Data driven reliability and resilience measure of maritime transportation systems considering disaster levels

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Abstract: With the development of economic globalization and increasing international trade, the maritime transportation system (MTS) is becoming more and more complex. A failure of any supply line in the MTS can seriously affect the operation of the system. Resilience describes the ability of a system to withstand or recover from a disaster and is therefore an important method of disaster management in MTS. This paper analyzes the impact of disasters on MTS, using the data of Suez Canal "Century of Congestion" as an example. In practice, the severity of a disaster is dynamic. This paper categorizes disasters into different levels, which are then modelled by the Markov chain. The concept of a repair line set is proposed and is determined with the aim to minimize the total loss and maximize the resilience increment of the line to the system. The resilience measure of MTS is defined to determine the repair line sequence in the repair line set. Finally, a maritime transportation system network from the Far East to the Mediterranean Sea is used to validate the applicability of the proposed method.

Keywords: reliability; resilience; Markov process; importance measure; repair analysis

1. Introduction

1.1. Background

With the development of economic globalization and China's *Belt and Road Initiatives*, trade between China and other countries in the world has become more frequent, and the international trade transportation network has shown an increasingly complex trend. As an important pillar of the international supply chain (Wan et al. 2019), the MTS carries out more than 80% of the world's trade activities. The MTS is easily affected by natural disasters and human factors, due to its characteristics of long distance, multiple routes and large flow. In 2021, the Ever Given ran aground in the Suez Canal, causing a "century blockage" for tens of days. The six-day blockage threw global supply chains into disarray and, according to Lloyd's List data, held up almost US$10 billion worth of trade[†]. .

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[†]Insurance Business Australia: https://www.insurancebusinessmag.com/au/news/marine/was-this-massive-suez-

With the occurrence of disasters, pre-disaster prevention and post-disaster intervention of systems are needed to reduce the damage. Due to the low frequency and high hazard of disasters, it is of great significance to study how MTS can recover quickly and minimize the damage after a disaster. This paper therefore aims to analyze the post-disaster MTS, and applies the Markov chain to model resilience and to determine post-disaster repair strategies.

1.2. Literature review and gap analysis

The word "*resilience*" is originally derived from the Latin word "resiliere", meaning "to rebound". Resilience is commonly used to indicate the ability of an entity or system to return to its normal state after a disruptive event. Holling (1973) introduced resilience to the scientific world through his seminal paper on ‘‘Resilience and Stability of Ecological Systems’’. In 2005, the World Conference on Disaster Reduction (WCDR) introduced the term "resilience" and clarified its importance, thus giving rise to a new culture of disaster response (Cimellaro et al. 2010). According to WCDR, resilience is used to describe “*the ability of an object that has been deformed by an external force to return to its original state after the force is removed*”. There are many other definitions of resilience. Allenby and Fink (2000) defined resilience as “*the ability of a system to maintain its function and structure over internally and externally changing surfaces, and to degrade when necessary*”. The American Society of Mechanical Engineers defined resilience as “*the ability of a system to sustain external and internal disruptions without interrupting the execution of system functions, or, if the function is disconnected, to fully recover the function rapidly*” (Hosseini et al. 2016). According to Hosseini et al. (2016), resilience refers to the ability of an entity or system to return to its normal state after being disrupted by a disruptive event. Woods (2015) presented the concepts of resilience as “*rebound, robustness, elastic extensibility, and sustained adaptability*”. Madni and Jackson (2009) described resilience as “*a multi-faceted capability, including avoiding, absorbing, adapting to, and recovering from disruptions*”. Jufri (2019) defined a resilient grid can as a grid which has four fundamental properties of resilience, namely anticipation, absorption, recovery, and adaptability after the damaging events.

In the context of the resilience measure, infrastructure resilience is the ability to reduce the magnitude and/or duration of disruptive events. Many resilience measures have been developed in various research fields (Yodo & Wang, 2016). Youn et al. (2011) applied the concept of resilience

canal-ship-damages-claim-caused-by-a-drone-419988.aspx measure to engineering, and they defined the resilience measure as the sum of reliability and restoration. Barker et al. (2013) proposed two resilience-based component importance measures, the first measure quantifying the potential adverse impact and the second one quantifying the potential positive impact on system resilience, respectively. Dui et al. (2021) proposed four importance measures based on the residual resilience. Mohammed et al. (2020) evaluated the green and resilience of suppliers and developed an order allocation plan and considered that resilience works to avoid or mitigate an expected or unexpected disruption, or at least mitigate its negative impact towards an ideal goal of environmental sustainability. Ouyang and Wang (2015) assessed the resilience of interdependent electric power and natural gas infrastructure systems under multiple hazards, noting how the performance of an interdependent network could be measured from both the perspectives of physical engineering and societal impact. Dinh et al. (2012) identified six factors relating to the resilience engineering of industrial processes, which are minimization of the probability of failures, limitation of effects, administrative controls/procedures, flexibility, controllability, and early detection. Adjetey-Bahun et al. (2016) proposed a simulation-based model to quantify the resilience of large-scale rail transportation systems by quantifying passenger delays and passenger loads as system performance metrics.

Infrastructure systems, such as MTS, can be considered as subfields of the engineering domain since their construction and recovery require engineering knowledge (2016). In the context of repair strategy for an infrastructure system, Verschuur et al. (2020) studied the extent of disruption and potential resilience of ports and maritime networks. Asadabadi and Miller-Hooks (2020) proposed a methodology to assess and improve the resilience and reliability of port networks. Bao et al. (2019) proposed a tri-level model explicitly integrating the decision making on recovery strategies of disrupted facilities with the decision making on protecting facilities from intentional attacks. Chen et al. (2019) took up age and periodic replacement models again to formulate the general models when replacement actions are also conducted at random times. Zhao et al. (2020a) proposed the preventive replacement policies for parallel systems with deviation costs between a replacement and a failure, which balances the deviation time between replacement and failure. Berle et al. (2010) proposed a structured formal vulnerability assessment methodology, attempting to transfer the security-oriented formal security framework to assess the vulnerability domain of the maritime transportation system. Zhao et al. (2020b) make the preventive replacement policies perform in a more general way, taking excess costs and shortage costs into considerations for periodic replacement policies. Sheu et al. (2021) studied and optimized two preventive replacement policies for a system subject to shocks. Bai et al. (2021) proposed an improved power grid resilience measure and its corresponding importance measures. The recovery priority of failed components after a disaster is determined and reflects the influence of the failed components on the power grid resilience.

From the above literature review, it appears that there are still some limitations on the resilience and maintenance of maritime systems in the existing research. Firstly, they did not study the mechanism of the impact of failed components on the whole system. Secondly, only binary component, namely normal and fault states, were considered. In the maritime system, however, a route may not be completely failed after being affected by a disaster. As such, maritime routes can be regarded as multistate components. Thirdly, they did not delve into the mechanism of the impact of different types and levels of disasters on the system.

1.3. Contributions of this paper

The above literature review suggests there be a bulk of research related to resilience, which focuses on complex systems. The limitations in the existing research motivate this research, which makes the following contributions.

(i). The disasters are classified into different levels. The transitions between the levels forms a Markov process, based on which a resilience model is developed. Disasters at each level incur costs of restoring system performance. The paper derives the expected values of those costs.

