Topology-based Resilience Assessment of Port Multimodal Transport Networks: A Case Study of Shanghai Port

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Abstract. As transit nodes in the field of international trade, ports are of critical importance for establishing and maintaining the effectiveness of the trade supply chain. However, the system performance of ports is vulnerable to disruptions caused by unexpected events such as natural disasters, accidental catastrophes, and public health emergency. These disruptive events will have serious negative impacts on the normal operation performance of ports and international trade among countries. This paper is to propose a comprehensive assessment framework of the system resilience of the port multimodal transport networks before and after the occurrence of disruption events, which can effectively improve its ability to deal with emergencies, minimize losses, and enhance the system performance levels. This paper also establishes several simulation experiments focusing on the full lifecycle of resilience based on topology of the transport networks, and simulates a variety of scenarios regarding different damage and recovery modes, such as deliberate attack, random attack, planned recovery, and random recovery, in the assessment process. Then the actual transport situation of Shanghai port is taken as a case study, and three multimodal transport networks including the sea-rail network, the sea-road network, and the sea-road-rail network under different disruption scenarios are compared， and evaluate the evolutions of the network resilience of the multimodal transport networks of Shanghai port stage by stage. In addition, managerial suggestions are also proposed based on the resilience assessments of different disruption scenarios to maximize the resilience of multimodal transport networks of Shanghai port.

Keywords: Port multimodal transport networks; Resilience assessment; Disruption events; Topology; Shanghai port.

1. Introduction

The significance of ports has grown increasingly prominent due to the pace of globalization and the growth in international commerce volume. Ports are considered vital terminals in this context, and play a crucial role in facilitating international trade. The operational efficiency of ports is closely connected to the establishment and development of port multimodal transportation networks (PMTNs), especially in cases of disruptions. Therefore, it is important to acknowledge that disruption events have been one of the primary factors contributing to the decline of PMTN performance. Disruptions such as natural disasters[1], terrorist attacks, or public health incidents have the potential to result in the closure of ports, delays in ship schedules, and the temporary breakdown of regional line networks. These circumstances can significantly disrupt the secure and steady functioning of PMTNs. Thus, it is of utmost significance to precisely evaluate the resilience of PMTNs in terms of their performance when faced with unforeseen disruptions.

The term *resilience* is originally derived from the Latin word *resilio*, which was introduced to ecosystems by Holling [2] in 1973 and began to be widely used in other fields. The U.S. National Academy of Sciences defines resilience as the ability to *prepare* for, *absorb*, *recover* from, and *adapt* to disturbances [3], which is also the four phases of resilience that this paper focuses on: preparation, absorption, recovery, and adaptation. In recent years, the topic of resilience has gained significant attention in academic studies due to the increasing frequency of calamities. The port emergencies that have been the focus of past studies are mainly natural disasters, such as floods [4], hurricanes [5], and earthquakes [6]. Secondly, the emergence of the COVID-19 pandemic in 2019 has repeatedly intensified public health concerns. Panahi et al. [7] and Gu et al. [8] studied the most influential factors on port resilience during the COVID-19 pandemic from different perspectives. The existing body of research pertaining to port transportation systems predominantly emphasizes maritime transit. Jiang et al. [9] investigated the system resilience of five major ports along the Mediterranean shipping center; Yang et al. [10] focused on the dominant and weak ports in maritime routes and analyze their strengths and weaknesses; Dui et al. [11] performed a comprehensive ranking of ports and routes in terms of their importance to study their resilience priorities to minimize residual resilience. In addition to the port's external maritime transport modes, Tsao et al. [12] designed an intermodal seaport-deport network considering both railway and road transport modes and proved that the development of dry ports and intermodal transport can reduce the carbon cost of road transport. Liao et al. [13] put forward proposals to improve the resilience of port intermodal transport networks and promote risk management countermeasure suggestions. In addition, from the perspective of the four phases of resilience, some scholars quantified the system performance in the pre-disaster (preparation) phase in terms of *rapid response capability*, which specifically refers to the system's speed of response and emergency response capability against disturbances [14]. The majority of existing studies primarily concentrates on the post-disaster stage. Within this stage, the *absorption* and *recovery* phases hold prominence. Key factors that are frequently studied include *damage speed*, *absorption capacity* and *recovery capacity* [15]. When studying the *adaptation* phase in research, scholars commonly employ the metric of *demand satisfaction rate* to quantitatively assess the system's performance throughout this period [16]. Despite the considerable amount of literature on port resilience, there are still several deficiencies that need to be addressed. (a) Emergencies are one of the main causes of port disruption, and the disruption scenarios of existing studies mostly consider a single situation of public health events or accidental disasters or natural disasters, and there are not many studies in which the disruption scenarios comprehensively take into account the nature of the emergencies;(b) The resilience assessment in existing studies tends to concentrate on the recovery phase, with limited attention given to the absorption or adaptation phase. Rarely do these studies examine both phases or more than two phases simultaneously; (c) Current research primarily focuses on port waterways or roads, neglecting the coupling of multiple modes within PMTNs.

