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IoT-enabled Spatiotemporal Resilience Analysis for an Unmanned System of Systems

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Abstract: As research on the Internet of Things (IoT) and unmanned equipment continues to advance, the unmanned system of systems (USS) has been developed unprecedentedly. Much of the existing research on USS focuses on the effects of changes of system resilience with respect to time, but little on spatial changes. However, USS missions might involve physical strikes against unmanned systems. Alternatively, they could involve signal jamming of data transmissions at the data layer. Therefore, it is crucial to account for variations in the performance of the data layer. Time plays a key role in determining the mission performance of the USS, while spatial location affects the transmission performance of the data layer. To examine how time and space issues impact the resilience of the USS, this paper introduces a spatiotemporal resilience assessment framework. This framework evaluates the resilience of USS from both time and space perspectives. Additionally, the paper proposes a spatiotemporal resilience optimization scheme for the entire USS mission process. The scheme enhances spatiotemporal resilience and focuses on optimization during the prevention and recovery phases. Finally, the proposed methods are validated using a case study involving a USS with positive hexagonal formation.

Keywords: Spatiotemporal performance; Spatiotemporal resilience; Unmanned equipment; Importance measure.

1. Introduction

The networked unmanned system of systems (USS) is primarily designed for and adapted to narrow domain-specific missions [1]. With ongoing advancements in Unmanned Aerial Vehicles (UAVs) and Unmanned Vehicles (UVs) technologies, USS has become a crucial component of the new Internet of Things (IoT) [2]. However, due to the limited endurance of UAVs, which restricts their operational range, USS has been developed to overcome these limitations. Today, USS has proven to be an efficient method for identifying hidden hazards in high-risk environments, outperforming traditional detection techniques [3]. With the continuous development of science and technology, USS has become a burgeoning research area for its own efficiency and collaboration. Li et al. [4] proposed an autonomous collaborative soft resource optimization method to enhance resilience and operation. Bi et al. [5] introduced a cooperative task allocation method for sea and air heterogeneous unmanned systems. Li et al. [6] analyzed the research status and application of USS in underground metal mining, demonstrating that unmanned technology can advance mining technology to an intelligent level. This highlights the necessity of studying USS. During their missions, unmanned systems may be exposed to a variety of strikes, such as enemy strikes against unmanned equipment and signal interference. These destructive factors may cause mission failures for the USS. Therefore, to ensure the normal operation of USS, it is necessary to study the state of both the data layer and the physical layer. Traditional performance and resilience analyzes are not able to consider the effects that time and space bring to the system of systems in IoT at the same time. Thus, finding a method that can measure the temporal and spatial performance and resilience of USS is necessary.

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With the development of IoT, to ensure the proper operation of USS, it is necessary to consider the changes in the data and physical layers. Lim et al. [7] investigated the reliability of the data layer in UAV swarms using an integrated dry-to-noise model. Dandapat et al. [8] explored a UAV-assisted communication design by optimizing the three-dimensional trajectory of the UAV, ensuring adequate coverage of mobile nodes to maximize the service duration of the UAV. Wang et al. [9] studied the energy minimization problem for UAV-assisted data acquisition sensor networks, combining sensor power and energy constraints to jointly optimize the UAV's trajectory and sensor power consumption, thereby minimizing energy loss in the data layer. Abd El-Malek et al. [10] analyzed the performance of UAV-assisted networks with multiple and single antennas to optimize data layer performance. In the study of physical layer strikes of UAV swarms. Liu et al. [11] investigated the problem of maximizing the achievable rate of downlink UAV communication systems assisted by intelligent surfaces and proposed an algorithm to augment the communication rate. Wu et al. [12] designed a co-evolutionary mechanism for unmanned groups on a community network based on game theory, providing theoretical references and decision support for enhancing the mission effectiveness of unmanned group operations. Many researchers study either the data or physical layer of a system but rarely consider both at the same time. The proper functioning of a system is determined by the operational status of both the data and physical layers of multiple systems.

The performance of USS is the main indicator of their operational state, making its study essential. In research of system performance, Lu et al. [13] optimized the walking performance of the lunar rover based on mechanical analysis. Gao et al. [14] proposed a set of data-driven UAV sharing algorithms to enhance urban points of interest and detect urban anomalous events, thereby improving UAV delivery performance. Ye et al. [15] introduced a stabilized transformer-based potential-driven reinforcement learning framework to optimize key network operations for energy efficiency and robust network performance. Chen et al. [16] demonstrated an ultra-yawn-driven light detection and ranging sensing aerial robot that extends sensor viewpoints by spinning, enhancing perception performance, mission efficiency, and flight safety. Guo et al. [17] investigated the performance of reconfigurable intelligent ground-assisted integrated satellite UAV ground networks under conditions of hardware damage and interference, with unavailable direct links. Khuwaja et al. [18] analyzed the impact of ground user mobility, propagation environment, and channel fading on UAV communication performance. Most of the research focuses on the impact of system performance over time, while the spatial state is also a key factor affecting system performance, and there is a lack of performance analysis of the system in the spatial state.

Resilience, as a measure of resistance and recovery capability of USS, has been widely studied by researchers. Xin et al. [19] proposed a rapid system resilience and component importance assessment method based on an analytical approach for system. Chen et al. [20] proposed an image-based UAV velocity observer method to enhance tracking stability, perturbation resistance, and resilience under dynamic rotating targets. Wei et al. [21] conducted a comprehensive review of the resilience of urban rail transit, summarizing the metrics and assessment methods used in this field. Kong et al. [22] proposed a resilience assessment method for UAV swarm, incorporating three levels of performance metrics and algorithms for resource supplementation. Li et al. [23] proposed a baseline resilience assessment method for UAV swarms under heterogeneous communication networks to make resilience assessment more realistic. Tropkina et al. [24] introduced a novel, accurate, and fast dispersive field evaluation method, which includes radio network planning for cellular deployments and link budget estimation for radar systems coexisting with UAV to enhance resilience. Kim et al. [25] investigated a secure offloading system where smart reflective surfaces mounted on UAVs assist in the offloading procedure between ground users and access points, enhancing

system resilience. Li et al. [26] constructed a soft resource optimization model to improve UAV swarm resilience under sustained strikes. Feng et al. [27] developed an optimization method for multi-UAV formation resilience to achieve fast and accurate reconfiguration under random strikes. Hu et al. [28] proposed a percolation-based UAV swarm resilience optimization method to achieve the maximum resilience of UAV swarms in the face of strikes. Addressing considerations related to network subsystems and the physical connectivity of information. Li et al. [29] proposed a generalized approach to assessing network resilience. These studies show that most of the system resilience research focuses on the factor of time, and little considering the effects of spatial location, indicating that the traditional resilience studies are not enough. The characteristics of USS change over time and space, making traditional importance metrics insufficient for comprehensive analysis.

In improving the resilience of USS, identifying the key components through importance metrics is common and vital for the prevention and recovery stages. Among these studies, Bizhao et al. [30] proposed an optimization method based on the artificial potential field method to enhance the resilience of the airspace to cope with air traffic congestion and delays. Dui et al. [31] proposed a maintenance cost-benefit-based importance metric to develop a cost-optimized dynamic maintenance strategy under threshold constraints. Brake et al. [32] used a resilience-based importance metric to quantify the impact of component failures. Wei et al. [33] proposed a distributed model predictive queue control framework for optimizing queue control resilience in constrained smart and connected cars. Fang et al. [34] utilized resilience reduction to measure the criticality of network system components. Importance metrics also guide system maintenance and recovery after a disaster. Dui et al. [35] proposed an importance-based resilience optimization strategy by analyzing different metrics of unmanned vehicles. Liu et al. [36] proposed a resilient optimization method based on novel indexing and reinforcement learning. However, the performance of the USS during the execution of the task will produce phase changes, and there are few studies that consider the optimization of the resilience of the USS at different stages, which is insufficient for the study of the resilience optimization strategy of the USS.

To summarize, current research on USS primarily focuses on resilience to physical shocks, with insufficient exploration of data layer signal interference and its resilience. Although significant progress has been made in USS resilience research, few studies have deeply examined how spatial variations affect overall resilience. In practice, the spatial layout and state of USS are crucial for its operational effectiveness and post-disaster resilience. To address this research gap, this paper aims to provide a comprehensive analysis of how dynamic changes in time and space impact USS resilience by introducing the concept of spatiotemporal resilience. The contributions are as follows.

1) Recognizing that existing studies have focused on the physical layer while neglecting the data layer, this paper leverages IoT to construct a multilevel USS model that deeply integrates physics and data aspects. This model aims to accurately map the real state of USS in complex mission environments, providing a comprehensive assessment of its resilience performance and recovery potential in the face of data interference.

2) Acknowledging that existing studies often overlook the impact of spatial distribution and temporal dynamics of USS resilience, this paper introduces the concept of spatiotemporal resilience. It establishes a quantitative assessment method to achieve a thorough and dynamic evaluation of USS resilience, considering both spatial and temporal changes.

3) Addressing the lack of spatiotemporal resilience optimization strategies for specific operational phases, this paper proposes tailored spatiotemporal resilience optimization schemes for USS. These schemes are designed for different operational phases to ensure that USS can maintain efficient operational and recovery capabilities in

dynamic environments.

The remainder of this paper is structured as follows. Section 2 introduces the architecture of USS under IoT. Section 3 analyzes some spatiotemporal properties of USS and then introduces the concept of spatiotemporal resilience. entire process. Section 4 proposes a spatiotemporal resilience optimization scheme for USS based on an importance metric. Section 5 verifies the feasibility of the spatiotemporal elasticity optimization scheme proposed in this paper by using a USS consisting of a UAV system in positive hexagonal formation and a single UV system as the simulation target. Section 6 closes the paper, identifies the limitations, and proposes future research.

