Computers & Industrial Engineering 214 (2026) 111836

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

# Reconfigurable operation-loop network modeling and resilience optimization considering mission load

Yuheng Dang [a], Hengte Du [a], Xu Wang [a], Xing Pan [a,b,*]

[a] School of Reliability & Systems Engineering, Beihang University, Beijing, China
[b] National Key Laboratory of Reliability and Environmental Engineering, Beijing, China

ARTICLE INFO

*Keywords:*
Reconfigurable
Multi-agent network
Resilience optimization
Mission load

ABSTRACT

Multi-agent systems (MAS), as a representative complex system, have become crucial for analyzing cluster and heterogeneous behaviors in various domains such as biology, social science, military weapon and manufacturing. The MAS exhibits adaptability to environmental changes and can dynamically reconfigure its structure to enhance resilience while reducing vulnerability. However, existing research primarily focuses on proposing reconfiguration strategies to enhance resilience but lacks in-depth exploration of reconfigurable design and capability constraints. The study proposes a reconfigurable operation-loop network (RON) model for resilience analysis and reconfigurable design of MAS based on the operation loop. Subsequently, the performance measurement and resilience metric are presented for RON considering mission load. Furthermore, the mathematical model and optimization framework of reconfiguration are established with the consideration of reconfigurable attributes and the resilience objective. Finally, the feasibility, effectiveness, and superiority of the proposed models and metrics are illustrated through extensive experiments on case based on an emergency response system. Numerical results demonstrate that the performance metric considering mission load contributes to a more accurate assessment of RON resilience than conventional network metrics. This work could yield valuable insights for the reconfigurable and resilient design of MAS, while providing guidance and serving as a reference for future research efforts.

## 1. Introduction

Multi-agent system (MAS) is a class of complex systems that exemplify both natural and socio-technical systems, including colonies (You and Liu, 2024), unmanned aerial vehicle (UAV) swarms (Zhou et al., 2024), equipment systems of systems (SoS) (Sun et al., 2022), decentralized autonomous manufacturing (Leng et al., 2023) among others. Each agent within the MAS represents an independent entity, equipped with distinct modular functionalities designed to fulfill specific mission requirements for perception, decision-making, and execution (Li et al., 2021). With the development of network information technology and artificial intelligence (AI) technology, MAS has been empowered with the interconnection and autonomous capability. Heterogeneous agent swarms can not only autonomously perceive, make local decisions and execute rapidly, but also achieve a closed loop of collaborative operation from perception to decision-making and then to execution for the target through network communication. Especially in the manufacturing field, within the context of Industry 5.0, the decentralized and autonomous manufacturing paradigm based on blockchain technology provides a decentralized and distributed approach for the implementation of the autonomous and collaborative behaviors of MAS (Leng et al., 2023). The closed-loop work flow of heterogeneous MAS aiming at a target under network interconnection conditions is defined as the operation loop (Pan et al., 2019). It models and abstracts the distributed collaborative working process of heterogeneous agents. A target can potentially have multiple parallel loops, which leads to the complex interconnection structure within MAS.

Due to the increasing complexity and interconnection, MAS exhibit heightened vulnerability exposed to the risks from internal faults as well as external disruption and interference. Traditional anti-interference and reliability methods are difficult to adapt to dynamic risks and disturbance conditions, especially in fields such as intelligent transportation (Pan et al., 2022), unmanned equipment swarms (Hu et al., 2025), and decentralized manufacturing (Leng et al., 2023), which emphasize the distributed and autonomous collaboration of agents. Passive resistance and redundancy measures alone are insufficient to

* Corresponding author at: School of Reliability & Systems Engineering, Beihang University, Beijing, China.
*E-mail address:* panxing@buaa.edu.cn (X. Pan).

https://doi.org/10.1016/j.cie.2026.111836
Received 18 September 2025; Received in revised form 13 January 2026; Accepted 17 January 2026
Available online 23 January 2026

fulfill the requirements of flexibility and self-organization of MAS. Consequently, resilience-oriented methods are proposed to mitigate the disturbances and risks and enhance robustness and recoverability of MAS (Li et al., 2023). Resilience, defined as a system's ability to absorb impacts and maintain the stable operation following exposure to disruptive events, is a critical concept in the study of sustainable systems, such as ecological, social and engineering systems (Ouyang and Wang, 2015; Liu et al., 2022; Leng et al., 2025). Resilience of MAS underscores the measures that ensure reliable and continuous operation based on flexible configuration, dynamic behavior and interactions among entities (Hu et al., 2025).

Reconfiguration serves as a typical resilient recovery strategy and represents a key manifestation of resilience in MAS (Chen et al., 2023). Reconfiguration has received considerable attention in research on enhancing the resilience of MAS. For unmanned equipment swarms, reconfiguration is an adaptive control method that adjusts formation in response to the environment, which helps enhance the resilience of the swarms (Feng et al., 2022; Shao et al., 2023). For networks, reconfiguration refers to the reconnection of network nodes to search for the optimal topological structure under specific disturbances (Shan et al., 2021). For decentralized manufacturing, reconfiguration is regarded as the real-time adjustment capability and approach of the manufacturing system in response to frequent disturbances (such as equipment failures and order changes), maintaining system stability by reallocating production tasks and optimizing resource paths (Leng et al., 2024).

However, recent research considers reconfiguration as a resilience-enhancement strategy rather than a designable attribute of MAS. Furthermore, mission load is seldom taken into account in the reconfiguration of MAS, leading to inaccuracy in resilience evaluation. Therefore, the research questions can be summarized as follows:

(i) Reconfigurable operation-loop network modeling of MAS.
(ii) Performance and resilience evaluation considering mission load of MAS.
(iii) Reconfiguration-based resilience optimization of MAS.

This work aims to address the above-mentioned questions and challenges of reconfigurable design and resilience evaluation for MAS. The main contributions of this study are summarized as follows:

(i) Reconfigurable operation-loop network (RON) model is proposed and designed based on the operation loop composed of sensor, decider, actor in MAS. The model comprehensively considers the reconfigurable attributes, including entity redundancy, functional substitution, load affordability and resource accessibility, which provides support for resilience design of MAS.
(ii) A performance measurement and a multi-parameter resilience metric for RON are developed based on node-load centrality considering mission load during reconfiguration. This resilience metric can effectively describe the resilience of the MAS and provide resilience optimization targets for the reconfiguration model.
(iii) The proposed model and metric support the optimal mathematical model of reconfiguration, and a framework for optimal reconfigurable scheme generation of RON is provided, mainly including resilience-oriented objective, constraints of reconfigurable attributes, encoding and decoding for reconfiguration, and optimization algorithm.

The remainder of this paper is organized as follows. A comprehensive literature review on resilience measurement and reconfiguration is provided in Section 2. In Section 3, brief definitions, network model, and performance measurement of RON are introduced. The proposed resilience metric considering mission load and model framework of optimal reconfiguration are presented in Section 4. The case study is presented to verify the proposed model in Section 5. Section 6 answers research questions and discusses our findings. Finally, concluding remarks and future work are presented in Section 7.

## 2. Literature review

In this section, a comprehensive review of the current research is conducted from two aspects: resilience measurement and resilience enhancement. The contributions and limitations of the existing research are demonstrated to reinforce the purpose and motivation of this paper.

### 2.1. Resilience measurement

Resilience refers to the capacity of systems to absorb disturbances, and is measured by an indicator that quantifies the magnitude of perturbations a system can withstand while maintaining a given steady state. Originally introduced by Holling in the field of ecology, this concept has since gained broad application across disciplines (Holling, 1973).

The resilience measurement is the cornerstone for resilience enhancing and design, which determine the choice of enhancement measures and design of structure (Kakadia and Ramirez-Marquez, 2020; Guo et al., 2020). Performance is normally the measurement of a MAS to efficiently operate in function, usually obtained from actual system operations and modeling and simulation. Quantitative assessment of resilience relies on the time function of performance, mainly divided into quotient and integral resilience models (Cheng et al., 2022). The quotient resilience model depicts the ratio of recovered performance to lost performance. Resilience triangle model is the well-known metric of integral resilience, where the performance of the disrupted system is compared to desired performance by integrating over time. With the consideration of comprehensive assessment for resilience, the multi-parameter model is proposed based on the factors of system performance, recovery, absorption, volatility, and recovery time. A variety of modified resilience metrics based on multi-parameter models are developed for diverse scenarios within MAS, such as UAV swarm and equipment SoS. Resilience is regarded as being independent of robustness in the manufacturing domain. The former refers to the ability of a system to maintain or quickly recover to a stable state during and after a major mishap under severe disruptions or in the presence of continuous significant stresses, while the latter refers to the system's capacity to absorb frequent disturbances with minimal impact on system performance. Therefore, the quantitative assessment of resilience should focus on situations where there are significant fluctuations in manufacturing system performance. Table 1 summarizes the related general resilience measurements used in previous studies.

Since these resilience metrics significantly contribute to the resilience analysis and optimal design for reconfiguration of MAS, they inadequately consider reconfigurable attributes and resilience constraints, especially insufficient recovered performance caused by mission-load during reconfiguration.

### 2.2. Resilience enhancement and reconfiguration

Research on resilience-enhancing measures has primarily focus the two prospective: pre-failure resistance and post-failure recovery. As for pre-failure resistance, allocating redundant entities and interconnection is the widely adopted approach to enhance resilience of MAS, as derived from traditional reliability theory (Li et al., 2020). Critical entities protection exerts a pivotal influence on robustness and resilience of MAS as well. Pre-failure resistance is a proactive resilience enhancement strategy that relies on predictive design and adaptive learning to build a defense line for the system before disturbances and damages occur. For instance, in the context of Industry 5.0, deep learning (DL) and neural networks are frequently employed to predict equipment deterioration, thus transforming equipment maintenance practices from reactive repairs to proactive interventions.

**Table 1**
Related resilience measurements.

| Reference | Year | Resilience measurement | Applicablescenario |
|---|---|---|---|
| Luo (Luo and Yang, 2002) | 2002 | Duration of the hazard and recovery periods | Infrastructure resilience |
| Bruneau (Bruneau et al., 2003) | 2003 | Performance integrating over time | Infrastructure resilience |
| Lloret (Lloret et al., 2011) | 2011 | Ratio of performance at the time of maximum loss to initial performance | Ecological resilience |
| Henry (Henry and Emmanuel, 2012) | 2012 | Ratio of recovered performance to degraded performance | Network resilience |
| Torabi (Torabi et al., 2015) | 2015 | Time-weighted sum of the lost capacity recovered by the resilience strategies | Manufacturing resilience |
| Tran (Tran et al., 2017) | 2017 | Piecewise function including multiple parameters of system performance, recovery, absorption, volatility, and recovery time | Network resilience |
| Zou (Zou and Chen, 2019) | 2019 | Weighted sum of recovered performance and degraded performance | Infrastructure resilience |
| Dhulipal (Dhulipala and Flint, 2020) | 2020 | Ratio of the performance integral over a time period and the length of the period | Infrastructure resilience |
| Bai (Bai et al., 2020) | 2020 | Modified function based on multi-parameter models of Tran | Network resilience |
| Sun (Sun et al., 2022) | 2022 | Multi-parameter function based on mission baseline | Network resilience |
| Chen (Chen et al., 2023) | 2023 | Weighted sum of resistance, adaptability, and recovery factors | Network resilience |
| Leng (Leng et al., 2025) | 2023 | Resilience triangle model under large performance fluctuations | Manufacturing resilience |
| Our study | 2025 | Multi-parameter function considering mission load during reconfiguration | Network resilience |

Furthermore, dynamic models of MAS response to disruption and attack are commonly studied with a consideration of uncertain and unpredictable environment. Effective restoration strategies for MAS can enhance both the speed of recovery and post-restoration performance (Pan et al., 2022). Programming models serve as conventional methodologies for generating recovery strategies, primarily by formulating the mathematical model of resilience optimization objectives and constraints based on actual disruption information and state of system. Additionally, the cost of resilience enhancement can not only be regarded as a fixed constraint but also as a trade-off factor in the design of system resilience (Zhang et al., 2021; Yousefi et al., 2019). In response to the emphasis on human-centricity and sustainability in the EU's Industry 5.0 White Paper, the resilience optimization problem can be extended to a multi-objective optimization problem aiming to maximize resilience, minimize resource consumption, and minimize the decision-making burden on personnel (Leng et al., 2024).

Moreover, reinforcement learning (RL) is considered a promising approach for addressing sequential recovery decisions in MAS without prior knowledge or a predefined model. RL enables continuous interaction with the disturbance environment and facilitates the self-recovery of MAS from a global perspective.

Reconfiguration is a kind of dynamic and spontaneous process aimed at post-failure recovery, which has garnered significant attention in the research on resilience enhancement of MAS (Zhao et al., 2023). Reconfiguration in MAS denotes its intrinsic capability to dynamically adapt its architecture in response to disruption. Such reconfiguration processes aim to re-instantiate a coordinated architecture that simultaneously addresses emergent operational demands and preserves systemic efficiency under dynamic constraints (Zhao et al., 2019). The current research studies several practical reconfiguration strategies for resilience enhancement. The formation reconfiguration strategies are proposed for cluster system, such as UAV swarms, to achieve the resilience optimization in the face of stochastic disruptions. For MAS with abundant connection, the remaining entities can be reconnected to form a new topology structure through the strategy of network reconstruction. Multiple MAS can share entities with same function to perform their respective missions, enabling distinct MAS ensembles to coalesce into an integrated MAS architecture. Furthermore, the decentralized reconfiguration strategy based on blockchain technology has been proposed. When an entity fails, adjacent entities can automatically negotiate the redistribution of tasks through predefined contract rules without the need for permission from the control center. The decentralized reconfiguration strategy incurs a certain performance cost but offers considerable resilience and data privacy (Leng et al., 2024). Table 2 summarizes the related resilience enhancing methods in previous studies.