This paper focuses on the assessment of the resilience of PMTNs, specifically the combined system of road, railway, and waterway. It employs complex network theory to construct a simulation framework that simulates the dynamic performance of Shanghai PMTNs under different scenarios of disruptions and recoveries. This study has made the following significant contributions in this context. This study aims to simulate the PMTNs and analyze their performance under different attacks and recovery methods. It also investigates the four stages of resilience (Preparation, Absorption, Recovery, and Adaptation) and the overall resilience of PMTNs. The findings of this research will provide targeted strategies for enhancing the resilience of Shanghai Port and other similar ports.

The remaining part of the paper is as follows. The framework of resilience assessment metrics and simulation models are discussed in section 2. The resilience evolutions of the Shanghai PMTNs during the four stages are detailed in Section 3. Concluding remarks are outlined in Section 4.

2. Methodology

2.1 Model Hypothesis

The following assumptions are made in this paper to ensure the implementation of simulation experiments: Assuming that the network is unweighted and bidirectional; Yards or ports with identical names but different geographic locations, as well as those with different names but similar geographic locations, will be merged and considered as a single node within the network; Only the presence or absence of directly connected routes, railways, or highways between nodes are considered, and multiple railways or highways between nodes are denoted as one edge; Only motorways and container seaports are considered in the road and port subnetworks of the PMTNs, respectively.

2.2 Resilience Assessment Metrics

This paper discusses the PMTNs incorporating subnetworks of road, rail, and waterways, and aims to assess the evolution of the system resilience across the complete cycle of *preparation*, *absorption*, *recovery*, and *adaptation* under the impacts of an emergency event. From time t_0, the system performance begins to decline due to the interference of emergencies, and reaches the lowest point at time t_1, which is the *absorption* phase; The system performance increases after certain countermeasures are taken from t_1 to t_2 in the *recovery* phase, and from t_2 to t_3 in the *adaptation* phase, the performance returns to a predetermined level when the system has adjusted to the disturbance and can meet the essential requirements of normal operation at this point. The metrics that are involved in the assessment process are as follows:

Network connectivity C refers to the ratio of the number of nodes in the maximum connected subgraph of the network after removing nodes to the total number of nodes in the original network.

$$C=\frac{n_{max}}{N} \tag{1}$$

Network efficiency E is the average of the reciprocal of the shortest path lengths between all nodes.

$$E=\frac{\sum_{i\neq j}\frac{1}{d_{ij}}}{N(N-1)} \tag{2}$$

where N denotes the total number of nodes in the network, d_{ij} denotes the shortest path from node i to node j, n_{max} is the number of nodes in the maximum connected subgraph in the network after removal of nodes

Resilience metric. A higher resilience metric indicates that the network is more resistant to attacks or failures at nodes or edges. In this paper, the resilience metric is represented by the degree of recovery of the network system performance $C(t)$, $E(t)$ as it evolves during the damage and recovery process. R_C and R_E are metrics used to measure the resilience of network connectivity and network efficiency, respectively.

$$R_C=\frac{\int_{t_0}^{t_2} C(t)\,dt}{\int_{t_0}^{t_2} C(t_0)\,dt} \tag{3}$$

$$R_E=\frac{\int_{t_0}^{t_2} E(t)\,dt}{\int_{t_0}^{t_2} E(t_0)\,dt} \tag{4}$$

3. Resilience Assessment of Shanghai PMTNs

In this section, we set up a sea-rail network, a sea-road network, and a sea-road-rail network in the context of the logistics network in the Shanghai port for simulation experiments. The sea-road-rail network, with 44 nodes and 121 edges, stands as the most extensive network. Specifically, the resilience evolutions of different transport modes at various stages are analyzed by simulating four damage and recovery modes.