2 IoT-enabled USS architecture

Performing missions such as reconnaissance strikes is most common in USS. USS includes UAV systems, UV systems, unmanned missile systems, and combat management systems, among others. These systems contain numerous unmanned devices like UAVs and UVs.

UAVs offer a wide field of view, fast navigation speed, and are not limited by routes and terrain. However, operating in the air leads to significant energy loss, resulting in shorter endurance. Additionally, if the distance from the base station is too great it will cause a lot of propagation loss and make the signal easy to interrupt. On the other hand, UVs have strong load capacities and sufficient endurance but are restricted by terrain and roads limitations, which can hinder their ability to perform tasks.

USS compensates for the shortcomings of multiple systems such as UAV system and UV system by combining the advantages of various systems. For example, UVs can serve as relay stations and mobile base stations to extend the power range and signal propagation of UAVs. They can also act as storage data centers, receiving and processing data collected by UAVs. This reduces the load and energy consumption of UAVs, allowing them to focus on tasks like filming, monitoring, or surveying.

In USS, the UAV system is responsible for the main missions, while the UV system provides signals to UAVs, receives data from UAVs, and backs up the data. During the deployment phase before the mission, UAVs form formations, search in sectors or grids along preset paths, or follow the characteristics of the target area, maintaining a relatively fixed speed and direction. UVs, serving as a data storage center, back up data collected by UAVs, ensuring efficient data management within the USS.

The traditional USS model may lack the analysis of the signal of UAV. It is difficult for USS to monitor the signals generated in the data layer during mission execution, such as poor quality of collected data, such as missing data, blurred images, etc., and the authenticity cannot be assessed. This leads to the overall operational inefficiency of the USS, weakened target search capability, and poor post-mission evaluation. To avoid the above problems, this paper proposes an IoT-based USS architecture. When the USS is strike, the decision maker can make timely adjustments to minimize the impact due to the strike. The IoT-enabled USS architecture is shown in **Fig. 1**.

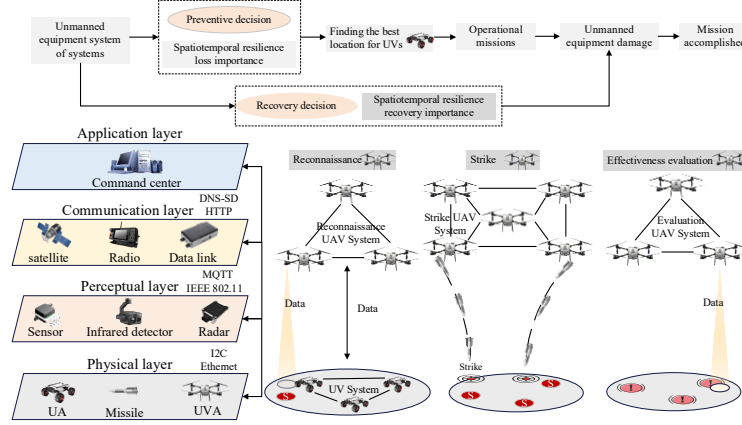


Fig. 1. IoT-enabled USS architecture

From **Fig. 1**, the USS can be divided into four layers: physical layer, perceptual layer, communication layer, and application layer.

The physical layer is dominated by unmanned equipment such as UAVs, UVs and missiles. The perceptual layer collects dynamic battlefield data mainly through sensors, radars and other equipment. The communication layer facilitates data flow and information sharing between different combat units and layers by utilizing various communication devices such as satellites and data connectors. The application layer is the command core of the USS and is responsible for the operations of the entire USS and the synergy among the unmanned systems. All UAVs within the USS transmits its position information, state parameters and environmental data to the central control system in real time via IoT, thus achieving efficient data sharing and spatiotemporal synchronization among the components. At the same time, a local feedback mechanism is introduced to the USS based on IoT, which enables each UAV to adjust its behavior based on real-time data and at the same time feed the updated data back to the control center, thus realizing adaptive dynamic control.

The USS mission process can be divided into several phases: reconnaissance, target identification, mission planning, strike execution, and effects assessment.

During the reconnaissance phase, the command center assigns the UAV to carry out reconnaissance missions based on battlefield requirements and mission objectives. The UAV takes off according to a predetermined route, guided by Global Positioning System (GPS) and other navigation systems, and flies to the target area. It uses onboard cameras, infrared imaging equipment, radar, and other sensors to conduct real-time monitoring and gather images and data of the target area. The UAV transmits the collected images and data back to the command center via satellite or ground station for analysis and judgment.

During the strike execution stage, the UAV reaches the designated strike position and prepares its onboard weapons (e.g., missiles, bombs, etc.). Using its sensors and targeting equipment, the UAV locks onto the target to ensure the strike accuracy.

In the effects assessment stage, after completing the strike, the UAV returns to the base while a reconnaissance drone monitors the target area to evaluate the strike's impact and assess enemy losses. The command center then conducts a detailed analysis of the returned data to confirm whether the target has been destroyed and to determine whether a second strike is necessary.

We note that, aside from the physical layer, there is data exchange among the three other layers. For convenience in subsequent analysis, we collectively refer the layers to the perceptual layer, communication layer, and application layer as the data layer. The hierarchical functional analysis architecture for USS is shown in **Fig. 2**.

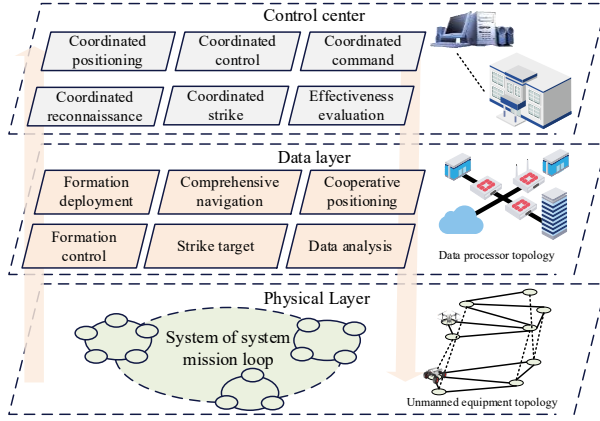


Fig. 2. Hierarchical Functional Analysis Architecture for USS

From **Fig. 2**, the physical layer is a multi-system structure where USS physical layers are interconnected to form a mission ring. Based on IoT, the data layer is responsible for executing the formation deployment in each system and analyzing and transforming commands. The command layer is tasked with sending mission orders and coordinating the entire mission. Throughout the mission process, each system cooperates under the unified architecture to form USS.

During a mission, UAV may malfunction due to enemy strikes or signal interference. The limited maintenance resources may be unable to address the issues, significantly impacting the progress of reconnaissance, strikes, and assessments. A compromised reconnaissance mission affects the accuracy of subsequent strikes, making precise targeting difficult. A single severe enemy strike could result in an insufficient number of drones available to carry out the mission, thus affecting the ability to accomplish the mission. If the assessment mission is compromised, accurately judging the effectiveness of strikes becomes impossible, affecting decisions for subsequent missions.

To mitigate the impact of strikes, this paper proposes the concept of spatiotemporal resilience to more accurately measure the performance change in the USS when it suffers from strikes. Based on this concept, a spatiotemporal resilience entire process optimization method is proposed. After a strike, minimizing the impact on the cluster using a repair and reconfiguration approach allows USS to maintain performance and complete operations more efficiently.

3 USS spatiotemporal resilience model

Spatiotemporal resilience is an indicator of the state of the USS with respect to time and space. Spatiotemporal resilience can be evaluated based on the variation of USS performance. Therefore, the concept of spatiotemporal performance of USS is proposed and modeled in this section. The calculation methods of spatiotemporal resilience at different stages are also given.

3.1 Spatiotemporal performance of USS

USS is composed of two layers: physical layer and data layer. The former performs tasks and the latter transfers data. Suppose that there are m UVs and n UAVs in USS and that the UVs and UAVs are the same model and the same batch of machines.

(1) Data layer performance analysis

A UV can be connected to multiple UAVs to perform data storage tasks. Signals from these UAVs may be propagated to the same UVs. Signal transmission at the data layer may be impacted because of the long distance between the UAV and the UV, which can result in high path losses. The data signal from the UAV is weakened so that it is unable to decode the signal at UV.

According to drones' displacements, we need to calculate the path loss based on the distance between each drone and the UV. The path loss of the signal transmission [37] between the UV and the UAV is shown in Eq. (1).

$$P_L(s_i^a) = 20\log_{10}\left(\frac{4\pi s_i^a f}{c}\right), \quad (1)$$

where s_i^a is the distance between the a th UV and the i th UAV, f is the frequency of the signal, and the c is the speed of light.

When the UAV encounters shocks, the degrees of signal interference vary depending on the type of shock. We introduce a shock factor, W , to represent this process. The shock factor indicates the magnitude of the external strike on the data layer, the greater the magnitude of the strike, the higher the value of the striking factor. The path loss of the USS data layer is calculated by Eq. (2).

$$P_L(s_i^a) = 20W \cdot \log_{10}\left(\frac{4\pi s_i^a f}{c}\right), \quad (2)$$

The calculation of s_i^a is shown in Eq. (3).

$$s_i^a = \sqrt{(x_a - x_i)^2 + (y_a - y_i)^2 + h_i^2}, \quad (3)$$

where $(x_a, y_a, 0)$ are the coordinates of the a th UV and (x_i, y_i, h_i) are the coordinates of the i th UAV.

