicators are proposed based on importance, and the resilience indicator of the unmanned ship swarm is determined. Finally, a numerical example is used to model and simulate the performance change and capricious process of the unmanned ship swarm. Most of the research on the resilience assessment model of unmanned ship swarms considered too single indicators. The model of the unmanned ship swarm under attack is constructed, and the superiority of the resilience optimization strategy proposed in this paper is verified.

Keywords- Reliability, Resilience, Maintenance, Unmanned ship.

1. Introduction
The development of unmanned ship systems has made outstanding progress in today's international battlefield, and with the development of unmanned ships, the reliability of unmanned ships on the battlefield has gained corresponding attention. In the actual battlefield, unmanned ships usually appear in the form of swarms, which have certain synergies between them. In the review, the terms "unmanned ship" and "unmanned swarm" are considered to be similar (Zaitseva et al., 2023), and unmanned swarms and unmanned ship swarms are considered to be similar when considering two-dimensional real-world battlefields. Most of the studies are also similar in considering the two-dimensional realities of the battlefield. Therefore, mission reliability analysis and formation reliability analysis of unmanned ship swarms and unmanned aircraft swarms are extremely common, and there are also studies that use swarm missions to model system missions with phases, and give the corresponding calculation methods of mission reliability (Feng et al., 2022). The UAV swarm mission reliability model for the k-out-of-n: F system is also an important analytical model for unmanned equipment systems, which includes the performance of UAVs in different coordinates and UAV swarms with different reliabilities, as well as the optimization of

the UAV swarm structure under the considerations of conditional reliability, conditional failure rate, and remaining service life (Dui et al., 2021). Dui et al. (2023a) developed a reliability assessment model based on machine learning. In addition, unmanned ship systems can also be modeled for reliability in terms of the spread of software viruses and the reduction of economic losses (Tao et al., 2022).

Individual unmanned ship systems have certain communication, navigation, and strike capabilities. In a single unmanned ship, a polar representation of reliability and redundancy can be obtained by varying the degree of blow to the ship's reliability through different sea states, ship speeds, and course directions (Decò et al., 2012). In Bayesian inference, BahooToroody et al. (2022) used Markov chain Monte Carlo simulations to quantify the uncertainty associated with ship operation from a likelihood function. Individual reliability under consideration of various failures is the basis for group system reliability and one of the conditions for subsequent consideration of group system resilience and changes in reliability (Yang et al., 2023). In a single unmanned ship, the probabilistic approach allows for the creation of ships with different levels of autonomy to estimate the plausible operating time of the ship system. The unmanned ships system possesses certain two-dimensional topological and recovery characteristics and is also an important method for establishing resilience evaluation by considering the amount, speed, and threshold of resource replenishment, together with the theory of complex networks, flow networks, and multi-intelligent body system simulation (Kong et al., 2024).

Resilience assessment is also an important metric to consider for unmanned ship swarm systems. The mathematical concept of resilience is mostly considered in conjunction with the specific characteristics of the swarm system, and resilience assessment methods also need to take into account resource supplementation, the use of complex networks, flow networks, and multi-intelligent body systems (Kong et al., 2024). The unmanned ship system resilience assessment is a more comprehensive and effective assessment of the ability of the unmanned ship to withstand an attack, following the reliability and robustness analyses. Li et al. (2023) proposed a dynamic resilience assessment framework for UAV swarms considering battlefield surveillance missions. Considering the resilience of unmanned ship ships leads to maintenance and optimization, which requires the involvement of redundant unmanned ships (Eriksen et al., 2021). A local path optimization method for unmanned ships based on particle swarm acceleration calculation and dynamic optimal control is also an important guarantee for unmanned ships to maintain navigation safety at all times (Wang et al., 2021). Some studies have analyzed the resilience of ship systems for cost and loss considerations, including comprehensive recovery metrics for shiploads, ship delays, and recovery costs (Wang et al., 2022). Liu and Bucknall (2016) developed a multi-task training framework for formation control and proposed a confident formation strategy. Abaei et al. (2022) used hierarchical Bayesian inference to analyze the resilience of the system. The static analysis process was perfect, but the analysis of the dynamic process was lacking. Li et al. (2023) proposed a resilience measure that incorporates costs and benefits. Dui et al. (2023b) proposed a performance improvement strategy based on Internet of Things technology. Wu et al. (2023) established an online mission planning model for multi-UAV formations. Liu et al. (2024) considered multi-state networks with conditional probabilities and modeled the information exchange of the system. However, there is a lack of some improvement strategy analysis.

An unmanned ship swarm is a swarm system that consists of multiple unmanned ships arranged in a particular way. In a swarm system, each unmanned ship has the ability to fulfill certain tasks, including communication, reconnaissance striking, etc. However, due to different arrangements and types of unmanned ships, the failure of different unmanned ships in the same system may cause different strikes to the system. There is also a certain degree of synergy between the individual unmanned ships, as they can communicate with each other and share reconnaissance ranges, so the unmanned ship swarm system has a certain degree of stability. Most of the studies on the resilience assessment model of unmanned ship swarms consider a single indicator, but we consider more comprehensive factors.

Some comparisons of the related papers are summarized following. Based on the evaluation of unmanned fleet system research methods and system index evaluation methods made by different papers, this paper deeply draws on the advanced aspects and reflects on the shortcomings of the current research on unmanned fleet system. Meanwhile, on the basis of the previous researchers, this paper establishes a more realistic index evaluation system to make reference to the reliability and resilience analysis of unmanned ship swarm under real missions. The relevant comparisons, as well as the objectives and scope of the research studied in this paper, are as follows:

(i) The above-mentioned papers provide certain theoretical significance or value for this paper. However, in the actual combat environment, the toughness change of unmanned ship swarm is dynamic and will decrease step by step with the degree of strikes, so we consider the toughness change process of unmanned fleet under multiple steps and the corresponding improvement strategies. There are also few papers apply the index resilience analysis and reconstruction strategy to the background of unmanned ship swarm, and few papers conduct detailed research on formation reconstruction in the actual operation of unmanned ship swarm. Although the above papers are insightful in analyzing the toughness index of unmanned ships swarm, they lack the analysis of the dynamic process and the corresponding response strategies.

