Evaluating recovery strategies for the disruptions in liner shipping networks: A resilience approach

Chengpeng Wan[1, 2], Jiale Tao[1, 2], Di Zhang[1, 2], Zaili Yang[3]*

1. Intelligent Transportation Systems Research Center, Wuhan University of Technology, Wuhan, China;
2. National Engineering Research Center for Water Transport Safety, Wuhan, China
3. Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK.
Emails: cpwan@whut.edu.cn; tjl@whut.edu.cn; zhangdi@whut.edu.cn
** corresponding author : Z.Yang@ljmu.ac.uk*

Abstract

Purpose: Since the start of the current century, the world at large has experienced uncertainties as a result of climate change, terrorism threats and increasing economic upheaval. These uncertainties create non-classical risks influencing global seaborne container trade and liner shipping networks (LSN). The purpose of this paper aims to develop a novel risk-based resilience framework to quantitatively measure the effectiveness of the recovery strategies designed for addressing the disruptions in LSN.

Design: Based on a resilience loss triangle model, an indicator of recover strategy effectiveness is created based on a resilience-cost ratio, which can aid and guide the performance measurement of LSNs during the recovery against a disruption. Four types of recovery strategies are evaluated to test the rationality and feasibility of the proposed indicator in aiding the recovery decision-making of LSNs from a resilience perspective.

Findings: The analysis results reveal that the preference of different recovery strategies varies depending on both the structures of the investigated LSNs and the specific requirements during recovery. Moreover, it tells how to optimize the sequence of ports being recovered to improve the overall recovery efficiency of the investigated LSN.

Practical implications: Understanding the resilience of individual ports in its LSN and calculating the recovery cost will benefit shipping liners in selecting the most cost-effective recovery strategies. The identified regional influential ports are suggested to have higher priorities during the recovery, in order to improve the overall performance of the whole LSN.

Originality: The conceptual risk-based resilience framework and the resilience-cost ratio indicator are newly developed in this research. They can effectively integrate LSNs' structural resilience and the total costs that a recovery strategy needs to restore the whole system simultaneously and holistically.

Keywords: liner shipping network, transport resilience, Maritime Silk Road (MSR), maritime safety, maritime security

1 Introduction

In recent years, the world has seen the rapid development of international trade. The world's top 100 container ports contributed a total of 616 million TEU of global trade in 2018 (Seanews, 2020). Maritime shipping is the kernel of international multimodal transportation and thus, a number of studies related to maritime shipping safety and security had been conducted to ensure the daily steady operations of liner shipping networks (LSN). However, recent accidents occurred in LSN demonstrate the insufficiency of purely relying on the existing risk methods (i.e. probabilistic risk analysis (PRA)) to deal with 1) emerging non-classical risks such as terrorist attacks and extreme weathers, 2) the shift of transport risk study focus from component to system levels, and 3) safety practice change from pure risk prevention to the combination of risk prevention (prior to the occurrence of an accident) and accident recovery (after the occurrence). It triggers new research needs for effective solutions to the disruptions in LSN from a resilience perspective.

In an LSN system, ports and shipping routes are often exposed to various kinds of disruptions caused by such risks as strike, tsunamis and explosions (Yang et al., 2018), which could lead to the degradation of ports operational functions and even the collapse of regional maritime shipping networks in extreme cases. The direct consequences include the reduction of transport network efficiency and high social and economic losses. Broadly speaking, there are two ways to reduce the impact of a disturbance on an LSN system. One is prevention-oriented, meaning that defensive measures are taken to reduce the probability and/or extent to which an LSN system will be affected by disruptions, to improve the system resistance and reduce the possible losses it may suffer. The other, being response-driven, is to improve the recoverability of the system after the occurrence of disruptions, so that it can return to the normal condition as soon as possible (Dai and Li, 2017). Both resistance and recoverability of LSN have a great impact on the efficient and reliable operation of maritime transportation.

Previous studies have revealed that LSN are vulnerable to deliberate attacks (e.g. Liu et al., 2018a). Under such a situation, ports are usually disable for a long time, and sometimes this will lead to large-scale failures of shipping networks. However, the deliberate attacks due to terrorist, regional conflicts and wars are relatively rare in reality. Compared to that, accidents including piracy (Liu et al., 2021), port strikes, and natural hazards (e.g. storms) are relatively frequent. The application and development of a resilience concept provides a new perspective for investigating the safety and security of LSN from a systematic network perspective. After being disrupted, an LSN usually needs to go through two stages before it can be restored to its original state, including the resilience loss and the resilience recovery. These two stages reflect the ability of a shipping network to absorb and resist disturbance and to quickly recover and adapt to new environment. A shipping network with higher resilience is believed to be able to respond to emergencies more effectively and recover more quickly. Thus, it is of great significance to measure and quantify the resilience of an LSN in order to ensure the transport capacity and efficiency of the shipping networks. However, most of the previous research in the area focused on the vulnerability analysis of LSNs, leaving the recovery of LSNs after disruptions not being well addressed. In addition, compared to the qualitative analysis of resilience, quantitative measurement of resilience itself or the recovery strategy is few in general and fewer in LSN context in specific. This paper addresses this knowledge gap by developing a novel risk-based resilience framework which enables the integrity of resilience and recovery cost in a holistic way to quantitatively measure the effectiveness of different recovery strategies for the disruptions in LSNs.

The rest of the paper is constructed as follows. Section 2 describes the review of the research related to complex shipping networks and the resilience of transportation systems. The framework of evaluating the recovery strategies for the disruptions affecting LSN resilience is constructed in Section 3. The proposed method is applied to analyse and validate via a real case on the Maritime Silk Road (MSR) shipping networks under storm disruptions in Section 4. Section 5 summarizes the research, including the limitations and future research.

2 Literature review

Since 1736, it was found that many complex systems in reality can be abstracted into networks, and thus be studied from a topological perspective (Li et al., 2017). Based on the complex network theory, a maritime transportation system can also be mapped into a network to analyse the characteristics of each part of the network. The mainstream research topics in maritime shipping networks can be grouped into the following three categories.

The first category is to investigate the hierarchy of LSNs. Hierarchical attribute is one of the basic characteristics of a maritime network. Analysis of a network hierarchical structure helps to better understand and grasp the relationship between network nodes and the structural characteristics of the network. Some research branches within this group include the analysis of topological characteristics of an LSN and its evolution mechanism (e.g. Yuan and Ji, 2017), design of measures to describe the topological properties of an LSN (e.g. Bian and Deng, 2017), and spatial distribution pattern of trade (e.g. Song et al. 2018). The second group is the design and optimization of LSNs, in which more operational-related components of LSNs have been considered including port and shipping companies, cargo owners and other service providers, traders, and involving such factors as ship scheduling, and capital and information flow, to optimize their objectives under various constraints (e.g. Yang et al., 2014; Zheng and Yang, 2016; Tu et al., 2018). The third group aims to investigate the vulnerability of LSNs under different types of disruptions, to which our research belongs.