In the s, t plane, the speed and direction of the UAV movement may be different from those of the UV movement, causing a relative velocity difference between them. To better analyze the spatial variability of the USS, we set all UAVs to sail at the same speed. This results in the same amount of spatial variation, which is denoted by s . Denote the relative velocity by v . We then calculate the displacement between the UV and the i th UAV as shown in Eq. (4).

$$s = s_i^a - s_{i,0}^a = \sqrt{\left(vt + \sqrt{s_{i,0}^a{}^2 - h_i^2}\right)^2 + h_i^2} - s_{i,0}^a, \quad (4)$$

where s is the distance between the i th UAV and the UV change at the ending moment, v_i is the lateral movement speed of the i th UAV, and t is the movement time.

Based on the UVs initial position, the performance of the signal transmission at the data layer can be optimized. With the increasing distance between the UAVs and the UVs, the path loss of the data layer increases. If the path loss is too large, the signal reaching the UAV is too weak and the UAVs signal receiver cannot be decoded, invalidating the UAVs signal commands and ceasing normal mission. Set the performance of the data layer at this point to be 0. The maximum path loss of the UAV is denoted by $P_{L,s}^{max}$, and therefore we can obtain the performance

of the data layer $P_i^d(s_i^a)$ by Eq. (5).

$$P_i^d(s_i^a) = \begin{cases} 1, & (P_i^d(s_i^a) \leq P_{L,s}^{max}, s_{i,0}^a \leq s_i^a) \\ \frac{\log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right)}{W \cdot \log_{10}\left(\frac{4\pi s_i^a f}{c}\right)}, & (P_i^d(s_i^a) \leq P_{L,s}^{max}, s_{i,0}^a \leq s_i^a), \\ 0, & (P_i^d(s_i^a) > P_{L,s}^{max}) \end{cases} \quad (5)$$

where $s_{i,0}^a$ is the initial distance between the i th UAV and the a th UV.

We define the s -axis as the average distance between UAVs and each UVs. As the mission proceeds, the position of the UAV relative to the UV system will change, mainly reflected in the change of the s -axis value in 3D space, and the spatial performance will decrease as the distance increases. The main reason for the variation in spatial performance is the variation in the distance between the UAVs and the UVs, which affects the path loss of the signal.

(2) Physical layer performance analysis

UAVs are widely used electromechanical devices, consisting of various mechanical and electronic components [38]. The performance degradation of UAVs is usually considered to conform to an exponential distribution [39]. Therefore, the performance change of the physical layer generally obeys an exponential distribution. Degradation of UAV components lead to a reduction in the UAV's formalizable operational time. We define the performance of the UAV physical layer when subjected to a strike as UAV component degradation, as shown in Eq. (6).

$$P_i^c(t) = e^{-\lambda_i t}, \quad (6)$$

where λ_i is the damage parameter of the UAV and the λ_i values are greater than 0. The damage parameter is given based on the assessment of the aging degree of the UAV, the susceptibility to damage, and other factors. In this paper, the aging degree of the UAV, vulnerability to damage, and other factors are assumed to be inversely proportional to the lapse time.

UAVs need to be repaired when their performance deteriorates to the point where they are unable to fulfill their mission. At the beginning of the restoration process, the repairman needs to check the UAV to locate the root cause of the damage. The performance of the initial repair can be slow. With the progress of the restoration process, the repairman becomes gradually skillful, and his performance improves. When the repair is about to be completed, the performance of the UAV reaches the perfect state. As such, the performance change of the UAV restoration process generally presents a logistic function [40], as shown in Eq. (7).

$$P_i^c(t) = \frac{1}{1 + e^{-\alpha_i t}}, \quad (7)$$

where α_i is the recovery parameter of the UAV and the α_i values are greater than 0.

UAVs may be damaged due to transiently generated destructive strikes. The data transmission state in the UAVs needs therefore consideration. We propose a concept of spatiotemporal performance by combining the performance variations of USS physical and data layers in time and space, and the spatiotemporal performance of USS is calculated as shown in Eq. (8).

$$P(s, t) = \frac{1}{n} \cdot \sum_{i=1}^n \frac{P_i^d(s + s_{i,0}^a) P_i^c(t)}{P_i^d(s_{i,0}^a) P_i^c(t_0)}, \quad (8)$$

where $P(s, t)$ is the performance of the USS, and $\sum_{i=1}^n P_i^d(s_{i,0}^a) P_i^c(t_0)$ is the performance of the system in the ideal state. We define spatiotemporal performance as the vertical axis in three-dimensional coordinates.

Synthesizing the previous discussion and considering the effects of spatiotemporal variations on the USS, we introduced a concept of spatiotemporal performance surface to better measure the performance variation of the system. The reason for the “spatiotemporal performance surface” is that we have expanded the USS performance metrics from a one-dimensional to a two-dimensional measure, from a “line” to a “surface”. The spatiotemporal performance variation of the USS is shown in **Fig. 3**.

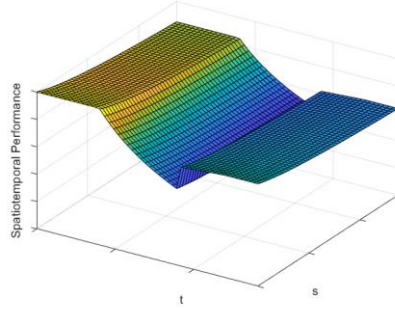


Fig. 3. Spatiotemporal performance change of USS

In **Fig. 3**, the t -axis represents the USS performance profile with time variation and the s -axis represents the USS performance profile with space variation. The proposed spatiotemporal performance by combining the variation in time and space is shown as a surface in **Fig. 3**. The concept of spatiotemporal performance can measure the variation of USS over any time and space. The surface describes the entire process of variation in spatiotemporal performance of the USS in performing a mission, and the spatiotemporal performance produces a decrease because of a strike on the USS. The spatiotemporal performance rises due to the recovery of the USS after a strike.

3.2 Spatiotemporal resilience assessment of USS

Resilience, as a measure of system performance, has received a lot of attention from researchers. Most of the existing studies on system resilience have examined the effects of changes over time on the system, with fewer studies on the spatial dimension.

The spatial location of UAVs and UVs runs through the entire process of performing tasks in USS. With the change of time, the position also changes, which causes the performance transmission of the data layer unstable. In mission, in addition to considering the mission time factor, the spatial location is equally important, and the different locations will affect the reliability of the task completion and system resilience. Therefore, how to consider both time and space factors when analyzing system resilience is challenging. Based on this, we introduce the traditional resilience calculation into the spatial location index and propose a concept of spatiotemporal resilience to measure the prevention, defense, and recovery capabilities of the USS during the execution of the mission.

We extend the concept of USS resilience from one to two dimensions and propose the concept of spatiotemporal resilience. spatiotemporal resilience facilitates the understanding of the dynamic resilience of USS. Spatiotemporal resilience not only analyzes the change of USS dynamic resilience in time but also explores the dynamic resilience change with the change of space, which can evaluate the system more comprehensively. We define the computation of spatiotemporal resilience as the ratio of the integral of the system's performance over the time and space in which the mission is executed to its integral in the ideal state. The changes in the performance of USS throughout the execution of a mission are divided into two stages: the prevention stage and the recovery stage.

Therefore, we divide the resilience into three categories: prevention spatiotemporal resilience, recovery spatiotemporal resilience and entire process spatiotemporal resilience, and calculate the spatiotemporal resilience as shown in Eq. (9), Eq. (10) and Eq. (11).

$$R_{prevent}(s, t) = \frac{\int_{t_m}^{t_n} \int_{s_m}^{s_n} P(s, t) ds dt}{\int_{t_m}^{t_n} \int_{s_m}^{s_n} P(s_0, t_0) ds dt}, \quad (9)$$

$$R_{recovery}(s, t) = \frac{\int_{t_p}^{t_q} \int_{s_p}^{s_q} P(s, t) ds dt}{\int_{t_p}^{t_q} \int_{s_p}^{s_q} P(s_0, t_0) ds dt}, \quad (10)$$

$$R(s, t) = \frac{\int_0^{t_{end}} \int_0^{s_{end}} P(s, t) ds dt}{\int_0^{t_{end}} \int_0^{s_{end}} P(s_0, t_0) ds dt}, \quad (11)$$

where s_0 is the initial distance of USS, $R_{prevent}(s, t)$ is the spatiotemporal resilience of the prevention stage of USS, $R_{recovery}(s, t)$ is the spatiotemporal resilience of the recovery stage of USS, and $R(s, t)$ is the spatiotemporal resilience of the full process of USS. t_m is the moment when the strike starts, and t_n is the moment when the strike ends. s_m is the change in the position of the drone away from the UV when the strike starts, and s_n is the change in the position of the drone away from the UV when the strike ends. t_p is the moment when the drone starts recovering, and t_q is the moment when the strike ends. s_p is the distance moved by the UAV from the UV at the start of the recovery, and s_q is the distance moved by the UAV from the UV at the end of the recovery. t_{end} is the total time at the end of the execution of the mission, and s_{end} is the total distance moved at the end of the mission.

Based on the formula of the spatiotemporal resilience metric, we find that: the greater the spatiotemporal resilience of the system, the higher the ability of the system to resist external interference in a certain time and space, and the better the recovery effect. The spatiotemporal resilience of the USS is shown in Fig. 4.

