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# Understanding the Resilience of Urban Rail Transit: Concepts, Reviews, and Trends

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ABSTRACT

As the scale of urban rail transit (URT) networks expands, the study of URT resilience is essential for safe and efficient operations. This paper presents a comprehensive review of URT resilience and highlights potential trends and directions for future research. First, URT resilience is defined by three primary abilities: absorption, resistance, and recovery, and four properties: robustness, vulnerability, rapidity, and redundancy. Then, the metrics and assessment approaches for URT resilience were summarized. The metrics are divided into three categories: topology-based, characteristic-based, and performance-based, and the assessment methods are divided into four categories: topological, simulation, optimization, and data-driven. Comparisons of various metrics and assessment approaches revealed that the current research trend in URT resilience is increasingly favoring the integration of traditional methods, such as conventional complex network analysis and operations optimization theory, with new techniques like big data and intelligent computing technology, to accurately assess URT resilience. Finally, five potential trends and directions for future research were identified: analyzing resilience based on multisource data, optimizing train diagram in multiple scenarios, accurate response to passenger demand through new technologies, coupling and optimizing passenger and traffic flows, and optimal line design.



## 1. Introduction

As an essential component of the urban public transport system, urban rail transit (URT) has the characteristics of safety, high efficiency, large volume, punctuality, energy savings, and environmental protection. It plays a highly crucial role in alleviating traffic congestion in big cities [1–3]. Therefore, they have developed rapidly in recent years. As of June 30, 2023, 57 cities in the mainland of China have opened 295 URT lines, with an operating mileage of 10 566.55 km. These rail transit lines have a total passenger volume of 17.59 billion people. Megacities, such as Beijing and Shanghai, have more than 800 km of URT lines in operation, with an average daily passenger flow of over ten million. However, with the expansion of the network scale and increasing traffic intensity, the URT system in operation under the condition of disturbance will experience many delays, regional passenger flow suddenly increases, passenger flow and train connections are inadequate, part of the line section congestion, and a series of problems [4,5], which will have a significant influence on the entire urban traffic system [6–8]. Therefore, studying the resilience of URT systems is essential, as it not only enhances the understanding of the inherent operational mechanisms but also provides new research directions to improve future resilience in URT, ensuring the normal functioning of mega-cities and preventing large-scale transport disruptions.

To address these issues better, researchers have conducted many studies in the field of URT resilience. The main contents are as follows: ① enhancing the ability of the URT system to absorb disturbances; ② rapidly recovering the ability of the URT system after its performance decreases; ③ reducing the vulnerability of the URT system in case of disruptions; and ④ improving the redundancy of the URT system. Big data technology is widely used in resilience research [9,10]. The above research work is meaningful

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for the progress of URT resilience research, but it is still difficult for current technologies to cover all the content. For example, the optimization of the train operation diagram under multiple disruption scenarios and the optimization of passenger and vehicle flow coupling need to be further promoted.

Several review papers are related to this work. A comprehensive review of the resilience of various transportation modes is presented in Ref. [11]. A review of the vulnerability and resilience of transportation systems is presented in Ref. [12]. These reviews focus on a wide range of aspects and encompass the resilience of various modes of transportation. There are few studies on mode-specific resilience. A systematic review of railway resilience was conducted in Ref. [13]. However, few relevant reviews have limited the topic to the URT field. This review aims to establish a definition of resilience in the URT field and provide a comprehensive and integrated summary of the current state of research and research methodologies.

This study provided a taxonomy and reviewed the metrics and approaches for URT resilience assessment. The main contributions of this study are as follows. First, a comprehensive definition of URT resilience was established, considering the properties of robustness, vulnerability, rapidity, and redundancy. Second, the resilience metrics are divided into topological, characteristic, and system performance metrics, and the evaluation approaches are classified as topology, simulation, optimization, and data-driven. Finally, various research methods in the field of URT resilience were summarized, and several future research directions were highlighted.

The remainder of this paper is organized as follows. Section 2 provides definitions and four characteristics of URT resilience. Section 3 provides a comprehensive review of resilience assessment metrics and approaches and offers several future research directions based on the shortcomings of existing studies. A summary and conclusions of this study are presented in Section 4.

## 2. How to define the URT resilience

Resilience originates from the Latin "*resilire*," which means to spring back or rebound to its original state after being compressed or destroyed [14]. Later, the study of resilience was widely applied in many fields, such as ecology, engineering, and economics. For example, Holling [15] regarded the persistence of natural systems in response to natural or anthropogenic causes as ecosystem resilience. Mostert and Von Solms [16] proposed a technique for identifying and specifying computer security and resilience requirements. Farber [17] examines the impact of national policies and climate change on the sustainability of economic resilience.

With the extension of resilience, scholars have begun to apply resilience-based thinking to complex ecosystems and cities. It primarily addresses issues related to climate change and disaster risks by emphasizing prevention and mitigation measures [18]. Urban resilience refers to the ability of cities to withstand disasters, mitigate losses, and deploy resources wisely to recover quickly. In the long run, cities can learn from past disasters and improve their resilience to disasters [19].

Transportation resilience belongs to the field of engineering. According to the research and practice of various national traffic management departments, transportation resilience can be defined as a transportation infrastructure that can predict and adapt to a changing natural environment, has high reliability and necessary redundancy, can withstand and respond to emergencies, and can achieve rapid recovery [12].

A widely accepted definition of resilience is that the ability of a society, economy, or environment to respond to and organize resources promptly when harmful scenarios or disruptions occur, allowing the system to maintain essential functions and structures and continuously adapt, learn, and transform [20]. In summary, when defining the resilience of each field, the core elements are the resistance and recovery of the system [21,22]. At different disruption stages, the system must exhibit diverse abilities to maintain resilience. Therefore, these abilities are essential and should be considered components of resilience.

### 2.1. Concept

URT resilience is defined as the ability of a system to react immediately, absorb disturbances (e.g., daily variations in operations), mitigate disruption losses (e.g., natural disasters, facility failures, or terrorist attacks), and recover quickly through reasonable deployment of resources [23]. When the additional resources are sufficient, they can be restored to a supernormal state.

Fig. 1 shows the elastic demand required by the URT system for resilience. The resilient URT system is mainly manifested in three aspects: ① The URT system has a strong absorption ability for internal and external interference; namely, the system can maintain a certain level of operation under the condition of disturbance impact. ② The URT system has a solid resistance to damage and operational disruptions, resulting in the lowest degree of destruction. ③ The URT system has a strong recovery ability after ruin; that is, the system can quickly recover to the primary or regular operation state after being disrupted by an emergency or operation disturbance or even to the supernormal operation state under the condition of additional resources [24–26].