2.1 Vulnerability analysis of LSN transport systems

A transportation system is inevitably affected by various internal and external uncertainties, and the high complexity of LSN due to its wide range cover in the world makes the situation even worse. Vulnerability becomes obvious when LSNs are attacked, as it is evident by the recent COVID-19 pandemic. The concept of vulnerability was first proposed by Timmerman (1981), who described vulnerability as the severity of adverse consequences caused by disruptive events. The concepts of the term “vulnerability” evolve in different research contexts (Liu et al., 2018b), including 1) the opposite perspective of the concept “network robustness”, 2) the importance of elements (i.e. “vulnerability index”), and 3) node dependence. Nevertheless, all follow the rule that the deeper the adverse impact of a disruptive event, the more vulnerable the system is. In the research by Cultter et al. (2003), vulnerability was defined as the possibility of a system that will suffer from adverse impacts, and they believed that the less the vulnerability of a system, the stronger its ability to cope with disruptive events. Woolleymeza et al. (2011) found that the world maritime transportation and aviation networks not only have similar topological characteristics, but also show similar robustness and vulnerability in the face of attacks. Zio and Sansavini (2011) simulated the impact of fault cascade propagation on the connectivity of the maritime network by deleting nodes and edges selectively. Although vulnerability has long been widely used in transportation systems such as aviation and road transport, it is not until Ducruet and Notteboom (2012) that the network indicators were firstly used to assess the vulnerability of maritime transport network, in which the authors studied the impact of removing the Panama and Suez Canals on the vulnerability of global container shipping network. More recently, Liu et al. (2018b) used the Maersk Line data to model its LSN vulnerability subject to random and deliberate attacks.

2.2 Resilience analysis of transport systems

The concept of resilience was first proposed by Canadian ecologist Holling in 1973. He defined resilience as "the ability of an ecosystem to return to a stable state after being disturbed by an emergency" (Gunderson and Holling, 2003). After that, researchers began to apply resilience to other disciplines. The theory of resilience abroad is mainly used to study engineering resilience, supply chain resilience (Lam and Bai, 2016, Liu et al., 2018, Ail et al., 2018), transportation resilience (Wan et al., 2018), economic resilience and social resilience (Zhou and Yuan, 2017). Among the representative viewpoints of resilience, Timmerman (1981) defined resilience as the ability of infrastructure to recover from disturbances and resist shocks.

Chen and Yang (2018) used the concept of "resilience" to describe the process of quickly recovering the maritime networks to an acceptable level through appropriate repair measures after port failures under the background of production capacity constraints. Folke et al. (2002) defined resilience as the ability, function, structure, and feedback performance of a system that can absorb interference and reorganize to keep the system unchanged when undergoing changes. Fiksel (2003) defined a resilient system as a system that can return to a stable equilibrium state after encountering perturbations. Rose and Liao (2005) proposed a similar definition in which they regarded resilience as the ability of a system to apply an adaptive response mechanism to avoid potential losses when encountering an interruption. Adjetey and Birregah (2016) believed that resilience describes the overall goal of the system, that is, when faced with a certain degree of pressure, the system will continue to maintain the basic structure and function of the system to the greatest extent possible. Hudeca et al. (2018) described the resilience system as the ability of the system to maintain a constant output level when it is disturbed. In a recent study, Wan et al. (2018) used a graphical way to describe the changes of the performance of the system when it encountered external shocks from the perspective of resilience. The schematic of performance of a resilient system developed by the authors intuitively embodies the concept of resilience, that is, the system's ability to absorb and resist external shocks, and to take measures to actively respond and prompt the system to quickly reach a new equilibrium state. In the same work, the authors also systematically documented and presented the different resilience concepts of resilience within the transportation context.

Although the previous studies made considerable contributions to the literature of the vulnerability and resilience analysis of LSNs and provided important theoretical implications for resilience assurance in maritime transportation, there are still research challenges that have theoretical implications that are not being dealt with holistically in current literature and cannot be solved easily without developing new conceptual methodologies. A comparison analysis of the relevant studies in the field is summarized in Table 1 to illustrate the research demand on a new risk-based resilience methodology.

Table 1 Comparisons of the research of vulnerability and resilience analysis of LSNs

Literature	**Centrality measures**			**Vulnerability**	**Recoverability**		**Resilience**
	Degree	**Closeness**	**Betweenness**		**Recovery cost**	**Recovery time**	
(Calatayud et al., 2017)	○		○	○			
(Chen et al., 2018)				○			○
(Liu et al., 2018)	○	○	○	○			
(Charłampowicz, 2018)					○	○	○
(Wu et al., 2019)	○	○	○	○			
(Shen et al., 2019)	○			○			
(Asadabadi and Miller-Hooks, 2020)					○		○
(Rousset and Ducruet, 2020)			○			○	○
This paper	○	○	○	○	○	○	○

The existing gaps in the literature on LNS resilience have led to the development of the following important research questions:

How to develop a conceptual methodology that can enable the quantitative analysis of LSN resilience?

It is reflected by the aim of this paper. The relevant sub-questions are relevant to the objectives of this paper, including:

(1) How to select the parameters influencing LSN resilience?

(2) How to quantify the parameters?

(3) How to integrate the quantified parameters to obtain a single resilience index value?

3 Recovery strategy evaluation for LSN resilience

3.1 Research methodology

In previous studies, researchers often constructed index systems consisting of multi-layer indicators with different weights in order to evaluate the performance of an LSN system. However, this will inevitably bring in subjectivity when developing the hierarchical structure of index systems. To overcome this drawback, this paper investigates the resilience of an LSN system considering its inherent characteristics (i.e. vulnerability and recoverability). Both vulnerability and recoverability will be quantified and then combined in a resilience triangle to evaluate the recovery strategies for the resilience of LSN according its performance under disturbance events. To achieve this goal, a new methodology containing the following steps is constructed (see Fig. 1). Each of them is described in detail in the ensuing sections.

Step 1: Construction and performance evaluation of an LSN.

Step 2: Development of the resilience index.

Step 3: Comparative analysis of the recovery strategies in terms of resilience and total recovery time of the disrupted LSN.

Step 4: Real case analysis for the model validation.