MAS represents a complex adaptive system wherein reconfiguration is an intrinsic and fundamental mechanism (Shan et al., 2021), rather than merely a strategic approach. Although previous studies have successfully enhanced resilience through reconfiguration strategies, they have not adequately illustrated the inherent reconfigurable characteristics that enable MAS to maintain stable and resilient operations under disturbances (Chen et al., 2023). Notably, there is a lack of a network model specifically designed to capture the reconfigurable characteristics, which would illuminate both its internal reconfiguration mechanisms and capability constraints. The reconfigurable attributes of MAS constitute the cornerstone of its resilience. To comprehensively and

**Table 2**
Related resilience enhancing methods.

| Reference | Year | Resilience enhancing method | Applicable scenario |
|---|---|---|---|
| Liu (Liu et al., 2024) | 2024 | Critical entities protection | Pre-failure resistance |
| Li (Li et al., 2020) | 2020 | Dynamic response to disruption and attack in uncertain and unpredictable environment | Pre-failure resistance |
| Leng (Leng et al., 2025) | 2025 | Reserve backup equipment, buffer inventory or dual supply chains in system design to ensure that local failures do not spread | Pre-failure resistance |
| Leng (Leng et al., 2024) | 2024 | By training predictive models through federated learning, the risk of equipment failure can be identified in advance, preventative maintenance instructions can be triggered | Pre-failure resistance |
| Leng (Leng et al., 2024) | 2024 | RL agent learns the optimal scheduling strategy, avoiding resource conflicts or bottlenecks in advance. | Pre-failure resistance |
| Almoghathawi (Almoghathawi et al., 2019) | 2019 | Recovery strategies generation based on programming models | Post-failure recovery |
| Sun and Tan (Tan et al., 2024) | 2024 | Self-recovery strategy based on RL | Post-failure recovery |
| Feng (Feng et al., 2022) | 2022 | Formation reconfiguration strategies to achieve the resilience optimization in the face of stochastic disruptions | Post-failure recovery |
| Tran (Tran et al., 2015) | 2015 | Network reconstruction strategies to form a new topology structure | Post-failure recovery |
| Chen (Chen et al., 2024) | 2024 | Entities share with same function enable the reconfiguration | Post-failure recovery |
| Our study | 2025 | Reconfigurable attributes modeling and reconfiguration-based resilience optimization | Post-failure recovery |

fundamentally elucidate the resilience, it is essential to augment the relevant reconfigurable attributes from a modeling perspective, thereby providing the theoretical support for resilience optimization and design of MAS.

## 3. Network modeling and assessment

In this section, the RON model of MAS is proposed based on the conception of reconfigurable operation loop, and then the performance measurement with a consideration of mission load is presented for resilience evaluation and optimization.

### 3.1. Reconfigurable operation loop

Perception, decision-making, and execution constitute essential functions that are pervasive across biological and automated systems. MAS can be regarded as consisting of a multitude of entities equipped with perception, decision-making, and action capabilities (Pan et al., 2019; Ling et al., 2005). To accomplish the specific mission, the entities responsible for perception, decision-making, and action constitute a closed operation loop aiming at the target entity of mission, as illustrated in Eq. (1) (Li et al., 2021):

$$T \rightarrow S \rightarrow D \rightarrow A \rightarrow T \quad (1)$$

where $S$, $D$, and $A$ represents the sensor entities, decider entities, actor entities in MAS, respectively, while $T$ denotes the target entities that MAS aims to achieve.

MAS is a complex adaptive system characterized by its resilience, which enables it to dynamically adjust its structure and functional relationships to adapt to varying tasks and environmental conditions (Guo et al., 2017; Mohd Subha and Mahyuddin, 2021). This dynamic adjustment, referred to as reconfiguration, is the process and capability by which an MAS maintain stable operation and accomplish mission, particularly it can replace damaged entities with either remaining or newly introduced entities to form a new closed loop that satisfies specific targets.

Reconfiguration of MAS can be regarded as the replacement of disabled entities (Sun et al., 2024). Consequently, the conception of reconfiguration entity can be established, representing the replacement entities with similar function of disabled entities. As shown in Fig. 1, reconfiguration entities are capable of substituting for the disabled entity to perform similar function, thereby establishing a new operation loop. The operation loop that possesses reconfiguration entities is defined as reconfigurable operation loop. Reconfiguration entities can be categorized into offline-reconfiguration entities and online-reconfiguration entities. Offline-reconfiguration entities refer to spare reconfiguration entities that provide similar functionality through either a dedicated backup or from a shared resource pool. The reconfiguration process for offline-reconfiguration entities necessitates additional attention to their startup time. In contrast, online-reconfiguration entities are in-service reconfiguration entities that possess redundant and analogous functions within the same loop or different operation loops. Replacing a faulty entity with an online-reconfiguration entity increases the workload on this reconfiguration entity.

Offline and online reconfiguration entities serve as the physical foundation for reconfiguration, while the functions and capabilities of these entities constitute the logical conditions for reconfiguration. From the perspectives of the physical basis and logical conditions, four types of reconfigurable attributes are systematically summarized as follows and Table 3 (Uday and Marais, 2013).

As the reconfiguration entity is the basic unit and essential resource of reconfiguration, ensuring entity redundancy is essential, as it is precondition of reconfigurability. In cases where inherent redundancy within an operation loop is inadequate, it is crucial to ensure a sufficient supply of accessible alternative resources available to support the reconfiguration process. Additionally, the logical condition for reconfigurable entities indicates that they exhibit equivalent functionality to disabled entities, while the capacity of these entities, particularly online reconfiguration entities, is sufficient to accommodate the load of the disabled entities. Therefore, four reconfigurable attributes can be illustrated as follow:

- **Entity redundancy**: the faulty entities have redundant entities that allow for the replacement of the faulty entity, which can be other entities with identical functions both within the same loop and

**Table 3**
Reconfiguration entities and corresponding reconfigurable attributes.

| Types of the reconfiguration entities | Source of reconfiguration entities | Corresponding reconfigurable attributes |
|---|---|---|
| Offline-reconfiguration entities | Backup for the faulty entity | Entity redundancy |
| | Backup for other entities with same function within the same loop | Entity redundancy |
| | Backup for entities with same function within other loops | Entity redundancy; Resource accessibility |
| | Resource pool of entities | Resource accessibility |
| Online-reconfiguration entities | Entity with redundant functions within the same loop | Load affordability; Functional substitutability |
| | Entity with redundant functions within other loops | Load affordability; Functional substitutability; Resource accessibility |
| | Entities with same functions within other loops | Load affordability; Resource accessibility |

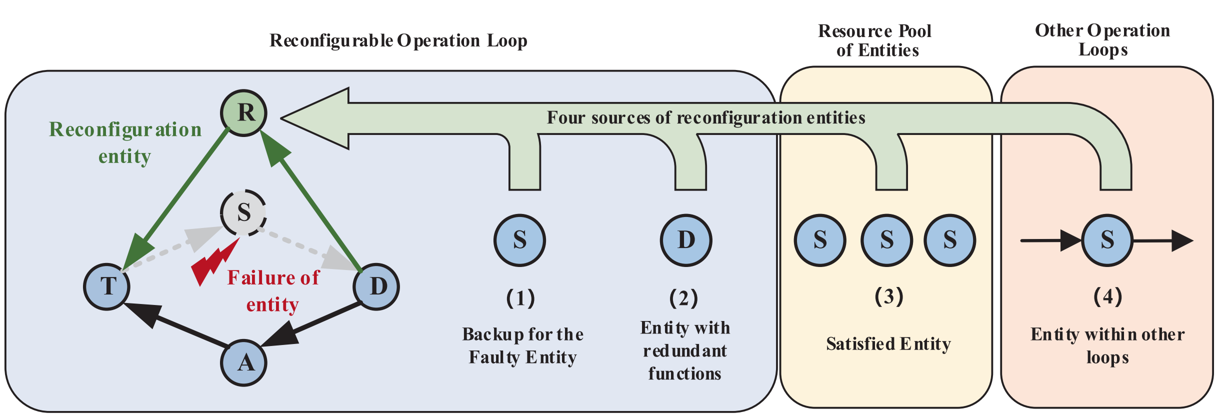



Fig. 1. Reconfigurable operation loop.

different loops. This highlights the static configuration characteristic of the MAS.

- **Resource accessibility**: entities for the replacement from other loops or from a shared resource pool must be able to reach the destination of the disabled entity.
- **Functional substitutability**: entities equipped with multiple functions can assume multiple responsibilities. This represents the core dynamic reconfiguration capability, which hinges on functional redundancy and comprehensive coverage among different entities.
- **Load affordability**: reconfiguration, particularly through the replacement of online reconfiguration entities, requires these entities to handle multiple mission targets. Therefore, reconfiguration entities must possess the operational capability to function effectively under high load.

The reconfigurable attributes of MAS capture the core reconfiguration capabilities that support the design of MAS resilience. Attributes such as entity redundancy and functional substitutability fundamentally reflect the modular design, ensuring that disturbances within MAS can be confined to individual or a limited number of agents (Leng et al., 2025). In such cases, operational entities can swiftly assume responsibilities of disabled entities through predefined interfaces. Furthermore, load affordability must be carefully considered, particularly in post-reconfiguration scenarios where a single entity might be required to undertake multiple missions.

Furthermore, the mathematical model of reconfiguration can be can be established based on constraints derived from these above attributes.

### 3.2. Reconfigurable operation-loop network model

MAS can be modeled as an operation-loop network to reveal the characteristics of various entities and their functional interactions (Li et al., 2017). The RON model is proposed based on the coupling of multiple reconfigurable operation loops, as depicted in Fig. 2.

RON model $G = (V, E, \varphi, \psi, \delta)$ contains vertex set $V$, edge set $E$, vertex type mapping $\varphi$, edge type mapping $\psi$, and reconfiguration mapping $\delta$.

- $V = V^T \cup V^S \cup V^D \cup V^A \cup V^R$ denotes the set of five types of vertexes.
- $E = E^{T\to S} \cup E^{S\to D} \cup E^{S\to S} \cup E^{D\to S} \cup E^{D\to D} \cup E^{D\to A} \cup E^{A\to T}$ denotes the edge set.
- $\varphi = V\to I$ represents that each vertex $v \in V$ has $\varphi(v) \in I$, where $I = \{S, D, A, T, R\}$ is the node type set.
- $\psi = E\to L$ represents that each edge $e \in E$ has $\psi(e) \in L$, where $L = \{T\to S, S\to D, S\to S, D\to S, D\to D, D\to A, A\to T\}$ is the edge type set.
- $\delta = R\to H$ represents that each vertex in reconfiguration type $v \in V^R$ has $\delta(v) \in H$, where $H = \{S, D, A\}$ is the set of node types that reconfiguration entities can transform to.

The reconfigurable operation loop is determined based on the definition of meta path of operation-loop network.

**Definition of *meta*-path** (Li et al., 2017): A *meta*-path $MP$ is a series of edges between vertex types:

$$MP = v_1 \overset{e_1}{\to} v_2 \overset{e_2}{\to} \dots \overset{e_u}{\to} v_{u+1}, MP \in \Omega^M \tag{2}$$

where $v_1, v_2, \dots, v_{u+1} \in V$ and $e_1, e_2, \dots, e_{u+1} \in E$. $\Omega^M$ denotes the set of *meta*-paths.

**Definition of operation loop:** The operation loop $OP$ ($OP \in \Omega^O$) is a path instance of $MP$, where $\varphi(v_1) = S$, $\varphi(v_{u-1}) = D$, $\varphi(v_u) = A$, $\varphi(v_{u+1}) = T$ and $\varphi(v_{u'}) \neq A$, $u' = 2, 3, \dots, u-2$. $\Omega^O$ denotes the set of operation loops, $\Omega^O \subseteq \Omega^M$.

**Definition of reconfigurable operation loop**: Reconfigurable operation loop $RP$ is as special kind of operation loop ($RP \in \Omega^O$), which involves the $v_i \in R$ in path:

$$\exists v_i \in R, RP = v_1 \overset{e_1}{\to} v_2 \overset{e_2}{\to} \dots \xrightarrow{e_{i-1}} v_i \overset{e_i}{\to} \dots \overset{e_u}{\to} v_{u+1} \tag{3}$$

### 3.3. Performance measurement of RON considering mission load

Performance measurement is the cornerstone of resilience analysis and evaluation, assessing the operational quality and mission capability of MAS. According to the aforementioned network model, the number of operation loops is a common and general indicator to evaluate the performance of MAS (Pan et al., 2019), which indicates the ability to accomplish the target of mission. However, this metric may not be suitable for post-reconfiguration performance assessment, particularly because reconfiguration can alter network topology, increase the number of operation loops, and impose additional workload on reconfiguration entities. Owing to the entity's constrained capacity for concurrent event and information processing, encountering an overload of simultaneous events or information can negatively impact the efficiency of

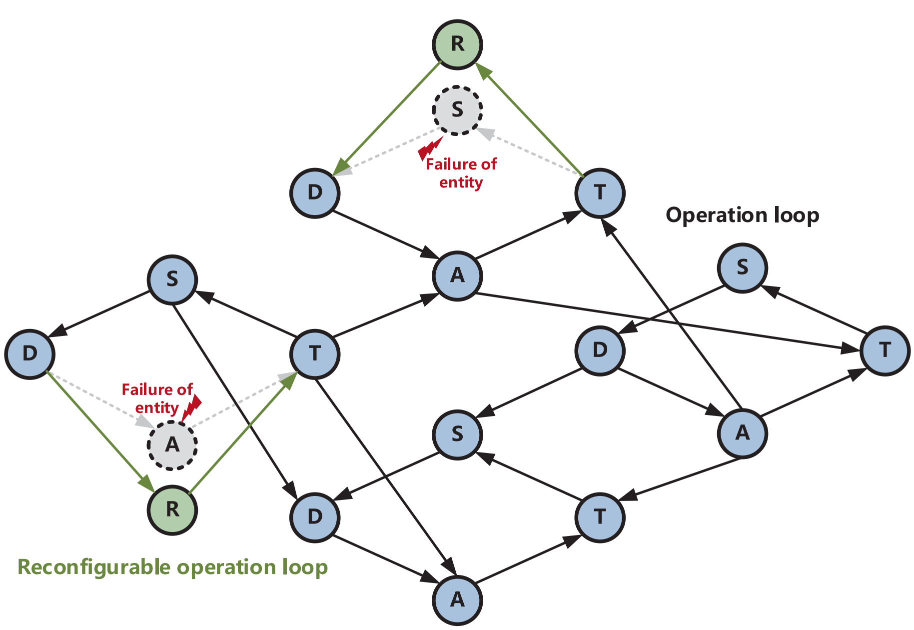



**Fig. 2.** The structure of RON model.

mission accomplishment (Du et al., 2019; Belgacem et al., 2022). Therefore, it is essential to consider mission load while assessing the performance based on RON.