3.1 Resilience of the PMTNs in the Preparation Phase

The preparation stage examines the topological characteristics of nodes in the sea-rail, sea-road, and sea-road-rail networks, as well as the raw resilience values such as network efficiency and connectivity. Table 1 presents the fundamental details of various networks.

Table 1. Topology configuration on the PMTNs of Shanghai Port

Network type	Number of nodes	Number of edges
Sea-rail network	16	16
Sea-road network	34	110
Sea-road-rail network	44	121

Table 2. Resilience Metrics on the PMTNs of Shanghai Port

Network type	Network efficiency	Network connectivity
Sea-rail network	0.356	1
Sea-road network	0.454	1
Sea-road-rail network	0.397	1

In the preparation phase, the resilience metrics for the PMTNs of Shanghai port are documented in Table 2. The network connectivity for all three networks is 1. The sea-road network has higher network efficiency compared to the sea-rail network due to a larger number of nodes and transport roads. Correspondingly, the sea-road network is less affected by damage to individual nodes compared to the sea-rail network. However, the sea-road network has lower network efficiency compared to the sea-rail network due to the latter's lower impact. The network efficiency of the sea-road-rail network is only slightly lower than that of the sea-road network. In terms of results, the sea-road network has the highest network efficiency. However, when considering factors such as road saturation and coverage, the sea-road-rail network also exhibits considerable resilience value.

3.2 Resilience of the PMTNs in the Absorption Phase

The absorption phase is mainly set up to damage the network by two types of deliberate and random attacks, which include four attack modes: degree centrality attack (DA), closeness centrality attack (MA), betweenness centrality attack (BA), and random attack (RA). The evolution in the resilience metric in its process is recorded.