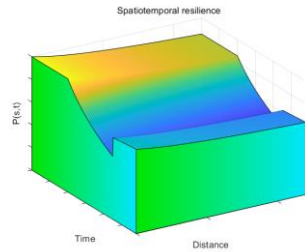


Fig. 4. Spatiotemporal resilience of USS

From Fig. 4, we can see that spatiotemporal resilience is related to the change in USS spatiotemporal performance. With the change of spatiotemporal performance of USS gradually becoming smaller, which leads to the spatiotemporal resilience obtained by the system in the subsequent unit of time and space is gradually becoming smaller. To decelerate the trend, how to reduce the spatiotemporal performance decline velocity of the USS is an important research direction for improving the spatiotemporal resilience of USS.

In what follows, we examine how to reduce the spatiotemporal performance degradation of USS and how to recover spatiotemporal performance of USS faster. To minimize spatiotemporal performance loss when resisting shocks and to improve the recovery efficiency when recovering.

On the other hand, we can see that the area surface in s, t is determined by the time t of the final execution of

the task and the distance changes of the UV and UAV. It is known that there is a fixed relationship between the time and the space of the difference in moving speed by $v = \frac{s}{t}$. The area of s, t , and the value of the s over t are both affected by the speed, and all these parameters will affect the calculation of the system resilience. Therefore, how to set the value of the moving speed of the USS is also one of the important methods to improve spatiotemporal resilience.

We need to find the best UAV base station arrangement location to ensure the reliability of data propagation of the cluster, and the position of the UAV. All the time during the mission. Therefore, the location of the UAV should travel to the location that maximizes the reliability of the overall data layer as the locations of multiple UAVs change. According to the spatiotemporal resilience optimization method proposed in this paper, the spatiotemporal resilience variation of the USS is shown in Fig. 5.

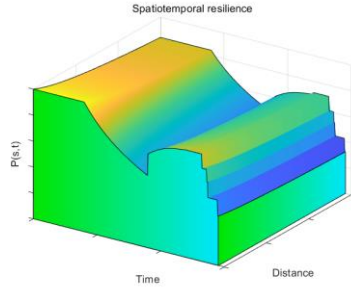


Fig. 5. Change in spatiotemporal resilience after optimization

As can be seen from Fig. 5, the spatiotemporal resilience of the system shows stepwise declination, which guarantees that the USS can obtain greater resilience. At the same time, the performance declines in the less-than-strike stage slowly, which illustrates the effectiveness of the early deployment.

4 Multi-stage spatiotemporal resilience optimization of USS

In this section, spatiotemporal resilience optimization is performed during the entire process of executing the mission. The multi-stage of USS includes the normal prevention stage, strike stage, and recovery stage. We chose to optimize the prevention and recovery stages to improve the spatiotemporal resilience of the USS.

Preventive maintenance (PM) is an effective means to improve system resilience. However, the economic feasibility of system design must also be considered [41]. In the PM stage, we propose two PM regimes:

1. Considering that the relative speeds of the UAV and the UV will have an impact on the performance and resilience of the USS, we need to find the optimal speed to obtain the maximum resilience of the system.
2. The location of UVs affects the performance of the UV data layer in the USS and thus the spatiotemporal resilience of the system. Based on the importance metric of spatiotemporal resilience loss, a UV deployment principle is introduced to enable the USS to obtain optimal spatiotemporal resilience.

In the entire process of the mission, we require the USS to complete the task in as quick as possible. Thus, the UAV in the general process will be operated at the maximum moving speed, which leads to the inevitable appearance of the speed difference between the UAV and the UV's position change. However, when the distance difference between the UAV and the UV is too large to receive signals, the speed of the UAV will be reduced to the same speed as the UV, to prevent the data layer failure situation caused by the distance being too large. The distance change

caused by the speed difference needs to be calculated. Changes in the value of v affect the t, s -axis area of the spatiotemporal resilience and the change in the spatiotemporal resilience of the USS.

To explore the speed effect on the overall USS spatiotemporal performance, we explore further derivations of the spatiotemporal performance of a single UAV to determine the effect of v on the spatiotemporal performance of the USS, by solving the partial derivatives of v separately. We replace distance with time as shown in Eq. (12).

$$Z^t = P_i(v, t) = \frac{\log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right) e^{-\lambda_i t}}{W \cdot \log_{10}\left(\frac{4\pi f}{c} \cdot \left(\sqrt{\left(vt + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)^2 + h_i^2}\right)\right)}, \quad (12)$$

where $P_i(v, t)$ is the spatiotemporal performance in the velocity-time dimension.

Find the partial derivative of v for $P_i(v, t)$ as shown in Eq. (13).

$$\frac{\partial P_i(v, t)}{\partial v} = \frac{-\frac{1}{W} \log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right) e^{-\lambda_i t} \cdot t \cdot \left(vt + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)}{\ln 10 \left(\log_{10}\left(\frac{4\pi f}{c} \cdot \sqrt{\left(vt + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)^2 + h_i^2}\right) \right)^2 \cdot \left(\left(vt + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)^2 + h_i^2 \right)}. \quad (13)$$

Commented [SW1]: Is 10 the base of the logarithm?

By Eq. (13) we can see that $\frac{\partial P_i(v, t)}{\partial v} < 0$, then Z^t shows a decreasing trend when v_i increases.

We replace distance by time as shown in Eq. (14).

$$Z^s = P_i(v, s_i^a) = \frac{\log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right) e^{-\lambda_i \left(\sqrt{(s_i^a)^2 - h_i^2} - \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)}}{W \cdot \log_{10}\left(\frac{4\pi s_i^a f}{c}\right)}, \quad (14)$$

where $P_i(v, s_i^a)$ is spatiotemporal performance in the velocity-distance dimension.

The partial derivative of v for $P_i(v, s_i^a)$ is shown in Eq. (15).

$$\frac{\partial P_i(v, s_i^a)}{\partial v} = \frac{\lambda_i \cdot \log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right) \left(\sqrt{(s_i^a)^2 - h_i^2} - \sqrt{(s_{i,0}^a)^2 - h_i^2} \right) \cdot e^{-\lambda_i \left(\frac{\sqrt{(s_i^a)^2 - h_i^2} - \sqrt{(s_{i,0}^a)^2 - h_i^2}}{v} \right)}}{W \cdot v^2 \cdot \log_{10}\left(\frac{4\pi s_i^a f}{c}\right)}. \quad (15)$$

By analyzing, we can see that $\frac{\partial P_i(v, s_i^a)}{\partial v} > 0$. As v increases, Z^s shows an increasing trend.

By comparing Z^t and Z^s , the effect of v on the spatiotemporal performance is paradoxical, and there is no monotonicity between the values of v and the overall performance. Therefore, when performing a certain task, the speed of the UV needs to be defined according to the actual situation.

When $I_c \left| \frac{\partial P_i(v, t)}{\partial v} \right| < I_d \left| \frac{\partial P_i(v, s_i^a)}{\partial v} \right|$, the v should be as small as possible within the allowed range. When $I_c \left| \frac{\partial P_i(v, t)}{\partial v} \right| > I_d \left| \frac{\partial P_i(v, s_i^a)}{\partial v} \right|$, the v should be as large as possible within the allowable range. I_d is the importance metric of the data layer, and I_c is the importance metric of the physical layer, and it is stipulated that the data layer and the physical layer of the USS are of equal importance in this paper. Managers can judge the importance degree relationship between the two to specify the traveling speed of UAVs and UVs through the actual situation.

Preventive deployment stage: We propose USS prevention deployment decision based on the spatiotemporal

importance of resilience loss.

The preventive deployment decision is deployed and implemented prior to the mission execution of the USS and does not affect the impact on the spatiotemporal performance of the USS during the execution of the mission. This deployment decision is based on IoT, which identifies critical UAVs for targeted preventive maintenance to ensure optimal resource allocation and a higher level of resilience of the USS. The first to be affected by signal interference is the UAVs with the highest path loss in USS, as shown in Eq. (16).

$$P_L(t) = \max\{P_L^1(t), P_L^2(t), \dots, P_L^n(t)\}. \quad (16)$$

For the USS to be less affected by signal jamming type strikes throughout the operational phase, the path loss of the UAV must be minimized. When the strike amplitude is small, we need to reduce the UAVs with the highest path loss in the fleet and deploy them according to this scheme. When the strike amplitude is too large, the operation of the data layer of all the UAVs in the fleet may be interrupted. As a result, we should redeploy according to the principle of the importance metric of spatiotemporal resilience loss, ensuring that the key UAVs are in a normal state.

When the spatiotemporal resilience loss importance of each UAV in the UAV system is the same, the distance between the UAV and each UV is also the same. When the strike amplitude is large within the specified mission range, the signal transmission of the UAVs will reach the maximum path loss value as the distance from the UV becomes larger. UAVs may produce an overall failure, at which time the loss is the greatest. To minimize the loss, at this time the deployment is selected based on the importance. Therefore, determining the size of the strike amplitude will be based on the path loss due to the distance between the UAV and the UAV with the same importance.

When signal interference strikes are small, we should try to ensure that all UAVs are in normal mission status and minimize the UAVs with the highest path loss in the fleet.