The operation loop represents the mission process to the specific target. The number of operational loops that an entity undergoes indicates the quantity of missions it is concurrently responsible for and the workload imposed. Drawing upon node betweenness centrality (Li et al., 2019; Gao et al., 2011), which quantifies a node's pivotability based on the frequency of shortest paths passing through it, we introduce the notion of node load factor, as illustrated in Eq. (4)

$$LF_i = \sum_{v_t \in V^T} \frac{f_t^i}{g_t} \tag{4}$$

where $g_t = |\Omega_t^O|, \Omega_t^O \subseteq \Omega^O$ denotes the total number of operation loops that both start and end at the target node $v_t \in V^T$, $f_t^i = |\Omega_{t_i}^O|$ denotes the number of operation loops that pass through node $v_i \in V^S \cup V^D \cup V^A$ and also start and end at $v_t$.

Then the node load weight is illustrated as

$$\omega_i = \frac{LF_i}{CF_i} \tag{5}$$

where $CF_i \in [0, \infty)$ is the node capacity factor that quantifies maximum potential capability or efficiency of an entity to perform a specific task or process mission load under ideal conditions. $CF_i$ is static and determined a priori based on the entity's inherent design specifications or historical operational data.

The node load weight represents the duration required for an entity to complete all assigned load. Entities on a single operation loop execute their mission load sequentially and independently following the connection order. Consequently, the running time factor of a certain loop is denoted as

$$\varepsilon_i = \sum_{v_j \in OP_i} \omega_j \tag{6}$$

where $\varepsilon_i$ denotes the running time factors of the operation loop $OP_i$.

A certain mission target is generally accomplished by multiple operation loops in parallel. The completion time should be determined by the loop with the longest operation duration. Therefore, the operational efficiency of the target vertex $v_t$ can be expressed as

$$\eta_t = \frac{1}{\varepsilon_{\max}^t} \tag{7}$$

where $\eta_t$ is the efficiency factor of $v_t$, $\varepsilon_{\max}^t$ is the maximum running time factor of the operation loops targeting at $v_t$.

The performance of RON is indicated by the number of operation loops weighted by efficiency, expressed as

$$P = \frac{1}{N_T} \sum_{v_t \in V^T} \eta_t g_t \tag{8}$$

where $N_T = |V^T|$ denotes the number of target vertexes.

## 4. Reconfiguration-based resilience optimization

In this section, we formulate the resilience enhancement through reconfiguration as an optimal mathematical model that incorporates both resilience-oriented objective and reconfiguration constraints. Additionally, a solution framework for achieving resilience optimization is proposed.

The terms, sets, parameters and variables involved in the model are denoted and defined as illustrated in Table 4.

**Table 4**
Definition of terms, sets, parameters and variables involved in the model.

| Notation | | Definition |
|---|---|---|
| Terms | $Я$ | Resilience of MAS |
| | $P(t)$ | Performance of MAS |
| | $\tau$ | Recovery time factor |
| | $\delta(\cdot)$ | Reconfiguration mapping function |
| | $\varphi(\cdot)$ | Vertex type mapping function |
| | $N_T$ | Number of target vertexes |
| | $g_t$ | Total number of operation loops that both start and end at a target node |
| | $v_t$ | Target vertex |
| | $V^T$ | Set of target vertexes |
| | $OP_i$ | Operation loop |
| | $\omega_j$ | Load weight of each entity |
| Sets | $V^U$ | Set of disrupted vertexes in RON,$V^U \subseteq (V^S \cup V^D \cup V^A)$ |
| | $V^R$ | Set of reconfiguration vertexes in RON,$V^R \subseteq V$ |
| Parameters | $t_0$ | Initial time when disruption occurs |
| | $t_e$ | Start time of reconfiguration process |
| | $t_c$ | Startup time of reconfiguration entities |
| | $LF_i^{before}$ | Mission load of $v_i$ before reconfiguration action,$v_i \in V$ |
| | $P_0$ | Initial performance value at time $t_0$ |
| | $P_e$ | Minimum performance before reconfiguration process at time $t_e$ |
| | $P_b$ | Desired performance according to load baseline |
| Variables | $X_{ij}$ | If $v_j$ is replaced by $v_i$, $X_{ij}$=1, otherwise$X_{ij} = 0$, $v_i \in V^R$,$v_j \in V^U$ |
| | $r_{ij}$ | Reachability if$X_{ij} = 1$,$r_{ij} \in \{0,1\}$ |
| | $t_{ij}$ | Allocation time if$X_{ij} = 1$ from $v_i$ to $v_j$, $v_i \in V^R$,$v_j \in V^U$ |
| | $t_r$ | Completion time of total reconfiguration process |
| | $LF_i^{after}$ | Mission load of $v_i$ after reconfiguration action,$v_i \in V$ |
| | $P_{ij}$ | If$X_{ij} = 1$, $P_{ij}$ can be measured by Eq. (8), otherwise$P_{ij} = 0$ |
| | $P_r$ | Performance value at completion time $t_r$ of total reconfiguration process |

### 4.1. Mathematical model of reconfiguration

#### 4.1.1. Problem description

The entities in MAS are inevitable to being disrupted due to complex operation environment. Reconfiguration is a critical approach that can dynamically adjust the network structure of MAS to adapt the disruption and enhance resilience. Based on the proposed RON model, the reconfiguration problem of MAS is conceptualized as the selection of appropriate reconfiguration entities for replacement of disabled entities and reconnection of post-disruption topology within RON. For example, if a sensor entity and an actor entity in the MAS fail, causing the disruption of originally connected operation loops and degradation of MAS performance, the failed entities can be replaced by searching for appropriate entities from the reconfiguration entities (e.g., a functioning sensor entity within other loop and an available actor entity in the resource pool), and the corresponding edges can be reconnected, thereby achieving the resilient recovery of the MAS, as illustrated in Fig. 3.

How to find the appropriate reconfiguration entities needs to be addressed through mathematical the programming model and optimization algorithm. Furthermore, the proposed reconfigurable attributes, including entity redundancy, functional substitutability, load affordability, resource accessibility for resilience, serve as constraints of resilience optimization. Therefore, there are several key assumptions for these reconfigurable attributes as follows, which serve to abstract the model in a manner that ensures its universality and clarity.

**Assumption 1**. *Each disrupted entity of MAS has been known, and it is completely disabled with all of its connections severed.*

**Assumption 2**. *Each disrupted entity can be replaced by at most one reconfiguration entity. If both connecting entities exist, the previously removed links can be reconnected.*

**Assumption 3**. *Startup time of offline-reconfiguration entities has been known, while startup time of online-reconfiguration entities can be ignored.*

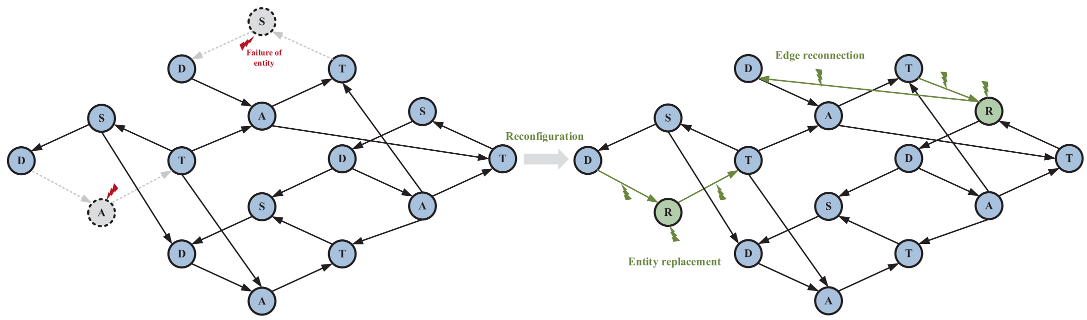



**Fig. 3.** The diagram of reconfiguration scenario in RON.

**Assumption 4.** *The duration of allocation from reconfiguration entities to the disrupted entities has been known.*

**Assumption 5.** *The reconfiguration is implemented at a specified time, and the replacement for all disrupted entities are initiated simultaneously.*

*4.1.2. Resilience-oriented objective*

Resilience serves as an indicator of reconfiguration capability, which can be assessed by the resilience process of RON indicated by Fig. 4. The selection of an appropriate resilience metric for RON is crucial for defining the optimization objective in the mathematical modeling of reconfiguration. Multiple-parameter model is a common and integration-based approach to assess resilience from multiple perspectives including recovery time, recovery volatility and recovery scale (Tran et al., 2017). In addition, the mission baseline serves as the fundamental requirement for MAS to accomplish its mission and is incorporated into resilience measurement as the basis for recovery targets (Sun et al., 2022). In light of the aforementioned research, we propose the resilience measurement Я based on the load baseline determined by load weight, as shown in Eq. (9).

$$\text{Я} = \frac{\sum_{t=t_0}^{t_r}\min(P(t),P_b)}{P_b(t_r-t_0)}\cdot\min\left(\frac{P_r}{P_b},1\right)\cdot\left[\frac{P_e}{P_0}+1-\tau^{\left(\frac{P_r}{P_b}\right)}\right] \tag{9}$$

where $t_0 \in [0,\infty)$ is the initial time when disruption occurs, $t_e \in [t_0,\infty)$ is the start time of reconfiguration process, $t_r \in (t_e,\infty)$ is the completion time of total reconfiguration process, $\tau \in (0,1]$ is the recovery time factor, $P(t) \in [0,\infty)$ is the performance at time $t$, $P_0 \in (0,\infty)$ is the initial performance value at time $t_0$, $P_e \in [0,P_0]$ is the minimum performance before reconfiguration process at time $t_e$, $P_b \in (0,P_0]$ is the desired performance according to load baseline, $P_r \in [0,\infty)$ is the performance value at completion time $t_r$ of total reconfiguration process and Я$\in [0,2)$ increases as $\tau$ decreases and $P_r$ increases. The recovery time factor $\tau$ is indicated as

$$\tau = \frac{t_r - t_e}{t_r - t_0} \tag{10}$$

where $\tau$ accounts for normalized temporal aspects of the MAS recovery and the closer $\tau$ is to 1, the lower the resilience.

The performance variables in the formula of Я can be obtained by sampling performance data from modeling and simulation for proposed performance measurement in Section 2.3. The performance of load baseline $P_b$ is determined as indicated by Eq. (11).

$$P_b = \frac{1}{N_T}\sum_{v_t\in V^T}\frac{g_t}{\max\left(\sum_{v_j\in OP_i}(\omega_j=1)\right)} \tag{11}$$

where $P_b$ is determined when load weight of each entity is assumed to be 1, indicating that the entity's load capacity precisely matches its mission load.

Therefore, Я is designed as the maximum objective for mathematical model of reconfiguration, and the objective function can be represented as

$$\text{maximum } \text{Я} = \text{Я}(\{P_{ij}|i\in V^R, j\in V^U\}, t_r) \tag{12}$$

The optimization objective Я incorporates the load growth of entities after reconfiguration, which serves as the performance penalty for resilience recovery. When optimizing resilience based on reconfiguration, performance is required to be restored to the load baseline at least, and the load after reconfiguration should not be concentrated on a few

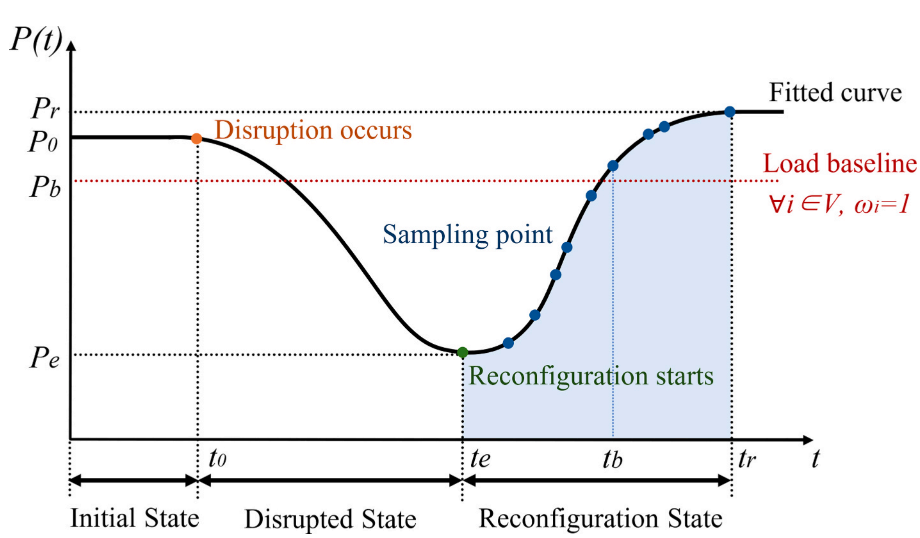



**Fig. 4.** Resilience process of RON expressed by performance fluctuation.

central entities.

#### 4.1.3. Constraints of reconfigurable attributes

Due to the proposed reconfigurable attributes: entity redundancy, functional substitutability, load affordability, resource accessibility, several sets of constraints are considered in the proposed optimization model.

(i) Constraint of entity redundancy indicates that disabled entities can be replaced by reconfiguration entities if feasible, as represented in Eq. (13).

$$\sum_{i \in V^R} X_{ij} \leq 1, \forall j \in V^U \tag{13}$$

where $\sum_{i \in V^R} X_{ij} \leq 1$ enforces a one-to-one replacement policy where feasible as illustrated in Assumption 2.

(ii) Constraint of functional substitutability indicates that only the faulty entity and reconfiguration entity of the same function can perform reconfiguration, as represented in Eq. (14).

$$X_{ij} = \mathbf{1}\{\delta(v_i) = \varphi(v_j)\}, \exists v_i \in V^R, v_j \in V^U \tag{14}$$

where $\delta(v_i) = \varphi(v_j)$ indicates type of a reconfiguration entity $v_i$ is identical to type of the faulty entity $v_j$, $\mathbf{1}\{\cdot\}$ is the indicator function, $\mathbf{1}\{\delta(v_i) = \varphi(v_j)\} = 1$ if $\delta(v_i) = \varphi(v_j)$, otherwise $\mathbf{1}\{\delta(v_i) = \varphi(v_j)\} = 0$.