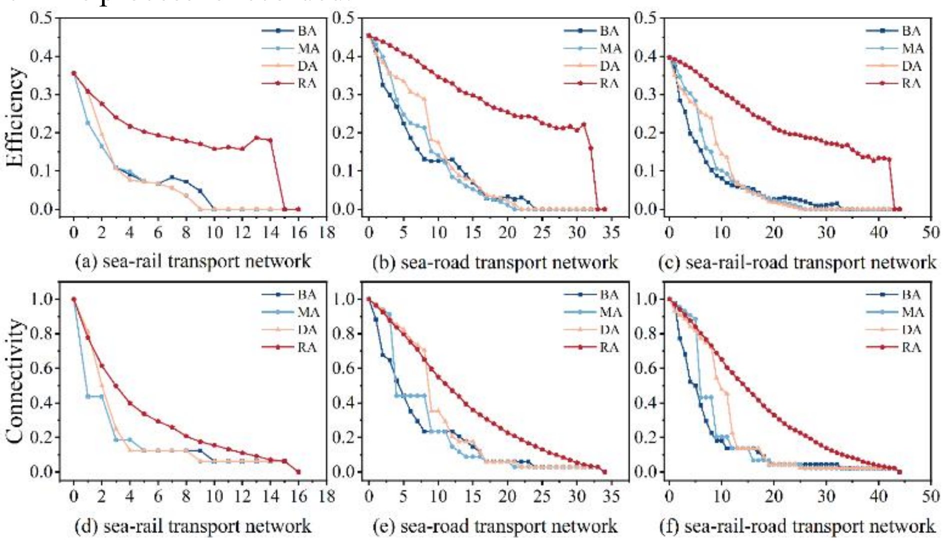

Fig. 1 Evolutions in resilience of PMTNs under the four attack modes

It is showed in Figure 1 that the evolutions in different metrics within sea-rail network, sea-road network, and sea-road-rail network in response to unforeseen circumstances. The *x* axis of each graph represents the number of failed nodes, while the *y* axis represents different resilience metrics. The resilience metrics are specifically the network efficiency in the first row and the network connectivity in the second row of the graph. It is illustrated in Figure 1 that the resilience metrics curves of the three networks exhibit the slowest decline when exposed to RA mode. This indicates that the network efficiency and connectivity of these networks are more robust in the RA mode. The sea-railway network has the fastest decline in the metrics under the MA mode. It indicates that the nodes of the sea-railway network with high node closeness are attacked first when the network encounters unexpected events, which will affect the resilience of the whole network system maximally. The evolutions of resilience of the sea-road and sea-road-rail networks shows a two-stage division, with both being most affected by BA mode in the early stage, and separately the sea-road network is most affected by MA mode in the later stage, and the sea-road-rail network is most affected by DA mode. It indicates that in the more complex system of the network, when the nodes that act as bridges of other nodes to the shortest paths are attacked in the early stage, the number of nodes affected is more and wider, and in the later stage, after several of the most critical nodes in the network that act as bridges have been destroyed, the importance of the closeness of a node to other nodes and the number of connections starts to come to the forefront.

The resilience value of the sea-road-rail network is greater than that of the other two networks when considering different attack modes. The gap between the sea-road-rail network and the sea-road-rail network is not significant. The network efficiency of the sea-rail, sea-road-rail, and sea-road-rail network are 0.036, 0.011, and 0.005, respectively. These values represent a reduction of 89.89%, 97.58%, and 98.74% compared to the original network. The network connectivity experiences significant decreases at 0.063, 0.029, and 0.022 with reductions of 93.75%, 97.1%, and 97.73%, respectively, when compared to the original network. The resilience metrics of the sea-road-rail network shows a smaller decline compared to the other two networks. Additionally, the degree of decline in the resilience metrics of the sea-road-rail network is slightly lower than that of the sea-road-rail network, but very close to each other, so that the sea-road-rail network has the best ability to absorb disturbances when subjected to emergencies, while the sea-road-rail network and sea-road-rail network are comparable in terms of their ability to absorb disturbances.

3.3 Resilience of the PMTNs in the Recovery Phase

The recovery phase builds on the absorption phase to do further analysis of the network recovery performance. Immediately after the end of each attack mode, the network is recovered with four recovery modes: degree centrality recovery (DR), closeness centrality recovery (MR), betweenness centrality recovery (BR), and random recovery (RR). It is essential to consistently monitor the fluctuations in resilience measurements during the entirety of the procedure.

Network connectivity for all three networks recovered fastest in BR mode. Regarding network efficiency, the difference in the trend of the three recovery modes under each attack mode is not significant except for the RR mode, but BR mode tends to restore the network performance to its original level more quickly. Hence, it can be argued that the BR mode assumes primary significance in the context of encountering unforeseen circumstances.

According to the evolutions in the resilience metrics of the three networks in this phase, a remarkable common point can be found: irrespective of the attack mode, all networks that employ RR mode consistently exhibit the least improvement in system performance. So, networks should prioritize the development of a plan after an unexpected event, and should not blindly and randomly start the recovery action. In addition, as the scope of the network expands, the reflection of the network becomes more sensitive to different recovery modes. From the sea-rail network to the sea-road network and then to the sea-road-rail network, the nodes and edges in the network continue to increase, and the network becomes more and more complex, and the gap in the time for its network connectivity to recover to its original level becomes larger.

3.4 Resilience of the PMTNs in the Adaptation Phase

The adaptation phase summarises the evolution in the overall resilience of the network mainly by calculating the ratio of the remaining system performance of the network after going through the first two phases of disruption and recovery to the original system performance in the preparation phase.

In Figure 2, it presents a summary of the resilience comparison among the networks in Shanghai port. The *x* axis represents the four attack modes, while the *y* axis represents the resilience metrics. The first line represents the network efficiency metric and the second one represents the network connectivity metric. The different colored columns in the figure reflect the evolutions of the resilience value of the network using different recovery modes under each attack mode.