In the first aspect, the URT network tends to rely on the redundancy of the system to absorb perturbations. For instance, trains cannot run precisely according to the operating diagram. Thus, a certain amount of redundancy is often set aside when the operating diagram is drawn, which is a strategic way to ensure the resilience of the URT system. The second aspect corresponds to situations in which a significant disturbance or accident occurs, causing a sudden and significant reduction or even disruption of the URT system performance. It is often necessary to implement emergency measures in the short term to regulate traffic and passenger flows. This reduces the impact on passengers and ensures the resilience of the URT system. The last aspect is resilience after a disaster; for example, if the URT system is damaged by an earthquake, all parts of the system must be overhauled before it can be opened to the public, and the cost of time and resources required for this overhaul is often an important factor in measuring the resilience of the system, which is a tactical way to ensure the resilience of the URT system.

### 2.2. Resilience properties

Based on the previously proposed definition of URT resilience, the resilience properties are summarized into four aspects: robustness, vulnerability, rapidity, and redundancy [27–29]:

- Robustness: The ability of the URT system to absorb disturbances during operation based on its capacity, that is, the extent to which the system can maintain operation when a disturbance occurs.
- Vulnerability: The sensitivity of the URT system to disturbances is characterized by the degree of consequence or performance degradation due to risk.
- Rapidity: The rapid recovery ability after a disturbance occurs. Through reasonable allocation of resources, the URT system can quickly recover to a particular functional level after disruptions and even to a super level when additional resources are sufficient.
- Redundancy: The key facilities in the URT system have spare modules. When a disturbance occurs, and some functions of the facilities are damaged, spare modules can be supplemented in time, and the entire system can still perform a certain level of function without complete paralysis.

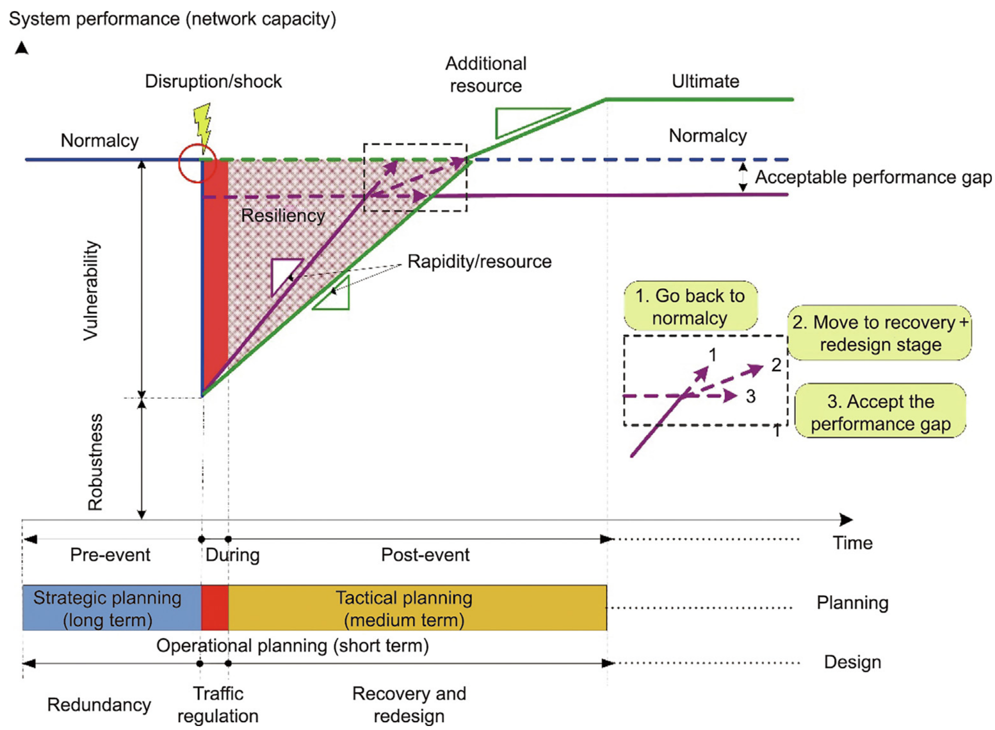


**Fig. 1.** Concept of the URT resilience.

## 3. How to study the URT resilience

This section is divided into two main parts: a summary of previous work and an outlook for future research. How can resilience be studied? First, it is necessary to understand how to measure the resilience of URT systems, focusing on both the evaluation metrics and approaches employed. Consequently, identifying the methods that can enhance resilience, particularly in relation to the critical system components of passengers, trains, and networks, is essential. The general framework for studying URT resilience is shown in Fig. 2. The symbols are listed in Table 1 for convenience in formulating the problem under consideration.

### *3.1. What has been done*

In this section, existing methods for measuring the resilience of URT systems are summarized. Initially, the metrics proposed for measuring URT resilience are reviewed. Subsequently, representative evaluation approaches for calculating these metrics are discussed.

#### *3.1.1. Resilience metrics of the URT system*

The existing metrics of URT network resilience studies can be broadly classified into three categories: topological, characteristic, and system performance.

(1) Topological metrics, such as the degree, betweenness, and size of the giant component, are mainly used to measure the static structural properties and reflect the connectivity of the transportation network in the case of disruption. Topological analysis is derived from the complex network theory, which can provide an effective logical basis for characterizing the resilience of URT systems [30]. Meng et al. [31] constructed a Space-L model of a URT network and quantified the impact of different failure strategies on network resilience by calculating various topological statistical indicators. The URT network has clear scale-free features. Zhang et al. [32] proposed a general framework for assessing the resilience of large and complex URT networks and proposed a method for the optimal recovery sequence. The optimal repair time for disrupted stations in the Shanghai URT system was calculated quantitatively. The proposed resilience assessment metric is expressed in Eq. (1), where $P(t)$ represents the system performance at time $t$. Table 2 [31–34] lists common network topology metrics and their definitions.

$$R = \frac{\int_{t_0}^{t_h}[P(t)]\mathrm{d}t}{(t_h - t_0)P_0} \tag{1}$$

Although topological metrics can represent the size and change in the transportation network under disruption to a certain extent, they have certain one-sidedness and limitations. For example, it ignores the actual supply capacity affected by transportation demand, such as passenger flow and travel time [35]. Therefore, in follow-up research, topology is often used as the fundamental element of the network, and the diversity and richness of the evaluation indicators are further improved.