(ii) In this paper, we consider an unmanned ship swarm system under a number of metrics: a single unmanned ship has a certain degree of reliability due to its design, which ensures that its ability to complete its mission will not be affected by a certain number of strikes, but when it suffers strikes that are outside of its range, the unmanned ship loses its ability to complete its mission, and it is considered to be removed from the unmanned ship swarm system; when a single unmanned ship fails, it may still have the ability to complete its mission due to the resilience of the system itself; when the unmanned ship swarm system loses its ability to complete its mission, it can rely on a redundant unmanned ship to replace the failing one. When a single unmanned ship in the Unmanned ship systems fails, it may still be able to complete the mission due to the resilience of the system. When the Unmanned ship system loses the ability to complete the mission, redundant unmanned ships can be relied upon to replace the failed unmanned ship to assist the system in continuing to complete the required mission. When the Unmanned ship system loses the last redundant unmanned ship, the use of unmanned ship reconfiguration schemes is considered to assist in maximizing the recovery of the performance of the Unmanned ship system. Since the above-mentioned stages have a certain sequence, we should analyze the indicators of individual unmanned ships in the unmanned ship group system one by one, adopt the appropriate reliability indicators, and consider the unmanned ship group system comprehensively to get the unmanned ship group system performance and toughness analysis which is more suitable for the actual combat status.

The rest of the paper is organized as follows. Section 2 analyzes the topology, performance metrics, and toughness modeling of unmanned ship systems. Section 3 presents the toughness analysis of unmanned ship systems and the toughness optimization strategy. Section 4 validates the effectiveness of the strategy proposed in this paper by means of relevant case studies and comparisons with conventional toughness optimization schemes. Section 5 concludes the full paper and the subsequent outlook.

2. Unmanned Ship Swarm System

In the process of unmanned vessel confrontation, joint operations of drones are often required. Due to the small size and covert nature of drones, they can carry out reconnaissance missions and transmit enemy information to unmanned vessel clusters for selective strikes.

In this paper, we first introduce the unmanned ship swarm model, and then we provide corresponding performance indicators.

If each unmanned ship in the unmanned ship swarm system is considered a node, assuming that the communication links between unmanned ships are bidirectional, undirected graphs can be used to describe the unmanned ship formation in the system. The mapping relationship between unmanned ship formation and the undirected graph is shown in Figure 1.

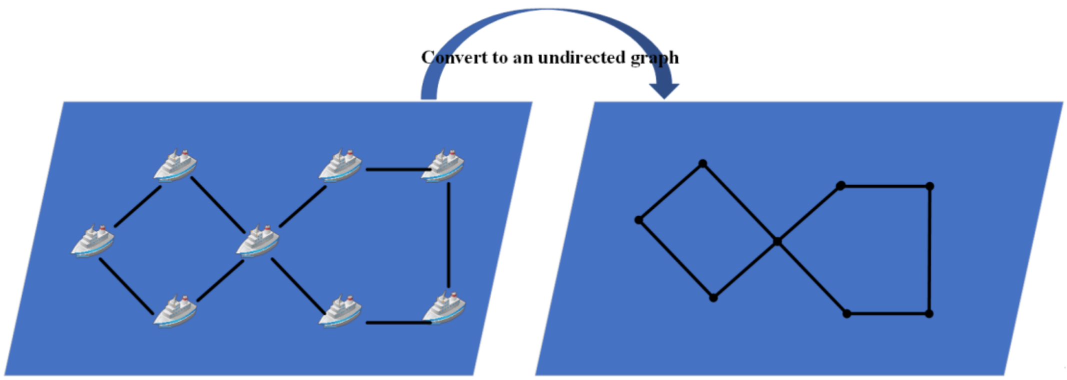

Figure 1. Unmanned ships.

Based on the enemy equipment network detected by drones, determine the nodes of the enemy equipment network, and prioritize attacking the enemy key nodes. On the contrary, the enemy can also focus on the nodes of our unmanned vessel swarm and prioritize attacking our key nodes. Use an example to illustrate the explanation of critical and non-critical nodes, as shown in Figure 2.

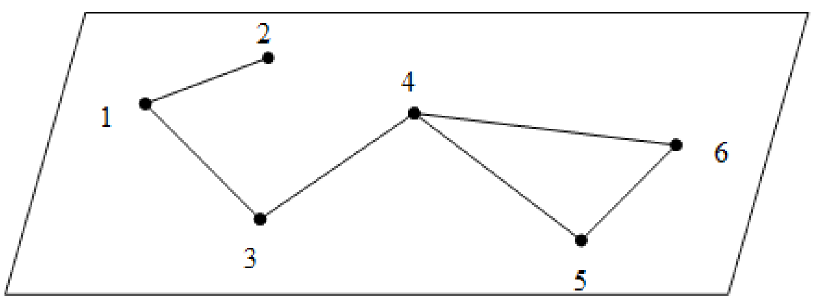

Figure 2. Description of critical versus non-critical nodes.

In Figure 2, when the fault of Node 1 causes Node 2 to detach from the entire topology, Node 3 causes Node 1 and Node 2 to detach from the entire topology, and Node 4 causes Node 5 and Node 6 to desulfurization the entire topology. At this point, Node 1, Node 3, and Node 4 are key nodes. The failures of nodes 2, 5, and 6 do not cause other nodes to detach from the entire topology, making them non-critical nodes.