Firstly, we need to find the optimal coordinates of the UAVs when all the UAVs are of the same size and importance. The optimal UV coordinates should minimize the positional distance from the UV to all UAVs so that the minimum value of path loss among all UAVs can be increased to reduce the impact on the system performance when the strikes are not too strong. To calculate the UAV coordinates corresponding to the case of minimizing the Y as shown in Eq. (17).

$$Y = \sum_{i=1}^n \sqrt{(x_a - x_i)^2 + (y_a - y_i)^2 + h_i^2}. \quad (17)$$

The coordinates of the UV that can be derived according to the formula are the optimal position of the UV, and during the execution of the mission, the position of the UAV will change with it, and the coordinates of the UV ($x_{best}, y_{best}, z_{best}$) will also change with it. Based on the IoT, we can realize the mobile route control for UAVs and UVs and evaluate the merits of the algorithm by the quality of the received and propagated signals. We propose an algorithm for the optimal moving position of the UV with the following pseudo code.

Algorithm: Optimal movement path algorithm for UV

Input: $(x_1, y_1, h_1), \dots, (x_n, y_n, h_n)$

Output: $(x_a, y_a, z_a), Y$

Initialize: $guess = [0, 0, 0]$;

1. Define the objective function to minimize.

$objective\ function = (coords)\ Y\ value(coords(1), coords(2));$

2. Use “fminsearch” to find the $(x_a, y_a, 0)$ that minimizes Y .

$$options = optimset('Display', 'iter');$$

$$[optimal\ coords, fval] = fminsearch(objective\ function, guess, options);$$

3. Calculation of the distance between all UAVs and UVs.

$$term\ 1 = \sqrt{(x_a - x_1)^2 + (y_a - y_1)^2 + h_1^2}, \dots, term\ n = \sqrt{(x_a - x_n)^2 + (y_a - y_n)^2 + h_1^2}$$

4. Write a function of Y .

$$Y = term\ 1 + \dots + term\ n$$

5. Output results (x_a, y_a, z_a) .

In the optimal movement path algorithm for UV, the “fminsearch” is a nonlinear optimization-based function in MATLAB for finding the input variables that minimize the objective function. It is an unconstrained optimization method mainly used to find local minimum of multivariate functions using the Nelder-Mead simplex method, an optimization algorithm that does not require the computation of derivatives.

The principle of the optimal movement path algorithm for UV is to find the optimal UV position based on the change distance of UAV. In USS, the mission routes of each UAV are predefined in advance, and the UV senses the positional changes of each UAV through IoT and travels by calculating the optimal position at the current moment, thus creating real-time movement. When the loss importance of all UAVs is the same, the movement route of the UV needs to be obeyed to minimize the sum of the position distance of all UAVs between UVs. At this time, the sum of the data layer performance of each UAV will be optimal, and the data layer performance of the USS will be optimal. When the loss importance of UAVs is different, we make corresponding improvements based on the loss importance. The principle is to try to make the UVs move close to the UAVs with larger loss importance and to ensure that the performance of such drones is minimally affected. The sum of the performances of all the UAVs is maximized, and the overall data layer performance of the USS is optimal.

After getting the coordinates of the UV (x_a, y_a, z_a) , it is brought into the original equation, and then according to the change of the position of the drone, the trajectory of the UV can be obtained.

When signal interference strikes are large and large-scale unattended equipment failures cannot be avoided, we should try to minimize the impact of the strikes by ensuring that UAV with a high spatiotemporal resilience loss importance can operate normally.

As the degradation of the i th UAV affects the overall performance of the system. We define the time when the failure of the UAV occurs as t_i^a , the coordinates of the datum point at the time of failure as (x_a, y_a) , the change distance of the UAV between UV as $s_{i,c}^a$, and the end time as t_i^b . The coordinates of the datum point at the time of ending as (x_b, y_b) , and the change distance of the UAV between UV as $s_{i,c}^b$, the performance loss of the USS during the time period is $Loss\ P = P(s_{i,c}^a, t_i^a) - P(s_{i,c}^b, t_i^b)$.

In order that the spatiotemporal resilience loss importance indicates the effect of the UAV's failure on the overall performance, the spatiotemporal resilience loss importance metric of the i th UAV can be shown by the following Eq. (18).

$$I_i^{Loss} = \frac{\int_{t_i^a}^{t_i^b} \int_{s_{i,c}^a}^{s_{i,c}^b} (P(s, t) - P(s_{i,c}^b, t_i^b)) ds dt}{(t_i^b - t_i^a)(s_{i,c}^b - s_{i,c}^a)}. \quad (18)$$

The spatiotemporal resilience loss importance metric can be derived for each UAV. The mathematical

implication of the spatiotemporal resilience loss importance metric is the spatiotemporal resilience loss brought to the whole USS per unit of time and space when the UAV is destroyed. When destruction occurs, the greater the importance metric of the spatiotemporal resilience loss of the UAV, the faster the spatiotemporal resilience of USS decreases. We want to keep the USS spatiotemporal resilience maximized and should try to avoid UAVs that have a large impact on USS spatiotemporal resilience.

The greater the importance metric of spatiotemporal resilience loss of a UAV, the greater the reliability of that UAV is needed to keep the system operating efficiently. Previously, we discussed that the UAV, as a mobile base station, can affect the data layer transmission loss of each UAV by changing its position, and its loss is mainly determined by the change of s_i^a . Therefore, the higher the reliability of the UAVs that makes the spatiotemporal resilience loss more important, the smaller their path loss is needed to ensure their normal operation when facing shocks. Therefore, the transformation of UAV is calculated as shown in Eq. (19).

$$Y = \sum_{i=1}^n \sqrt{I_i^{loss}((x_a - x_i)^2 + (y_a - y_i)^2 + h_i^2)}. \quad (19)$$

Similarly, the optimal deployment location of UVs can be obtained based on the UV optimal movement location algorithm.

Recovery stage: We propose a repair and reconfiguration decision based on the importance metric of spatiotemporal elastic recovery.

In the recovery phase, we can prioritize the recovery of UAVs with higher recovery importance, and the non-failed UAVs still perform their tasks normally. This type of recovery does not affect the task execution process and performance of the remaining UAVs. We rank the importance metric of spatiotemporal resilience recovery of damaged UAVs based on UAV damage data collected by IoT. It is difficult to repair all UAVs with limited resources. A high recovery importance metric of a UAV implies a high recovery speed of spatiotemporal resilience to the UAS. Therefore, choosing to reconfigure the UAS after repair is a good option.

The reconfiguration principle lies in the fact that when there is a damaged UAV in the UAV system, the importance metric of spatiotemporal resilience recovery can decide whether the normal UAVs need to carry out the task conversion, replace the damaged UAVs for task execution, and form a new UAV system queue.

The difficulty of the judgment is that when the queue reorganization is carried out, the position in which its UAVs are located is changed, and the optimal position of the UVs needs to be recalculated.

The reconfiguration process needs to follow three principles:

- (1) We prioritize the position reconfiguration of UAVs with a higher importance metric of spatiotemporal resilience recovery.
- (2) All UAVs in the process of reconfiguration must satisfy the normal operation of the data layer.
- (3) We should minimize the sum of the movement distance of UAVs in the process of reconfiguration and that of the UAVs to ensure the saving of resources.

We define the starting time of the recovery of the UAV system as t_i^c , and the change distance of the UAV between UV as s_i^c . The end time is t_i^d , and the change distance of the UAV between UV as s_i^d . The performance recovery of the system during this time period is $Recovery P = P(s_{i,c}^d, t_i^d) - P(s_{i,c}^c, t_i^c)$. Therefore, the spatiotemporal resilience recovery importance metric of the i th UAV is calculated by Eq. (20).

$$I_i^{Recovery} = \frac{\int_{t_i^c}^{t_i^d} \int_{s_{i,c}^c}^{s_{i,c}^d} (P(s, t) - P(s_{i,c}^c, t_i^c)) ds dt}{(t_i^d - t_i^c)(s_{i,c}^d - s_{i,c}^c)}. \quad (20)$$

From Eq. (20), we can see that the mathematical significance of the spatiotemporal resilience recovery importance for the recovery of UAVs leads to the USS unit time, and unit space under the spatiotemporal resilience of the change, the larger the change indicates that the system resilience of USS rises more quickly. Therefore, prioritizing the recovery of UAVs with higher spatiotemporal resilience recovery importance metrics can make the system obtain the maximum spatiotemporal resilience.

When UAVs undergo queue reconfiguration, some of the tasks cannot be executed. To ensure the completion of the mission, it is necessary to wait for the UAVs that can operate normally to complete their own tasks and then continue the remaining missions, and the process often consumes a lot of time. Therefore, as far as the situation allows, we can recover UAVs, and the recovery method can be dispatching new UAVs or repairing the damaged UAVs. When multiple UAVs are destroyed, this paper proposes a recovery sequence based on the importance metric of spatiotemporal resilience recovery to maximize the spatiotemporal resilience of the USS.