(2) Characteristic metrics focus on measuring the specific ability of resilience representation. Each of these attributes corresponds to a measure of resilience over time, such as robustness, rapidity, or redundancy. For example, Derrible and Kennedy [36] defined robustness as the ability to provide alternative routes in the event of failure. After an in-depth study of 33 metro networks, it was found that creating new transfer stations at the periphery of the URT network core helped cluster the network and further improve its resilience. Zhang et al. [37] proposed a double-weighted vulnerability model that considered path distance and passenger flow. The proposed resilience metric is represented by Eq. (2).

$$C = \frac{1}{n(n-1)} \sum_{i \in V} \frac{s_{ij}}{d_{ij}}, i \neq j \tag{2}$$

This is a modification of the traditional network efficiency formulation, where $C$ is the network connectivity. They found that there were significant differences in the changes in network

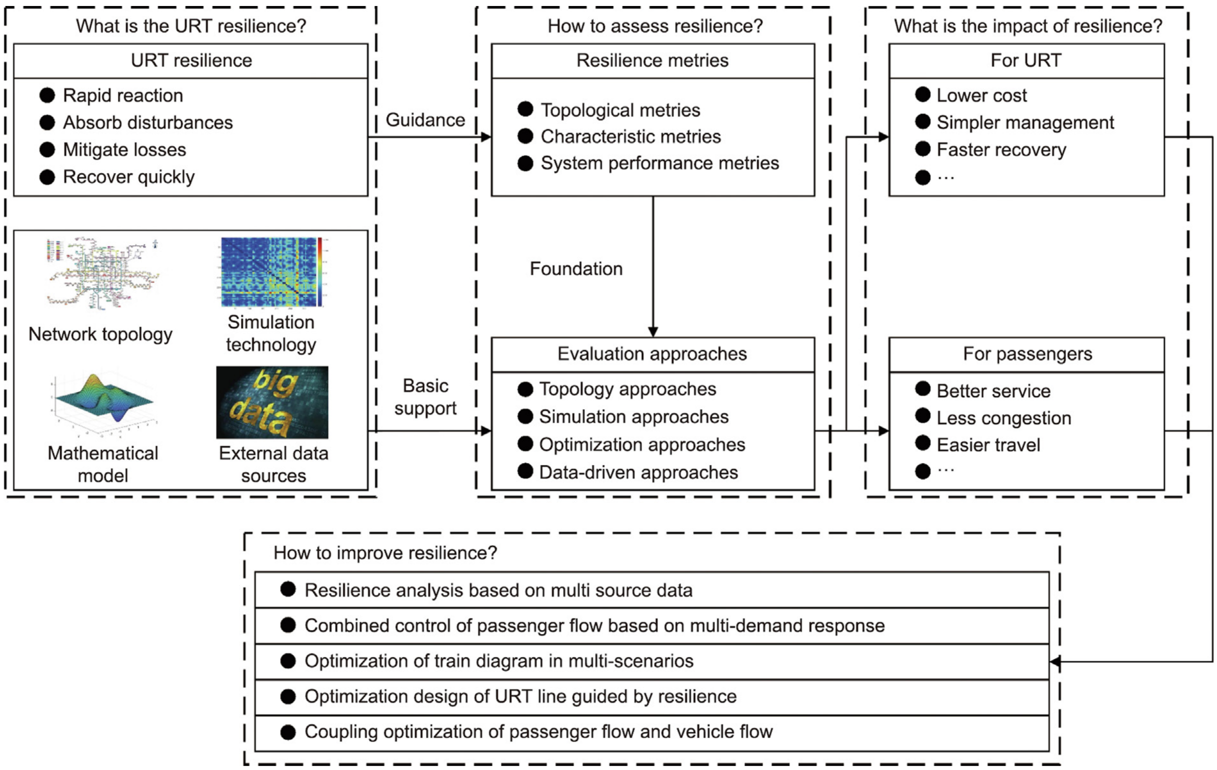


**Fig. 2.** A general framework for studying URT resilience.

**Table 1**
Summary of symbols.

| Symbols | Description |
|---|---|
| $V$ | Set of all stations |
| $K_{ij}$ | Set of effective travel paths from stations $i$ to $j$ |
| $\Omega$ | Set of all origin–destination (OD) pairs |
| $\Psi$ | Set of all trains |
| $R$ | Network resilience |
| $P$ | System performance |
| $P_0$ | Initial performance in the presence of no disruption |
| $t_0$ | Start time point of the disruption |
| $t_h$ | End time point of the disruption |
| $C$ | Network connectivity |
| $n$ | Number of rail stations |
| $d_{ij}$ | Shortest path length from stations $i$ to $j$ |
| $s_{ij}$ | Normalized connection strength of stations $i$ to $j$ |
| $q_i$ | Passenger flow for station $i$ |
| $\hat{q}$ | Sum of the passenger flow of all stations |
| $p_i$ | Performance of station $i$ |
| $v_{ij}$ | Total number of passenger trips from stations $i$ to $j$ |
| $w_{ij}$ | Travel importance from stations $i$ to $j$ |
| $p_{ij}^k$ | Probability of path $k$ being selected from stations $i$ to $j$ |
| $t_{ij}^k$ | Tavel time on path $k$ from stations $i$ to $j$ |
| $\rho_{ij}$ | Minimum generalized travel time from stations $i$ to $j$ |
| $\varepsilon$ | Coupling coefficient |
| $L$ | Relative size of the largest component |
| $E$ | Normal operational efficiency |
| $\tilde{E}$ | Network operational efficiency when there are failed stations |
| $q_i^\omega$ | Passenger flow with OD pair $\omega$ queueing at station $i$ |
| $l_v^\omega$ | Passenger flow with OD pair $\omega$ on-board in train $v$ |

**Table 2**
Topology metrics for URT resilience.

| Metric | Definition | Ref. |
|---|---|---|
| Average node degree | Average value of degrees of all nodes in the network | [32] |
| Characteristic path length | Average value of the shortest path length of all node pairs | [33] |
| Betweenness centrality | The ratio of the shortest path through a node to all shortest paths | [31] |
| Size of giant component | Subnetworks with the maximum number of nodes | [34] |
| Network efficiency | Average of the inverse of the shortest paths length between all network nodes | [32] |

resilience for different failure sizes and failure modes. Moreover stations that are most critical for maintaining network accessibility do not necessarily coincide with those having the highest passenger throughput or the greatest structural connectivity [38]. In evaluating the network recovery ability, Li et al. [39] combined the parallel scheduling algorithm and user equilibrium algorithm to design a two-layer optimization model. The resilience of the URT system is measured from both the recovery result and the recovery process, which can be represented in Eq. (3).

$$P = \sum_{i \in V} \frac{q_i}{\hat{q}} p_i \tag{3}$$

In addition, it is common to improve the resilience of URT systems to help damaged networks recover their basic operation via integration with bus services [40–42]. Table 3 [36,37,39–47] summarizes the commonly used feature-based URT resilience assessment metrics.