The failure process of the unmanned ship swarm network is the superposition of the failure process of all network nodes. In addition, the network presents different utilities due to the combined influence of each node state. Therefore, this paper first considers the use of network performance to quantitatively represent the loss of network performance caused by node failure. This document uses $a_0 \leq a_1 \leq \cdots \leq a_M$ to indicate the level of network performance, perfect function, and failure (denoted by 1 and 0, respectively) corresponding to the state space of the system $\{0,1,2,\ldots,M\}$. Suppose that all nodes of the Unmanned Ship swarm network have two states: perfect function and failure (represented by 1 and 0, respectively). The state of a node is represented as $X_i(t)$, the network state represents the combination of the state of all network nodes, and the state of the network is represented by $S\big(X(t)\big)$, which is the state space of all network nodes. By default, when the network is in state 0 (complete failure), $a_0 = 0$. Therefore, the performance of a system can be measured by system utility expectations for different system states, expressed as,

$$P\big(X(t)\big) = \sum_{j=0}^{M} a_w Pr\big[S\big(X(t)\big) = w\big] = \sum_{w=0}^{M} a_w Pr\big[S\big(X_1(t), X_2(t), \ldots, X_n(t)\big) = w\big] \tag{1}$$

where, a_w represents the network performance level when the network status is w.

3. Resilience Assessment and Optimization Based on the Importance

According to Fei Aiguo's research, the process of system resilience is shown in Figure 3. System resilience indicators can be divided into preventive indicators, robustness indicators, recoverability indicators, and reconfigurability indicators. Preventability indicates the probability that the system can autonomously prevent faults from occurring. Robustness indicates the ability of the system to still perform tasks when faults occur. Recoverability indicates the degree or speed at which performance can be restored in the event of a system failure. Reconfigurability indicates the system's ability to restructure its structure in response to faults. Therefore, the overall resilience index of the system can be expressed as,

$$I = I_1 + (1 - I_1)I_2 + (1 - I_1)(1 - I_2)I_3 + (1 - I_1)(1 - I_2)(1 - I_3)I_4 \tag{2}$$

Among them, I refers to the overall resilience index of the system, I_1 refers to preventive index, which is the probability of self-preventive faults occurring $(0 < I_1 < 1)$, I_2 refers to robustness index, which is the probability that the unmanned ship swarm will complete the task when attacked $(0 < I_2 < 1)$, I_3 refers to recoverability index, which is the probability of a swarm completing tasks by increasing redundancy after the unmanned ship loses combat capability $(0 < I_3 < 1)$, I_4 refers to reconfigurability index, which is the probability of ensuring task completion through structural reconstruction when there are no redundant unmanned ships in the unmanned ship swarm system $(0 < I_4 < 1)$.

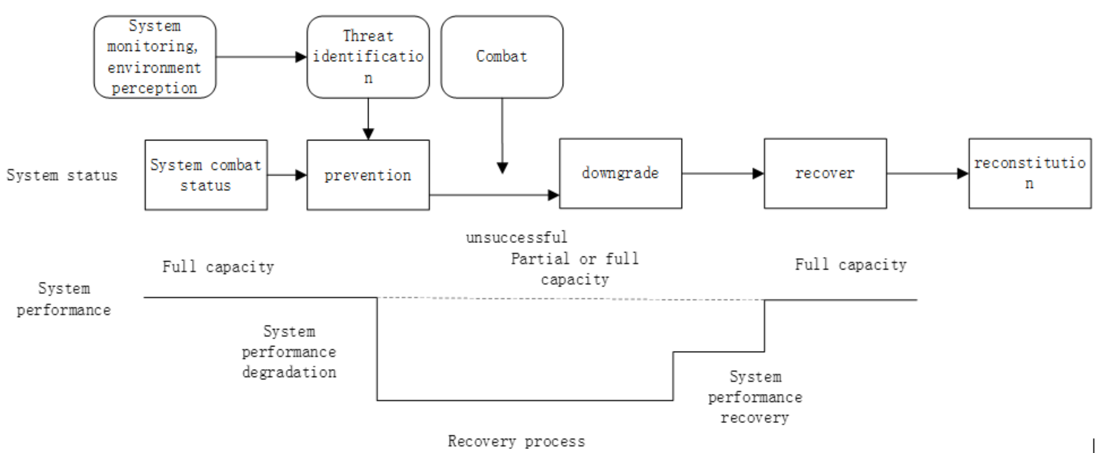

Figure 3. System resilience process.

When encountering certain threats, such as poor weather or weak communication signals, it may lead to swarm system failures. During the design of the system, comprehensive consideration was given to factors that may lead to its own faults and preventive maintenance was carried out on the unmanned ship swarm before performing tasks to improve overall performance. Therefore, during the task execution process, the system itself has the probability of independently preventing faults, which is the system's own reliability. System reliability is a function of the reliability of unmanned ships. Before the swarm is hit, the reliability of the unmanned ship swarm system itself is taken as a precautionary indicator of the system, as in Equation (3).

$$I_1(t)=R(t)=f\left(R_1(t), R_2(t), \dots, R_i(t), \dots, R_n(t)\right) \tag{3}$$

When the unmanned ship swarm is hit during mission execution, the swarm itself has a certain degree of robustness and the system will not immediately become paralyzed. At this point, communication reliability indicators can be used as robustness indicators for executing tasks.