(ii). The paper proposes a novel resilience importance measure and a novel method to measure the impact of the changes due to the change of a single line flow on the resilience is measured, contributing the literature of importance measures.

(iii). A section from the Far East to the Mediterranean Sea is simulated as an example, to propose specific repair strategies and to validate the proposed resilience model in this paper.

The remainder of the paper is organized as follow. Section 2 presents the analysis of a Markov process-based MTS. Section 3 proposes an optimization model for the resilience of the MTS based on the Markov process. Section 4 proposes a new method of evaluating the resilience measure. Section 5 uses the MTS via the Suez Canal as an example to verify the feasibility of the proposed model. Section 6 concludes the paper and proposes future work.

2. Reliability analysis of MTS based on Markov process

2.1. Question description

The Suez Canal directly connects the Mediterranean Sea and the Red Sea and indirectly connects the Atlantic Ocean and the Indian Ocean. It is an important waterway in North Africa and West Asia. It is reported that about 25% of the world's container transport and 100% of the Asian and European maritime container trade pass through the Suez Canal. Currently 60% of China's exports to Europe go through the Suez Canal. The Suez Canal is known as the "choke point" for maritime transport, partly due to the incident that the shipping system involving the Suez Canal was "paralyzed" after the Ever Given was stuck in it.

The four diagrams in Fig. 1 show a part of the shipping network of China Shipping Lines from the Far East to the Mediterranean Sea. Fig. 1 illustrates the change in state before the disaster, at the time of the disaster, and after the repair. The severity of the disaster can cause different damage to the maritime transportation system. Fig. 1. (2) and 1. (3) show the state changes of the system when a severe disaster and a minor disaster occur, respectively.

(1). No disaster occurs, all lines were optimal and MTS was operating at normal flow Q_0.

(2). The occurrence of a severe disaster causes severe congestion in the Suez Canal, with a significant drop in flow on both routes from Singapore to Malta and Piraeus, as illustrated by the red lines.

(3). The occurrence of a minor disaster results in minor congestion in the Suez Canal, with a slight drop in flow on both routes from Singapore to Malta and Piraeus, as illustrated by the pink lines.

(4). The congested section of the Suez Canal was unblocked, and the MTS returned to normal. Routes from Singapore to Malta and Piraeus is indicated by the green lines.

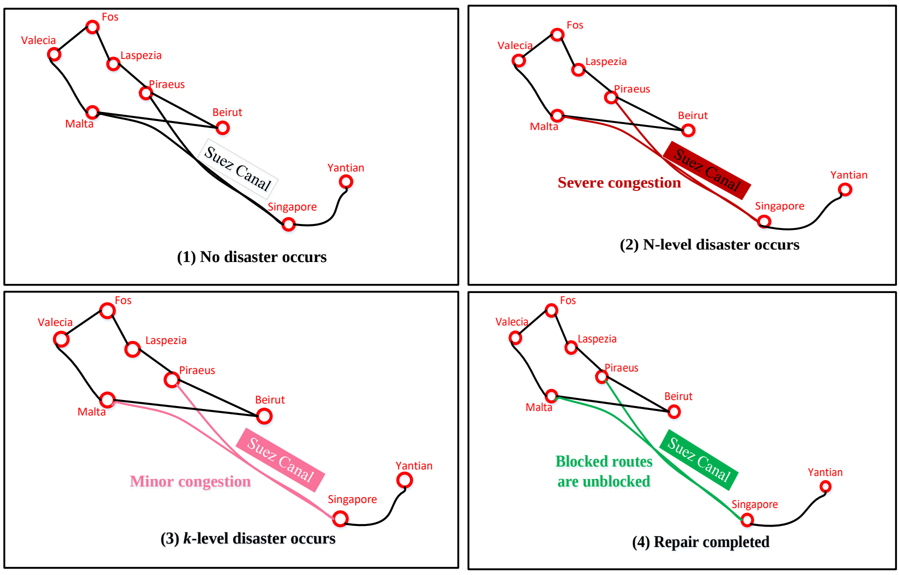

Fig. 1 The process of performance change of MTS when disasters with different levels occur

For this congestion, there are only 2 feasible alternatives: bypassing the Cape of Good Hope route or changing to the Arctic route. The Suez Canal route covers 11,600 km and the Cape of Good Hope route covers 19,800 km, so it takes more than 10 days to bypass the Cape of Good Hope. The Arctic route can save 12 days, compared with the Suez Canal route, but unfortunately, it is only navigable in summer. In comparison with the Cape of Good Hope route and the Arctic route, we can see the absolute advantage of the short distance and low cost of using the Suez Canal.

The following issues will be presented and studied in this paper, based on the importance and irreplaceability of the Suez Canal in the international trade.

(1) As one of the most important routes for the international trade, the Suez Canal blockage has taught us a lesson that any disaster can cause a "butterfly effect". Damage to any of the lines could significantly degrade the performance of MTS and affect the world economy. How will a change in the line state affect system performance? What are the differences in the impact of different lines on the system?

(2) From the perspective of the impact of a single component, existing studies on system resilience management merely consider binary components, i.e., components are considered to have only two states, operating and fault, which is apparently not applicable to MTS. In this paper, a line flow is

considered to have multiple states. How does the line state change with respect to the occurrence of a disaster?

(3) From the perspective of MTS, how does the change of the performance of MTS during the transitions between the three states: resisting disasters, adapting to disasters, and recovering functions? How can we define the resilience of MTS based on the performance of MTS? How can we specify the post-disaster repair strategy in MTS?

2.2. Model description

An MTS network $G(N, A)$ consists of nodes and lines. Ports are abstracted as nodes, and the set of nodes is denoted by N, routes are abstracted as lines, and the set of lines is denoted by A. l_{ij} is the line between node i and node j, $l_{ij} \in A$, and $i, j \in N$. There are three kinds of nodes, the set of supply nodes N_S, the set of transit nodes N_T, and the set of demand nodes N_D, There are totally m lines, each of which is numbered. Let $A = \{l_{ij}|l_{ij} = 1,2 \dots, m\}$. $l_{ij} = p$ represents the p-th line, $1 \le p \le m$. Denote the failed line set as $F = \{l_{ij}|l_{ij} = 1,2 \dots, f\}$, $1 \le p \le f$, where a failed line is defined as the route with reduced flow affected by disasters. Denote $W = \{l_{ij}\big|l_{ij} = f + 1, \dots, m\big\}, f + 1 \le p \le m$ the work line set. It is assumed that all lines work properly under normal conditions, and the system performance is degraded when a disaster occurs. The initial flow of the line l_{ij} is $C_{ij}(0)$ and the initial flow of node i is $C_i(0)$, and we call the initial flow as a normal flow.

Since the nodes are assumed to be highly redundant, stable in operation, and less affected by disasters, this paper only studies the effect of the changes between line states on system performance in MTS. When the system encounters a disaster u_k with disaster level $X(t) = k(1 \le k \le N)$, the flow of line l_{ij} at timed t becomes $C_{ij} = C_{ij}^k(t)$. The state of the line is defined by 0-1 variable $h_{ij}(t)$, indicating whether the line is failed or not at time t. If $l_{ij} \in W$, $C_{ij} = C_{ij\_max}, h_{ij}(t) = 1$, or $C_{ij} \neq C_{ij\_max}$, $h_{ij}(t) = 0$. The system flow at time t is denoted as $Q^k(t)$, it is a function of the flow of each line, as shown in Eq. (1).

$$Q^k(t) = Q\big(C_{ij}^k(t)|l_{ij} \in A\big), \tag{1}$$

where $Q\big(C_{ij}^k(t)|l_{ij} \in A\big)$ represents the function of the flow of each line and $Q^k(t)$ is the flow of MTS at time t under the k-th level disaster, A is the set of lines.