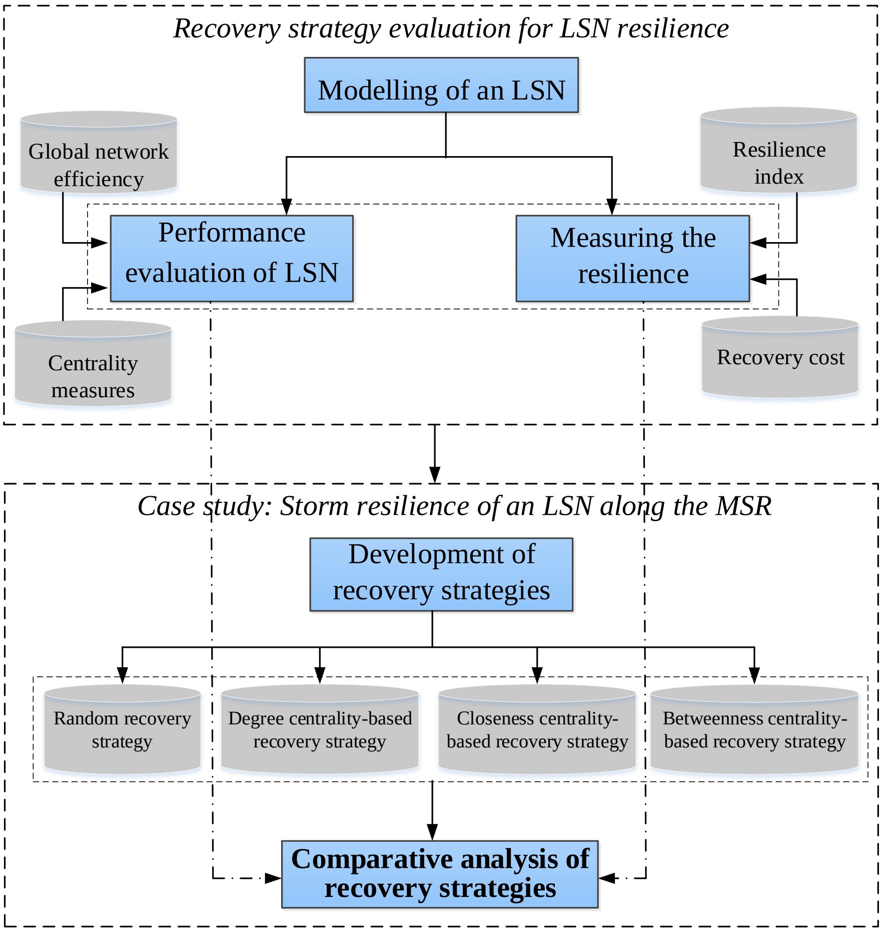

Fig.1 Flowchart of the proposed framework

3.2 Performance evaluation of an LSN

3.2.1 Global network efficiency

Network efficiency is defined as the average of the reciprocal of the shortest path lengths between each node pair in a network, indicates how efficiently the network transmits information. The concept of network efficiency was firstly proposed by (Latora and Marchiori, 2001) to characterize the properties of small-world networks. Since then, this measure has been widely used in different types of transport networks, including urban road networks (Sergio et al., 2006), subway networks (Vito and Massimo, 2002), and airline transport networks (Zhang et al., 2019). It suits the topic of this research well. This work chooses global network efficiency as an index to characterize the performance of an LSN.

$$E_f = \frac{1}{n(n-1)} \sum_{i \neq j} \varepsilon_{ij} \tag{1}$$

Where, E_f indicates the global network efficiency, n is the total number of ports in the investigated LSN. The global network efficiency reflects the connectivity between ports within the network and the overall efficiency of the whole network. Normally, the higher the global network efficiency of an LSN, the more the operational benefit it will gain (Wu et al., 2019).

Supposing that the initial global network efficiency of an LSN is E_{f_0}, and the global network efficiency after a disruption to a certain port is E_{fr}, then the vulnerability of the network with respect to this port can be expressed by Eq. (2)

$$V_r = \frac{(E_{f_0} - E_{f_r})}{E_{f_0}} \tag{2}$$

Where, V_r indicates the influence of port r on the global efficiency of the LSN.

3.2.2 Centrality measures

Centrality is an important indicator for determining the importance of a node in a network. In this study, three centrality measures are calculated and used as a reference to develop different recovery strategies of LSNs. They are degree centrality, closeness centrality, and betweenness centrality.

(1) Degree centrality

Degree centrality of a port refers to the number of ports directly connected to it, and it represents the connectivity of a port with other ports in a maritime shipping network (Wu et al., 2019). Degree centrality can be calculated using Eq. (3).

$$D_{c_i} = \sum_j^n \delta_{ij} \tag{3}$$

Where, D_{c_i} indicates the degree centrality of port *i*, *n* represents the total number of ports in the LSN, and δ_{ij} is the number of links between port *i* and *j*.

(2) Closeness centrality

The closeness centrality is the reciprocal of the sum of the shortest distance from all ports to the target port, which is used to evaluate the reachability and spatial advantage of a certain port in the shipping network (Wu et al., 2019). The closeness centrality can be calculated using Eq. (4).

$$C_{c_i} = \frac{n-1}{\sum_{i \neq j \in n} d_{ij}} \tag{4}$$

where d_{ij} represents the shortest distance between two ports.

(3) Betweenness centrality

Betweenness centrality reflects the degree to which a port is located "in the middle" of other port pairs, which can be be calculated using Eq. (5).

$$B_{c_i} = \sum_{s,t \in V, s,t \neq i} \frac{\delta(s,t|i)}{2} \tag{5}$$

where *s* and *t* represent a set of port pair, and $\delta_{(s,t|\, i)}$ is the number of times the shortest distance between port pairs that pass through port *i*.

3.3 Measuring the resilience

3.3.1 Resilience index

When a disruptive event occurs, the capacity of the influenced ports will be damaged to a certain extent, leading to a decline of the transport efficiency of the entire LSN, as shown in Fig 2. Assuming that the disturbance caused by the disruption minimizes the performance of the shipping network in an instant, then the sudden decline of the performance curve reflects the vulnerability of the system, the depth of the resilience loss triangle indicates the degree of performance degradation of the system, and the length of the resilience triangle indicates the total time required for the system to return to its normal state. The greater the slope of the rising curve during the recovery stage, the stronger the recoverability of the shipping network.

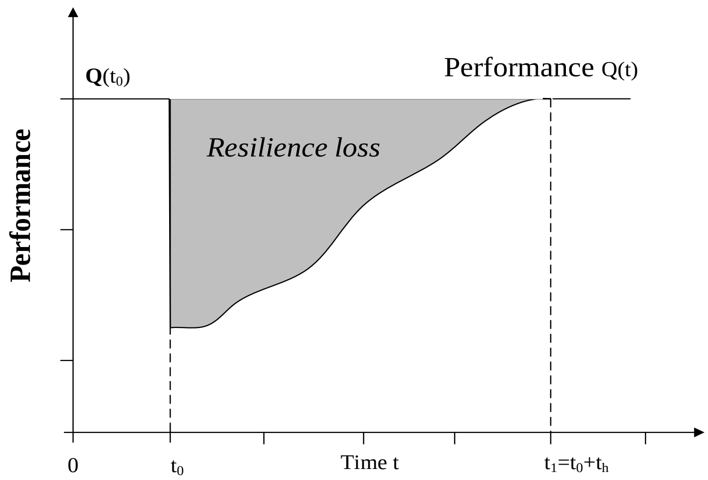

Fig 2 The graphical measure of system resilience

(Source: adapted from Brunea et al., 2003)

The vertical axis represents the performance *Q(t)* of the system, and the horizontal axis is time. At time t_0, the system is disrupted, and the performance drops instantaneously. After T_l, the performance *Q(t)* restores to the original level at time t_1. The loss of resilience is indicated by the grey areas in the figure.