As seen in Figure 2, the network has the largest resilience value when it is attacked by RA mode, but the resilience is much lower than the other recovery modes when RA mode is used for recovery. As a whole, the network efficiency resilience value of each network is higher than the network connectivity. From the network perspective, the mean values of network efficiency of the sea-rail, sea-road, and sea-road-rail network are 0.579, 0.680, and 0.641, respectively. And the mean values of network connectivity of the above three networks are 0.372, 0.500, and 0.492, respectively. Therefore, the overall resilience of the sea-rail network is the worst, and all of its metrics are lower than those of the other two networks. The resilience of the sea-road network is better than that of the sea-road-rail network, and greatly better than that of the sea-rail network.

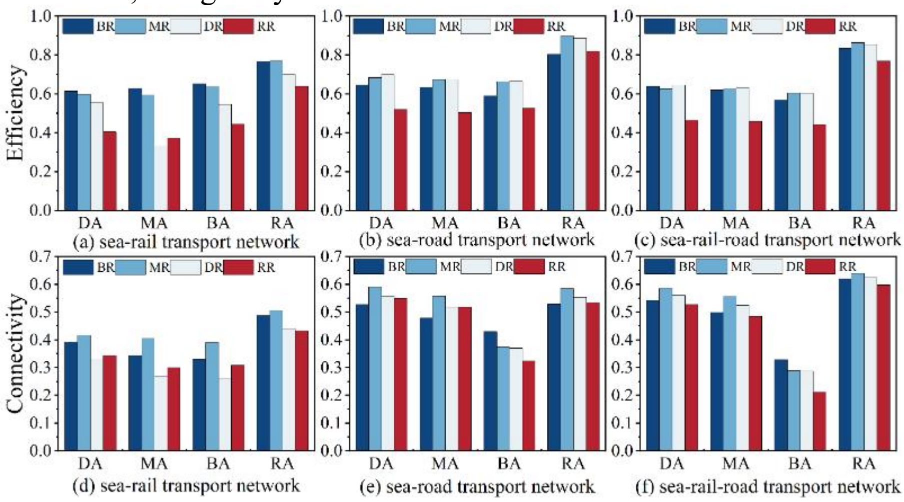

Fig. 2 Comparison of resilience across networks at Shanghai Port

4. Concluding Remarks

This paper aims to conduct a resilience assessment of the port multimodal transport networks (PMTNs), taking the Shanghai PMTNs as a case study. The study utilizes the complex network theory and incorporates the real traffic network data of Shanghai port. The topological characteristics of the PMTNs are analyzed, and specific topological diagrams for sea-road-rail, sea-road-rail and sea-rail-rail multimodal transport networks are constructed, respectively. The resilience metrics of network efficiency and network connectivity are adopted, and simulation experiments are conducted to explore the impacts of several attack and resilience modes on the resilience of PMTNs. The primary findings of this study can be summarized as follows.

The network efficiency of the sea-road network in the preparation stage is the highest, followed by the sea-road-rail network, and the network efficiency of the sea-rail network is the lowest. The sea-road-rail network possesses a higher capacity for absorbing disturbances during the absorption stage, in comparison to the other two networks. Furthermore, it is important to mention that the capacity for absorbing traffic is similar between the sea-road network and the sea-road-rail network. Research has demonstrated that the sea-road network has a superior network efficiency during the recovery phase, regardless of whether it is in the MA or DA mode. Moreover, it is commonly observed that each network achieves optimal responsiveness when employing the BR mode. In the recovery process, the primary mode utilized is the BR mode, which focuses on restoring the network nodes that serve as bridges most frequently. The sea-road network exhibits greater overall resilience in comparison to the sea-road-rail network. The volume of the sea-road network and sea-road-rail network is close to each other due to that most nodes of the sea-road-rail network come from the sea-road network, the difference in the resilience between the sea-road-rail network and the sea-road network is not substantial, although the former is slightly lower than the latter. The enhancement of the sea-road-rail network can serve to bolster the resilience of the sea-road network and optimize its effectiveness within the integrated sea-road-rail network.

Some limitations in this study are expected in further exploration. The study overlooked the variation in transportation capacity among different modes of transport, resulting in the omission of nodes and links with distinct weights in the network configuration. Consequently, the topological network was simplified. To address this issue, it is imperative to employ a weighted network during the initial configuration of the topological network. Additionally, it is crucial to integrate the effects of various transportation modes into the metric system inside the resilience evaluation model. This work requires a more refined assessment framework for transport systems, which is one of our future tasks.

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