2.3. Disaster classification of MTS

Let $\{X(t),\ t > 0\}$ be a stochastic process taking values on $E = \{1, 2 \dots N\}$. If for any natural number n, and any moment $0 \ll t_1 < t_2 < \cdots < t_n$, we have $P\{X(t_n) = i_n | X(t_1) = i_1, X(t_2) = i_2, \dots X(t_{n-1}) = i_{n-1}\} = P\{X(t_n) = i_n | X(t_{n-1}) = i_{n-1}\}$, $i_1, i_2, \dots i_n \in E$. Then $\{X(t), t \geq 0\}$ is said to be a continuous-time Markov process on the discrete state space E (Ross S, 1996).

The term disaster in this article refers to natural disasters such as earthquakes and typhoons. Poisson processes are widely used to simulate the occurrence of disasters. However, existing studies describe disasters in a more general way, the impact of the class of disaster on the MTS is rarely considered. In practice, the higher the earthquake's magnitude, the more severe the damage caused. Research on disaster classification has not yet resulted in a uniform standard. Bore (1990) identified six factors that influence the classification of hazards: the effect on the surrounding community, the cause, the duration of the cause of disaster, the radius of disaster, the number of casualties, the nature of the injuries sustained by living victims, the time required by the rescue organizations for initiation of primary treatment, organization of trans- port facilities, and evacuation of the injured. Zhang and Li (2014) provided an introduction to natural disaster risk classification in China: Disaster risk classification (R) is related to the probability of a disaster risk occurring (P) and the severity of the damage caused (C). Caldera and Wirasinghe (2022) developed a new universal severity classification scheme for natural disasters, and it is supported by historical data, they focus on the number of casualties as a criterion for classifying disasters. In the context of this paper, we focus on the severity of the damage caused by the disaster and the probability of the occurrence of the disaster.

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X denotes the level of the disaster and there are N levels of disasters. The occurrence of a disaster is modelled by a Poisson process to find the number of disasters per unit of time. The probability level X_P of disaster occurrence is determined based on the number of disasters per unit of time, and there are N_P levels. The damage caused by the disaster includes economic and human losses, and the severity of the damage caused by the disaster is determined as X_C, with a total of N_C levels. The two dimensions are multiplied together to obtain the disaster level. The method proposed in this paper is a general method and will have different classification criteria in different industries. As the focus of the paper is not on the classification of disasters, methods of classifying disasters is therefore not investigated in detail in this paper.

When the level state of a disaster is given, the probability law of the future development of the process is independent of the history of the process. In this paper, we assume that the severity of disaster can be classified into *N* levels. The occurrence of a disaster is modeled by a continuous-time Markov process on a discrete state space. Let the disaster level $\{X(t), t \geq 0\}$ be a continuous-time Markov process on a discrete state space *E* with $E = \{1,2 \dots, N\}$. The smaller the value of $X(t)$, the lower the disaster level. The transition rate of a disaster level from *i* to *j* is $q_{i \to j}$, the transition rate matrix *Q* of a disaster level can be obtained as $\begin{bmatrix} q_{1\to 1} & \cdots & q_{1\to N} \\ \vdots & q_{i\to j} & \vdots \\ q_{N\to 1} & \cdots & q_{N\to N} \end{bmatrix}$.

Let $P_j(t) = P\{X(t) = j\}, j \epsilon E$, which represents the probability that the disaster is in state *j* during time period $(0, t)$, $P_j(t)$ can be calculated from matrix *Q*. The larger the value of disaster level represents, the more serious disaster. $X(t)$ takes the value of *N* to represent the most serious disaster, and $X(t)$ takes the value of 1 to represent the least serious disaster.

2.4. Analysis of line state based on Markov process

Similar to Zeng et al. (2021), we make the following assumptions: the time required to recover from state i to state *j* $(j > i)$ follows an exponential distribution with a rate v_{ij}, there are no damages caused by extreme events during the recovery processes. Let $\left\{Y(\mathrm{t}),\ \mathrm{t} \geq 0\right\}$ represent the state of the line of MTS under the threat of possible disaster at time t. Then we can assume that $\left\{Y(\mathrm{t}),\ \mathrm{t} \geq 0\right\}$ is a Markov process taking values on discrete state space $E = \{1,2 \dots \mathrm{M}\}$. The larger the value of $Y(\mathrm{t})$, the larger the representative flow. The value of *M* represents the normal flow (perfect performance). In the event of the k-th level disaster $(1 \leq k \leq N)$, let the state of the failed line l_{ij} in the failed line set be denoted by $Y_{ij}^k(t)$. The relationship between the state of the line and the actual flow is shown in Eq. (2), *γ* is the capacity rating factor and can be estimated from historical data. Under the same disaster level k, the states of these lines are different.

$$C_{ij}^k(t) = \frac{Y_{ij}^k(t)}{\gamma} C_{ij}(0), \tag{2}$$

where $Y_{ij}^k(t)$ is state of the failed line l_{ij} in failed line set at time t, $C_{ij}(0)$ is the normal flow of the line l_{ij}.

Disaster occurrences and repairs of MTS cause the states of lines to shift, and the transition rate matrix V of the line states is given as $\begin{bmatrix} v_{1\to 1} & \cdots & v_{1\to M} \\ \vdots & v_{i\to j} & \vdots \\ v_{M\to 1} & \cdots & v_{M\to M} \end{bmatrix}$, where $v_{ij}, 1 \leq i, j \leq M, i \neq j$ denotes the rate that the line departs from state I and ends in state j. $\sum_{j=1}^{M} v_{i\to j} = 0$, $i = 1,2 \ldots M$. The jumps of degradation of line performance (from state i to state j, where $i > j$) are results of damage caused by disasters. The jumps of improvement of line performance (from state i to state j, where $i < j$) are results of repairing failed lines. After line l_{ij} suffers the k-th level disaster, a state transfer occurs from state M to state $Y_{ij}^{k}(t)$. The value of $Y_{ij}^{k}(t)$ is taken to be any value on the state space E. If $Y_{ij}^{k}(t)$ takes the value of s, the transition rate of this line from state M to s is $v_{M\to s}$, and the losses are $d_{M\to s}$, as shown in Fig. 2.

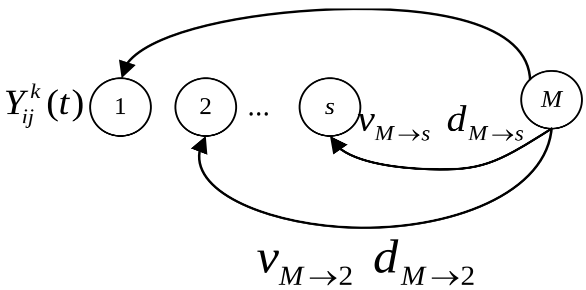

Fig. 2 The state transfer of line when a disaster occurs

In this paper, a failed line is defined as a route with reduced flow affected by disasters. Due to the characteristics of MTS, the parameters that affects the state of the shipping routes include channel width, channel depth, current, wind speed, etc. For some deeper and wider waterways, the route state can be quickly returned to normal after a disaster and does not need to be repaired. Since whether a shipping route needs repair or not is uncertain, , we use a probability to quantify the uncertainty. Let the probability that route l_{ij} needs repair be P_{ij}, and P_{ij} is the ratio of repair times to failure times in a period of time. P_{ij} represents the probability that the failed route l_{ij} needs to be repaired, which can be obtained from historical data. A repair probability takes values in the range $(0, 1)$, 1 means that this failed line will definitely be repaired. For a line with a repair probability of 0, it means that this line need no repair.