Based on the resilience triangle, the resilience index R_e can be expressed as the ratio of the area covered by the interrupted performance curve *Q(t)* to the area covered by the uninterrupted curve $Q(t_0)$ during the recovery time t_h. The system's resilience metrics are expressed by Eq. (6).

$$R_e = \frac{\int_{t_0}^{t_0+t_l} Q(t)dt}{t_l Q_0} \tag{6}$$

In this research, the global network efficiency is selected to reflect the performance of the shipping network. Therefore, we replace the performance index in Eq. (6) with the global network efficiency to obtain the new resilience index of the shipping network as expressed using Eq. (7).

$$R_e = \frac{\int_{t_0}^{t_0+t_l} [E_f(t)]dt}{t_l E_{f0}} \tag{7}$$

where $E_{f_{(t)}}$ represents the global network efficiency at the moment *t*, and $E_{f_{(0)}}$ represents the initial global network efficiency of the shipping network.

Resilience index (R_e) is a value between zero and one. The higher the value of R_e, the smaller the resilience loss and the greater the structural resilience of the shipping network. If R_e =1, it indicates that the network has not been affected by the disruptive event, the performance of the network after the disruption remains the original state; If R_e <1, it indicates that the disruptive events have a negative impact on the shipping network, and recovery countermeasures are needed to recover the shipping network function; If R_e << 1, it indicates that the network has been severely destroyed by the disruptive event, and it will take a long time to recover.

3.3.2 Recovery cost

During the recovery of an LSN, the total cost C of can be calculated using Eq. (8).

$$C = \sum_{i=1}^{n} C_i T_i \tag{8}$$

Where T_i is the time needed for port i to recovery, and C_i is the daily cost of port i's operation.

It can be seen from Eq. (8) that the total cost is determined by the recovery time and daily cost of each port. Regarding the recovery time of a port after a disruption, it is mainly determined by its scale and the economic condition. Usually, a port with larger scale and poorer economic development status should take longer time to recover, because the larger the scale, the more resources are needed when conducting reconstruction of a port after being destroyed. In this study, the length of port shoreline and the gross domestic product (GDP) of the country are selected to reflect the port scale and economic development of hinterland of port respectively. The GDP will have a positive impact on port recovery, while the length of port shoreline has a negative influence on recovery time. In addition, an adjustment coefficient k is set to adjust the recovery time and make it suitable under different situations, as shown in Eq. (9).

$$T_i = k \frac{L_i}{G_i} \tag{9}$$

Where, L_i is the sum of the coastal line length of port i, and G_i is the GDP of the state where port i belongs to.

Regarding the daily cost of a port, it can be understood as the loss of the port's operating expenses due to its functional degradation. It consists of harbour dues C_{i_1}, facility security fees C_{i_2}, pilotage fees C_{i_3} and berthing fees C_{i_4}. Thus, it can be calculated using Eq. (10).

$$C_i = C_{i_1} + C_{i_2} + C_{i_3} + C_{i_4} \tag{10}$$

Here containerships are used for a demonstration, while the daily cost model itself is generic and accommodate different types of ships. Currently, the containership market is dominated by the fifth-generation container vessels, typically carrying 4800 TEU[1], with a standard aspect ratio of 7 to 8. The size of a 20-foot standard container is 6.058×2.438×2.591 meters, and the gross weight of it is 17.5 tons. When fully loaded,

[1] This is also partially evidenced by the research of Charłampowicz (2018) that the number of vessels with a capacity below 5000 TEU accounts for more than 70% of the total number of container ships in the global maritime shipping market.

each standard container can generally carry 12 tons of goods.

Table 2 Type parameters of the fifth-generation container ships

Capacity/TEU	Standard Size/m	Length-Width Ratio	All-Up Weight/t
4800	6.058×2.438×2.591	7~8	12

Let the annual container throughput of a port is set as M_i. According to Table 2, the annual throughput M_i is converted into the number of container ships passing through the port every day by using Eq. (11).

$$F_i = \frac{M_i}{365 \times 4800} \tag{11}$$

Assuming that the port is destroyed by disasters, then the daily cost of port will be the loss of operating income of it before it is restored to its original state. According to the foreign trade cargo port charge rate (Table 3), the import rate for a 20-foot standard container for general cargo is 34 CNY/container, and the export rate is 17 CNY/container. The security fee for a 20-foot standard container is 8 CNY/container. Pilotage fees and berthing fees are charged in accordance with the provisions of the benchmark rate of port charges for ships sailing on international routes. The rate of 40,000 net tons and below is 0.45 CNY/ton, the rate of 40001-80000 net tons is 0.40 CNY/ton, and the rate of 80000-120000 net tons is 0.375 CNY/ton. It is noted that

Table 3 Port charges for ships of international routes

Number	Category	Charge Unit	Charge/CNY	Illustrate
1	Harbour Dues	Box (20 feet)	34	Import
			17	Export
2	Port Facility Security Fees	Box (20 feet)	8	
3	Pilotage (Mooring) Fees	Ton	0.45	40000 net tons and below
			0.40	40001-80000 net tons
			0.375	80000-120000 net tons
4	Berthing Fees	Ton/Day	0.25	

Source: The Ministry of Transport of the People's Republic of China, (2019)

Assuming that the number of container ships imported and exported every day is equal, both are $F_i / 2$, then the daily harbour dues C_{i_1}, and port facility security fees C_{i_2} can be calculated by using Eq. (12) and (13), respectively. Assuming that each ship is fully loaded with 4800 TEU and each container weighs 12 tons, and then each ship will have a net cargo load of 57,600 tons. Then, the daily pilotage fees C_{i_3} and the pilotage fees C_{i_4} can be calculated by using Eq. (14) and (15), respectively.

$$C_{i_1} = (34 \times 4800 F_i / 2) + (17 \times 4800 F_i / 2) \tag{12}$$

$$C_{i_2} = 8 \times 4800 F_i \tag{13}$$

$$C_{i_3} = (0.45 \times 40000 + 0.40 \times 17600) F_i \tag{14}$$

$$C_{i_4} = 0.25 \times 57600 F_i \tag{15}$$

3.3.3 Resilience-cost ratio

To maximize the benefits of LSNs during recovery, it is necessary not only to consider the resilience of a shipping network, but also to pay attention to the cost needed in response to disasters. Based on the aforementioned resilience index model and LSNs recovery cost model, a resilience-cost radio indicator λ for evaluating the overall performance of an LSN is developed which can be calculated using Eq. (16).

$$\lambda = \frac{R_e}{C} \tag{16}$$

The resilience-cost ratio λ indicates the performance of a recovery strategy. The larger the λ, the higher the resilience-cost ratio of the recovery strategy for LSNs.