Theorem 1: *If the loss parameter of a UAV is larger, it means that the impact on the USS caused by the destruction of that UAV is larger, and the spatiotemporal resilience decreases faster.*

Proof: In the process of UAVs being stricken, to facilitate the calculation, we set the volumetric performance at the beginning as the initial state, then $P(s_{i,c}^a, t_i^a) = 1$, $s_{i,c}^a = 0$. To avoid monotonous contradiction due to time and space, we use t instead of s for the calculation as shown in Eq. (21).

$$\begin{aligned} I_i^{Loss} &= \frac{\int_0^{t_i^b} \int_0^{s_i^b} \left(\sqrt{\left(v \cdot t_i^b + \sqrt{(s_{i,0}^a)^2 - h_i^2} \right)^2 + h_i^2 - s_{i,0}^a} \right) P(s, t) ds dt}{t_i^b s_i^b} \\ &= \frac{\int_0^{t_i^b} \int_0^{s_i^b} \left(\sqrt{\left(v \cdot t_i^b + \sqrt{(s_{i,0}^a)^2 - h_i^2} \right)^2 + h_i^2 - s_{i,0}^a} \right) \frac{\log_{10} \left(\frac{4\pi(s_{i,0}^a)f}{c} \right) e^{-\lambda_i t}}{W \cdot \log_{10} \left(\frac{4\pi(s_{i,0}^a + s)f}{c} \right)} ds dt}{t_i^b \cdot \left(\sqrt{\left(v \cdot t_i^b + \sqrt{(s_{i,0}^a)^2 - h_i^2} \right)^2 + h_i^2 - s_{i,0}^a} \right)}. \end{aligned} \quad (21)$$

The integral is too cumbersome but physically meaningful as spatiotemporal resilience varies per unit of time. We only need to analyze its monotonicity and therefore assign a value to the constant without changing its monotonicity. We define $s_{i,c}^b = s_{i,0}^a = h_i = v = t_i^b = W = f = c = \vartheta$. ϑ can be of any value greater than 0. Here we make $\vartheta = 1$ for ease of computation. Then we obtain a function of λ about $I_i^{Loss}(\lambda_i)$.

$$I_i^{Loss}(\lambda_i) = 1 - \frac{\log_{10} 4\pi \cdot (1 - e^{-\lambda_i})}{\lambda_i \cdot \log_{10} 4\pi \sqrt{2}}. \quad (22)$$

The derivation of it can be obtained as $I_i^{Loss'}(\lambda_i) = -\frac{\log_{10} 4\pi}{\log_{10} 4\pi \sqrt{2}} \cdot \frac{(1+\lambda_i)e^{-\lambda_i}-1}{\lambda_i^2}$. $I_i^{Loss'}(\lambda_i) > 0$ for $\lambda_i > 0$.

It can be observed that $I_i^{Loss}(\lambda_i)$ is monotonically increasing with $\lambda_i > 0$. The larger the UAV's damage parameter λ_i is, the more spatiotemporal resilience the system loses when damaged. Therefore, focusing on and deploying UAVs with larger damage parameters can reduce the spatiotemporal resilience loss of the USS.

□

Theorem 2: *If the recovery parameter of the UAV is larger, it means that the better the boosting effect on the USS caused when recovering that UAV, the faster the spatiotemporal resilience is recovered.*

Proof: If multiple UAVs are damaged, the system's initial recovery rate stays the same regardless of which UAV is prioritized for recovery. We define the recovery process of UAVs as the change process of physical layer performance enhancement. To facilitate the exploration of the importance metric of spatiotemporal resilience, we set the change distance between the UAV and the UV at the beginning of the recovery to be $s_{i,c}^e = 0$, and the change distance at the end of the recovery to be $s_{i,c}^d$. The time at the beginning of the recovery is 0, and the time at the end of the recovery is t_i^d . To avoid the contradictory effects of time and space on spatiotemporal resilience, we analyze the spatiotemporal resilience recovery importance metric of UAVs using time instead of space. The importance metric of UAV spatiotemporal resilience recovery is calculated by Eq. (23).

$$I_i^{Recovery} = \frac{\int_0^{t_i^d} \int_0^{\left(\sqrt{\left(v \cdot t_i^d + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)^2 + h_i^2 - s_{i,0}^a}\right)} \frac{1}{1 + e^{-\alpha_i t}} \cdot \frac{\log_{10}\left(\frac{4\pi s_{i,0}^a f}{c}\right)}{W \cdot \log_{10}\left(\frac{4\pi(s_{i,0}^a + s)f}{c}\right)} ds dt}{t_i^d \cdot \left(\sqrt{\left(v \cdot t_i^d + \sqrt{(s_{i,0}^a)^2 - h_i^2}\right)^2 + h_i^2 - s_{i,0}^a}\right)}, \quad (23)$$

where α_i is the recovery parameter, which is jointly determined by the difficulty of repairing the UAV by the repairman, recovery time consumption and other factors. In this paper, α_i is determined by the area of the UAV's executable mission.

The process of solving the dual integration in this formula is too complicated. To simplify the process, we choose to assign certain constants without changing the overall monotonicity. Similarly, we only need to analyze its monotonicity and therefore assign a value to the constant without changing its monotonicity. We set $W = s_{i,0}^a = h_i^2 = v = f = c = t_i^d = s_i^f = \forall$. $\forall$ can be any value greater than 0, here we make $\forall = 1$ for ease of computation. We use the Gaussian approximation to solve the problem to obtain an expression for α_i , as shown in Eq. (24).

$$I_i^{Recovery}(\alpha_i) = \frac{\int_0^1 \int_0^{\sqrt{2}-1} \frac{1}{1 + e^{-\alpha_i t}} \cdot \frac{\log_{10}(4\pi)}{\log_{10}(4\pi\sqrt{(t)^2 + 1})} dt dt}{\sqrt{2} - 1}. \quad (24)$$

This part of the integral is difficult to solve analytically. We derive $I_i^{Recovery}(\alpha_i)$ and obtain $I_i^{Recovery'}(\alpha_i) = \frac{\int_0^1 \int_0^{\sqrt{2}-1} \frac{e^{-\alpha_i t} \times t}{(1 + e^{-\alpha_i t})^2 \log_{10}(4\pi\sqrt{(t)^2 + 1})} dt dt}{\sqrt{2} - 1}$. The $\frac{e^{-\alpha_i t} \times t}{(1 + e^{-\alpha_i t})^2}$ with $\frac{\log_{10}(4\pi)}{\log_{10}(4\pi\sqrt{(t)^2 + 1})}$ is always positive, so that for $\alpha_i > 0$, $I_i^{Recovery'}(\alpha_i) > 0$.

It can be observed that $I_i^{Recovery}(\alpha_i)$ increases monotonically in $(0, \infty)$. The larger the recovery parameter α_i of the UAV is, the faster the spatiotemporal resilience of the system grows. Therefore, optimally prioritizing the recovery of UAVs can benefit the fastest growth in the spatiotemporal resilience of the USS. $\square$

Combining Eq. (18) and Eq. (20), the spatiotemporal resilience importance metric of UAVs can be obtained as Eq. (25).

$$I_i^{resilience} = \frac{I_i^{Recovery}}{I_i^{Loss}} = \frac{(t_i^a - t_i^b) \cdot (s_{i,c}^a - s_{i,c}^b) \cdot \int_{t_i^a}^{t_i^d} \int_{s_{i,c}^a}^{s_{i,c}^d} (P(s, t) - P(s_{i,c}^c, t_i^c)) ds dt}{(t_i^d - t_i^c) \cdot (s_{i,c}^d - s_{i,c}^c) \cdot \int_{t_i^a}^{t_i^b} \int_{s_{i,c}^a}^{s_{i,c}^b} (P(s, t) - P(s_{i,c}^b, t_i^b)) ds dt}. \quad (25)$$

The mathematical implication of the spatiotemporal resilience importance metric is the ratio of the rate of the spatiotemporal resilience reduction of the system per unit of time and per unit of space during UAV destruction to the rate of the spatiotemporal resilience recovery of the system per unit of time and per unit of space during UAV destruction. In other words, a UAV with a high resilience importance metric has a high priority to be restored over other UAVs and the benefit of recovering this UAV is higher than other UAVs. The performance assessment methods can produce different results, depending on the mission scenarios. The importance metric can be calculated by simulation.

5 Simulation results and discussions

We take a USS consisting of six UAVs and one UV as an example. The mission is defined as a strike destroying event of the UAVs, and the strikes are divided into two kinds, the precise strikes facing the physical layer and the disruptive strikes facing the data layer. A strike may destroy the UAV. In the process of UAV cluster execution, there are two types of detection methods, namely, aggregation to keep the distance of formation and diffusion detection, and diffusion detection is selected as the research content in this paper. Among the UAV cluster formations that implement detection, hexagonal formations, V-shaped formations, and snake-shaped formations are the most common, and this algorithm selects the positive hexagonal formation with structural stability as the object of study, which can ensure the stability of the signal transmission between UAVs and UAVs in the process of implementing diffuse detection. In this paper, to facilitate the discussion of the performance variation of UAVs, we define that the detection speed of UAVs is the same, and the UAV system conforms to the minimum collision avoidance distance and carries out the straight-line detection according to a certain route.

We monitor the USS to calculate the three-dimensional performance and spatiotemporal resilience concepts proposed in this paper and to demonstrate the feasibility of the entire process optimization method of spatiotemporal resilience of the system proposed in this paper.

We define the impact magnitude as $W = 1.0$, and the importance metric of the data and physical layers of the USS are the same, i.e., $I_d = I_c$. According to the relevant regulations and standards, the maximum transmit power of a UV as a mobile base station cannot exceed a certain threshold. For example, in the U.S., the FCC (Federal Communications Commission) stipulates that the maximum transmit power of a UV as a mobile base station must not exceed 30dBm. The sources are from <https://www.fcc.gov/consumers/guides/human-exposure-radio-frequency-fields-guidelines-cellular-and-pcs-sites>. In the EU, ETSI specifies that the maximum transmit power of an UV as a mobile base station must not exceed 25dBm. We therefore define the maximum value of the signal transmit power of a UV to be 25dBm. The message is derived from <https://www.fcc.gov/help/public-safety-tech-topic-17-propagation-characterization>. Common UAV communication standards such as FSK (Frequency Shift Keying) or FSK modulation in telemetry systems, the receiver sensitivity may range from -100dBm to -90dBm depending on the quality of the wireless module and the modulation used. Therefore, we define the power sensitivity received by the UAV as -100dBm. Then the maximum path loss between the UAV and the UAV is 125dBm. the frequency is taken as $f = 2.4\text{GHz}$, $c = 3 \times 10^8$, $\pi = 3.14$.