The direct loss refers to the damage caused by the disaster to the infrastructure, which is only related to the processes of the system resisting and absorbing the disaster. The direct damage to the system is equal to the sum of the direct damage to all failed lines. The direct loss of the line is the cost incurred due to the disaster causing irreversible damage to the line and requiring maintenance personnel to repair it. Due to the uncertainty of the repair of the failed line, the direct loss of the failed line is equal to the repair cost multiplied by the repair probability. Denote the direct losses of the failed line l_{ij} under the k-th level disaster as $L_{D(ij)}^k$, and the system direct losses of the system under the k-th level disaster as L_D^k, as shown in Eq. (3). Due to the uncertainty of disaster levels, the expected value of the direct loss under different levels of disasters is used as the final direct loss L_D of MTS, as shown in Eq. (4).

$$L_D^k = \sum_{l_{ij}\in F} P_{ij} \times L_{D(ij)}^k, \tag{3}$$

and

$$L_D(t) = \sum_{k=1}^{N} L_D^k \times P_k(t). \tag{4}$$

The indirect loss is caused by the failure of the system to work properly, which is mostly related to the process of the system recovering. Denote the indirect loss of the system at time t as $L_{ID}^k(t)$ when the k-th level disaster occurs. The expected value of indirect losses at different levels is used as the final indirect loss at time t, which is denoted as $L_{ID}(t)$, as shown in Eq. (5).

$$L_{ID}(t) = \sum_{k=1}^{N} L_{ID}^k(t) \times P_k(t). \tag{5}$$

From Eqs. (3)-(5), the total loss of the MTS at time t after a disaster is denoted as $Loss(t)$, as shown in Eq. (6).

$$Loss(t) = L_D(t) + L_{ID}(t) = \sum_{k=1}^{N}\left(P_k(t) \times \sum_{l_{ij}\in F} L_{D(ij)}^k\right) + \sum_{k=1}^{N} L_{ID}^k(t) \times P_k(t). \tag{6}$$

Assuming that only one line is repaired at a time, and the total time is less than T. Due to time constraints and resource limitations (human, material and financial resources), it is significant to determine the optimal repair strategy within a defined time frame. The purpose of our study is to determine the repair strategy, with goals of the maximizing the resilience increment of MTS and minimizing the loss of MTS. A 0-1 variable $W_{ij}(t)$ is defined: 1 means repairing failed lines l_{ij} successfully in time period $(0, t)$, and 0 represents no repair in time period $(0, t)$. Variable T_{ij} indicates the repair time of line l_{ij}. Let the repair time of the MTS be T_w, as shown in Eq. (7),

$$T_w = \sum_{l_{ij}=1}^{f} W_{ij}(t_4) \times T_{ij}, \tag{7}$$

where t_4 is the time when repair is completed, $W_{ij}(t_4)$ indicates whether the line l_{ij} is being repaired or not in time period $(0, t_4)$, T_{ij} is the repair time of the line l_{ij}, and f is the total number of failed lines.

We assume that the failed line can be repaired from state i $(0 < i < M)$ to the best state M, so the recovery time of the line obeys the exponential distribution with rate parameter $v_{i \to M}$.

The mean value is used as the transfer time of the failed line from state *i* to state *M*. Thus, the repair time of line l_{ij} is only relevant to post-disaster state $Y_{ij}^{k}(t_1)$. The state transition in the line during the repair process is shown in Fig. 3.

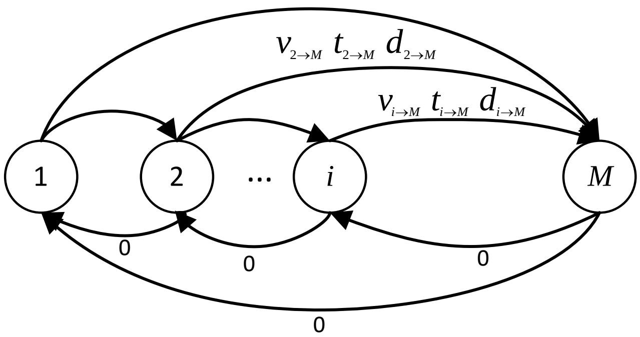

Fig. 3 The state transfer of line during the repair process

Considering the performance degradation of the failed line when the k-th level disasters occur and the performance improvement of the failed line during repair, the full process of the transition of the states of the line under different levels of disasters is shown in Fig. 4.

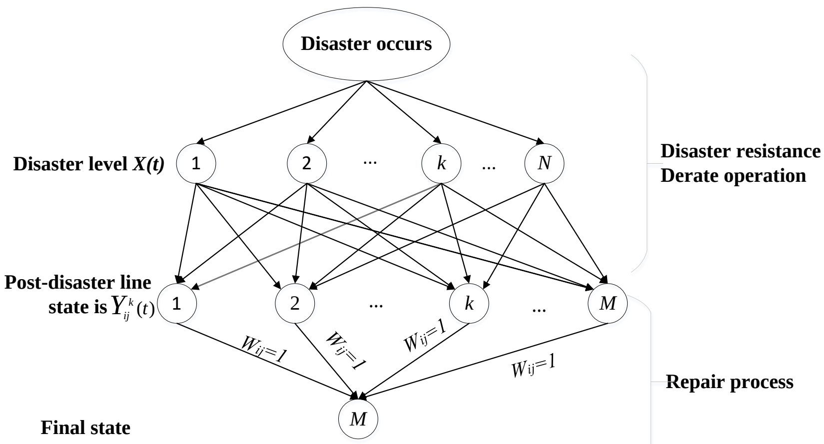

Fig. 4 The whole process of line state transfer under different levels of disasters

3. Resilience model of MTS based on Markov process

3.1. MTS indicator

There are two main formulations of resilience: one defining resilience in terms of the instantaneous performance of a system, the other defining it based on the resilience triangle model and considering the accumulation of performance. In relation to the actual situation of MTS, the MTS resilience is defined as the ability to resist, absorb, and quickly recover from a steady state in this paper. The accumulation of system performance therefore needs to be taken into account in the resilience equation.

The system performance curve differs for different levels of disaster occurrence, as shown in Fig. 5. Fig. 5 shows the system performance over time for four phases: normal operation, resisting disaster, derating operation, and recovery process. The system performance curve for a k-th level disaster occurrence is analyzed for the four processes as follows.

(1) t_0: the system operates normally at time t_0, and the system flow is maximum Q_0.

(2) t_1-t_2: the occurrence of the k-th level disasters causes the line flow to become $C_{ij}^{k}(t)$， $1 \le l_{ij} \le f$, and the system flow gradually declines.

(3) t_2-t_3: the performance of the system is reducing, the input to the system equals the output. The system is in the derating phase of operation and the system flow reaches the minimum Q_k.