(3) The system performance metrics, such as delay time, passenger flow loss, and travel costs, mainly respond to changes in URT performance under a disruption scenario. From a supply perspective, studies based on performance metrics have focused on train delays and the economic costs of the relevant departments. Zhang and Lo [48] established a mathematical model to minimize the cost of initiating substitute bus services based on the probability distribution of the metro disruption duration. Li et al. [49]

**Table 3**
Characteristic metrics for URT resilience.

| Metric | Simple connotation | Refs. |
|---|---|---|
| Robustness | Ability to absorb disturbance during the disturbance | [36,43] |
| Rapidity | Speed and ability to recover after the disruption | [39–42] |
| Redundancy | Ability to provide alternative resources in case of the disruption | [44,45] |
| Vulnerability | The extent of performance degradation after the disruption | [37,46] |
| Adaptability | Ability to self-learn and adjust to the disruption | [47] |

simulated the passenger flow congestion propagation process in a train delay scenario and proposed trip betweenness centrality (TBC) to measure network resilience. In a comprehensive assessment of resilience, the authors incorporated the TBC in conjunction with delay time and other factors.

Based on the disaster-spreading theory, Huang et al. [50] explored the relationship between the self-recovery capability and the number of final failed stations under different accident scenarios. More studies focus on the demand side and explore the resilience metrics of passenger-oriented travel services. Among them, passenger flow loss over time [51] and the travel cost of passenger delay [52] after a disruption are the most common resilience evaluation metrics.

Chen et al. [53] proposed a system resilience metric that can reflect passengers' route choice behavior and travel time, which can be represented by Eq. (4).

$$R = \frac{1}{n(n-1)} \sum_{i\in V} \sum_{j\in V} \frac{v_{ij} w_{ij}}{\sum_{k\in K_{ij}} p_{ij}^k t_{ij}^k}, i \neq j \tag{4}$$

This metric is used to depict the performance curve of the URT system during attack and repair. It is referred to as the resilience triangle to measure the cumulative performance loss. The resilience triangle was first proposed by Bruneau et al. [54], as shown in Fig. 1, where the system performance decreases to a minimum when a disruption occurs and is gradually restored under certain conditions. It can effectively describe the comprehensive ability of infrastructure networks to deal with disaster events, and this theory has also been used to measure the passenger flow recovery level after metro disruptions [55]. Cong et al. [56] identified passengers affected by passenger tap-in time in unplanned URT disruptions and evaluated different rescue measures based on passenger delay time. Additionally, route accessibility and diversity of options are essential metrics of URT network resilience during the epidemic [57,58]. Table 4 [48–53,55–58] lists some common system performance metrics from the literature.

Compared to topological and characteristic metrics, system performance metrics are more closely matched with the resilience connotation; thus, they are also widely adopted. However, in an actual application process, reasonably quantifying the performance variation is the key to ensuring scientific results. Nagurney and Qiang [59] separately developed generalized cost indices that incorporated multiple factors to assess the impact of disturbances on the robustness of transportation systems under both user-optimal and system-optimal conditions. Zimmerman et al. [60] evaluated the resilience of urban transportation networks under weather conditions by considering various practical factors. However, in practice, it is often necessary to assess the changes in resilience under different extreme weather or disaster scenarios using different evaluation indicators.

**Table 4**
System performance metrics for URT resilience.

| Category | Metric | Refs. |
|---|---|---|
| Supply side | Economic costs | [48] |
| | Train delays | [49,50] |
| Demand side | Generalized travel costs | [52,53] |
| | Route accessibility | [57,58] |
| | Affected passenger flow | [51,55,56] |

*3.1.2. Measurement approaches for URT system*

In this subsection, several measurement approaches for calculating resilience metrics are discussed. For this study, the evaluation approaches were divided into four categories: topology, simulation, optimization, and data-driven.

(1) Topological approach: stepping stone. The topology, which is based on graph theory and developed from complex network theory, is one of the first widely used approaches to assess URT resilience. The topology construction methods for the URT network include Space-L and Space-P. The meanings and characteristics of different construction methods differ, as shown in Fig. 3 [31]. These models were established based on a complex network model to analyze URT network characteristics. This measurement approach is mainly based on the static structure of the URT network and calculates the topology metrics of the network to assess its robustness [36,61], vulnerability [62], resilience [32], and efficiency [63]. In some studies, it has been used to study node degree distribution and URT network evolution [23,64,65].

However, modern views usually consider that the pure topology approach of a static network can hardly reflect the real state of a URT network, and its calculated resilience metrics deviate significantly from the actual situation. Therefore, to better reflect the URT network state and calculate the URT network resilience, many recent studies have used a combination of topology and other measurement approaches; for example, to evaluate the efficiency of the URT network in both random failure and malicious attacks, topology, and simulation analysis are combined to evaluate the variations in network performance [66]. A network topology-based route diversity index and a solution algorithm were proposed to evaluate the vulnerability of stations [67]. A modified topology vulnerability analysis that considers generalized travel time based on the traditional topology approach was proposed to evaluate URT network resilience, as shown in Eq. (5) [68].