(iii) Constraint of load affordability ensures that the mission load of the faulty entity transfer to the reconfiguration entity, as represented in Eq. (15).

$$LF_i^{after} = LF_i^{before} + LF_j^{before}, \exists i \in V^R, j \in V^U, X_{ij} = 1 \tag{15}$$

(iv) Constraints of resource accessibility indicate the reconfiguration entity from other loops or from a shared resource pool are able to reach the destination of the disabled entity in a certain time, as represented in Eq. (16)-(17). Eq. (16) ensures that the reconfiguration entity can reach the destination of the disabled entity that can be further refined if the allocation path model is established. Eq. (17) ensures that the completion time of total reconfiguration process is equal to the maximum of the allocation time plus by the startup time of reconfiguration entities.

$$r_{ij} = 1, \exists i \in V^R, j \in V^U, X_{ij} = 1 \tag{16}$$

$$t_r = \max\{t_{ij} + t_c | r_{ij} = 1, i \in V^R, j \in V^U\} \geq t_{ij} + t_c \tag{17}$$

### 4.2. Optimal reconfiguration scheme generation of RON

The proposed mathematical model for reconfiguration integrates both the reconfigurable attributes and resilience objective of RON, formulated as a nonlinear mixed-integer programming problem. The solution of this model essentially represents the generation process of an optimal reconfiguration scheme, which corresponds to a dynamic reconfiguration mechanism based on static reconfigurable design according to different disruption conditions. For solving the reconfiguration model, we proposed an algorithm framework suitable for optimal reconfiguration scheme generation and resilience enhancement of RON as illustrated in Fig. 5.

The encoding and decoding of solution are essential for optimization, as they determine the solving difficulty and efficiency of algorithm. The encoding and decoding for reconfiguration are proposed based on the natural numbers, as shown in Fig. 6.

Set of faulty entities $V^U$ and set of reconfiguration entities $V^R$ are ordered sets. If the decision variable$X_{ij} = 1$, code of entity $v_j \in V^U$ is equal to index of $v_i$ in $V^R$, otherwise code of $v_j$ is equal to 0. The initial solution encoded by this approach can be generated randomly or based on priori knowledge of reconfiguration, while ensuring compliance with

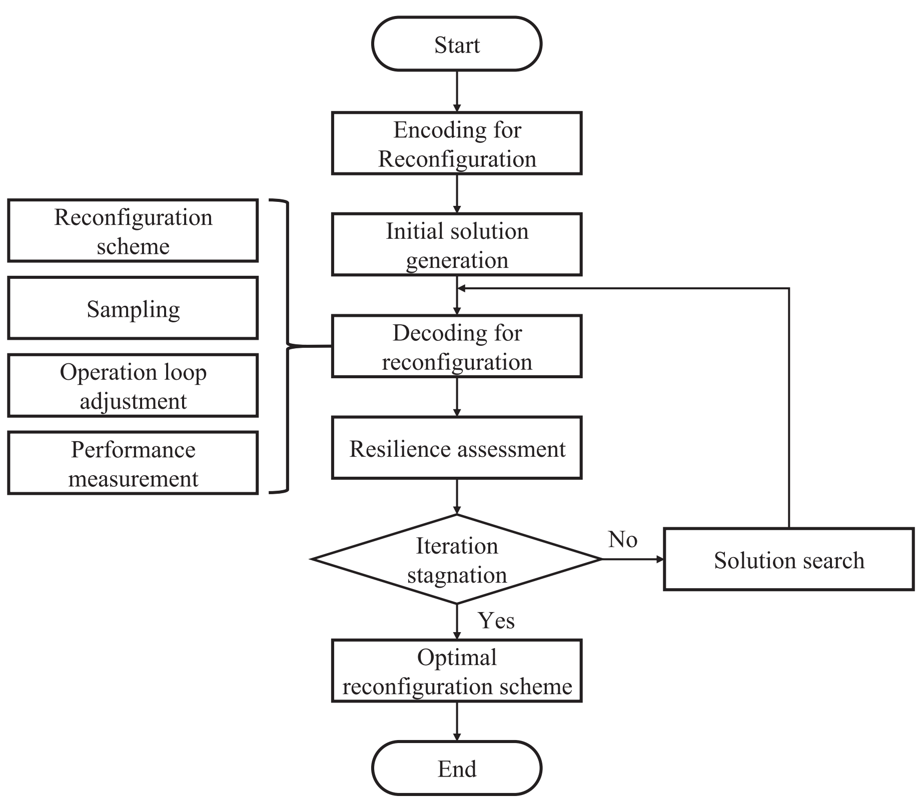



**Fig. 5.** Algorithm framework for optimal reconfiguration scheme generation.

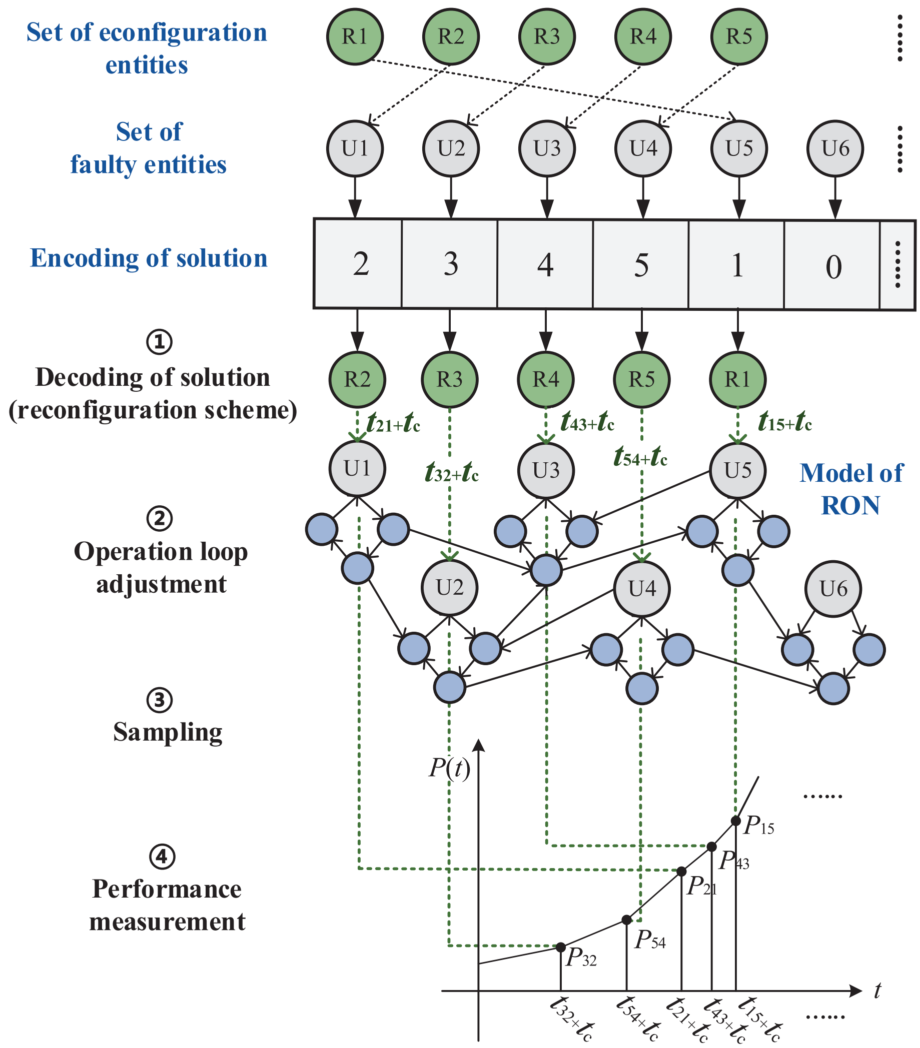



**Fig. 6.** Encoding and decoding for reconfiguration of RON.

the proposed constraints.

The process of decoding for reconfiguration mainly consists of reconfiguration scheme generation, operation loop adjustment, sampling, performance measurement. First of all, the reconfiguration scheme is generated according to code sequence of reconfiguration entities, which represents the reconfiguration entity corresponding to a certain faulty entity. Then, each faulty entity is replaced by the corresponding reconfiguration entity and its original predecessors and successors are reconnected to the reconfiguration entity. Finally, the structure of RON is sampled and performance $P_{ij}$ is evaluated based on performance measurement at reconfiguration time $t_{ij} + t_c$ mapped by the code. The time sequence of $\{(P_{ij}, t_{ij} + t_c)|i \in V^R, j \in V^U, X_{ij} = 1\}$ is obtained supporting to the resilience assessment.

The genetic algorithm is used to search the optimal solution. These generate feasible solutions by employing crossover and mutation steps, followed by a selection step to evaluate and filter these solutions (Li et al., 2019). Inferior solutions are eliminated in this process, while superior genetic traits are effectively propagated to subsequent generations in next iteration. The stagnation condition can be set as the point at which the optimal resilience of the superior solution no longer increases with further iterations.

## 5. Case study

The case study based on an emergency response system is provided to verify the feasibility, effectiveness and superiority of the proposed model and indicators of RON. Owing to cyclic process of perception, decision-making, and action, the emergency response system can detect and deal with the emergencies like natural and man-made accidents promptly and efficiently (Yang et al., 2023; Huang, 2015). The emergency response system can be abstract as a MAS, in which the sensor entities comprise on-site personnel, sensors, and Closed-Circuit Television (CCTV), among others. The decider entities encompass the alarm response center, command center, and emergency management bureau, among others. The actor entities include departments such as fire services, public security, and medical enforcement. These entities establish multiple operation loop based on the disposal target and functional interconnections, thereby forming a operation-loop network as depicted in Fig. 7. When a natural disaster or man-made damage causes entities to fail in fulfilling the response function, the operation loop may not be able to close and respond to the disposal targets in time. This could impact performance and efficiency of the entire emergency response system. To address this issue, the emergency response system should leverage its inherent mechanisms of reconfiguration to improve resilience.

### 5.1. Network establishment and resilience analysis

Based on the emergency response system of a city, this study identifies key entities according to the emergency targets and services such

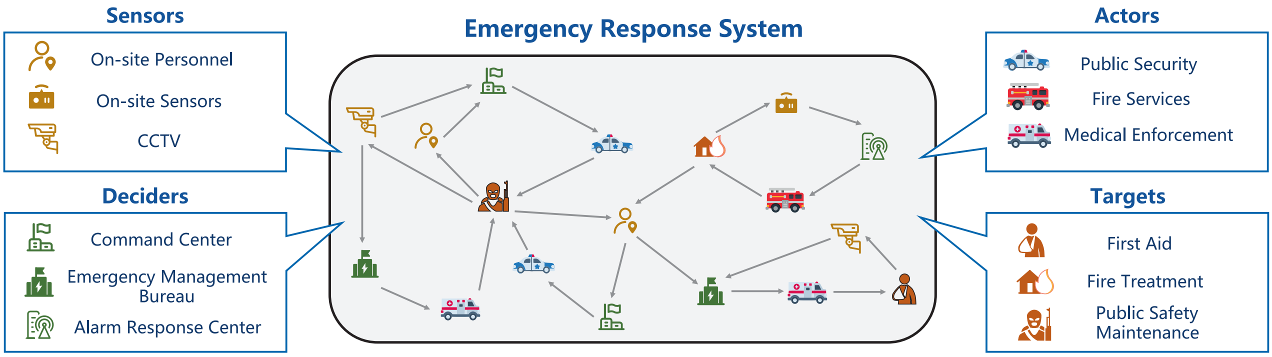



**Fig. 7.** Schematic diagram of emergency response system.

as fire services, public security, medical care, traffic management, and other. The model of RON is then constructed by these entities. As depicted in Fig. 8, the RON model for an emergency response system consists of 9 groups of entities, encompassing a total of 36 entities.

The fluctuation of different performance indicators is obtained through Monte Carlo simulation of the RON model under the conditions of random disruption and random selection of reconfiguration entities, including the proposed performance measurement considering mission load (PMML), index of operation loop (IOL), network global efficiency (NGE) and network operation loop efficiency (OLE). IOL represents the normalized value of the number of operation loops, which is the most common index for networks based on operation loops (Li et al., 2017). NGE is defined as the average of the reciprocal hops of the shortest path between all pairs of nodes, and serves as a classical evaluation index in complex network theory (Pan and Wang, 2018). OLE is defined as the average of the reciprocal number of hops passed by the operation loops (Zhong et al., 2024). PMML is validated against established performance metrics via qualitative and quantitative analysis.

Furthermore, the impact of two types of independent reconfiguration entities (online-reconfiguration entities and offline-reconfiguration entities, whose quantities are respectively regarded as known fixed constraints in the resilience optimization model) on the performance recovery and resilience of the MAS is analyzed, thereby providing support for the resilience optimization experiments in the case.

#### 5.1.1. Resilience analysis with offline-reconfiguration entities

The quantities of each type of offline-reconfiguration entities (map to S/D/A) in the resource pool are set to 0, 5, 10, 15, 20, and 25 respectively. The configuration of parameters is set as shown in Table 5.

Repeated tests are conducted to obtain the average values of performance and resilience, thereby analyzing the variations in performance metrics and their resilience under different numbers of cold-reconfigurable entities, as illustrated in Figs. 9 and 10.