(4) t_3-t_4: the failed lines are repaired, the flow of the failed line gradually rises, and the system performance gradually improves. The system function returns to stability at time t_4, and the recovered flow is equal to or lower than Q_0.

Where t_1 refers to the time when the disaster occurs, t_2 refers to the time when the system performance drops to a minimum, t_3 refers to the time at which repair on the system begins, t_4 refers to the time when system repair is completed. The time between t_1 and t_4 is a time period including four processes of resisting, absorbing, stabilizing, and recovering, and $Q_k < Q^k(t) < Q^k(t_4) \le Q_0$.

For a MTS with demand nodes, the larger the flow received by the demand nodes, the better the capacity of the MTS (Dui et al. 2021). The sum of the maximum flows of the network in all supply chains is used as the system flow, as shown in Eq. (8). In Eq. (8), $maxflow(G, N_S, N_D)$ denotes the network maxflow of a supply chain from supply node N_S to demand node N_D in network *G*. $\sum_{N_S}\sum_{N_D} maxflow(G, N_S, N_D)$ denotes the sum of the maximum flows from supply nodes to demand nodes of all supply chains in the network *G*, as shown in Eq. (8).

$$Q^k(t) = \sum_{N_S} \sum_{N_D} maxflow(G, N_S, N_D). \quad (8)$$

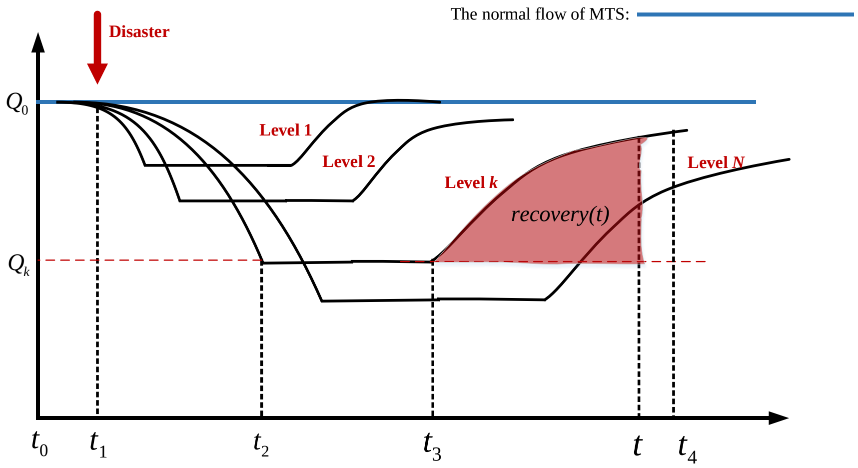

Fig. 5. System performance curves under different levels of disasters

In this paper, the resilience model is based on the resilience triangle model, considering the accumulation of the system recovery performance. The recovery and loss values of the system performance are in the form of integrals. Therefore, the system resilience is shown below.

$$R(t) = \frac{recovery(t)}{loss(t_4)} = \frac{\sum_{k=1}^{N} P_k(t) \times recovery_k(t)}{\sum_{k=1}^{N} P_k(T) \times loss_k(t_4)} = \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{t} [Q^k(u) - Q_k] du}{\sum_{k=1}^{N} P_k(T) \times \int_{t_1}^{t_4} (Q_0 - Q_k) dt} = \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{t} [Q^k(u) - Q_k] du}{\sum_{k=1}^{N} P_k(T) \times (Q_0 - Q_k)(t_4 - t_1)}, \quad (9)$$

where $R(t)$ represents the system resilience at time t, $recovery(t)$ indicates the recovery value of the system performance at time t, and $loss(t_4)$ indicates the maximum loss of the system at time t_4. $recovery_k(t)$ denote the recovery value of system performance at time t under k-th level disaster. $loss_k(t_4)$ denote the maximum loss value of system performance under k-th level disaster. The recovery and loss values of the performance of MTS are obtained, by multiplying the recovery or loss value under the k-th level disaster by the probability that the disaster level is at k in time period $(0, t)$. $\int_{t_3}^{t} [Q^k(u) - Q_k] du$ denotes the recovery value of system performance under the k-th level disaster. $\int_{t_1}^{t_4} (Q_0 - Q_k)\, dt$ denotes the loss value of system performance under the k-th level disaster. The system resilience can be calculated by substituting Eq. (8) into Eq. (9).

The indirect loss of the system under the k-th level disaster is $L_{ID}^k(t)$, which can be expressed by Eq. (10):

$$L_{ID}^{k}(t) = \int_{t_1}^{t} \left(Q_0 - Q^k(u)\right) du. \tag{10}$$

3.2. Resilience optimization of MTS

This section determines the set of repair lines with the dual objectives of maximizing the sum of resilience increments (Eq. (11)) and minimizing the total loss (Eq. (12)).

$$\max \sum_{l_{ij}\in F} W_{ij} \times P_{ij} \times R(t|W_{ij}(t) = 1), \tag{11}$$

and

$$\min \sum_{k=1}^{N} (P_k(t) \times \sum_{l_{ij}\in F} P_{ij} \times L_{D(ij)}^{k}) + \sum_{k=1}^{N} \left(L_{ID}^{k}\left(t|W_{ij}(t) = 1\right) \times P_k(t)\right). \tag{12}$$

Eq. (11) and Eq. (12) represent the objective function. In Eq. (11), $W_{ij}(t)$ indicates whether the line l_{ij} is repaired or not in time period $(0, t)$, P_{ij} represent the repair probability of failed line l_{ij}, $R(t|W_{ij}(t) = 1)$ indicates the resilience increment of the system at time t when only the line l_{ij} is repaired. Eq. (11) indicates that the set of repair lines is determined, so that the resilience increment of the system is maximized. In Eq. (12), $L_{D(ij)}^{k}$ is the direct loss of the line l_{ij} under the k-th level disaster, which is only related to the state of the line at time t_2. Thus, $\sum_{l_{ij}\in F} P_{ij} \times L_{D(ij)}^{k}$ denotes the direct loss of all failed lines under the k-th level disaster, i.e., the direct loss under k-th level disaster. $L_{ID}^{k}\left(t|W_{ij}(t) = 1\right) = \int_{t_1}^{t} \{Q_0 - Q^k\left(u|W_{ij}(\mathrm{u}) = 1\right)\}\mathrm{du}$ denotes the indirect loss of the system when only the line l_{ij} is repaired in all failed lines, where $Q^k\left(u|W_{ij}(\mathrm{u}) = 1\right)$ denotes the flow of the system when only line l_{ij} is repaired in all failed lines under k-th level disaster. An indirect loss is the expected values of losses under different disaster levels. Eq. (12) indicates that determining the repair line set can minimize the total loss.