Assuming that the communication radius of each unmanned ship is R, when some unmanned ships are hit and their performance status drops below the threshold, and there are no redundant unmanned ships, they need to exit the battlefield. At this point, the range of swarm communication will change and the reliability will decrease. The reliability indicators of communication can be represented by the communication range of unmanned ships, as shown in Figures 4 and 5. Figure 4 shows the communication range of the unmanned ship swarm before the attack, represented by R_{before}, while Figure 5 shows the communication range of the unmanned ship swarm after the upper right unmanned ship was hit and malfunctioned, represented by R_{after}. The robustness index of the unmanned ship swarm can be expressed as,

$$I_2 = \frac{S_{after}}{S_{before}} = \frac{\bigcup_{i=1}^{n} S_i(t)}{\bigcup_{i=1}^{N} S_i(t)} \tag{4}$$

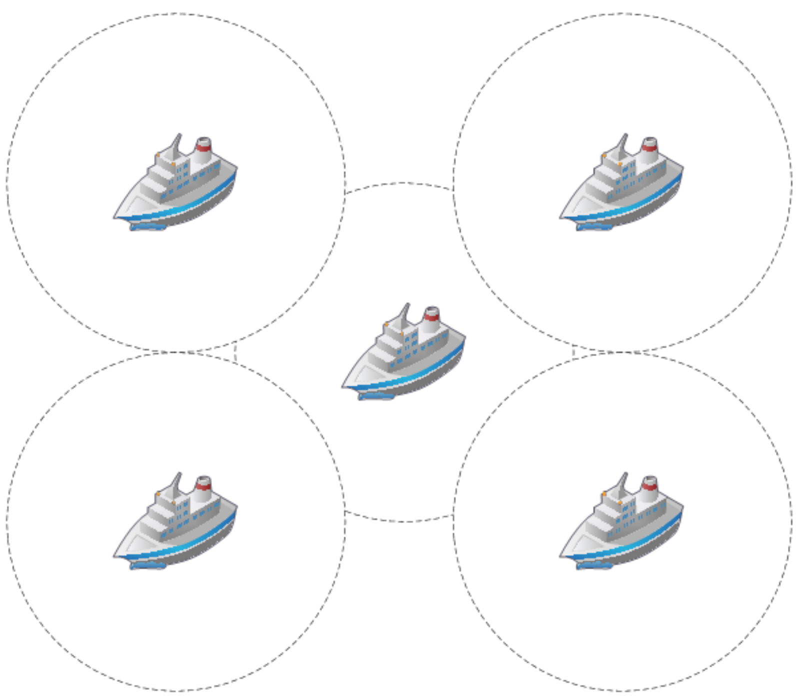

Figure 4. The communication range of the unmanned ship swarm before the strike.

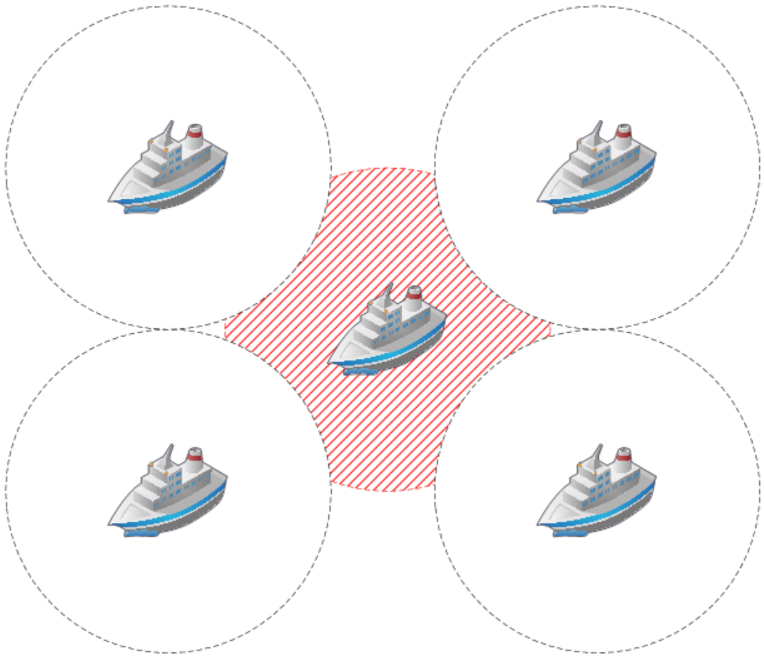

Figure 5. The range of communication of unmanned ships after receiving a strike.

When the unmanned ship is hit, it directly loses its combat capability, in order to avoid its scrapping, it needs to withdraw from the battlefield, there will be redundant unmanned ships in the unmanned ship swarm during the mission, redundant unmanned ships will be outside the enemy's strike range, after the hit unmanned ship withdraws from the battlefield, the redundant unmanned ship replacement continues to complete the task, at this time the distance of the redundant unmanned ship from the faulty unmanned ship i is indicated by d_i, and the speed is indicated by v_0. At this time, the system performance is improved, and the efficiency of adding redundancy to the system to improve the overall performance can be regarded as an indicator of swarm recoverability.

When redundant unmanned ships are used instead of unmanned ships damaged by blows, their performance becomes optimal, and the performance of the entire system is improved, and recoverability indicators can be expressed by the efficiency of the entire system performance improvement. where, $t_i = \frac{d_i}{v}$.

$$I_3 = \frac{P\big(X(t)\big|X_i(t) = 1\big) - P\big(X(t)\big|X_i(t) = 0\big)}{t_i} \quad (5)$$

When there are no redundant unmanned ships in the system, and the unmanned ships are attacked and withdrawn from the battlefield again, network reconstruction is required to improve the overall performance of the system and continue to perform tasks.

When the performance of an unmanned ship drops below the threshold, it needs to be withdrawn from the battlefield, which can be represented on the undirected graph by removing its mapping point, as shown in Figure 6.