The results indicate that the metrics of PMML, IOL, and OLE exhibit a resilient trend characterized by an initial decrease followed by an increase, whereas NGE demonstrates a contrasting trend of first increasing and then decreasing. This is because NGE only reflects the network's performance in term of connectivity and tightness, without considering

**Table 5**
Configuration of parameters in resilience analysis with offline-reconfiguration entities.

| Parameter | | Configuration |
|---|---|---|
| $CF_i$ | | $CF_i$ is set according to the initial $LF_i$ of the node, i.e.$LF_i = CF_i$ |
| $t_c$ | | $t_c$ is set to 1 time step |
| $t_{ij}$ | | $t_{ij}$ is set to the number of time steps that equals the absolute value of the difference between the entities' digital numbers |
| Disruption model | | Random disruption |
| Offline-reconfiguration entities | Number | 0, 15, 30, 45, 60, 75, respectively |
| | Resource pool structure | The quantities of each type of offline-reconfiguration entities (map to S/D/A) in the resource pool are set to 0, 5, 10, 15, 20, and 25 respectively |
| Online-reconfiguration entities | Number | 0 |
| | Functional-substitution relations | do not have |

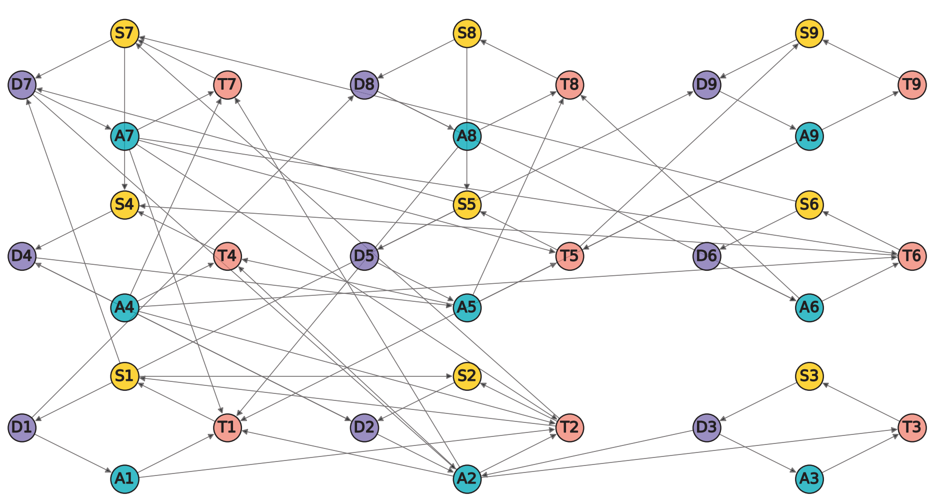
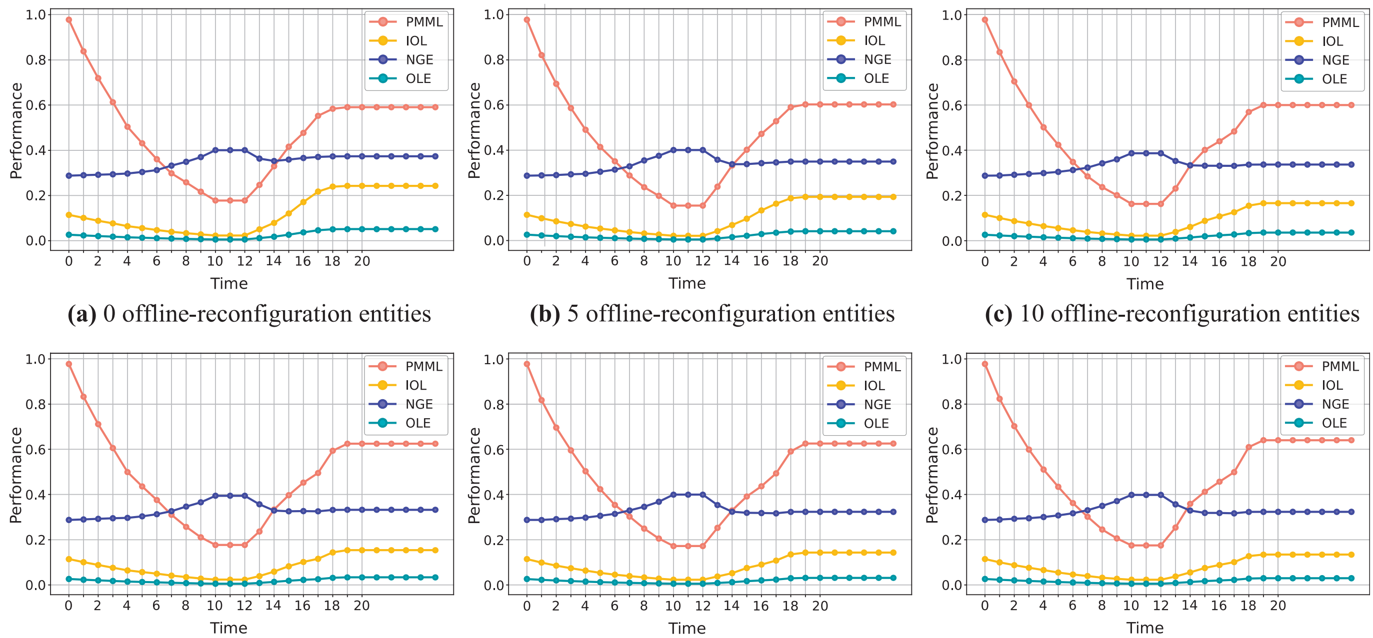



**Fig. 8.** RON model for an emergency response system.




**(a)** 0 offline-reconfiguration entities **(b)** 5 offline-reconfiguration entities **(c)** 10 offline-reconfiguration entities

**(d)** 15 offline-reconfiguration entities **(e)** 20 offline-reconfiguration entities **(f)** 25 offline-reconfiguration entities

**Fig. 9.** Performance fluctuation under different quantity of offline-reconfiguration.

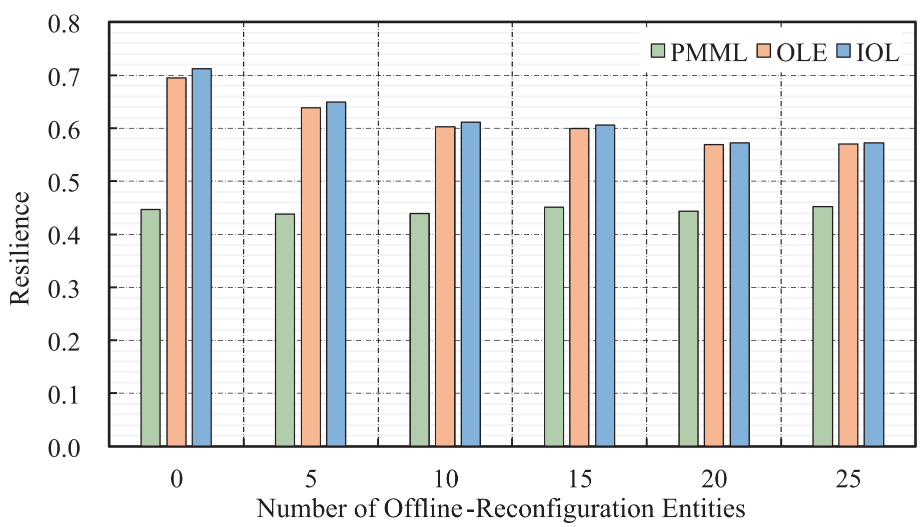



**Fig. 10.** Resilience under different quantity of offline-reconfiguration.

the topology based on the operation loop. When nodes in the network are damaged, network connectivity is not immediately affected due to redundancy. However, the reduction in the number of nodes results in a decrease in network communication hops, thereby enhancing efficiency. In conclusion, NGE proves to be insufficient for characterizing the resilience properties of networks based on operation loops.

To quantitatively validate PMML against the other three performance metrics, a correlation analysis is also conducted, and the resulting correlation heatmap is shown in Fig. 11. The result shows that PMML is significantly positively correlated with typical operation loop indicators (i.e., OLE and IOL), while negatively correlated with NGE, confirming its effectiveness in capturing the performance of the operation-loop network. Notably, the analysis reveals an extremely high correlation between IOL and OLE, suggesting potential information redundancy between these two established metrics. In contrast, PMML, by integrating the mission load, provides an independent and complementary assessment, explaining unique variance not captured by IOL/OLE alone.

The recovery effect of the reconfiguration on the IOL and OLE is greater than the impact of the damage, resulting in higher resilience. This is because these two indicators demonstrate that reconfiguration can be achieved without incurring additional costs, especially online-reconfiguration entities are selected to replace the faulty ones, the number of operation loops will exceed the number before the damage occurred. For instance, an emergency response system comprising two target entities, two sensor entities, two decider entities, and two actor entities establishes the RON model as illustrated in Fig. 12. This model has 1 and 2 operation loops for T1 and T2, respectively. If S2 fails, the reconfiguration entity selects the sensor entity S1 that has an identical function, as a substitute. Owing to the sensing effect of S1 on T2, two new loops, T2-S1-D1-A1-T2 and T1-S1-D2-A1-T1, have been introduced. Currently, the network consists of five operation loops, which is a result of the increased number of operational loops due to offline-

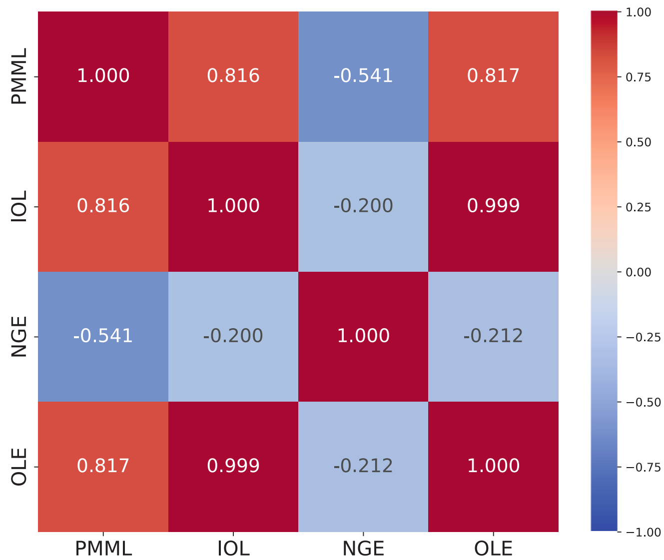



**Fig. 11.** Correlation analysis of performance measurements.

reconfiguration.

Theoretically, this effect becomes more pronounced when the network model is more complex and features a higher density of links between operation loops. If it is assumed that all failed entities opt for offline-reconfiguration entities for reconfiguration, the number of operational loops will remain unchanged, and both the IOL and OLE should be restored to their initial states. In terms of the number of operational loops, online-reconfiguration entities exert a more significant influence on network performance recovery compared to offline-reconfiguration entities. However, this is unfavorable for reconfiguration scheme generation and resilience design of the emergency response system, as it tends to create a more compact structure where fewer entities possess a higher number of connected edges, leading to a concentration of mission load.

From the resilience results based on PMML in Fig. 10, it is evident that that adding offline-reconfiguration entities can enhance resilience to a certain extent. This is because the probability of a faulty entity randomly selecting an offline-reconfiguration entity for reconfiguration increases. Additionally, since the offline-reconfiguration entity does not participate in other operation loops, its initial mission load is zero. Consequently, a higher number of offline-reconfiguration entities can lead to greater performance improvements. However, given the random reconfiguration scheme employed in this experiment and the extended reconfiguration time required for offline-reconfiguration entities, the increase in the number of offline-reconfiguration entities does not significantly enhance resilience. Furthermore, the recovery process of the performance curve exhibits a downward convex trend due to the time needed for offline-reconfiguration entities to allocate resources and activate.

However, the resilience results using IOL and OLE as indicators fail to account for the influence of offline-reconfiguration entities on performance recovery, and even show an obvious trend of resilience decline with the increase of the number of offline-reconfiguration entities. This is because a higher participation of cold-reconfigured entities in the reconfiguration process implies that fewer existing entities are likely to undergo offline-reconfiguration, thereby resulting in a reduced number of reconnected operational loops.

### 5.1.2. Resilience analysis with online-reconfiguration entities

To analyze the impact of the number of hot-reconfigurable entities on recovered performance and resilience, various functional redundancy relationships are established. For instance, the relationship between the sensor entity and the decider entity indicates that the sensor entity possesses a certain level of decision-making capability and can functionally substitute for the decider entity when necessary. This type of relationship is prevalent in emergency response systems. For example, some networked CCTV cameras are equipped with edge computing capabilities and can perform basic information processing, enabling them to make timely decisions based on perceived data. The number of online-reconfiguration entities with functional substitution in the model is set to 0, 9, 18, 27, 36, and 45, respectively. The configuration of parameters is set as shown in Table 6.

The average values of performance and resilience are obtained by Monte-Carlo simulation, and the performance fluctuation and resilience under different numbers of online-reconfiguration entities are analyzed, as shown in Figs. 13 and 14. The result of correlation analysis among each indicator is shown in Fig. 15.