The model constraints are shown in Eq. (13) - (28) below.

$$Q^k(t) = \sum_{N_S} \sum_{N_D} maxflow(G, N_S, N_D) \tag{13}$$

$$T_w = \sum_{l_{ij}=1}^{f} W_{ij}(t) \times T_{ij} \leq T \tag{14}$$

$$T_{ij} = \sum_{k=1}^{N} P_k(t_4) \times T_{ij}^{k} \tag{15}$$

$$C_{ij}^{k}(t) = \frac{Y_{ij}^{k}(t)}{\gamma} C_{ij}(0) \tag{16}$$

$$C_{ij}^{k}(t) \leq C_{ij}(0) \tag{17}$$

$$C_i(t) \leq C_i(0) \tag{18}$$

$$h_{ij}(0) = 1, l_{ij} \in A \tag{19}$$

$$h_{ij}(t) = 0, t \geq t_1 \cap l_{ij} \in F \tag{20}$$

$$h_{ij}(t) = 1, l_{ij} \in W \tag{21}$$

$$\sum_{l_{ij} \in A} C_{ij}^k(t) - \sum_{l_{ji} \in A} C_{ij}^k(t) = 0,\ j \in N_T, \forall t \tag{22}$$

$$h_{ij}(t+1) - h_{ij}(t) \geq 0\ ,\ l_{ij} \in F \tag{23}$$

$$W_{ij}(t) \in \{0,\ 1\}\ , l_{ij} \in F \tag{24}$$

$$W_{ij}(t) = 0,\ l_{ij} \in W, t \in \forall t \tag{25}$$

$$\text{if } W_{ij}(t) = 1,\ l_{ij} \in F, \text{ then } h_{ij}(t + \omega | \omega = 1,2 \ldots N) = 1 \tag{26}$$

$$\text{if } W_{ij}(t) = 0,\ l_{ij} \in F, \text{ then } h_{ij}(t - \omega | \omega = 1,2 \ldots N) = 0 \tag{27}$$

$$\sum_{l_{ij} \in F} \left[h_{ij}(t+1) - h_{ij}(t)\right] \leq 1 \tag{28}$$

In Eq.(13), the sum of the maximum flows of all supply chains in MTS is used as system performance. Eq. (14) indicates that repair activities should be less than T. Eq. (15) indicates that repair time of line l_{ij} is the expected value of the repair time under each disaster level. Eq. (16) indicates that the relationship between the actual line flow $C_{ij}^k(t)$ and the corresponding state $Y_{ij}^k(t)$ when the k-th level disaster occurs, γ is the capacity level coefficient and can be derived from historical data. Eq. (17) and (18) indicate that the flow of line and node does not exceed their normal flow. Eqs. (19-21) indicate that lines in the working line set are normal, and lines in the failed line set resume to the normal operating state after being repaired. Eq. (22) indicates that the inflow is equal to the outflow on the transit node. Eq. (23) indicates that the repair can only make the failed line better and will not make the normal line fault. Eqs. (24) and (25) indicate that the repair is only for the fault line, and lines in work line set will not be serviced. Eq. (26) indicates that the failed line becomes the normal operating state after the failed line is repaired. Eq. (27) indicates that the failed line does not operate normally until it is repaired. Eq. (28) indicates that only one failed line can be repaired at a single time.

4. Resilience measure of MTS

In maritime route planning, it is critical to understand which components (ports, waterway connections, etc.) have the greatest impact on network performance. Importance measures are used to determine the direction and priority of operations related to system improvements, with the aim of finding the most efficient way to maintain the system state. In the following, the concept of resilience importance measure of the MTS will be proposed, by combining importance measure with resilience. Using the metric of resilience importance measure, the repair sequence of the failed lines can be determined on the basis of identifying the repair line set.

Importance measure is the degree to which the failure or state change of one or more components of a system affects the reliability of the system. Importance measure is a function of component (part) reliability and system structure (Birnbaum, 1969). The resilience importance measure in this paper refers to the degree of the impact of the failure of a single line or multiple lines in the MTS on the system resilience. The resilience importance measure formula is proposed, as shown in Eq. (29).

$$I_{ij}(t) = \frac{|R(t_4) - R(t|W_{ij}(t) = 0)|}{C_{ij}(t_0) - C_{ij}(t_2)}, \tag{29}$$

and

$$C_{ij}(t) = \sum_{k=1}^{N} C_{ij}^{k}(t) \times P_k(t). \tag{30}$$

Where $C_{ij}(t)$ refers to the expected value of the N levels post-disaster flow, which is the flow of the failed line l_{ij}after considering N levels of disasters. $C_{ij}(t_0)$represents the flow of the failed line l_{ij} in the initial state, that is the normal flow. $C_{ij}(t_2)$ denotes the minimum flow when line l_{ij} is damaged. $R(t_4)$ indicates the maximum resilience of the system after being damaged by disaster. $R(t|W_{ij}(\mathrm{t}) = 0$ denotes the resilience of the system when only line l_{ij}in the repair line set has not been repaired, we call it the resilience increment of the line l_{ij} to system. The resilience importance measure I_{ij} measures the impact of state changes of the failed line l_{ij} on the system resilience in time period $(0, t)$. The larger the value, the more important the line l_{ij} is represented and the more advanced its repair sequence.

The resilience importance measure of different typical systems has different characteristics. Fig. 6 shows a maritime line from Piraeus to Malta and the state and flow of the line in the following four processes.

(1) No disaster occurs, the series MTS works normally, each line is in the best condition M and the flow is at maximum.

(2) The k-th level disaster occurs, the series MTS is failed. Two routes from Piraeus to Laspezia and from Laspezia to Fos have a minor breakdown, system performance is degraded. The state and flow of failed lines is decreased to $Y_{ij}^{k}(t)$, $C_{ij}^{k}(t)$, respectively. And the failed lines are marked light red.

(3) The N-th level disaster occurs ($N > k$), the series MTS is failed, two routes from Piraeus to

Laspezia and from Laspezia to Fos encounter a serious breakdown, system performance is degraded. The state and flow of failed lines is decreased to $Y_{ij}^{N}(t)$, $C_{ij}^{N}(t)$, respectively. And the failed lines are marked purple.

(4) The fault series MTS is repaired successfully, the two failed lines from Piraeus to Laspezia and from Laspezia to Fos are repaired to normal states successfully, the two lines are marked in green, and the overall performance of the system is improved.

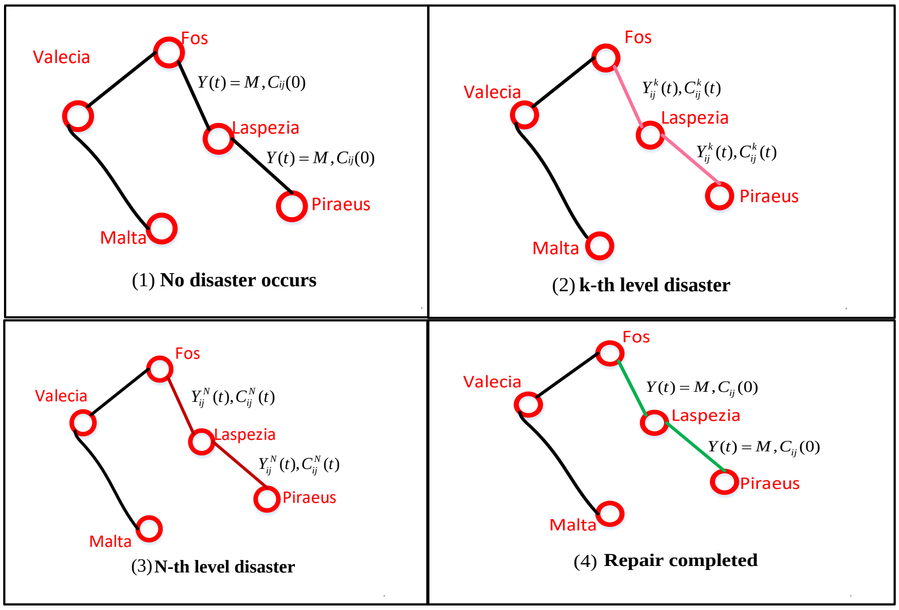

Fig.6 One maritime line from Piraeus to Malta

In a series MTS consisting of n mutually independent lines, the performance of MTS is expressed as the minimum flow of the lines, i.e., $Q^{k}(t)=\min\{C_{ij}^{k}(t), l_{ij}\epsilon A\}$, then the series MTS resilience is shown in Eq. (31).