4 Case study: Storm resilience of an LSN along the MSR

4.1 Background information

The 21st-Century Maritime Silk Road (MSR) is an important strategy for countries and regions to strengthen infrastructure connectivity with others, and it is an economic belt with a large population and most of the participating countries are developing countries and emerging economies. Given its growing importance in international trade and economic development, this study selects the LSN along the MSR as a case study to demonstrate the proposed method and conduct the resilience evaluation and selection of recovery strategies of maritime transportation. According to Liu et al. (2018a), typhoons and tropical cyclones are the most typical and serious natural hazards affecting the MSR. Tropical cyclones will cause violent winds and heavy rains. In view of this, this paper mainly focuses on the LSN resilience of the routes involved in the Pacific Northwest and North Indian Ocean parts of the MSR facing the threat of storms. Fig. 3 shows the geographical distribution of the affected ports in these two regions, in which red dots indicate the ports in the Pacific Northwest region (47 out of 254 sea ports) and the green in the North Indian Ocean region (27 out of 254 sea ports).

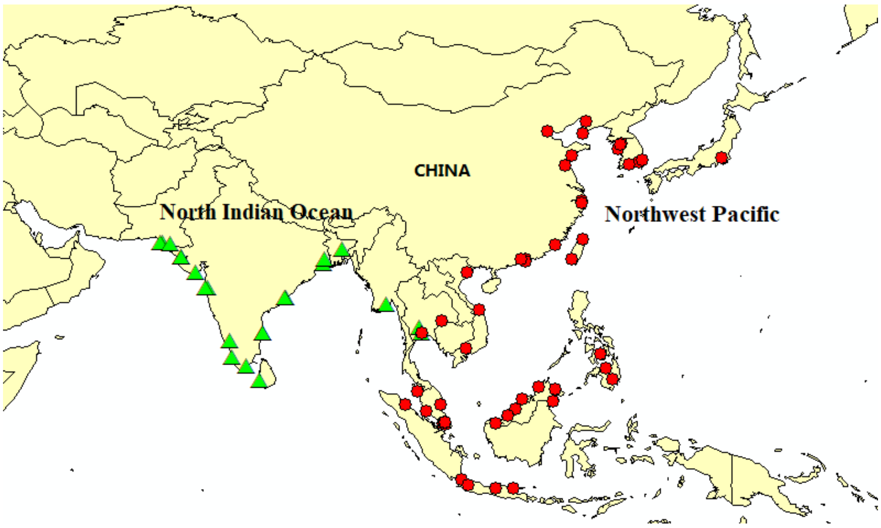

Fig 3. Distribution of the ports which are frequently affected by typhoons

4.1.1 Data sources

Based on the official published information, this work finally screened out 43 countries participating in the MSR, including 32 Asian countries, 7 European countries, 3 African countries, and 1 Oceania country.

According to the transport capacity information provided by Alphaliner in 2018, the top 16 container shipping companies in the world have a total shipping capacity of 18,395,500 TEU, accounting for 88.05% of the total global container shipping capacity (Chen et al., 2018). Thus, the service information (including ports of call, time schedule, ship fleet, and ship capacity) of the top 16 shipping companies is considered in this research, to make the analysis and result representative. According to the service information provided by these container shipping companies from October 2016 to December 2016, this paper divides the service areas of global shipping into nine main routes according to their service areas, including Southeast Asia Line, Mediterranean Line, and European routes, etc. Finally, there are altogether 1249 liner shipping routes related to the investigated LSN along the MSR, connecting 37 countries and altogether 254 sea ports (Wu et al., 2019).

4.1.2 Construction of the MSR LSN

From the perspective of spatial layout, liner shipping can be abstract into a network where ports and routes consist of the sets of nodes and edges, respectively. Two main approaches to constructing a network are the graph of direct linkages (GDL) and the graph of all linkages (GAL). In an LSN, a GDL only considers the direct links between each port in a sequence of the service, while, in a GAL, all the ports within the shipping network are linked no matter they are adjacent or not. Considering that in reality, the actual shipping transportation is better reflected by the GAL model when they navigate from one port to another, and GAL can better explain the dominant position of the network hub port (Ferber, 2009). Thus, this research applied GAL when constructing the MSR LSN. By using the UCINET software, a network composed of 254 nodes and

1,249 links is developed, as shown in Fig. 4. It is noted that Fig. 4 only highlights the top 50 ports in terms of the degree value in order to improve the readability.

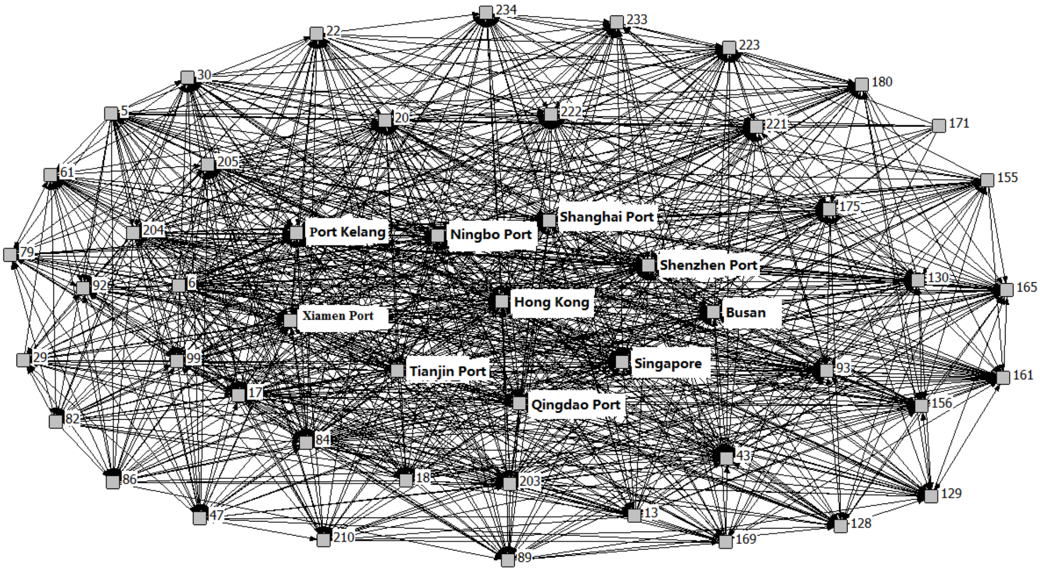

Fig 4. Demo of the investigated MSR LSN

4.2 Evaluating the recovery strategies of the MSR related LSNs

As mentioned in Section 3.2, the global network efficiency is selected to measure the performance of the MSR LSN of different regions under storm disruptions. In addition, the total recovery time of the LSN is considered to compare the efficiency of different recovery strategies. For the Northwest Pacific region, the GDP values of eight countries (which are China, Indonesia, Malaysia, Vietnam, the Philippines, Thailand, South Korea and Japan) in 2018 and the length of the shoreline of 47 ports in these countries are collected. For the Northern Indian Ocean region, the GDP values of six countries (which are Thailand, Myanmar, Pakistan, Bangladesh, Sri Lanka and India) in 2018 and the length of the shoreline of 27 ports are collected.