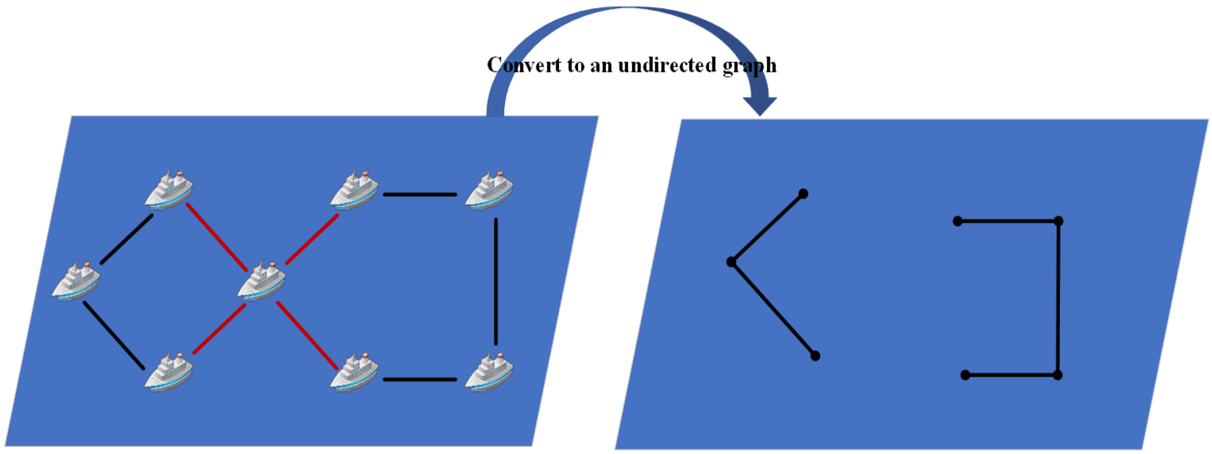

Figure 6. The mapping relationship between the formation and the undirected graph when the unmanned ship swarm fails in the unmanned ship swarm.

When there is no redundant unmanned ship in the unmanned ship swarm system, an unmanned ship in the unmanned ship swarm is hit, a node in the network topology mapped to the swarm is attacked, and the system performance is reduced

$$I_{loss} = \frac{dP_{loss}(t)}{dt} = \frac{dP(S(X(t))=M|X_i(t)=1)-P(S(X(t))=w|X_i(t)=0))}{dt} \tag{6}$$

When the system performance is improved through swarm network reconstruction, the distance between the unmanned ship j moving at this time and the faulty unmanned ship i is denoted by d_{ji}, and the speed is denoted by v_0. In this case, due to the reconstruction of the system network structure, the importance of system performance recovery based on system performance can be obtained:

$$I_{recovery} = \frac{dP_{recovery}(t)}{dt} = \frac{d(P(S(X(t))=u|X_i(t)=1,X_j(t)=0-P(S(X(t))}{dt} \tag{7}$$

Based on the importance of performance recovery, the greater the importance of a node's recovery efficiency, the higher the network performance recovery when moving it to a failed node, which means that these nodes should be given a higher refactoring priority to maximize swarm network performance.

However, from the perspective of the whole system, the study of system resilience needs to consider both system failure and recovery, so it is necessary to consider the performance loss process and performance recovery process of the swarm network, and the reconfigurability index can be obtained as $I_4(t) = \frac{I_{recovery}}{I_{loss}}$.

Based on the above importance analysis, the resilience index of the unmanned ship swarm can be obtained as follows:

$$\begin{aligned} I &= I_1 + (1-I_1)I_2 + (1-I_1)(1-I_2)I_3 + (1-I_1)(1-I_2)(1-I_3)I_4 \\ &= {R_1}^n(t) + \left(1-{R_1}^n(t)\right) \times \frac{\cup_{i=1}^{m} S_i(t)}{\cup_{i=1}^{n} S_i(t)} + \left(1-{R_1}^n(t)\right) \times \left(1-\frac{\cup_{i=1}^{m} S_i(t)}{\cup_{i=1}^{n} S_i(t)}\right) \times \frac{P(X(t)|X_i(t)=1)-P(X(t)|X_i(t)=0}{t_i} + \\ &\quad (1-{R_1}^n(t)) \times \left(1-\frac{\cup_{i=1}^{m} S_i(t)}{\cup_{i=1}^{n} S_i(t)}\right) \times (1-\frac{P(X(t)|X_i(t)=1)-P(X(t)|X_i(t)=0}{t_i}) \times \frac{I_{recovery}}{I_{loss}} \end{aligned} \tag{8}$$

4. Numerical Example

The role of each node in the unmanned ship swarm system has been evaluated from different time perspectives by simulating the system performance. In the strike phase, the vulnerability of the system was analyzed through the performance loss importance metrics and an attempt was made to avoid a large degradation of the system performance. In the recovery phase, the performance recovery importance metrics were analyzed with a view to obtaining a better recovery. Throughout the phase, system toughness metrics were used to measure system toughness and find the nodes where the system is prone to show poorer toughness.

As an example, a swarm formation of unmanned ships in a theatre of operation that is performing a strike mission is shown in Figure 7. The whole formation is arranged in a square shape, and this formation has more significant advantages for searching and striking multiple targets in the target area. This formation can improve the coverage of the search in the mission, quickly find the target, and conduct coordinated strikes. In the swarm network, the line Unmanned Ship swarm formations on adjacent sides have the same node Unmanned ships, and since the node Unmanned Ships affect different Unmanned Ship swarm sequences, their reliability status as shared nodes are extremely important.