$$R(t)=\frac{\sum_{k=1}^{N} P_k(t)\times\int_{t_3}^{t}\min\{C_{ij}^{k}(t), l_{ij}\epsilon A\}-Q_k]dt}{\sum_{k=1}^{N} P_k(t)\times(Q_0-Q_k)\times(t_4-t_1)} \quad (31)$$

The maximum value of the resilience of the series MTS can be denoted by Eq. (32). The performance of the system is expressed as $\min\{C_{ij}^{k}(t_1)\cup C_{ab}^{k}(t), l_{ij}, l_{ab}\in A\}$ when the line l_{ij} is not repaired, so the resilience of the series MTS when the line l_{ij} is not repaired is expressed as Eq. (33). From Eq. (32) and Eq. (33), the resilience importance measure of the failed line l_{ij} in the series

MTS can be derived as shown in Eq. (34).

$$R(t_4) = \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{t_4} [min\left\{C_{ij}^{k}(t), l_{ij} \epsilon A\right\} - Q_k] dt}{\sum_{k=1}^{N} P_k(t) \times (Q_0 - Q_k) \times (t_4 - t_1)}, \tag{32}$$

$$R\left(t \middle| W_{ij}(\mathrm{t}) = 0\right) = \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{t} [\min\left\{C_{ij}^{k}(t_1) \cup C_{ab}^{k}(u), l_{ij}, l_{ab} \in A\right\} - Q_k] du}{\sum_{k=1}^{N} P_k(t) \times (Q_0 - Q_k) \times (t_4 - t_1)}, \tag{33}$$

and

$$I_{ij} = \frac{\left| \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{T} [\min\left\{C_{ij}^{k}(t), l_{ij} \epsilon A\right\} - Q_k] dt}{\sum_{k=1}^{N} P_k(t) \times (Q_0 - Q_k) \times (t_4 - t_1)} - \frac{\sum_{k=1}^{N} P_k(t) \times \int_{t_3}^{t} [\min\left\{C_{ij}^{k}(t_1) \cup C_{ab}^{k}(u), l_{ij}, l_{ab} \in A\right\} - Q_k] du}{\sum_{k=1}^{N} P_k(t) \times (Q_0 - Q_k) \times (t_4 - t_1)} \right|}{C_{ij}(t_0) - C_{ij}(t_2)}. \tag{34}$$

Fig. 7 shows two maritime lines from Beirut to Fos. The four diagrams show the states of the line and its flow in the following four processes.

(1) No disaster occurs, the parallel MTS works normally, each line is in the best state M and the flow is at maximum.

(2) The k-th level disaster occurs, the parallel MTS fails, two lines from Beirut to Malta and from Malta to Valecia encounter minor failures, minor degradation of system performance occurs. The state and flow of failed lines is decreased to $Y_{ij}^{k}\ (t)$, $C_{ij}^{k}(t)$, respectively. And the failed lines are marked in light red.

(3) The N-th level disaster occurs ($N > k$), the parallel MTS fails, two routes from Beirut to Malta and from Malta to Valecia have serious failures, significant degradation of system performance occurs. The state and flow of failed lines is decreased to $Y_{ij}^{N}\ (t)$, $C_{ij}^{N}(t)$, respectively. And the failed lines are marked in purple.

(4) The fault serious MTS is repaired successfully, and the two failed routes from Beirut to Malta and from Malta to Valecia are repaired to normal states successfully, marked as green, and the overall performance of MTS is improved.

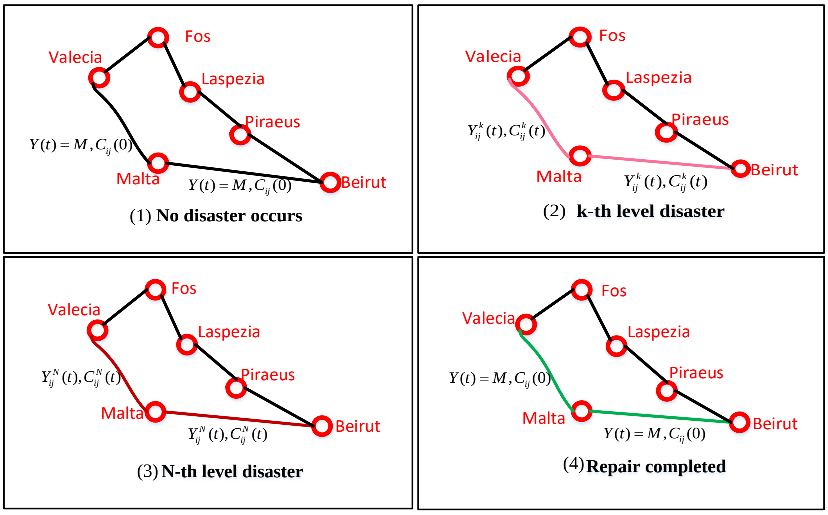

Fig. 7 Two maritime lines from Beirut to Fos

According to Si & Levitin (2013), there are two general ways to represent the system performance of a typical parallel system. The first one is that the system performance is the maximum of the performance of all components, i.e., $\varphi(X) = max\{X_1, X_2, X_3, \dots X_n\}$. The second one is that the parallel system performance is the sum of the performance of all components, i.e., $\varphi(X) = X_1 + X_2 + \dots + X_n$. In the MTS as shown in Fig. 7, the maximum flow of MTS is used as the system performance, so the second method should be used to represent the MTS performance. There are n branches in a parallel MTS, L_m refers to line set in the m-th branch.The performance of the m-th branch is expressed as $min\{C_{ij}^k(t)\}, l_{ij} \in L_m$. Therefore, the performance of the parallel MTS is expressed as $Q(k,t) = \sum_{m=1}^{n}\left[min\{C_{ij}^k(t)\}, l_{ij} \in L_m\right]$. Then the resilience of parallel MTS is represented as Eq. (35).

$$R(t) = \frac{\sum_{k=1}^{N} P_k(t)\times\int_{t_3}^{t}[\sum_{m=1}^{n} min\{C_{ij}^k(u)\}, l_{ij}\in L_m - Q_k]du}{\sum_{k=1}^{N} P_k(t)\times(Q_0-Q_k)\times(t_4-t_1)} \quad (35)$$

The maximum value of the resilience of the parallel MTS is shown in Eq. (36). Let the failed line l_{ij} be in the n-th branch, let $B = \{l_{ij}\}$ represent the failed line set in the n-th branch, let $U = L_n$ represent the set of lines belonging to the n-th branch. The system performance when line l_{ij} is not repaired is expressed by $Q^k(t) = \sum_{m=1}^{n-1}\left[min\{C_{ab}^k(t)\}, l_{ab} \in L_m\right] + \left[min\{C_{ab}^k(t), C_{ij}^k(t_1)\}, l_{ab} \in \complement_U B\right]$. Thus, the resilience of the parallel MTS when line l_{ij} is not repaired is expressed as Eq. (37). The resilience importance measure formula of the typical parallel system can be derived in this paper, by substituting Eq. (36) and Eq. (37) into Eq. (29).