To model the reconstruction of ports after being destroyed by natural hazards, we take the performance of the Port of Tokyo (Japan) hit by the earthquake and tsunami in 2011 as a baseline when calculating the recovery time of other ports. In terms of the disaster, it took around 30 days for the Port of Tokyo to recover. According to Eq. (8), the k value can be calculated as 64 in this case, and assuming that the other ports in the MSR shipping network share the same k. Then, the recovery time of other ports can be obtained accordingly.

Taking the Port of Shanghai as an example, GDP of China was 13,457.267 billion USD in 2018, and the length of shoreline of the Port of Shanghai was 72,473 meters, so its recovery time is 34 days according to Eq. (8). Similarly, the recovery time of all ports can be calculated, partly as shown in Table 4.

Table 4 The recovery time of the top 10 most connected ports in the MSR shipping network

No.	Port	Country	Region	Recovery Time/day
1	Port of Hong Kong	China	Northwest Pacific	9
2	Port of Singapore	Singapore	Northwest Pacific	264
3	Shanghai Port	China	Northwest Pacific	34
4	Ningbo Port	China	Northwest Pacific	43
5	Shenzhen Port	China	Northwest Pacific	15
6	Port Kelang	Malaysia	Northwest Pacific	90
7	Port of Busan	Korea	Northwest Pacific	106
8	Qingdao Port	China	Northwest Pacific	14
9	Xiamen Port	China	Northwest Pacific	14
10	Tianjin Port	China	Northwest Pacific	17

A previous study by Wu et al., (2019) revealed that the MSR network can survive from no more than 60% of the disruption of ports, or it will collapse. Therefore, in this study, we assume that a maximum of 60% of the ports in the MSR regional shipping network will be destroyed by random in the case study, and different recovery strategies will be quantitatively assessed and compared with respect to their influence on the resilience of the MSR shipping network. The four recovery strategies considered in this study are listed as follows.

- Random recovery strategy

The destroyed ports will be recovered in a random sequence without the consideration of the difference of the ports within the MSR shipping network.

- Degree centrality-based recovery strategy

The destroyed ports will be recovered in a descending order of their degree centrality, which means the port with higher degree centrality will be recovered first.

- Closeness centrality-based recovery strategy

The destroyed ports will be recovered in a descending order of their closeness centrality, which means the port with higher closeness centrality will be recovered first.

- Betweenness centrality-based recovery strategy

The destroyed ports will be recovered in a descending order of their betweenness centrality, which means the port with higher betweenness centrality will be recovered first.

4.2.1 Northwest Pacific Region

According to Eq. (1), the initial global network efficiency of the Northwest Pacific shipping network is 37.67%, and after 60% of the ports being destroyed by storms, the global network efficiency of the MSR shipping network in the Northwest Pacific Region declines to 18.35%, losing 51.29% of its functions. In order to carry out different recovery strategies, the degree centrality, closeness centrality and betweenness centrality of each port need to be calculated first based on Eq. (3) to (5). Considering that in reality, it is not usually the case that only one port can be recovered in a certain time period and all the ports wait to be recovered one by one. Instead, different countries and regions tend to work together so that the whole shipping network can return to normal as soon as possible. In this study, we assume that 20% of the destroyed ports will be recovered at the same time during a certain period. Thus the total time of the period depends on the port which spends the longest time to recover in each port group. Based on this idea, the performance of the shipping network in the Northwest Pacific region under different recovery strategies can be depicted, as shown in Fig. 5. The horizontal ordinate shows the total time that the whole shipping network needs to be fully recovered.

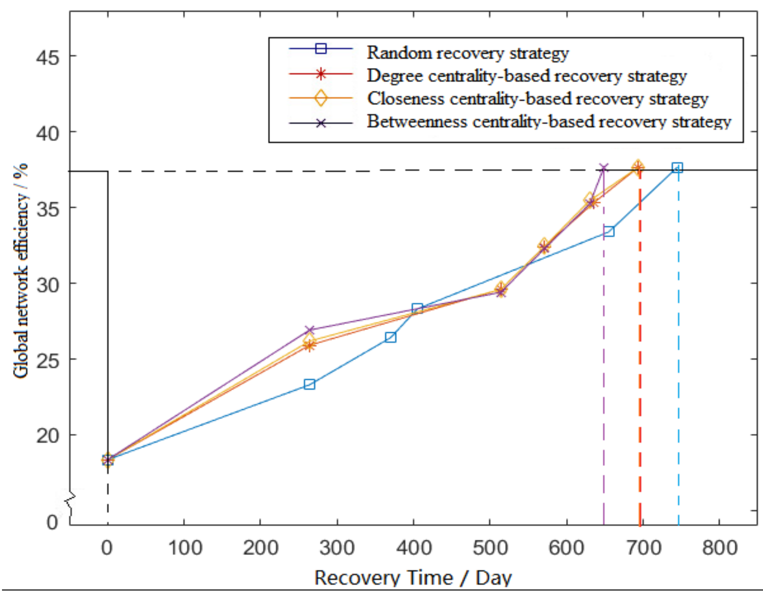

Fig 5. Recovery time of the Northwest Pacific LSN under different recovery strategies

According to Eq. (6) to (16), the resilience index, recovery time, recovery cost, and resilience-cost ratio under different recovery strategies are calculated. The results are shown in Table 5.

Table 5 Performance of recovery strategies in the Northwest Pacific LSN

Recovery strategy	**Resilience index**	**Recovery time (days)**	**Lost operating cost (Billion CNY)**	**Resilience-cost ratio (10^{-2})**
Random recovery strategy	0.7127	745	18.098	0.394
Degree centrality-based	0.7217	694	14.761	0.489
Closeness centrality-based	0.7253	694	13.461	0.540
Betweenness centrality-based	0.7140	649	17.006	0.420

As shown in Table 5, the LSN in the Northwest Pacific region takes the shortest recovery time when using the betweenness centrality-based recovery strategy, which is

649 days. This means that if the primary goal is to minimize the total shutdown time and reduce ship delays as much as possible, betweenness centrality-based recovery strategy will be the best choice. The recovery strategy based on closeness centrality lead to the largest resilience index, and the least recovery costs at the same time. This means that in the Northwest Pacific region, closeness centrality-based recovery strategy performs the best, which can achieve higher comprehensive benefits.