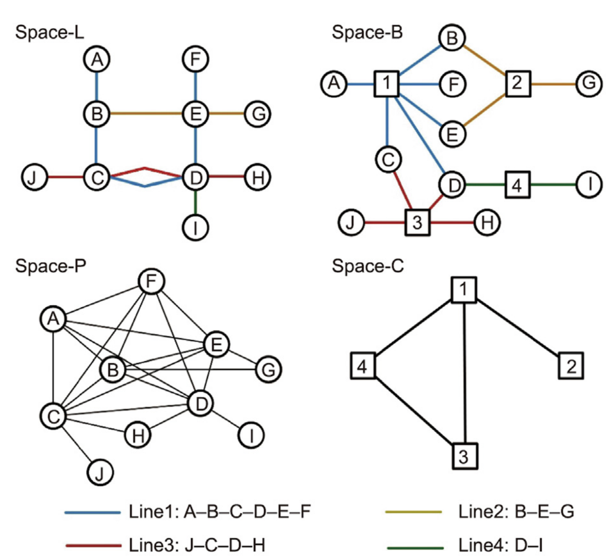


**Fig. 3.** Common topology network construction methods in Ref. [31].

$$R = \frac{1}{n(n+1)} \sum_{i,j \in V} \frac{1}{\rho_{ij}}, i \neq j \tag{5}$$

In addition, to describe the states within the URT system more precisely, many studies have proposed more refined descriptions based on topology. For example, a topological heterogeneity and vulnerability analysis of URT networks considering transit constraints has been proposed to determine URT system vulnerability [69], the simulation of different types of failure scenarios on stations or lines has been analyzed [70], an integrated coupled map lattice has been proposed to evaluate the station state and vulnerability of weighted URT network [71].

(2) Simulation approach: collision of thoughts. Based on the literature review, it was found that evaluating URT network resilience independently is often challenging, and attribute- or performance-based network evaluation metrics are usually employed. To measure the resilience of a system, a series of attacks must be simulated. The most common attack patterns are intentional and random. If extreme weather events such as floods or hurricanes are encountered, regional damage will also occur. The common simulation patterns are shown in Fig. 4. In general, intentional and area attacks have a much worse impact on networks than random attacks.

D'Lima and Medda [51] investigated shock diffusion using a stochastic model for underground London. Zhu et al. [72] verified the effectiveness of their breadth tree coefficient strategy for enhancing URT network robustness through simulations. Huang et al. [50] analyzed the cascading failure in the Chengdu URT network using five evaluation factors and simulation methods. Cong et al. [56] developed a multiagent simulation system to estimate the impact of unplanned disruptions on passenger travel behavior in URT systems.

In addition, simulations have been combined with other methods in some studies. For example, Hassannayebi et al. [73] integrated simulation methods with optimization techniques, aiming to minimize passenger waiting time as the optimization objective. They assessed even-headway timetables through simulations and derived disturbance-resistant train schedules. Fan et al. [74] simulated the evolution of a dynamic temporal subway network by using a linear threshold model. The robustness metric is given by Eq. (6).

$$R(t) = \varepsilon \cdot L + (1-\varepsilon) \frac{E(t) - \tilde{E}(t)}{\max\limits_{T \in [t_1, t_2, t_3, \ldots]} \{E(T)\}} \tag{6}$$

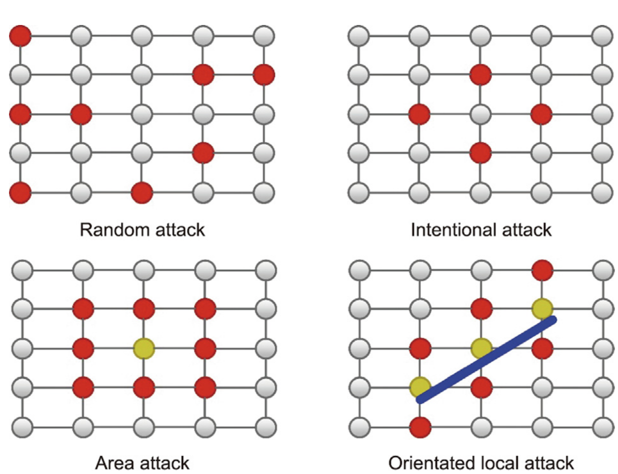


**Fig. 4.** Examples of patterns under attack.

where $\max\{E(T)\}$ is the maximum operational efficiency at different times $T$. They considered not only the static network structure but also passenger flow as essential factors and finally evaluated the robustness of the network.

(3) Optimization approach: a critical part. Optimization approaches typically focus on URT system resilience enhancement or system capacity recovery in specific disaster scenarios [75].

The goal of optimization models that enhance the resilience of URT systems is to enhance the resilience of the entire system. Jin et al. [76] developed a two-stage stochastic programming model to evaluate the URT network resilience and optimize local bus service integration with URT. Chen et al. [77] proposed a bilevel programming model that minimizes network accessibility using Eq. (7) and maximizes the network efficiency of the URT network using Eq. (8).

$$\min Z_1 = \sum_{i \in V} \sum_{j \in V} t_{ij} w_{ij}, i \neq j \tag{7}$$

$$\max Z_2 = \frac{\sum_{i \in V} \sum_{j \in V} \sum_{k \in K_{ij}} \min(1/t_{ij}^k)}{n(n+1)}, i \neq j \tag{8}$$

On the other hand, many scholars have studied the problem of restoring the capacity of URT systems under specific disaster scenarios; for example, the URT system recovery time is uncertain (service may not be available for an extended period), and it is critical to enable bus service instead of URT at the right time. Therefore, an optimization model for URT system breakdown was proposed to solve this problem [48]. In the event of a station crash, passenger redistribution is usually problematic, and a flow distribution method is used to enhance the ability of the URT network to withstand disruptions [78]. To recover URT capability as soon as possible, a new repair strategy called the simulation repair strategy was proposed to enhance network resilience after being disturbed [77]. Additionally, the problem of optimal passenger flow allocation under multiple disruptions was investigated in Ref. [55] and is represented by Eq. (9).

$$\min Z = \frac{\left(\sum_{\omega \in \Omega} \sum_{i \in V} q_i^{\omega} + \sum_{\omega \in \Omega} \sum_{v \in \Psi} l_v^{\omega}\right)}{t_h - t_0} \tag{9}$$

In addition, optimization methods have been used to study the alignment of new URT lines [52]. Table 5 summarizes the aforementioned optimization models.

(4) Data-driven approach. With the continuous development of bigdata technology, the capabilities shown by data-driven approaches have become increasingly powerful. Therefore, it has been applied to the study of URT system resilience. The data-driven approach is based on a large amount of historical passenger and traffic flow data [43], and different metrics are calculated to determine the changes in system performance under different scenarios [79], thereby helping people evaluate the URT system state and develop reasonable methods to improve URT system resilience.