It is assumed that the failure time of the nodes of the unmanned ship swarm network obeys the Weibull distribution $W(t,\theta,\gamma)$, the node reliability $R(t) = exp\left[-\left(\frac{t}{\theta}\right)^{\gamma-1}\right]$, the failure rate $\lambda(t) = \frac{\gamma}{\theta}(\frac{t}{\theta})^{\gamma-2}$, and that all the nodes have the same parameters, of which the scale parameter θ is 2758 and the shape parameter γ is 3.86, and it is assumed that each unmanned ship's communication range is a circular area with a radius of =10KM centered on itself. All the states of the network are simplified, assuming that at most two nodes fail at the same time, there are 19 states, and the network states and the corresponding performance parameters are shown in Table 2.

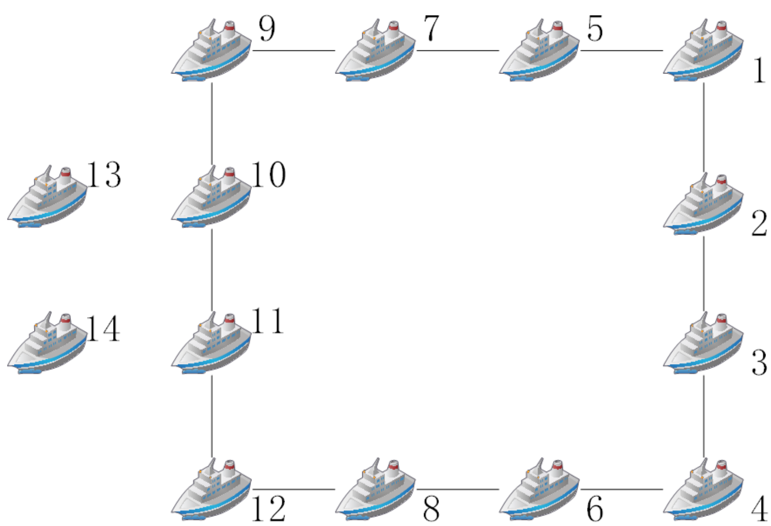

Figure 7. Unmanned ship swarm formations.

There are 14 unmanned ships in the above figure, among which there are 2 redundant unmanned ships, which are 13 and 14 unmanned ships, and the sailing speed v is set to be 20m/s. Taking the unmanned ship 1 as the reference coordinate, the initial relative position of the unmanned ships is shown in Table 1.

Table 1. Initial relative position of the unmanned ships.

Unmanned ship number	Abscissa /km	Ordinate /km	Unmanned ship number	Abscissa /km	Ordinate /km
1	0	0	7	-20	0
2	0	-10	8	-20	-30
3	0	-20	9	-30	0
4	0	-30	10	-30	-10
5	-10	0	11	-30	-20
6	-10	-30	12	-30	-30

Table 2. The status of the network and the corresponding performance parameters.

w	Status of the network	a_w	w	Status of the network	a_w
1	2	0.9	11	2,11	0.6
2	3	0.9	12	2,12	0.55
3	1	0.8	13	1,2	0.6
4	2,3	0.81	14	1,3	0.77
5	2,5	0.75	15	1,4	0.45
6	2,6	0.72	16	1,6	0.57
7	2,7	0.7	17	1,8	0.52
8	2,8	0.65	18	1,12	0.4
9	2,9	0.62	19	Perfect condition	1
10	2,10	0.65			

The network state column indicates the failed nodes at different states, for example, the failed nodes in state 12 are node 2 and node 12, and when all nodes of the network are intact, the network state is 12 and the network performance value is 1.

When there is no redundant unmanned ship in the system, a single node is hit, at which point the system performance decreases, and the magnitude of the impact of a single node on the system performance, i.e., the performance loss importance, can be obtained, as shown in Figure 8.

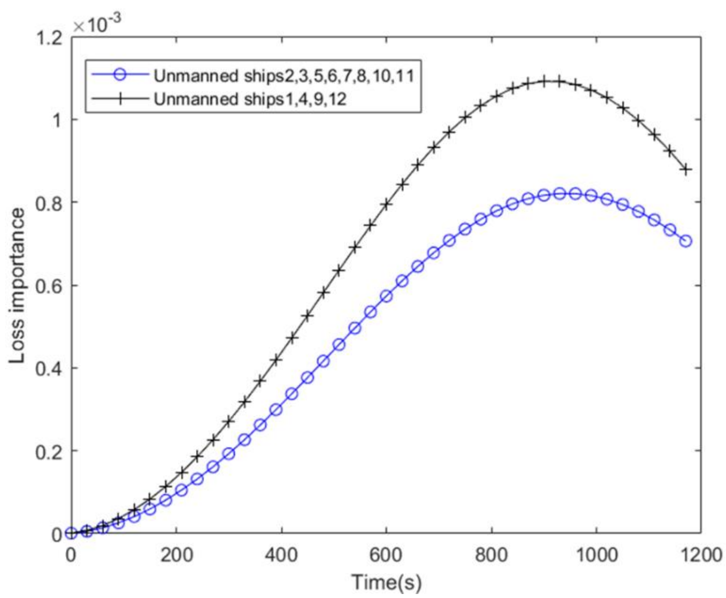

Figure 8. The importance of the performance loss of each unmanned ship.

From Figure 8, it can be seen that the performance loss importance of each unmanned ship shows an increasing and then decreasing trend and the performance loss importance of each unmanned ship reaches the maximum when the strike time t is in the interval (800, 1000), in addition to this, it can also be seen from the figure that the failure of unmanned ships 1,4,9,12 will cause a bigger blow to the performance of the system.

When the node fails, without destroying the original square formation, through the above network reconfiguration strategy can be obtained to recover the recovery importance of each unmanned ship, as shown in Figure 9, as well as the performance change as shown in Figure 10.