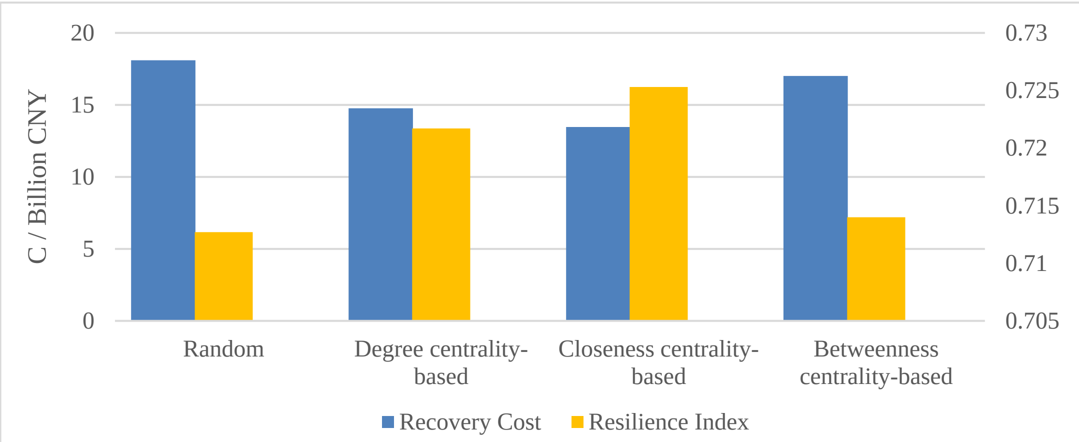

Fig 6. Comparison of different recovery strategies in the Northwest Pacific region

As shown in Fig. 7, according to the resilience-cost ratio of different recvoery strategies in the Northwest Pacific LSN, closeness centrality-based recovery strategy ranks first, followed by recovery strategies based on degree centrality, betweenness centrality, and random recovery strategy.

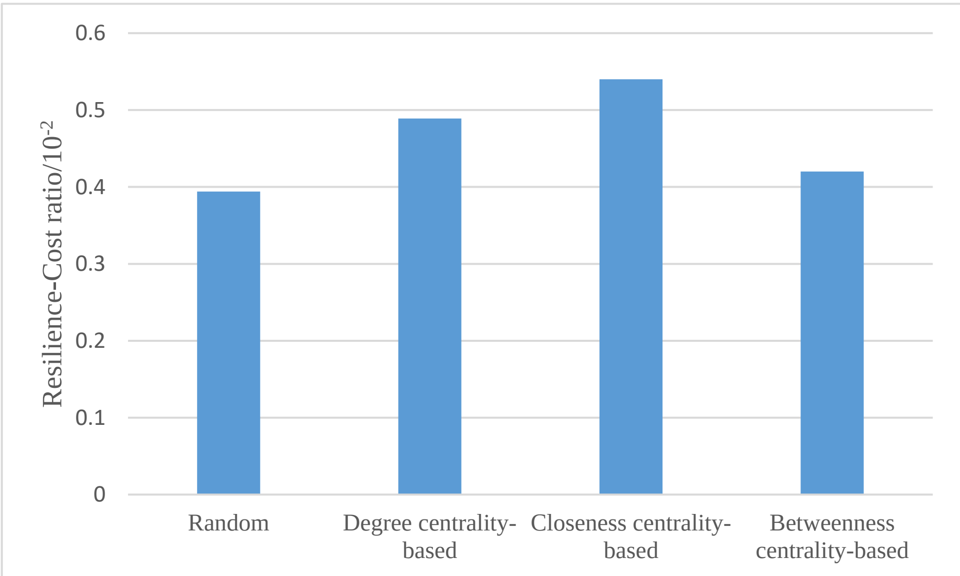

Fig 7. Resilience-Cost ratio of the LSN in the Northwest Pacific region

4.2.2 Northern Indian Ocean region

In a similar way, the performance of the Northern Indian Ocean shipping network under storms can be evaluated. The initial global network efficiency of the Northern Indian Ocean shipping network is 37.67%, and after the storms, the global network efficiency of the MSR shipping network in the Northern Indian Ocean declines to 29.24%, losing 22.38% of its capacity. Based on the same restoration process, the performance of the shipping network in the Northern Indian Ocean region under different recovery strategies can be depicted, as shown in Fig. 8.

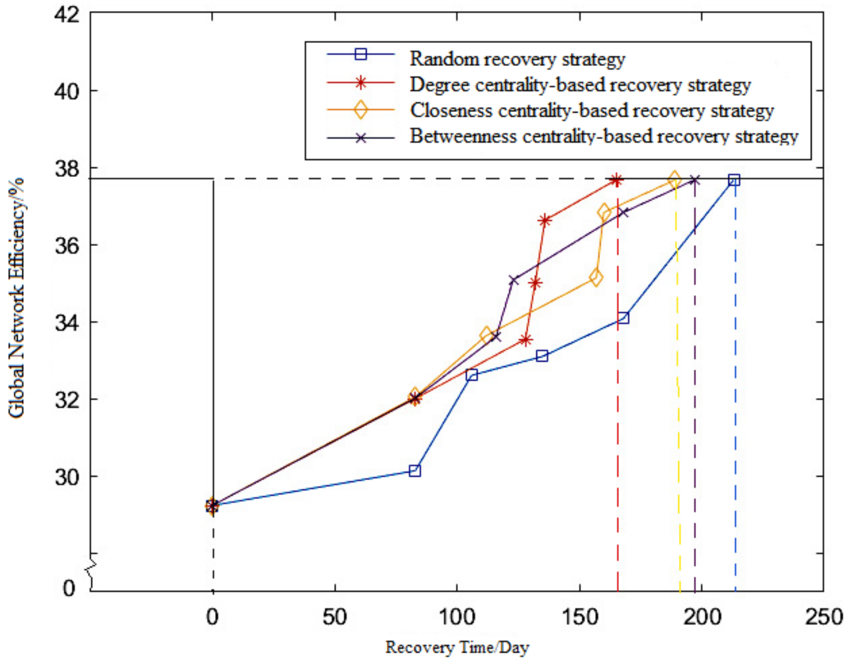

Fig 8. Recovery time of the North Indian Ocean LSN under different recovery strategies

In a similar way, the resilience index, recovery time, recovery cost, and resilience-cost ratio under different recovery strategies in the Northern Indian Ocean are calculated. The results are shown in Table 6.

Table 6 Performance of recovery strategies in the Northern Indian Ocean LSN

Recovery strategy	**Resilience index**	**Recovery time (days)**	**Lost operating cost (Billion CNY)**	**Resilience-cost ratio**
Random recovery strategy	0.8552	213	0.685	0.125
Degree centrality-based	0.8647	165	0.647	0.134
Closeness centrality-based	0.8753	189	0.681	0.128

Betweenness centrality-based	0.8845	197	0.676	0.131

From the Table 6, it can be seen that the LSN in the North Indian Ocean region takes the shortest recovery time when using the degree centrality-based recovery strategy, which is 165 days. Regarding resilience index, betweenness centrality-based recovery strategy performs the best with a value of 0.8845, which is suitable for the situation when minimum resilience loss is required during the recovery. Taking degree centrality-based recovery strategy is the best in terms of comprehensive recovery effect, with a maximum resilience -cost ratio of 0.134.