In many studies of transportation networks, the network composed of passenger or vehicle flows is usually referred to as a dynamic traffic network [80–82]. In the URT field, the most commonly used dynamic traffic network is passenger flow data, typically from automatic fare collection (AFC), whereas train operation information can be obtained from management. In this literature review, numerous studies were identified that utilized passenger flow data to examine the vulnerability of URT systems. For example, the vulnerable segments of the San Francisco URT system were estimated in Ref. [83]. Using a large amount of passenger flow data from the Shanghai URT system, Sun et al. [46] analyzed the vulnerability of a network under attack. Sun et al. [84] combined the network topology and passenger flow data to

**Table 5**
The optimization model mentioned above contains the objective function and constraints.

| Objective | Constraints | Ref. |
|---|---|---|
| Minimize total costs and operational disruptions | Timetabling; passengers; rolling stock | [75] |
| Maximize travel demand fulfillment rate | Budget; number of plans; travel demand; line capacity; station capacity | [76] |
| Maximize network accessibility and efficiency | Travel time; line capacity; network scale; station connectivity | [77] |
| Minimize total costs | Substitute bus service initiation time; URT service recovery time; substitute bus service capacity | [48] |
| Minimize passenger delays | Flow balance; capacity limit; accessibility; train operation | [55] |
| Minimize network vulnerability and maximize new ridership utility | Total construction costs | [52] |

assess the vulnerability of the Beijing URT system. Using passenger flow data, Lu and Lin [38] analyzed the vulnerability of a multimodal public transport network in Shenzhen when URT stations were disrupted. Deng et al. [85] also obtained quantitative data on the Nanjing Metro through interviews to assess the vulnerability of the URT network.

In addition, a data-driven approach has been applied to research on URT network reliability analysis, assessing network resilience [86,87], identifying critical stations [57], and evaluating the resilience of URT network infrastructure [88]. The data sources used in these studies are listed in Table 6. As shown in Table 6, the researchers' primary sources of data are URT operators, government statistics, and AFC data.

The data-driven approach enables the exploration of inherently diverse characteristics within big data, thereby aiding in the enhancement of the understanding of complex nonlinear relationships among factors such as train operations, passenger travel, and disruptive events within URT systems [73,89]. This offers a novel perspective and methodology for assessing or enhancing the resilience of urban rail transportation. However, a data-driven approach can further advance the development of URT resilience research if multiple data sources are available.

### 3.2. What should be done

The existing URT network resilience research is primarily based on the physical topology of a network. It rarely considers multisource data, such as train operation and passenger flow information [90,91]. In terms of optimization, the existing research is mainly based on a large number of assumptions and the traditional operations research method is applied to build a phased decision optimization model, which ignores many practical factors in the research process. Moreover, obtaining a globally optimal solution that considers passenger and train flows is difficult [92]. Therefore, it is crucial to use new technologies such as artificial intelligence, big data, and distributed computing in combination with traditional optimization methods of operations research [93,94]. Moreover, building precise coupled optimization models and designing effective algorithms for large-scale problems play crucial roles in improving network resilience. Here, the five directions for enhancing the resilience of URT systems are summarized. Figs. 5 and 6 show the technical roadmap and specific implementation methods, respectively.

(1) Resilience analysis of URT systems based on multisource data. Starting from the multisource data of the URT network topology, passenger flow, train diagram, and vehicle parameters, Zhan et al. [95] constructed a multidimensional URT network resilience evaluation system that considered the absorption capacity before interference, ability to resist damage during interference, and ability to recover after interference. The impact of events on the operational efficiency of a URT network has also been studied [96]. Using considerable traffic data-related methods to determine the different operating states of URT under different disruptions. A multi-state resilience curve for the rail transit system was established, considering changes in disruption factors, to examine the correlation and computation method of resilience across different scenarios and periods in the network. The performance of the URT system under multiple scenarios and periods was analyzed and evaluated.

(2) Combined control of passenger flow in the URT network based on multidemand. The deep neural network learning method was used to analyze various passenger flow entry scenarios and the characteristics of points, lines, and networks during congestion periods [93,97]. Combined with the transport capacity and personalized travel demands of passengers under different congestion scenarios, Lu et al. [98] built a URT passenger flow control optimization model under various demand responses. Based on this, an efficient and intelligent solution algorithm based on distributed computing was designed. Finally, a unique and refined joint network traffic control optimal solution is generated for each station. In addition, the intelligent linkage of the passenger flow control strategy of multiple lines and stations in the network [99] achieves rapid passenger flow dissipation and improves network affordability [100] to ensure the smooth operation of the URT network and

**Table 6**
Information about the data used in the data-driven approaches paper mentioned above.

| Data used | Data source | Ref. |
|---|---|---|
| Between 5:00 a.m. and 9:00 a.m., 256 958 passengers flow data | Provided by the operator or government | [43] |
| Daily commuting data | | [83] |
| Average daily OD trip matrix | | [38] |
| Unexpected events in the Beijing URT network from 2013 to 2018 | | [87] |
| Passenger flow data from 06:00 a.m. to 01:00 a.m. (+1 day) | | [88] |
| Between 7:45 a.m. and 8:00 p.m., within 8 weeks, passenger flow data | AFC data | [79] |
| The OD matrix of 16 September 2013, from 7:30 a.m. to 8:30 a.m., a total of 370 414 raw records | | [46] |
| Weekday morning peak (7:30 a.m.–9:30 a.m.) within a week in August 2016 | | [84] |
| Peak hour OD data | | [86] |
| Data of constructing rail transit network, passenger flow of rail transit station, OD passenger flow, and the spatial distribution data of epidemic | | [57] |
| Face-to-face interviews in June 2015 and a special meeting held on July 2, 2015 | Interview and meeting | [85] |