From the results of network resilience, the resilience expressed by IOL and OLE shows a trend of increasing with the increase of the number of online-reconfiguration entities, which is exactly the opposite of the

**Table 6**
Configuration of parameters in resilience analysis with online-reconfiguration entities.

| Parameter | | Configuration |
|---|---|---|
| $CF_i$ | | $CF_i$ is set according to the initial $LF_i$ of the node, i.e.$LF_i = CF_i$ |
| $t_c$ | | $t_c$ is set to 1 time step |
| $t_{ij}$ | | $t_{ij}$ is set to the number of time steps that equals the absolute value of the difference between the entities' digital numbers |
| Disruption model | | Random disruption |
| Offline-reconfiguration entities | Number | 0 |
| | Resource pool structure | do not have |
| Online-reconfiguration entities | Number | The number of online-reconfiguration entities with functional substitution in the model is set to 0, 9, 18, 27, 36, and 45, respectively |
| | Functional-substitution relations | The S-D, D-A, and S-A entities can functionally replace each other. |

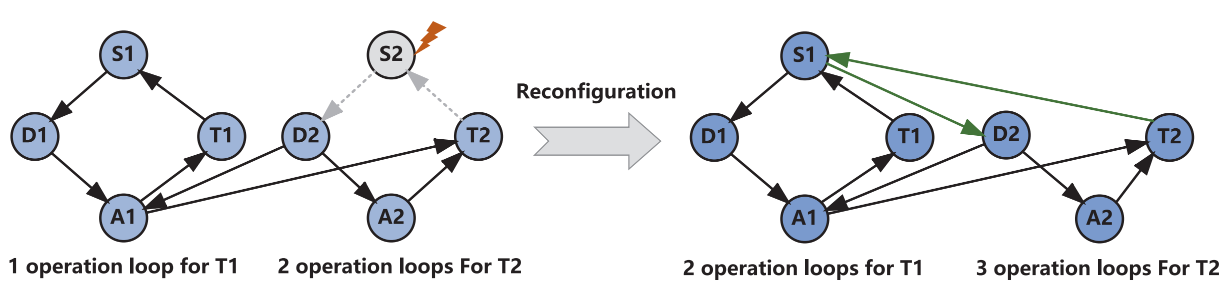
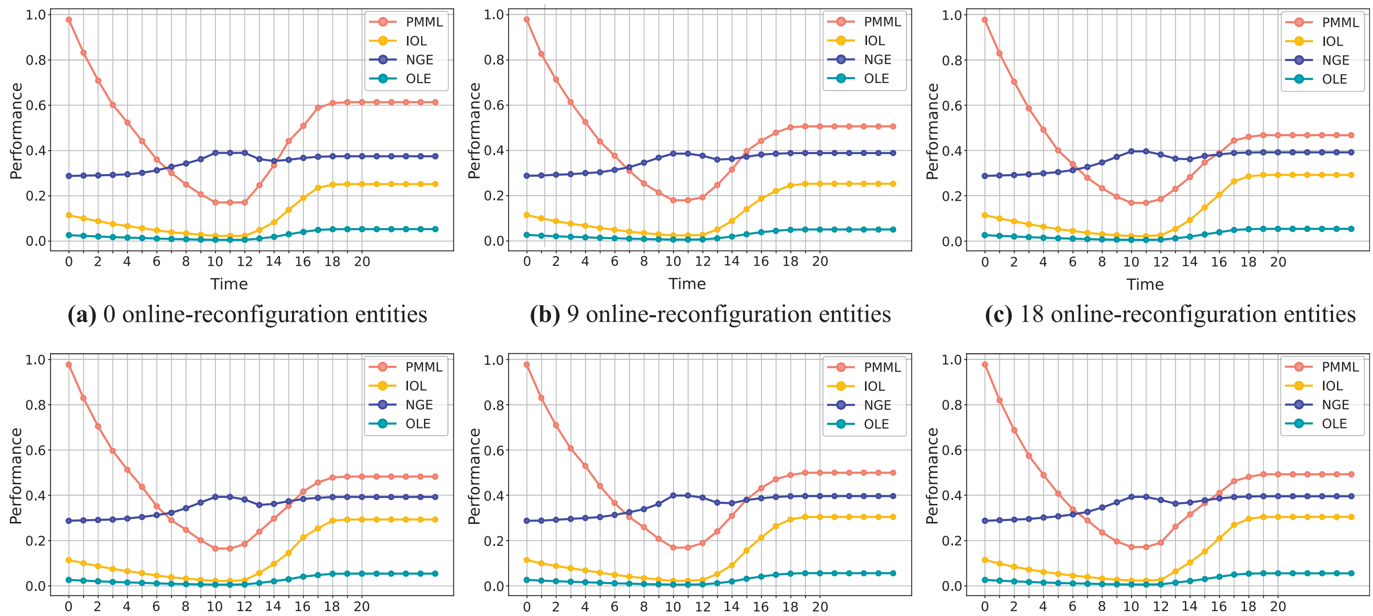



**Fig. 12.** An example of an offline-reconfiguration process for RON.




**(a)** 0 online-reconfiguration entities

**(b)** 9 online-reconfiguration entities

**(c)** 18 online-reconfiguration entities

**(d)** 27 online-reconfiguration entities

**(e)** 36 online-reconfiguration entities

**(f)** 45 online-reconfiguration entities

**Fig. 13.** Performance fluctuation under different quantity of online-reconfiguration.

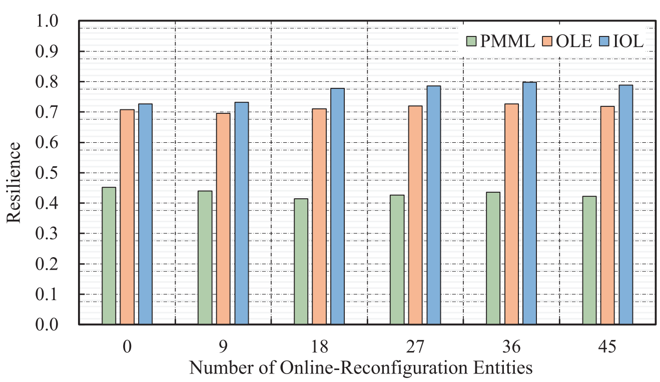



**Fig. 14.** Resilience under different quantity of online-reconfiguration.

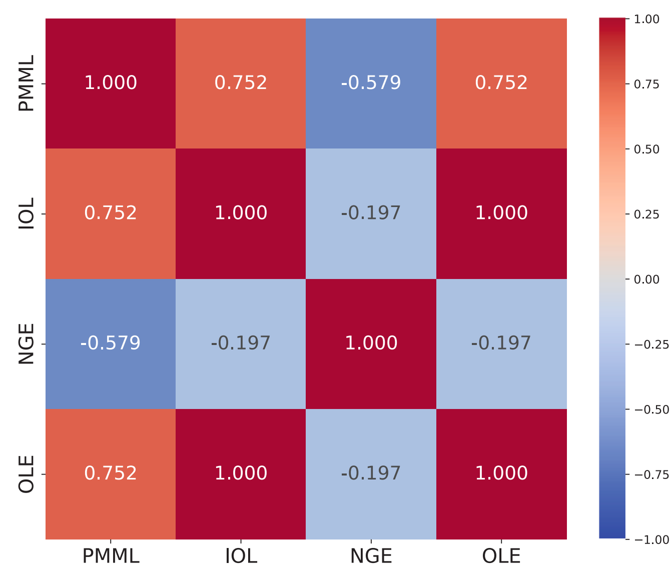



**Fig. 15.** Correlation analysis of performance measurements.

results shown in the previous experiment, and also due to the effect of the increase of the operation loops caused by the offline-reconfiguration operation. However, the resilience trend of PMML does not change significantly with the increase of the number of online-reconfiguration entities. This further highlights the rationality of PMML, as the “curse” of load significantly undermines the effectiveness of recovery resulting from the offline-reconfiguration operation. If indicators such as the number of operation loops are employed as criteria for evaluating resilience, the positive resilience design of MASs, such as emergency response systems, will likely favor a tight structure. This, in turn, may result in the emergence of central entities responsible for encompassing all missions. If these entities are attacked or interfered with, the MAS is likely to lose its fundamental capabilities, making such a system inevitably vulnerable (Ma et al., 2022).

*5.1.3. Sensitivity analysis*

To further verify the rationality of PMML, a sensitivity analysis of configuration has also been conducted in this experiment, as shown in Fig. 16.

The results indicate that the influence of both the number of offline-reconfiguration entities and the number of online-reconfiguration entities on resilience based on PMML does not exhibit significant bias. Specifically, the sensitivity of the number of offline-reconfiguration entities is approximately zero, while an increase in the number of online-reconfiguration entities has a minor impact on resilience. However, the sensitivity analysis for both IOL and OLE demonstrated a clear trend: the sensitivity of the number of online-reconfiguration entities is positive and greater than that of the number of offline-reconfiguration entities, which is negative. The reason lies in the fact that the IOL and OLE indexes fail to account for the load increase resulting from offline-reconfiguration. In contrast, the PMML index achieve an evaluation balance between workload distribution and the number of operation loops, ensuring that the resilience of the random reconfiguration scheme remains relatively stable regardless of the number of reconfiguration entities configured within the emergency response system. This is consistent with the practical utility of various reconfiguration entities, which indicates that reconfiguration is subject to constraints and entails

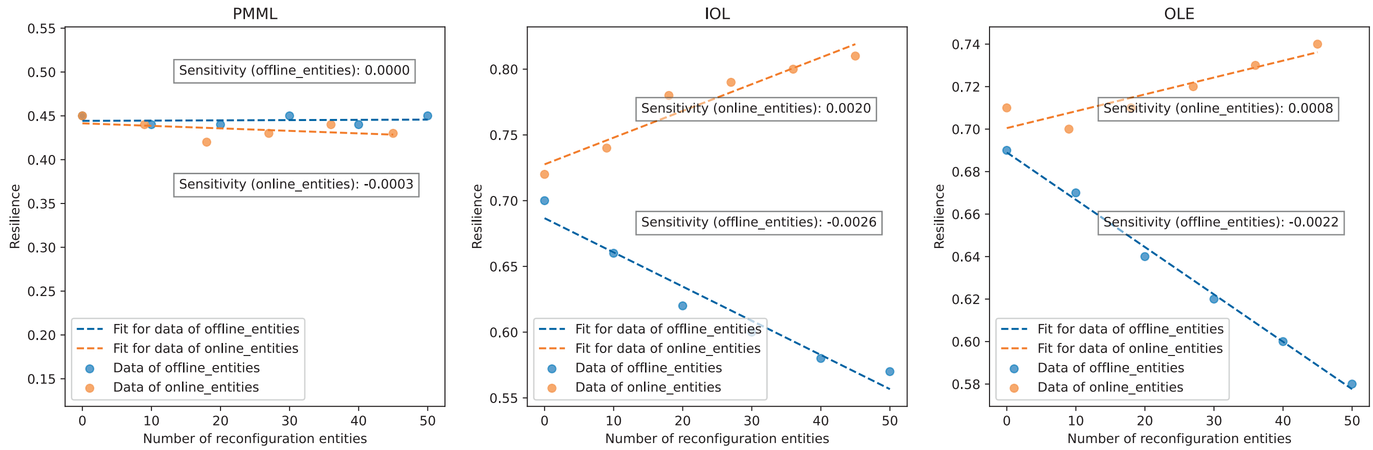



**Fig. 16.** Sensitivity analysis.

associated costs. On the one hand, this highlights the advantages of PMML in assessing the performance of heterogeneous MASs based on operational loops, such as emergency response systems. On the other hand, it reveals the limitations of the random reconfiguration. Therefore, it is essential to investigate more optimal reconfiguration schemes, as well as advanced methods for generating such schemes.

### *5.2. Reconfiguration scheme generation and resilience optimization*

In the aforementioned experiments, the random reconfiguration scheme demonstrated inadequate recovery effect on the emergency response system. Consequently, a more effective reconfiguration scheme is required to enhance and optimize the resilience of the emergency response system. This study validates the feasibility and effectiveness of the proposed method by comparing common reconfiguration schemes with the optimized reconfiguration scheme generated through the optimal reconfiguration scheme generation method, thereby providing guidance for the reconfiguration of the emergency response system. The settings of optimal reconfiguration scheme generation method are shown in Table 7.

#### *5.2.1. Reconfiguration scheme generated by different methods*

In this experiment, we compare the performance fluctuation of RON under common reconfiguration schemes against the optimized reconfiguration scheme based the proposed method, as depicted in Fig. 17. Common reconfiguration schemes include random reconfiguration scheme, online-prior reconfiguration scheme, offline-prior reconfiguration scheme and greedy-based reconfiguration scheme. Online-prior reconfiguration scheme represents that the faulty entities prefer the nearest online-reconfiguration entities for reconfiguration (Chen et al., 2023). On the contrary, faulty entities preferentially select offline-reconfiguration entities to replace in the offline-prior reconfiguration scheme. Moreover, the greedy algorithm operates on the principle of selecting, for each faulty node, an alternative node that minimizes reconfiguration time while maximizing the potential improvement in current performance of RON.

It is evident that the RON model reconfigured according to the optimal reconfiguration demonstrates superior performance recovery, with its resilience surpassing that of other schemes. Among the common reconfiguration schemes, the RON under the online-prior reconfiguration scheme exhibits the fastest performance recovery. This is because online-reconfiguration does not take into account allocation time and activation time. Therefore, the RON has higher resilience at the beginning of reconfiguration, but owing to the online-reconfiguration entities' increasing workload, the recovered performance is lower at the end of reconfiguration. In contrast, performance of RON under the offline-prior reconfiguration scheme initially recovered slowly but eventually reached a higher level.

Generally, a GA exhibits polynomial-time complexity, primarily determined by population size, chromosome length, the number of iterations, and the costs of selection, crossover, and mutation operations. In the proposed framework, however, the complexity is significantly higher due to the scale of the network reconfiguration problem, especially in large-scale settings. The expanded decision space for reconfiguration necessitates longer chromosomes, and the fitness evaluation involves computationally intensive steps such as performance and resilience assessment considering mission load. Consequently, the overall computational complexity of the proposed framework is higher compared to a GA applied to simpler problems, and the actual runtime is also longer.

Furthermore, the greedy algorithm can produce a relatively high-quality solution within a short computational time. However, owing to its short-sighted nature, it makes locally optimal decisions at each step without taking global optimality into account. Consequently, the reconfiguration scheme generated based on the greedy algorithm is generally inferior to that based on GA, although GA typically requires longer computation times.

**Table 7**
Settings of optimal reconfiguration scheme generation method.

| Component of GA | Setting |
|---|---|
| Encoding | The proposed encoding for reconfiguration based on the natural numbers |
| Initialization | Random initialization |
| Selection operator | Combination of the binary tournament method and the retention of the elite strategy |
| Crossover operator | Partially Matched Crossover |
| Mutation operator | Adaptive mutation operator |
| Population size | 200 |
| Termination condition | Fitness stagnation of the optimal solution |

#### *5.2.2. Resilience optimization based on different performance measure*

This case also carried out a comparative experiment on the generation of optimal reconfiguration schemes with different resilience-oriented objectives, utilizing IOL, OLE, and PMML as performance parameters, respectively. This experiment demonstrates the superiority of PMML in reconfiguration optimization and resilience enhancement for the emergency response system, as shown in Fig. 18. It is clear that the optimal reconfiguration scheme based on PMML achieves the most effective performance recovery and exhibits the highest level of resilience.