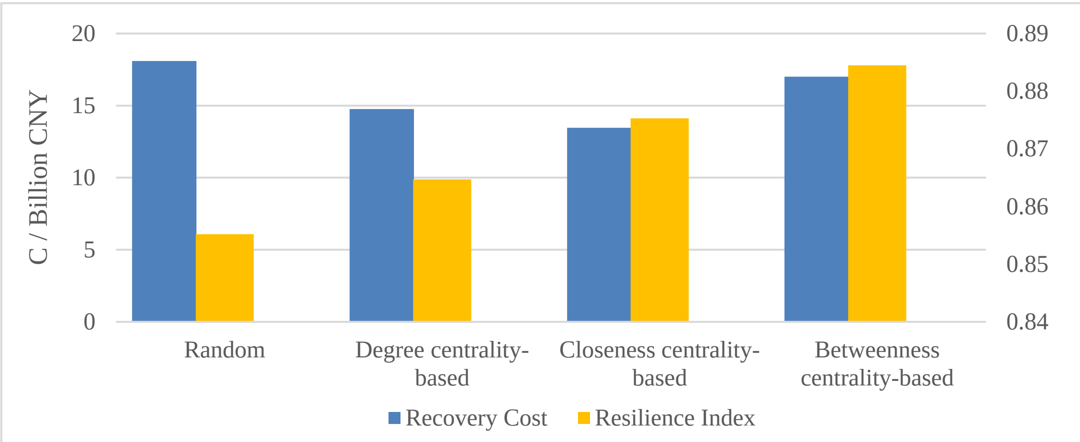

Fig 9. Comparison of different recovery strategies in the North Indian Ocean region

As shown in Fig. 10, according to the resilience-cost ratio of different recvoery strategies in the North Indian Ocean LSN, degree centrality-based recovery strategy ranks first, followed by recovery strategies based on betweenness centrality, closeness centrality and random recovery strategy.

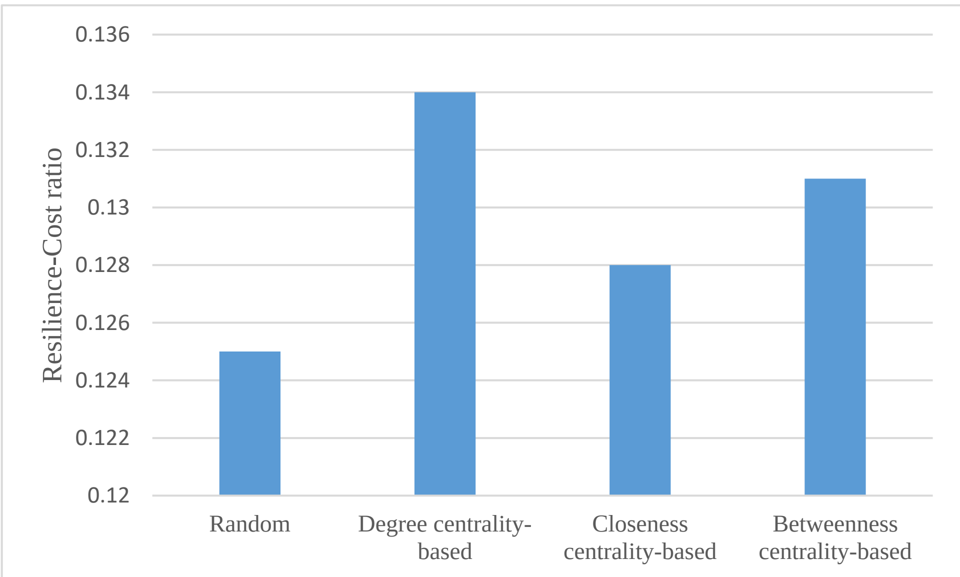

Fig 10. Resilience-Cost ratio of the LSN in the North Indian Ocean region

4.2.3 Section summary

The resilience-cost ratio of the LSN in the Northwest Pacific region is much smaller than that of the North Indian Ocean, due to the relatively higher total recovery time and cost of the 47 ports in the Northwest Pacific region. The resilience-cost ratio of the random recovery strategy is the lowest in both the Northwest Pacific and the North Indian Ocean regions.

The research results also indicate that in the Northwest Pacific region, the ports with relatively higher value of closeness centrality will have a greater impact on the structural resilience of LSNs, such as the Port of Singapore, Hong Kong and Shenzhen. While, in the North Indian Ocean region, ports with relatively higher value of degree centrality will have a greater impact on structural resilience, such as Port of Navassiwa Laem Chabang and Jeddah. Therefore, these ports are suggested to have higher priorities during the recovery after being disrupted, in order to improve the overall performance of the whole LSN.

5 Conclusion

As a crucial component of global trade, maritime container shipping has made a significant contribution to the global economy, and thus it requires a resilient system to resist disturbance in today's uncertain environment. This study developed a novel risk-based resilience framework to measure the effectiveness of different recovery strategies for the disruptions in LSN. The case study of the recovery of a specific LSN along the MSR under storm disruptions was conducted and four types of recovery strategies are compared to demonstrate how the newly proposed method can effectively aid resilience decision of LSNs. The contributions of this research are summarized as follows.

From a theatrical perspective, it contributes to knowledge of risk management of maritime shipping networks from a resilience perspective. A directed complex network model of liner shipping along the MSR is constructed based on the liner service information covering 254 ports from 37 countries, which provides a model basis for the vulnerability of LSNs in other regions from a topological structure perspective. The methodology is conceptual and generic, providing scientific insights in terms of evaluating the resilience of LSNs under disruptions and it could be easily tailored to accommodate more parameters when appropriate so as to provide targeted evaluation results under different scenarios. The methodology provides insightful reference for the safety assurance of maritime transportation from a systemic perspective.

Practically, the findings provide some managerial implications. First, the proposed resilience model is able to identify the influential ports in different regions, and calculate the total cost of the recovery of whole LSN, which helps to develop and select suitable recovery strategies. Second, this research also provides useful insights on the rational emergency response and resource allocation for maritime transportation, and also scientific guidance for stakeholders in terms of the investment of ports of global LSNs and the practical stakeholders can use it for better plan adaptation to extreme weather events. The ports of low resilience can learn the best practice with respect to different parameters from those of high resilience. Furthermore, the proposed resilience framework has a good generality and can be tailored when it is applied for dealing with other types of risks like earth quake, and tsunamis. More extended applied work based on the proposed methodology will further broaden the application range of the proposed methods[2].

Although showing some attractiveness, this paper still reveals some limitations in applications. As an exploratory research on the risk-based resilience evaluation of LSNs, port scale and economy are considered as the main parameters at the current stage when estimating the time needed to fully recover the whole LSN. In future research, more attributes will be tested and incorporated, if valid, into the proposed model to further extend its ability and application scopes. Besides, due to the incomplete and unavailable cargo volume information of shipping routes among different port pairs, the importance of all links in the LSN is treated equally. Despite the fact that many transport network resilience studies used the same setting to support their analysis, it is still believed that when more information of the traffic volume of each shipping route is collected, a directed and weighted LSN model can be constructed to generate new findings. More application of the proposed framework in dealing with other types of risks is nevertheless encouraged to further 1) test the generality of the model and 2) generate useful guides for LSN resilience to different disruptions in the future.

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[2] Based on the proposed framework, the authors are currently trying to investigate the changes of the spatial pattern of the world shipping network, and to test how resilient the global LSN is in face of the impact of COVID-19, according to the service information of some world-leading container liners from February to December 2020.

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