The spatial positions, detection speeds, and reconnaissance distances of the UAVs are shown in **Table 1**.

Table 1. Distribution of UAVs locations and mission execution distance

<i>UVA</i>	<i>X/km</i>	<i>Y/km</i>	<i>Z/km</i>	<i>V km/h</i>	<i>s_{mission}/km</i>
1	0	3	2	60	20
2	$\sqrt{3}$	0	2	60	20
3	$3\sqrt{3}$	0	2	60	20
4	$4\sqrt{3}$	3	2	60	20
5	$3\sqrt{3}$	6	2	60	20
6	$\sqrt{3}$	6	2	60	20

Since $I_d = I_c$, the effect of the velocity difference on the spatiotemporal resilience of the system is not considered. Based on the detectable area of the six UAVs we can see that the UAVs do not all have the same importance. However, we need to determine whether the deployment of UAVs at that shock amplitude according to the case of equal importance will lead to the failure of many UAVs.

According to Eq. (17), when the value of Y is minimized, the initial position of the UV can be obtained as (3.46,3.00). We find that the position of the UAV does not change when the UAV swarm practices diffuse detection, so $v^{UV} = 0$. According to the UAV detection speed given in the table, we know that $v_i = v^{UVA} - v^{UV} = 60km/h$.

We define that the physical layer strike occurs at $4 < t \leq 9min$ and the data layer strike lasts until the end of the detection mission. Calculate the path loss at the maximum detection distance under the strike: $P_{L,i}^{max} = W \cdot 20 \cdot \log_{10}\left(\frac{4\pi\sqrt{445 \times 10^3}f}{c}\right) = 126.5dBm > 125dBm$. By calculating the maximum path loss, the maximum distance that the UAV can be operated under the strike amplitude is $W \cdot 20 \cdot \log_{10}\left(\frac{4\pi s f}{c}\right) = 125dBm$, and the maximum distance between UAV and UV is 17.7km.

Based on the positive hexagonal formation and the arrangement of UVs, all the UVs have the same positional distance from the UAVs of $2\sqrt{3}km$. Then the initial positional distance between the UAVs and the UVs is 4 km. then, when $s \geq 13.7km$, the sensors on the UAVs cannot decode the signals received from the UVs due to the distance is too long, and the signal frequency received is too small to decode the signals, which results in the performance of the data layer of 0. The UV swarm needs to carry out 18km detection mission. A detection mission of an 18km is required. Therefore, the UAV swarm will produce a collective failure when it does not complete the detection mission. Therefore, in the prevention strategy for UAV swarm, we can use the spatiotemporal resilience loss of importance for the deployment of UAV locations.

The damage and recovery parameters and durations of the UAVs are shown in **Table 2**.

Table 2. Strike duration and recovery duration

<i>UVA</i>	λ_i	<i>time/min</i>	α_i	<i>time/min</i>
1	0.5000	5	0.01	3
2	0.1111	5	0.5	3
3	0.0667	5	2.5	3
4	0.0833	5	0.001	3
5	0.1111	5	1.5	3

6 0.0625 5 0.2 3

We calculate and rank the spatiotemporal resilience loss importance, spatiotemporal resilience recovery importance, and resilience importance metric of UAVs, as shown in **Table 3**.

Table 3. Importance metric of spatiotemporal resilience at different stages

UAV	I_i^{Loss}	Rank	$I_i^{Recovery}$	Rank	$I_i^{Resilience}$	Rank
1	643	1	500	4	0.778	6
2	255	2	944	2	3.702	4
3	174	4	950	1	5.460	1
4	206	3	477	5	2.316	5
5	255	2	950	1	3.725	3
6	166	5	845	3	5.090	2

From **Table 3**, we can know the spatiotemporal resilience loss importance, spatiotemporal resilience recovery importance, and spatiotemporal resilience importance metric of each UAV. It is worth mentioning that the spatiotemporal resilience loss importance metric of UAV 1 and UAV 5 are the same, and it is impossible to distinguish the importance metric of prevention, so when ranking UAVs 1, and 5, we refer to the spatiotemporal resilience importance as a reference basis for reordering the importance metric of UAVs. We can see that $I_5^{Resilience} > I_1^{Resilience}$. Therefore, in the deployment of importance, UAV 1, 5 can be considered at the same time if there are enough resources. Similarly, when analyzing UAV 3 and UAV 5, both have the same spatiotemporal resilience recovery importance. Thus, the recovery order needs to be judged with the help of spatiotemporal resilience importance $I_3^{Resilience} > I_5^{Resilience}$, when resources are limited, the prevention priority of UAV 5 is greater than that of UAV 1, and the recovery priority of UAV 3 is greater than that of UAV 5.

To visualize the difference in the spatiotemporal resilience importance metric of UAVs, we magnified the spatiotemporal resilience importance by 10 times and performed bar chart statistics on the data in this table, as shown in **Fig. 6**.

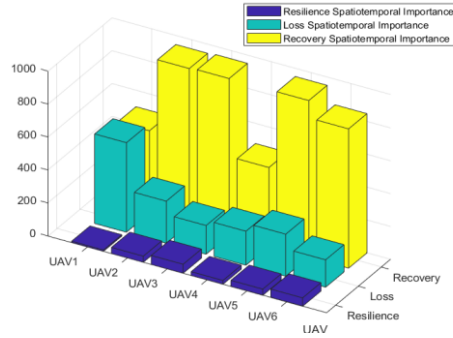


Fig. 6. Resilience value of each UAV in the USS

Because of the different importance metrics of spatiotemporal resilience loss, when the UAV swarm is detecting, the UV will change according to the location distance, and its path follows $Y = \sum_{i=1}^n \sqrt{I_i^{loss}((x_a - x_i)^2 + (y_a - y_i)^2 + h_i^2)}$. Bringing the coordinate points of each UAV, according to the optimal movement path algorithm for UV, we can obtain the initial UAV coordinates as (2.60,2.95,0). According to the

position change of the UV, we can calculate the distance change between the UV and each UAV. The height of each UAVs is the same, we plot the trajectory of the UV and the position of the UAV, and the 3D image is shown in Fig. 7.

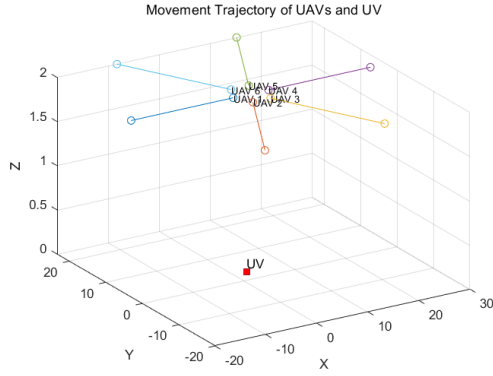


Fig. 7. Location deployment of the UV and the trajectory of the UAVs

It is obvious from the figure that the UAV is arranged close to UAV 1. Because the loss importance metric of UAV 1 is larger, the path loss of UAV 1 should be minimized to make UAV 1 more reliable. This also justifies the arrangement.

The temporal performance of UAVs when no strike occurs is unchanged, and the spatial performance varies the same, to see the change of UAVs' performance more conveniently, we analyze the performance of each UAV. At $0 < t \leq 4$, the UAV is only strike by the data layer, the physical layer performance is not affected, and the physical layer performance is constant at 1. We only count the performance changes that occur with spatial changes. When $4 < t \leq 9$, the physical layer strikes, and the spatial performance changes are the same, so we compare the performance changes of the UAV over time. Following the destruction and performance changes of the UAVs, combined with Eq. (5), we can plot the performance changes of the six UAVs, which are shown in Fig. 8.

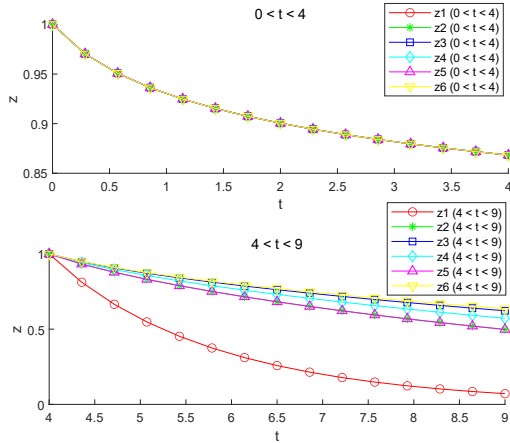


Fig. 8. Performance change of UAVs in the USS

From Fig. 8, we can see that UAV 1 causes the performance of the system to drop faster when it is struck,

which also coincides with the importance metric of temporal and spatial resilience loss in the prevention stage proposed in this paper.

Combining the spatiotemporal performance changes of the six UAVs, we can obtain the three-dimensional performance changes of the USS with the spatiotemporal strike stages as shown in **Fig. 9**.

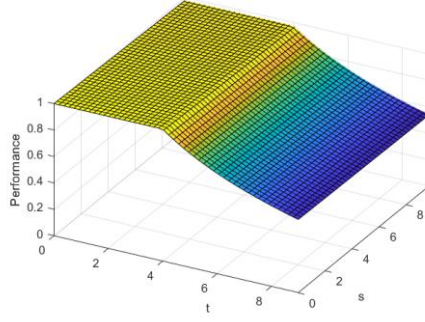


Fig. 9. Performance change when the USS suffers a strike

Recovery stage: we consider two recovery strategies: repair and reconfiguration. We define that with limited resources; we can only choose to repair no more than two UAVs. According to the principle of spatiotemporal resilience recovery importance, we choose to prioritize the repair of UAVs with high spatiotemporal resilience recovery importance.