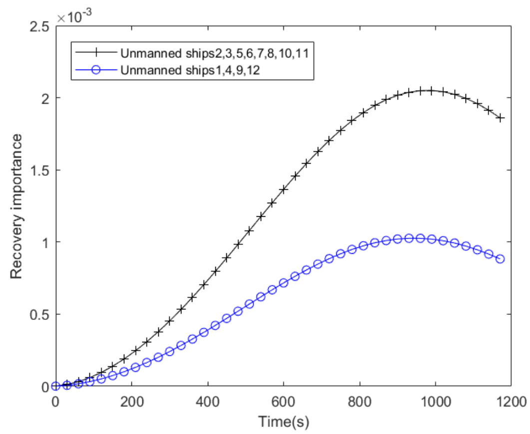

Figure 9. The importance of performance recovery for each unmanned ship.

From Figure 9, it can be seen that the performance recovery importance of each unmanned ship shows an increasing and then decreasing trend, and at time t in the interval (900, 1000), the network reconfiguration of the corresponding nodes of unmanned ships 1,4,9,12 reaches the maximum performance recovery importance, and at time t in the interval (800, 1000), the network reconfiguration of the corresponding nodes of unmanned ships 2,3,5,6,7,8,10,11 reaches the maximum performance recovery importance. corresponding nodes for network reconfiguration, the performance recovery importance will be maximum. In addition to this, it can be seen from the figure that priority sharing of Unmanned Ships 1,4,9,12 will result in a greater increase in system performance.

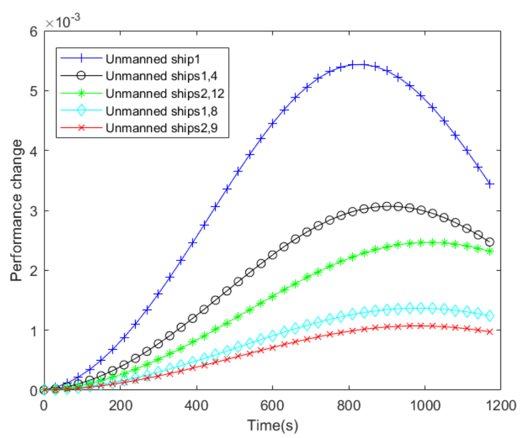

Figure 10. Performance improvement after network reconstruction when a node fails.

As can be seen in Figure 10, when each unmanned ship fails, the change in the performance of performing network reconfiguration first increases and then decreases with time. When Unmanned Ship 1 fails, time t is in the interval (750,850), the performance increase is the largest, and then gradually decreases, and when Unmanned ships 1 and 4 fail at the same time, time t is in the interval (800-1000), the performance increase is the largest, and then gradually decreases. When drones 1 and 8 fail at the same time, time t is in the interval (950-1050), the performance gain is maximum, and then gradually decreases. When drones 2 and 9 fail at the same time, time t is in the interval (900-1000), the performance gain is maximum, and then gradually decreases. When Unmanned ships 2 and 12 fail at the same time, time t is in the interval (900-1000), the performance improvement is maximum, and then gradually decreases.

If unmanned ships 1 and 2 are destroyed, as shown in Figure 11, the formation structure needs to be guided and recovered. Based on the recovery method above, the reconfiguration scheme guided by the recovery importance degree is obtained. To show the usability of the reconfiguration strategy in this chapter, a stochastic reconfiguration scheme is given in this section as a comparison, as shown in Figure 12. Figure 11 means at the time of the destruction of unmanned ships 1 and 2, the refactoring strategy considers the designation of unmanned ships to replace the deactivated unmanned ships. Figure 12 shows a random replacement strategy at the time of the destruction of unmanned ships 1 and 2. The advantages and disadvantages between the different strategies are given in the Table 3.

Table 3. Comparisons of the related strategies.

Advantages / strategies	Economy	Greater resilience recovery	Time-saving	More system performance improvements	Greater redundant unmanned ships utilization
Stochastic refactoring strategy	√		√		
The refactoring strategy proposed in this paper		√		√	√

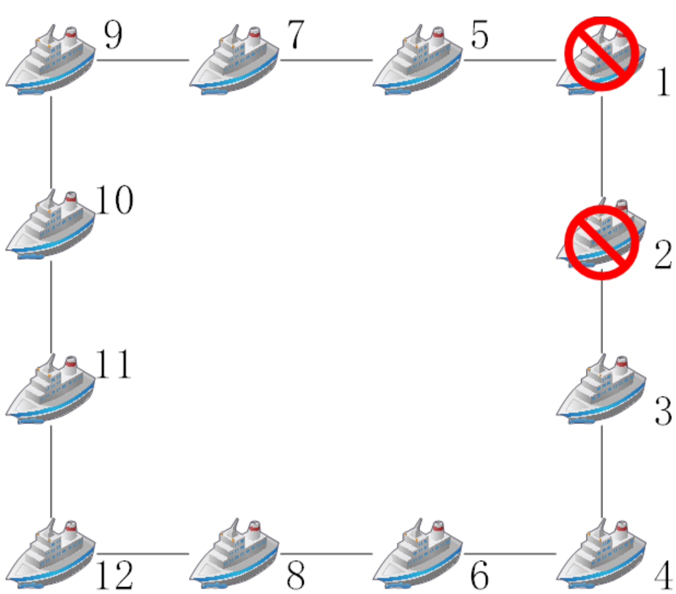

Figure 11. Unmanned ship formations at the time of the destruction of unmanned ships 1 and 2.