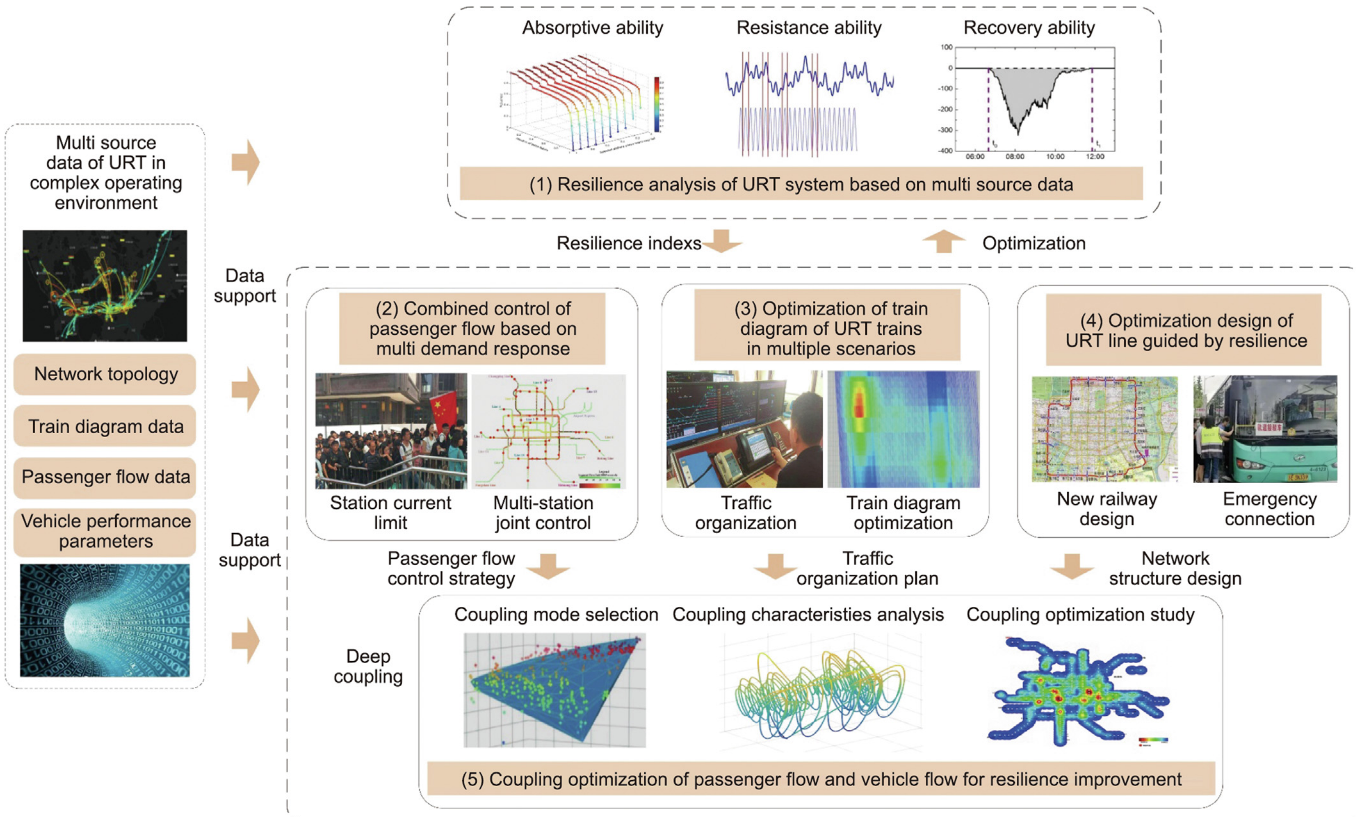


**Fig. 5.** The technology roadmap for resilience enhancement in future research.

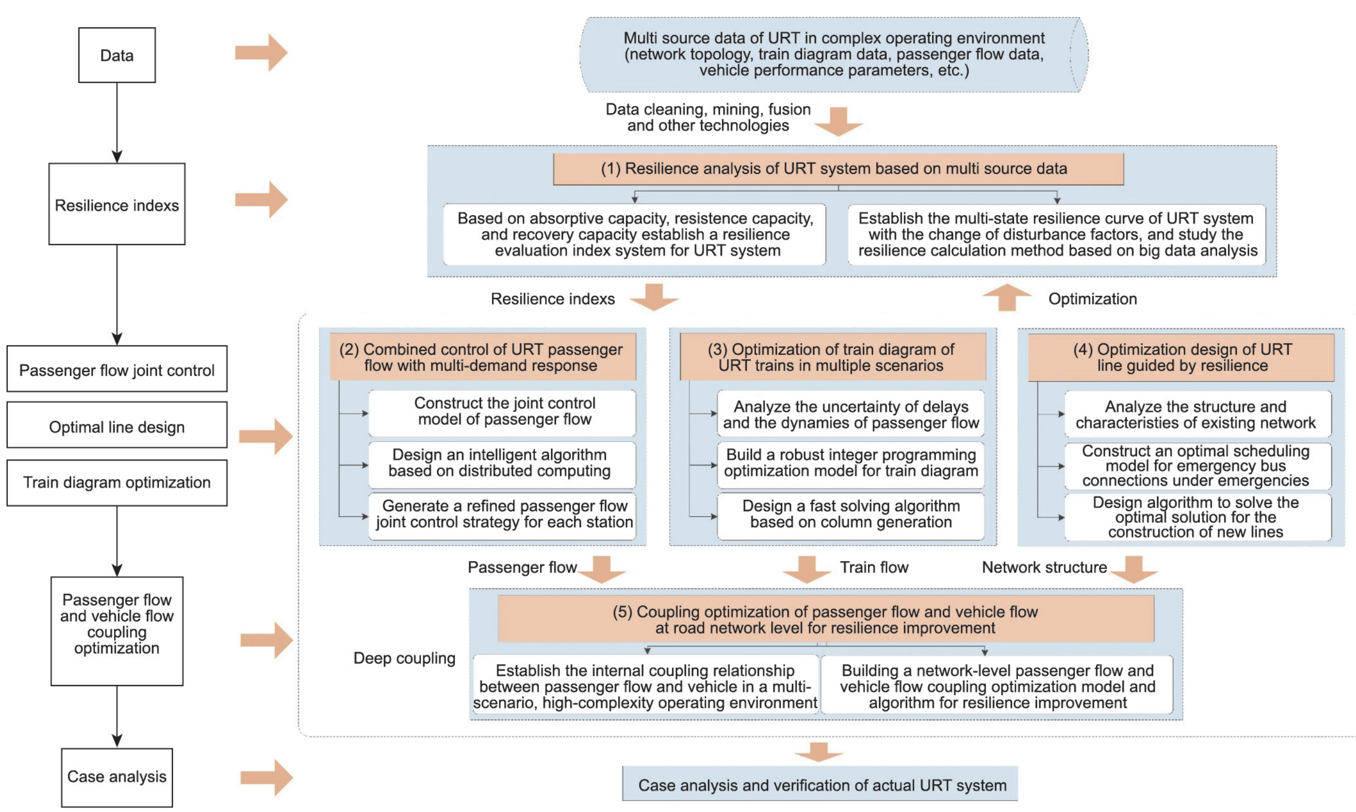


**Fig. 6.** Specific implementation methods for different research directions.

stations, and enhances the ability of the URT system to resist passenger flow interference in a variety of demand periods.