Based on this experiment, the network topology of RON after reconfiguration guided by different schemes is also analyzed. It is

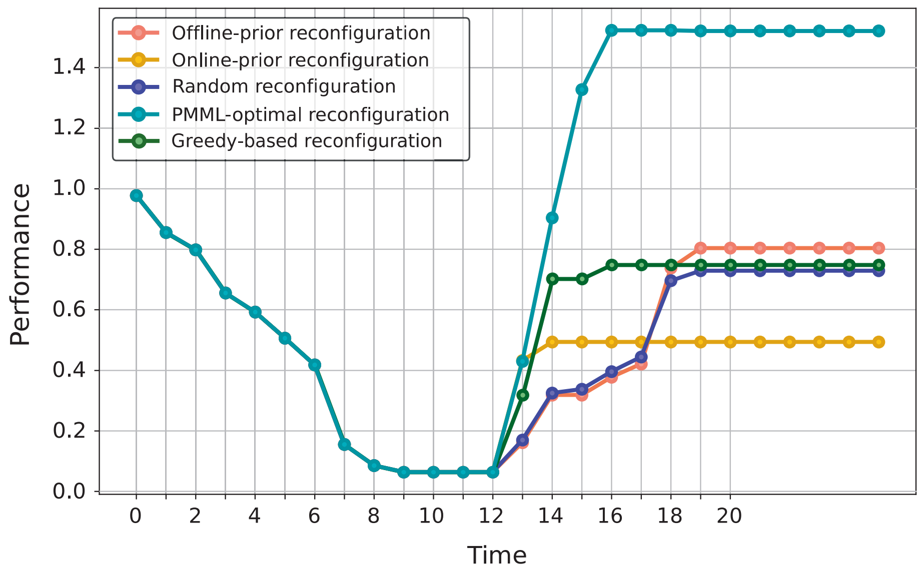



**Fig. 17.** Comparison of different reconfiguration schemes.

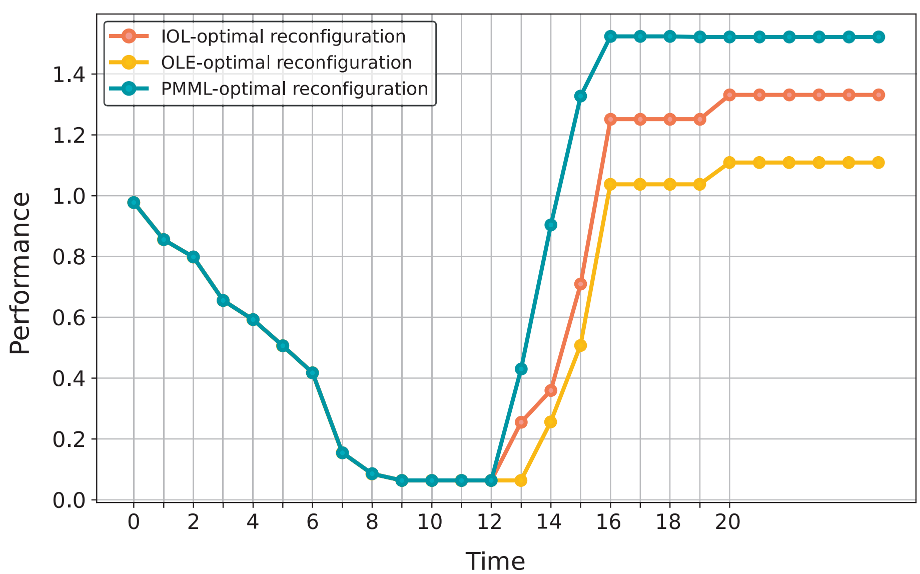



**Fig. 18.** Comparison of optimal reconfiguration schemes based on different performance metrics.

observed that the reconfiguration scheme based on IOL tends to form a network topology containing central nodes (i.e., nodes with greater centrality, such as nodes D4 and A2, as shown in Fig. 19 and Table 8. The finding aligns with the experimental analysis and assumption proposed in Section 4.1.1.

Strong connectivity serves as a critical metric for evaluating the connectivity of a directed graph. It denotes the presence of bidirectional paths between any two nodes within the graph. The robustness of a digraph can be assessed by analyzing changes in strong connectivity upon the removal of specific nodes or edges (Artime et al., 2024). We carried out high-degree node removal on the reconfigured network based on IOL, OLE and PMML respectively. Our analysis revealed that the maximum sizes of the strongly connected components for the three networks were initially 28, 27, and 28, respectively, indicating relatively similar disparities. However, following the removal of the high-degree nodes, the sizes of the largest strongly connected components changed to 19, 20, and 23 respectively, as presented in Table 9. This indicates that the network structure reconfigured according to the PMML-based resilience objective exhibits greater robustness, thereby further validating the superiority of the PMML measurement.

## 6. Findings and discussion

In this section, we have explicitly answered each of our research questions and elaborated on its managerial implications in sequence, providing clear and actionable insights for practitioners regarding.

Firstly, we developed the RON model based on the operation loop composed of sensors, deciders, and actors in MAS. This model encompasses four reconfigurable attributes: entity redundancy, functional substitutability, load affordability, and resource accessibility. For managers, these attributes serve as a practical checklist for resilience-oriented design. In practice, it is recommended to proactively plan these attributes during the system design phase. For instance, as demonstrated in the Case Study, well-planned reconfigurable attributes can significantly improve the resilience of an emergency response system. The RON model provides a foundation for both evaluating and optimizing MAS resilience, thereby assisting managers in formulating effective enhancement plans. Furthermore, it enables a modular design

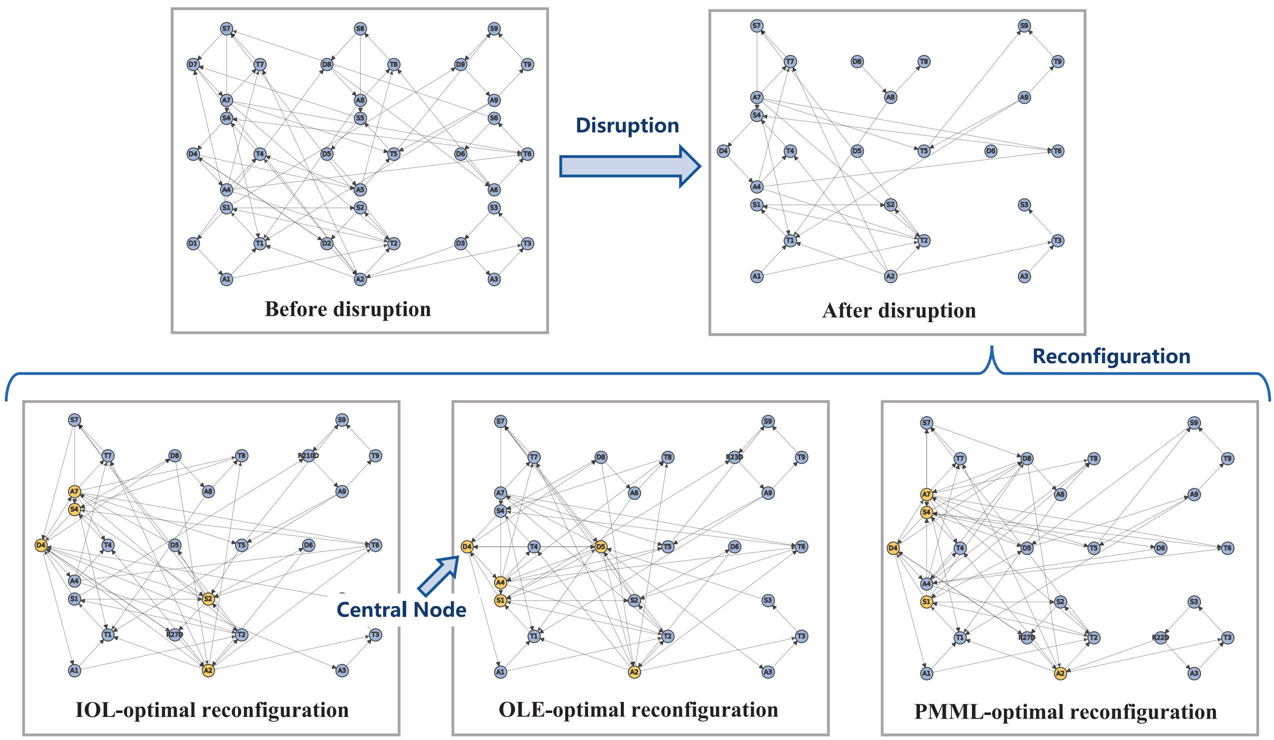



**Fig. 19.** Topology of RON under different optimal reconfiguration schemes.

**Table 8**
Network centrality of central nodes under different optimal reconfiguration schemes.

| | IOL-optimal reconfiguration | | OLE-optimal reconfiguration | | PMML-optimal reconfiguration | |
|---|---|---|---|---|---|---|
| No. | Node | Centrality | Node | Centrality | Node | Centrality |
| 1 | D4 | 0.113 | D5 | 0.087 | S4 | 0.087 |
| 2 | A2 | 0.0956 | A2 | 0.087 | A7 | 0.087 |
| 3 | S2 | 0.087 | A4 | 0.0696 | S1 | 0.0696 |
| 4 | A7 | 0.0782 | S1 | 0.0696 | A2 | 0.0696 |
| 5 | S4 | 0.0609 | D4 | 0.0609 | D4 | 0.0696 |

**Table 9**
Robustness of reconfiguration optimization scheme based on different performance metrics.

| Reconfiguration scheme | Maximum strongly connected component size | |
|---|---|---|
| | Before node removal | After node removal |
| IOL-optimal reconfiguration | 28 | 19 |
| OLE- optimal reconfiguration | 27 | 20 |
| PMML- optimal reconfiguration | 28 | 23 |

approach for MAS. Managers can also integrate this model with predictive technologies (e.g., multi-agent simulation, deep reinforcement learning) to proactively allocate resources or implement reconfiguration measures against potential risks, shifting from reactive recovery to preventive resilience enhancement.

Subsequently, we proposed a performance measurement and a multi-parameter resilience metric based on node-load centrality, which considers mission load during reconfiguration. Compared to conventional metrics (e.g., number of operation loops, global efficiency) that neglect load variations and may inadvertently encourage centralized, load-imbalanced structures, our measurement balances workload distribution and operational capacity. This provides managers with a more accurate tool for decision-making. Specifically, managers can use this metric to: (1) objectively compare the resilience of different system configurations or design proposals, and (2) make informed trade-offs between the level of resilience achieved and the associated costs of resource consumption and agent workload. Prioritizing this balance is crucial for sustainable and efficient resilient design.

Furthermore, we presented a framework for generating optimal reconfiguration schemes. Its feasibility and effectiveness are verified in the Case Study, where it produced schemes with superior resilience and post-reconfiguration robustness. For implementation, managers should consider the choice of optimization paradigm. The centralized optimization framework ensures global optimality and is suitable for scenarios requiring efficient, pre-planned decisions. However, managers must be aware of its risk: a single point of failure at the decision center. In contrast, for systems operating in highly complex and uncertain environments where decision robustness is paramount, a distributed or decentralized framework leveraging swarm intelligence is advisable, as it eliminates the central point of failure. The choice depends on the specific trade-off between optimality and robustness that the operational context demands.

## 7. Conclusion

With the increasing complexity and interconnection, the MAS is susceptible to collapse, which leads to the decline of the operation performance and the loss of personnel and social property. In order to ensure the continuous and stable operation of MAS and rapid recovery after damage, reconfiguration-based resilience enhancement has become a widely adopted practice. Aiming to address the challenge of reconfigurable design and resilience enhancement for MAS, the main conclusions of our work can be summarized as follows: (i) the RON model is developed based on the operation loop composed of sensors, deciders, and actors, which incorporates reconfigurable attributes and constraints of MAS; (ii) a performance measurement and a multi-parameter resilience metric are proposed based on node-load centrality considering mission load during reconfiguration; (iii) the framework for generating the optimal reconfigurable scheme of RON is presented, mainly including the resilience-oriented objective, the constraints of reconfigurable attributes, the encoding and decoding for reconfiguration, and the optimization algorithm.

The RON model and reconfigurable attributes can facilitate the resilient design of MAS in practical. offers a framework for resilience research on MAS, which supports resilience evaluation and optimization and assists decision-makers and managers in formulating a resilience enhancement plan for MAS. Additionally, the proposed performance measurement and resilience metric achieve an evaluation balance between mission load distribution and the number of operation loops, ensuring the accuracy of resilience assessment for MAS. This can assist managers in comparing the resilience and making decisions regarding the resilient design of MAS. Moreover, the optimal reconfiguration scheme generated by the proposed optimization framework enables MAS to attain greater resilience and robustness compared to other schemes in practical scenarios.

However, our study still has deficiencies in the objectives, constraints, and algorithms of reconfiguration-based resilience optimization. Additionally, the RON model is a deterministic model that does not take uncertainty into account, weakening the model's applicability to a certain extent. Future research will systematically incorporate economic cost, energy, and personnel load into the multi-objective optimization of resilience to conduct a reconfigurable design of MAS. In addition, the application of intelligent learning algorithms such as RL and DL can better solve the problems of decentralized reconfiguration and proactive preventive reconfiguration in complex and uncertain environments. Furthermore, given the continuous and unpredictable nature of disruption, resilience enhancement based on reconfiguration is no longer achieved in a single effort but rather through a series of consecutive and iterative processes along with disruption. Thus, there is a need to explore more complex and precise reconfigurable design.

## CRediT authorship contribution statement

**Yuheng Dang:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Conceptualization. **Hengte Du:** Writing – review & editing, Methodology, Investigation. **Xu Wang:** Writing – review & editing, Methodology, Conceptualization. **Xing Pan:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgment

This work was supported by the National Natural Science Foundation of China under Grant No. 72071011.

## Data availability

Data will be made available on request.

## References

Almoghathawi, Y., Barker, K., & Albert, L. A. (2019). Resilience-driven restoration model for interdependent infrastructure networks. *Reliability Engineering and System Safety, 185*, 12–23. https://doi.org/10.1016/j.ress.2018.12.006

Artime, O., Grassia, M., De Domenico, M., Gleeson, J. P., Makse, H. A., Mangioni, G., et al. (2024). Robustness and resilience of complex networks. *Nature Reviews Physics, 6*(2), 114–131. https://doi.org/10.1038/s42254-023-00676-y

Bai, G., Li, Y., Fang, Y., Zhang, Y.-A., & Tao, J. (2020). Network approach for resilience evaluation of a UAV swarm by considering communication limits. *Reliability Engineering and System Safety, 193*. https://doi.org/10.1016/j.ress.2019.106602

Belgacem, A., Mahmoudi, S., & Kihl, M. (2022). Intelligent multi-agent reinforcement learning model for resources allocation in cloud computing. *Journal of King Saud University - Computer and Information Sciences, 34*, 2391–2404. https://doi.org/10.1016/J.JKSUCI.2022.03.016

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., et al. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*.