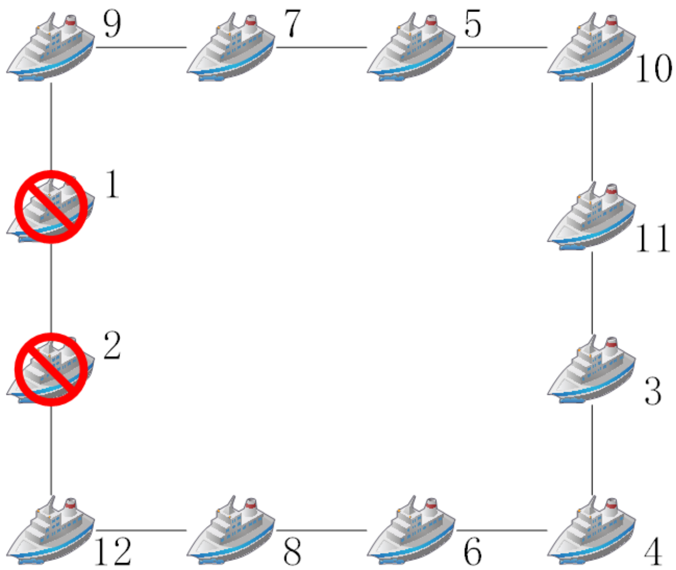

Figure 12. Network stochastic reconstruction strategy.

Through the network reconfiguration strategy proposed in this paper and compared with the network random reconfiguration strategy, the performance recovery effect and performance changes during the recovery process are shown in Figure 13.

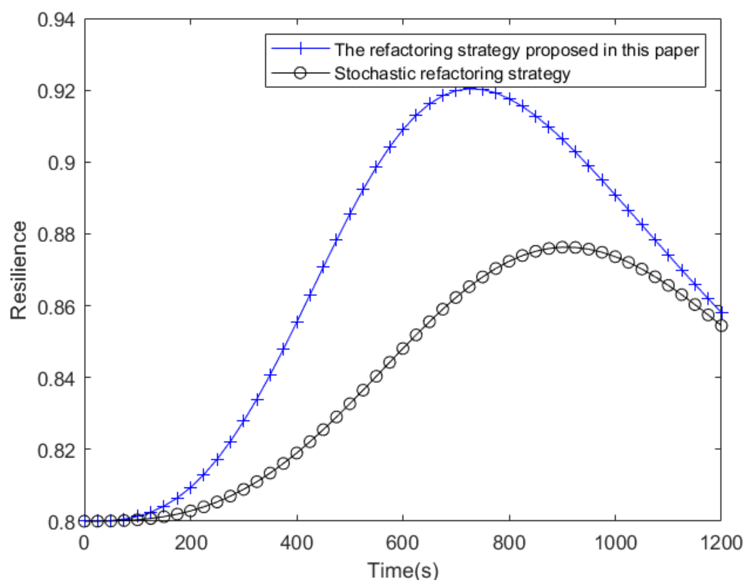

Figure 13. Comparison of network reconstruction performance recovery under the two strategies.

In addition, in this paper, the combined consideration of preventive index, robustness index, recoverability index and reconfigurability index can make the system toughness significantly improved, and the toughness values under the two reconfiguration strategies are as shown in Table 4.

Table 4. System resilience under two strategies.

Strategy	Importance-based resilience optimization	Stochastic refactoring strategy optimization
Resilience	0.9204	0.8762

From Table 4, it can be seen that the combined consideration of the preventive index, robustness index, recoverability index, and reconfigurability index in this paper can effectively improve the system toughness, which is 4.42% higher than the toughness under the random reconfiguration strategy, which proves the feasibility of the importance-based toughness optimization method proposed in this paper. The multi-angle and multi-index resilience analysis shows the rigor of the resilience analysis in this paper. To a certain extent, the improvement of elasticity under different strategies shows the superiority of the reconstruction strategy proposed in this paper compared with the traditional stochastic reconstruction strategy. Then, in actual operations, by using the reconstruction strategy proposed in this paper, the reliability of the unmanned ships swarm network system can be improved in the preparation stage on the one hand, and the resilience of the unmanned ships swarm network in the combat stage can be improved on the other hand.

5. Conclusions and Future Work

This paper takes the unmanned ship system as the research object, takes a number of reliability indexes of the unmanned ship system as the research background, and discusses how the unmanned ship system can take the strategy to improve the performance and resilience of the system after being struck.

By disassembling the indicators of the unmanned ship system after being struck, the reliability, robustness, recoverability, and reconfigurability are analyzed layer by layer, and the indicators are obtained to model the performance and toughness of the unmanned ship system. Combined with the actual combat and mission scenarios, the unmanned ship is analyzed one by one from node failure to node recovery to node reconfiguration of a complete strike process after the strike, and the important representation of toughness is obtained, which lays a certain foundation for the subsequent research.

In-depth consideration is given to the formation structure of the unmanned ship system from the design process to the completion of the mission, and two concepts about the recovery importance and loss importance of the unmanned ship system are put forward, and a more suitable reconfiguration strategy for the unmanned ship system after the damage caused by the strikes is finally determined by the recovery importance and loss importance, and finally, the expected results are obtained through the simulation and the comparison of the traditional reconfiguration strategy. However, the reliability and resilience analysis of the unmanned ships swarm is not seeped enough, and the performance indicators can be more selective.

In the future, we can continue to study one of the mission reliability aspects of unmanned ship systems by adding multilayer networks to the mission reliability analysis of unmanned ship systems. Unmanned ship systems are often classified as single-mission driven for the convenience of model calculation, but in actual combat, unmanned ship systems have more multi-tasks in parallel or complete mission chains, such as reconnaissance, communication, fire strikes, etc. Furthermore, we can consider the mission reliability of unmanned ship systems more comprehensively and the mission reliability of unmanned ship systems can be considered more comprehensively. In the end, the network reliability of unmanned ship swarm systems driven by complete mission chains can also be analyzed more comprehensively.

Conflict of Interest
The authors confirm that there is no conflict of interest to declare for this publication.

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