(3) Optimization of URT train diagrams in multiple scenarios. Based on the dynamic evolution characteristics of passenger flow demand and the uncertainty of train operation delay, a robust optimization model of the train diagram under peak scenarios was established [101,102]. Considering factors such as the URT network passenger flow demand during the operation period of the last train, accessibility of the last train connection network, and waiting time of passengers for transfer, an optimization model of the last train diagram considering random disruptions was established. In this manner, the anti-disruption and recovery ability of the URT system under multiple scenarios and periods can be enhanced, and an overall improvement in train operation and passenger travel efficiencies can be realized [21,57,103].

(4) Optimization of URT line guided by resilience. The structure and characteristics of existing urban transportation complex networks were analyzed, and the coupling direction between URT and other transportation modes was explored [76]. Build resilience metrics to quantitatively evaluate the changes in network passenger transport performance and design an emergency feeder bus scheduling model under URT accidents [104]. Enhancing network resilience by quickly evacuating stranded passengers affected by disruptions. Reconstructing the transportation network to reasonably allocate vehicle resources, ensure transportation succession, and improve the system recovery ability. Improve the URT network function and design heuristic algorithms to solve the construction scheme for new lines with the best resilience [65]. Promote the cross-line operation of URT networks, improve the travel efficiency of passengers, and reduce travel costs. These additional links and lines help improve travel path redundancy during disruptions.

(5) Coupling optimization of passenger and vehicle flows at the URT network level for resilience improvement. Based on an accurate analysis of the URT line network passenger flow in a high-density strong space-time correlation environment, combined with the multiscale passenger flow travel law, line-network association rules, and the complexity and uncertainty of the train operation process, the dynamics of passenger flow demand are comprehensively considered. Then, the internal coupling relationship between traffic and passenger flows in a multi-scenario, high-complexity operating environment was established [105]. Clarify the dissipation and evolution mechanism of passenger flow in the rail transit network and study the modeling method of static cohesion organization and dynamic cooperative operation of the URT network. Subsequently, a cooperative management mechanism for passenger–vehicle flow under uncertain disruption scenarios was proposed, which breaks through the inherent mode of separate management of passenger–vehicle flow [106]. This ensures that the train flow has a strong absorption capacity, damage resistance, and recovery capacity in a highly complex operating environment to enhance the resilience of the system to cope with operational disturbances.

## 4. Conclusions

This paper presents a systematic and comprehensive review of research on URT resilience. It starts with the origin of the definition of resilience, introduces an understanding of resilience in different fields, and then provides the meaning of resilience in the field of URT. In this study, URT resilience was divided into three aspects: ① the ability of the URT system to absorb disturbances, ② the ability of the URT system to resist disruptions, and ③ the ability of the URT system to recover after disruptions. Based on these three points, combined with previous research results on URT system resilience, the four properties of URT system resilience can be summarized as robustness, vulnerability, rapidity, and redundancy. Next, the metrics and calculation approaches for URT resilience are reviewed and classified into three categories: topological, characteristic, and system performance. Furthermore, the calculation approaches of these metrics are categorized into four distinct types: topological, simulation, optimization, and data-driven. Finally, five directions for future research are proposed. The summary provides a research map for researchers in this field and a reference for future work related to the resilience of URT systems. For similar areas of research, our work provides some experiences that can be considered, such as road and railroad network resilience [107].

Existing research findings and ongoing research trends indicate that the conventional practice of utilizing static network data to calculate topological metrics for evaluating network resilience is no longer sufficient to accurately capture the impact of dynamic factors, such as passenger and traffic flow, on URT systems. Consequently, numerous studies have amalgamated the topological approach with other methodologies to analyze resilience, thereby facilitating the transition from a static to a dynamic topology. Simulation-based techniques that offer diverse methods have been employed to study URT resilience under various scenarios, including disruption simulations and post-disruption recovery strategy simulations. However, the optimization approach, which is more mature and rapidly advancing, has proven effective in addressing highly complex issues in the realm of URT resilience. Notably, the optimization approach has been extensively applied to train operation diagram optimization, optimal strategies for post-disaster recovery [108,109], integration optimization of public transportation systems, and passenger flow distribution optimization. Furthermore, the advent of information technology has provided researchers with access to increasing volumes of historical data related to URT system operations, leading to the growing application of data-driven approaches in URT resilience research. Typically, data-driven approaches are combined with other research methods, such as topology, simulation, and optimization, to yield more precise assessments of network resilience, enhance model accuracy in real-world scenarios, and lend greater credibility to optimization outcomes [110–112].

Enhancing the resilience of URT is a comprehensive engineering endeavor that encompasses the assessment of resilience [113], simulation of practical scenarios [114], and optimization of system resilience [115], which are intricately interconnected. A precise evaluation of the system resilience often necessitates more refined and diverse data sources. Accurately assessing the resilience of URT plays a vital role in identifying critical stations and sections within the network and serves as a crucial step in establishing goals for subsequent resilience enhancement [116]. The optimization of network resilience can effectively mitigate the losses incurred during disturbances in URT systems, reduce passengers' perceived disruptions, and enhance their satisfaction. Throughout this process, the simulation of practical scenarios remains integral, as it not only ensures the accuracy of resilience assessment methods but also verifies the effectiveness of resilience enhancement strategies. In essence, it is imperative to refine disturbance scenarios and employ various measures, such as flow control and station closure, in accordance with pre-established emergency plans to minimize the impact of disturbances on URT systems [117].

URT resilience has become an increasingly important research direction, attracting the attention of many researchers. This study not only refines the optimization theory of URT operation but also provides significant instructions for the actual operation and rapid disposal of URT systems under disruption. Current metrics for resilience are as realistic as possible; however, inevitably, there is still a gap in reality. New methodologies and techniques are being proposed, and existing technical approaches are maturing. In the future, combining various approaches may promote an effective study of URT resilience.

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## Compliance with ethics guidelines

Yun Wei, Xin Yang, Xiao Xiao, Zhiao Ma, Tianlei Zhu, Fei Dou, Jianjun Wu, Anthony Chen, and Ziyou Gao declare that they have no conflict of interest or financial conflicts to disclose.

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