We assume that UAVs 1, 5 and 6 cannot complete their work normally when $t = 9min, s = 10.8km$. From **Table 2**, it can be noticed that the spatiotemporal resilience recovery importance for UAV 1 is low. Therefore, UAV 1 has a lower repair priority and is not selected for repair. UAVs 5 and 6 have greater importance metric of spatiotemporal resilience recovery and it is more cost-effective to repair them to a normal state. We repair UAVs 5 and 6, and the recovery process produces an improvement in the spatiotemporal performance of the USS.

Reconfiguration: the restoration process shows that UAV 1 did not perform recovery, but the normal situation is no longer able to complete the detection. Therefore, when the USS cannot be restored to the original state, we choose to reconfigure it by calling the UAV that has already completed the detection mission to reorganize its structure to complete the detection mission instead of UAV 1, and the reconfiguration process obeys the shortest path principle.

According to the principle of shortest path, we choose UAV 2 or 3 to reconfigure the position of UAV 1, comparing the importance metric of spatiotemporal resilience recovery of UAVs 2 and 3, we find that $I_2^{Loss} > I_3^{Loss}$, which indicates that timely UAV 2 will have a greater impact overall USS if it is damaged in the reconfiguration process. Therefore, UAV 3 is selected to continue the detection mission of UAV 1, and the reconfiguration process is shown in **Fig. 10**.

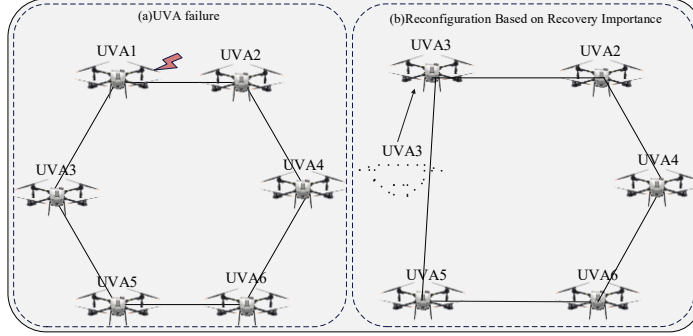


Fig. 10. Reconfiguration process of UAV system

After forming the new USS structure and continuing the mission, we can obtain the entire mission process spatiotemporal performance change of the USS, which is as shown in **Fig. 11**.

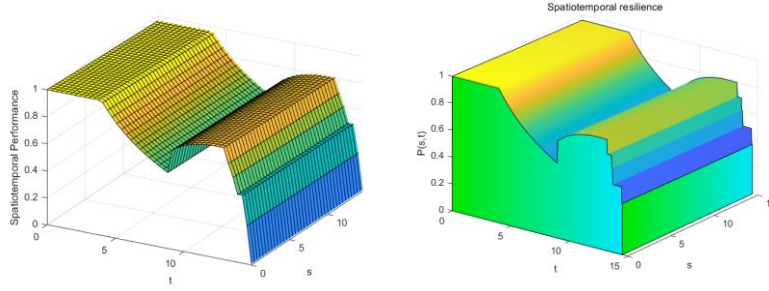


Fig. 11. Spatiotemporal Performance and resilience change of the USS

By calculating its dual integration, we can calculate the spatiotemporal resilience of the USS in the prevention stage, the spatiotemporal resilience in the recovery stage, and the spatiotemporal resilience of the whole system, respectively:

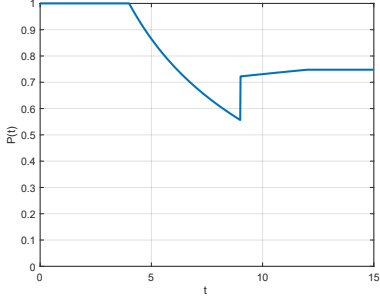
$$R_{prevent} = \frac{\int_4^9 \int_{3.727}^{8.624} P(s, t) ds dt}{\int_4^9 \int_{3.727}^{8.624} P(s_0, t_0) ds dt} = 0.461$$

$$R_{recovery} = \frac{\int_9^{12} \int_{8.624}^{11.593} P(s, t) ds dt}{\int_9^{12} \int_{8.624}^{11.593} P(s_0, t_0) ds dt} = 0.478$$

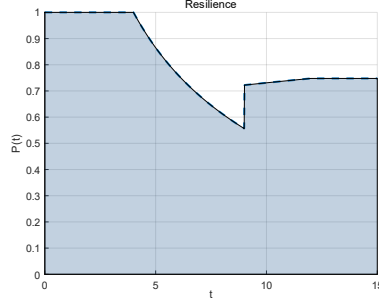
$$R = \frac{\int_0^{14.98} \int_0^{14.55} P(s, t) ds dt}{\int_0^{20} \int_0^{20} P(s_0, t_0) ds dt} = 0.276$$

To demonstrate the advantages of the spatiotemporal resilience modeling and the whole process optimization strategy for USS proposed in this paper, we chose to compare with the latest USS resilience study. We select the base station arrangement carried out during the prevention process of the USS in a random state and assume that the strength of the strikes received is unchanged and the performance of each UAV changes consistently. In the prevention stage, we arrange the location of base stations according to equal distance. In the recovery stage, we choose to prioritize the recovery of UAVs 1 and 6. Repeating the above simulation process, we can obtain the comparison of the spatiotemporal performance and spatiotemporal resilience variation curves of the USS proposed

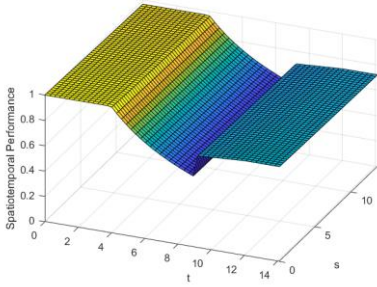
in this paper with the current latest research, as in Fig. 12.



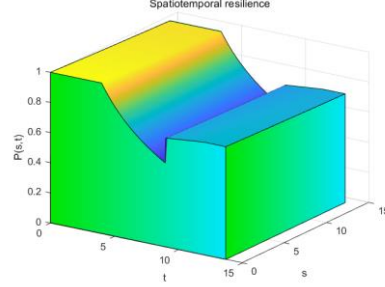
(a) Performance value of the latest studied USS



(b) Resilience value of the latest studied USS



(c) Spatiotemporal performance value of USS



(d) Spatiotemporal resilience value of USS

Fig. 12. Performance and resilience change of USS in whole process

Through the comparison of Fig. 12 (a)-(d), we clearly find that the model of spatiotemporal resilience proposed in this paper adds a measure of the spatial dimension of the USS to the original concept of the time dimension, and the model has obvious advantages when compared to the latest resilience studies of the USS.

In Fig. 12, we can see that when there is no advance deployment based on the importance metric of spatiotemporal resilience loss as proposed in this paper, the USS will reduce the spatiotemporal performance to 0 at $t = 14.12min$, $s = 15.05km$ and the spatiotemporal resilience generated by recovering UAVs in the recovery stage at $t = 9$ is lower.

We can calculate the spatiotemporal resilience of the prevention stage, the spatiotemporal resilience of the recovery stage and the spatiotemporal resilience of the whole system according to the randomized prevention arrangement and the randomized recovery strategy, respectively:

$$R_{prevent} = \frac{\int_4^9 \int_{3.727}^{8.624} P(s, t) ds dt}{\int_4^9 \int_{3.727}^{8.624} P(s_0, t_0) ds dt} = 0.460,$$

$$R_{recovery} = \frac{\int_9^{12} \int_{8.624}^{11.593} P(s, t) ds dt}{\int_9^{12} \int_{8.624}^{11.593} P(s_0, t_0) ds dt} = 0.441,$$

$$R = \frac{\int_0^{14.123} \int_0^{13.700} P(s, t) ds dt}{\int_0^{20} \int_0^{20} P(s_0, t_0) ds dt} = 0.248.$$

After comparing with the whole-process momentary resilience optimization strategy proposed in this paper, it

is found that the method improves the spatiotemporal resilience of the USS by 0.22% in the prevention stage and by 7.80% in the recovery stage. The spatiotemporal resilience of the whole USS is improved by 11.30%, which makes the USS more resistant to strikes.

6 Conclusions

This paper proposed a new spatiotemporal resilience model to describe USS states. It modelled the USS based on the Internet of Things, focusing on the performance changes in the physical and data layers of the USS in the event of enemy strikes. To measure the performance of USS with respect to time and space more accurately, this paper proposed a concept of spatiotemporal performance. It also introduced a method to optimize the spatiotemporal resilience of USS at different stages. In the prevention stage, a UV best path algorithm is proposed for data layer optimization based on loss importance. This paper considered the case of being strike by the physical layer and selected the appropriate deployment scheme according to the different intensities of the strike. In the recovery stage, this paper proposed a recovery scheme based on the spatiotemporal resilience recovery importance. Prioritizing the recovery with high spatiotemporal resilience recovery importance improves the system's spatiotemporal resilience the fastest.

The research in this paper has some limitations. During the simulation, we did not study the more complex USS, which consisted of only six UAVs and one UV. When there are multiple UVs and many UAVs in the USS, how to divide the UVs and UAVs into subsystems and how to evaluate the effect of multiple division methods is still a difficult problem. In the future, we will study more complex USSs, as well as the problem of optimizing and evaluating the subsystem division of USSs and strategies.

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