Chen, Z. W., Hong, D. P., Cui, W. W., Xue, W. K., Wang, Y., & Zhong, J. L. (2023). Resilience evaluation and optimal design for weapon system of systems with dynamic reconfiguration. *Reliability Engineering and System Safety, 237*. https://doi.org/10.1016/j.ress.2023.109409

Chen, Z. W., Yin, S. Y., Li, L. F., Cui, W. W., & Hong, D. P. (2024). Resilience metric and dynamic assessment of unmanned system-of-systems considering cooperative reconfiguration strategies. *IEEE Transactions on Reliability*. https://doi.org/10.1109/TR.2024.3438810

Cheng, Y., Elsayed, E. A., & Huang, Z. (2022). Systems resilience assessments: A review, framework and metrics. *International Journal of Production Research, 60*. https://doi.org/10.1080/00207543.2021.1971789

Dhulipala, S. L. N., & Flint, M. M. (2020). Series of semi-Markov processes to model infrastructure resilience under multihazards. *Reliability Engineering and System Safety, 193*. https://doi.org/10.1016/j.ress.2019.106659

Du, W., Yang, G., Pan, C., & Xi, P. (2019). A Heterogeneous multi-Agent system model with navigational feedback for load demand management of a zonal medium voltage dc shipboard power system. *IEEE Access, 7*, 148073–148083. https://doi.org/10.1109/ACCESS.2019.2946644

Feng, Q., Hai, X., Sun, B., Ren, Y., Wang, Z., Yang, D., et al. (2022). Resilience optimization for multi-UAV formation reconfiguration via enhanced pigeon-inspired optimization. *Chinese Journal of Aeronautics, 35*, 110–123. https://doi.org/10.1016/j.cja.2020.10.029

Gao, J., Buldyrev, S. V., Havlin, S., & Stanley, H. E. (2011). Robustness of a network of networks. *Physical Review Letters, 107*. https://doi.org/10.1103/PhysRevLett.107.195701

Guo, Q., Amin, S., Hao, Q., & Haas, O. (2020). Resilience assessment of safety system at subway construction sites applying analytic network process and extension cloud models. *Reliability Engineering and System Safety, 201*. https://doi.org/10.1016/j.ress.2020.106956

Guo, M., & DImarogonas, D. V. (2017). Task and motion coordination for heterogeneous multiagent systems with loosely coupled local tasks. *IEEE Transactions on Automation Science and Engineering, 14*, 797–808. https://doi.org/10.1109/TASE.2016.2628389

Henry, D., & Emmanuel, R.-M. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering and System Safety, 99*, 114–122. https://doi.org/10.1016/j.ress.2011.09.002

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245

Hu, M., Zhang, W., Ren, X., Qin, S., Chen, H., & Zhang, J. (2025). A novel resilient scheduling method based on multi-agent system for flexible job shops. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2025.2456577

Hu, T., Zong, Y., Lu, N., & Jiang, B. (2025). Toward the resilience of UAV swarms with percolation theory under attacks. *Reliability Engineering and System Safety, 254*. https://doi.org/10.1016/j.ress.2024.110608

Huang, Y. (2015). Modeling and simulation method of the emergency response systems based on OODA. *Knowledge-based Systems, 89*, 527–540. https://doi.org/10.1016/J.KNOSYS.2015.08.020

Kakadia, D., & Ramirez-Marquez, J. E. (2020). Quantitative approaches for optimization of user experience based on network resilience for wireless service provider networks. *Reliability Engineering and System Safety, 193*. https://doi.org/10.1016/j.ress.2019.106606

Leng, J., Guo, J., Wang, D., Zhong, Y., Xu, K., Huang, S., et al. (2024). Blockchain-of-things-based edge learning contracts for federated predictive maintenance toward resilient manufacturing. *IEEE Transactions on Computational Social Systems, 11*, 7990–8004. https://doi.org/10.1109/TCSS.2024.3395467

Leng, J., Ruan, G., Xu, C., Zhou, X., Xu, K., Qiao, Y., et al. (2024). Deep reinforcement learning of graph convolutional neural network for resilient production control of mass individualized prototyping toward industry 5.0. *IEEE Transactions on Systems Man Cybernetics-Systems, 54*, 7092–7105. https://doi.org/10.1109/TSMC.2024.3446671

Leng, J., Xie, J., Li, R., Zhou, X., Gu, X., Liu, Q., et al. (2025). Resilient manufacturing: A review of disruptions, assessment, and pathways. *Journal of Manufacturing Systems, 79*, 563–583. https://doi.org/10.1016/J.JMSY.2025.02.006

Leng, J., Zhong, Y., Lin, Z., Xu, K., Mourtzis, D., Zhou, X., et al. (2023). Towards resilience in Industry 5.0: A decentralized autonomous manufacturing paradigm. *Journal of Manufacturing Systems, 71*, 95–114. https://doi.org/10.1016/J.JMSY.2023.08.023

Leng, J., Zhu, X., Huang, Z., Xu, K., Liu, Z., Liu, Q., et al. (2023). ManuChain II: blockchained smart contract system as the digital twin of decentralized autonomous manufacturing toward resilience in industry 5.0. *IEEE Transactions on Systems Man Cybernetics-Systems, 53*, 4715–4728. https://doi.org/10.1109/TSMC.2023.3257172

Li, J., Ge, B., Yang, K., Chen, Y., & Tan, Y. (2017). Meta-path based heterogeneous combat network link prediction. *Physica A: Statistical Mechanics and Its Applications, 482*, 507–523. https://doi.org/10.1016/j.physa.2017.04.126

Li, J. C., Jiang, J., Yang, K. W., & Chen, Y. W. (2019). Research on functional robustness of heterogeneous combat networks. *IEEE Systems Journal, 13*, 1487–1495. https://doi.org/10.1109/JSYST.2018.2828779

Li, Z., Jin, C., Hu, P., & Wang, C. (2019). Resilience-based transportation network recovery strategy during emergency recovery phase under uncertainty. *Reliability*

*Engineering and System Safety, 188*, 503–514. https://doi.org/10.1016/j.ress.2019.03.052
Li, X. Y., Li, Y. F., & Huang, H. Z. (2020). Redundancy allocation problem of phased-mission system with non-exponential components and mixed redundancy strategy. *Reliability Engineering and System Safety, 199*, Article 106903. https://doi.org/10.1016/J.RESS.2020.106903
Li, H., Sun, Q., Zhong, Y., Huang, Z., & Zhang, Y. (2023). A soft resource optimization method for improving the resilience of UAV swarms under continuous attack. *Reliability Engineering & System Safety*. , Article 109368. https://doi.org/10.1016/j.ress.2023.109368
Li, J., Tan, Y., Yang, K., Zhang, X., & Ge, B. (2017). Structural robustness of combat networks of weapon system-of-systems based on the operation loop. *International Journal of Systems Science, 48*, 659–674. https://doi.org/10.1080/00207721.2016.1212429
Li, J. C., Zhao, D. L., Jiang, J., Yang, K. W., & Chen, Y. W. (2021). Capability oriented equipment contribution analysis in temporal combat networks. *IEEE Transactions on Systems Man Cybernetics-Systems, 51*, 696–704. https://doi.org/10.1109/TSMC.2018.2882782
Ling, M. F., Moon, T., & Kruzins, E. (2005). Proposed network centric warfare metrics: From connectivity to the OODA cycle. *Military Operations Research, 10*, 5–13. https://doi.org/10.5711/morj.10.1.5
Liu, X., Li, D., Ma, M., Szymanski, B. K., Stanley, H. E., & Gao, J. (2022). Network resilience. *Physics Reports, 971*, 1–108. https://doi.org/10.1016/j.physrep.2022.04.002
Liu, J., Xu, R., Li, J., Yang, K., & Lou, Z. (2024). Enhancing the resilience of combat system-of-systems under continuous attacks: Novel index and reinforcement learning-based protection optimization. *Expert Systems with Applications, 251*. https://doi.org/10.1016/j.eswa.2024.123912
Lloret, F., Keeling, E. G., & Sala, A. (2011). Components of tree resilience: Effects of successive low-growth episodes in old ponderosa pine forests. *Oikos, 120*, 1909–1920. https://doi.org/10.1111/j.1600-0706.2011.19372.x
Luo, M.-Y., & Yang, C.-S. (2002). Enabling fault resilience for web services. *Computer Communications, 25*, 198–209. https://doi.org/10.1016/S0140-3664(01)00363-2
Ma, L., Zhang, X., Li, J., Lin, Q., Gong, M., Coello, C. A. C., et al. (2022). Enhancing robustness and resilience of multiplex networks against node-community cascading failures. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52*. https://doi.org/10.1109/TSMC.2021.3073212
Mohd Subha, N. A., & Mahyuddin, M. N. (2021). Distributed adaptive cooperative control with fault compensation mechanism for heterogeneous multi-robot system. *IEEE Access, 9*, 128550–128563. https://doi.org/10.1109/ACCESS.2021.3112571
Ouyang, M., & Wang, Z. (2015). Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering and System Safety, 141*, 74–82. https://doi.org/10.1016/j.ress.2015.03.011
Pan, X., Dang, Y., Wang, H., Hong, D., Li, Y., & Deng, H. (2022). Resilience model and recovery strategy of transportation network based on travel OD-grid analysis. *Reliability Engineering and System Safety, 223*. https://doi.org/10.1016/j.ress.2022.108483
Pan, X., & Wang, H. (2018). Resilience of and recovery strategies for weighted networks. *PLoS One, 13*, Article e0203894. https://doi.org/10.1371/JOURNAL.PONE.0203894
Pan, X., Wang, H. X., Yang, Y. J., & Zhang, G. Z. (2019). Resilience based importance measure analysis for SoS. *Journal of Systems Engineering and Electronics, 30*, 920–930. https://doi.org/10.21629/JSEE.2019.05.10.
Shan, Q., Teng, F., Li, T., & Chen, C. L. P. (2021). Containment control of multi-agent systems with nonvanishing disturbance via topology reconfiguration. *Science China Information Sciences, 64*, 1–3. https://doi.org/10.1007/S11432-018-9695-2/METRICS
Shao, J., Zhou, Q., Ye, D., Xiao, Y., & Sun, Z. (2023). Finite-time synchronization control scheme for underactuated satellite formation reconfiguration. *Advances in Space Research, 72*. https://doi.org/10.1016/j.asr.2023.04.011
Sun, Q., Li, H., Wang, Y., & Zhang, Y. (2022). Multi-swarm-based cooperative reconfiguration model for resilient unmanned weapon system-of-systems. *Reliability Engineering and System Safety, 222*. https://doi.org/10.1016/j.ress.2022.108426
Sun, Q., Li, H. X., Zeng, Y. F., & Zhang, Y. C. (2024). Resilience-driven cooperative reconfiguration strategy for unmanned weapon system-of-systems. *Journal of Systems Engineering and Electronics, 35*, 932–944. https://doi.org/10.23919/JSEE.2024.000088
Tan, E., Ma, X., Du, Y., & Zhang, Z. (2024). Enhancing urban metro system resilience under disruptive events through multi-agent reinforcement learning. *Journal of Transportation Safety & Security*. https://doi.org/10.1080/19439962.2023.2300272
Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E: Logistics and Transportation Review, 79*, 22–48. https://doi.org/10.1016/J.TRE.2015.03.005
Tran, H. T., Balchanos, M., Domerçant, J. C., & Mavris, D. N. (2017). A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering and System Safety, 158*, 73–84. https://doi.org/10.1016/j.ress.2016.10.014
Tran, H.T., Domerçant, J.C., Mavris, D.N. 2015. A system-of-systems approach for assessing the resilience of reconfigurable command and control networks. AIAA Infotech at Aerospace, American Institute of Aeronautics and Astronautics Inc. https://doi.org/10.2514/6.2015-0640.
Uday P, Marais K. Exploiting stand-in redundancy to improve resilience in a system of-Systems (SoS). Procedia Comput Sci, vol. 16, Elsevier B.V.; 2013, p. 532–41. https://doi.org/10.1016/j.procs.2013.01.056.
Yang, D., Li, Q., Zhu, F., Cui, H., Yi, W., & Qin, J. (2023). Parallel emergency management of incidents by integrating OODA and PREA loops: The C2 mechanism and modes. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53*, 2160–2172. https://doi.org/10.1109/TSMC.2022.3229036
You, R., & Liu, Q. (2024). Deep Luenberger observer-based consistency tracking for nonlinear heterogeneous multi-agent systems with uncertain drift dynamics. *Knowledge-based Systems, 284*, Article 111264. https://doi.org/10.1016/J.KNOSYS.2023.111264
Yousefi, N., DavidW, C., Song, S., & Feng, Q. (2019). Optimization of on-condition thresholds for a system of degrading components with competing dependent failure processes. *Reliability Engineering & System Safety*.
Zhang, J., Li, L., & Chen, Z. (2021). Strength–redundancy allocation problem using artificial bee colony algorithm for multi-state systems. *Reliability Engineering & System Safety*. , Article 107494. https://doi.org/10.1016/j.ress.2021.107494
Zhao, J., Si, S., & Cai, Z. (2019). A multi-objective reliability optimization for reconfigurable systems considering components degradation. *Reliability Engineering and System Safety, 183*, 104–115. https://doi.org/10.1016/j.ress.2018.11.001
Zhao, T., Tang, Y., Li, Q., & Wang, J. (2023). Resilience-oriented network reconfiguration strategies for community emergency medical services. *Reliability Engineering and System Safety, 231*. https://doi.org/10.1016/j.ress.2022.109029
Zhong, Y., Li, H., Sun, Q., Huang, Z., & Zhang, Y. (2024). A kill chain optimization method for improving the resilience of unmanned combat system-of-systems. *Chaos, Solitons and Fractals, 181*, Article 114685. https://doi.org/10.1016/J.CHAOS.2024.114685
Zhou, X., Xiong, J., Zhao, H., Liu, X., Ren, B., Zhang, X., et al. (2024). Joint UAV trajectory and communication design with heterogeneous multi-agent reinforcement learning. *Science China Information Sciences, 67*, 1–21. https://doi.org/10.1007/S11432-023-3906-3/METRICS
Zou, Q., & Chen, S. (2019). Enhancing resilience of interdependent traffic-electric power system. *Reliability Engineering and System Safety*.