$$R(t_4) = \frac{\sum_{k=1}^{N} P_k(t)\times\int_{t_3}^{t_4}[\sum_{m=1}^{n} min\left\{C_{ij}^{k}(t)\right\},l_{ij}\in L_m-Q_k]dt}{\sum_{k=1}^{N} P_k(t)\times(Q_0-Q_k)\times(t_4-t_1)} \tag{36}$$

and

$$R\left(t\middle|W_{ij}(t_4)=0\right) = \frac{\sum_{k=1}^{N} P_k(t)\times\int_{t_3}^{t}[\sum_{m=1}^{n-1}[min\{C_{ab}^{k}(u)\},l_{ab}\in L_m]+[min\left\{C_{ab}^{k}(u),C_{ij}^{k}(t_1)\right\},l_{ab}\in \complement_U B]-Q_k]du}{\sum_{k=1}^{N} P_k(t)\times(Q_0-Q_k)\times(t_4-t_1)}. \tag{37}$$

5. Application

According to the 2020 route products released by China COSCO Shipping Corporation Limited in September, 2020, the Ocean Alliance provides four groups of direct routes from Far East to Mediterranean Sea, two groups of special lines to the west of the Mediterranean Sea, one group of special lines to the Adriatic and the only direct route to the Black Sea. The routes continue to maintain distinctive services with comprehensive yet differentiated coverage. All of these four groups of routes go through the Suez Canal. AEM1 and AEM2 are two of the routes, both of which pass through Ningbo, China. From the above 4 groups of routes, a MTS network from Ningbo, China, to the Mediterranean Sea is extracted and simplified, as shown in Fig. 8.

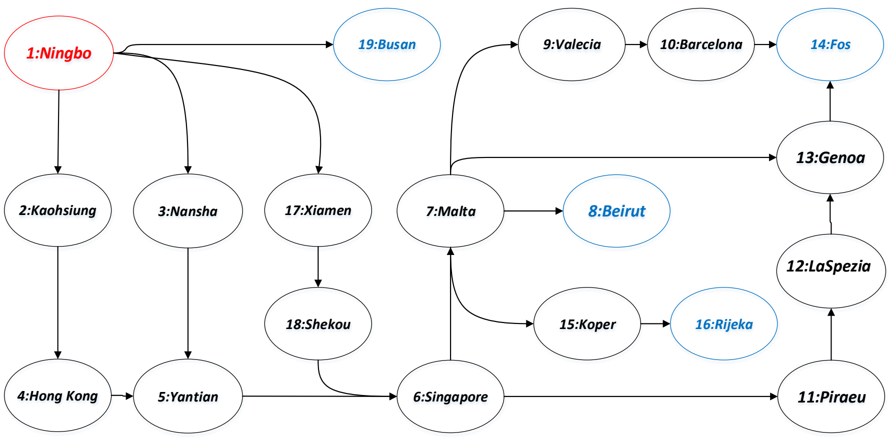

Fig. 8 The network diagram of MTS

The normal flow for each line in MTS is given, as shown in the Table 1.

Table 1 The normal flow for each line of MTS

line	normal flow
l_{12}	890
l_{13}	800

l_{24}	825
l_{35}	800
l_{45}	800
l_{56}	1350
l_{67}	785
l_{6-11}	605
l_{78}	512
l_{79}	390
l_{9-10}	485
l_{10-14}	510
l_{11-12}	750
l_{12-13}	790
l_{13-14}	842
l_{1-17}	520
l_{17-18}	421
l_{18-6}	320
l_{1-19}	210
l_{7-13}	300
l_{7-15}	290
l_{15-16}	320

The transition rate matrix can be estimated on historical data. To facilitate the simulation, this paper assumes that there are 3 levels of disasters. $P_j(t) = P\{X(t) = j\}$, $j = 1, 2, 3$ represents the probability of the line being in state j . The transition rate matrix Q for the disaster level is given as $\begin{bmatrix} -0.075 & 0.075 & 0.0 \\ 0.025 & -0.05 & 0.025 \\ 0 & 0.075 & -0.075 \end{bmatrix}$.

Assuming that the disaster level is constant during time period $(0, T)$ and the value of T is 10 days, the probability of a disaster staying at a certain level during time period $(0, T)$ is found as shown in Table 2.

Table 2 Probability of a disaster staying at a certain level during time period $(0, T)$

level of the disaster	1	2	3
probability	0.25	0.5	0.25

There are five states of the line. $Y_{ij}^k(t) = \{1, 2, 3, 4, 5\}$, γ is numbered as 5, so $Y_{ij}^k(t) = 1, 2, 3, 4,$ and 5 indicates that the actual flow becomes 1/5, 2/5, 3/5, 4/5, and 1 of the normal flow, respectively. From the relationship between line flow and state $C_{ij}^k(t) = \frac{Y_{ij}^k(t)}{\gamma} C_{ij\_max}$, it follows that actual flow of the line can be derived from the state of the line. The transition rate matrix V for the state of the line is given as $\begin{bmatrix} -0.9 & 0.1 & 0.15 & 0.30 & 0.45 \\ 0.3 & -0.9 & 0.2 & 0.3 & 0.4 \\ 0 & 0.3 & -1.1 & 0.4 & 0.5 \\ 0 & 0 & 0.3 & -0.9 & 0.6 \\ 0 & 0 & 0 & 0.3 & -0.3 \end{bmatrix}$.

The failed line set at the time of the disaster occurs is $= \{l_{12}, l_{13}, l_{45}, l_{56}, l_{6-11}, l_{78}, l_{9-10}, l_{10-14}, l_{11-12}, l_{12-13}, l_{13-14}, l_{1-17}, l_{1-19}, l_{7-13}, l_{7-15}, l_{15-16}\}$, it is assumed that the failed line set is the same for different levels of disasters. State 1 indicates the state of lines when a disaster of level 1 occurs, State 2 indicates the state of lines when a disaster of level 2 occurs, and State 3 indicates the state of lines when a disaster of level 3 occurs in Table 3.

Table 3 Failed line states

line	line number	State 1	State 2	State3
l_{12}	line1	1	1	1
l_{13}	line2	1	1	1
l_{24}	line3	5	5	5
l_{35}	line4	5	5	5
l_{45}	line5	3	2	1
l_{56}	line6	3	2	1
l_{67}	line7	5	5	5
l_{6-11}	line8	2	1	1
l_{78}	line9	1	1	1
l_{79}	line10	5	5	5
l_{9-10}	line11	4	3	2
l_{10-14}	line12	3	2	1
l_{11-12}	line13	3	2	1
l_{12-13}	line14	4	3	2
l_{13-14}	line15	3	2	1
l_{1-17}	line16	3	2	1
l_{17-18}	line17	5	5	5
l_{18-6}	line18	5	5	5
l_{1-19}	line19	3	2	1
l_{7-13}	line20	4	3	2
l_{7-15}	line21	2	1	1
l_{15-16}	line22	2	1	1

In this paper, three different levels of disasters are considered. Under each level of disaster, the line has a corresponding repair time, and the expectation of the repair time of different levels of disasters is used as the repair time of the line. Thus, the repair time of line l_{ij} is $T_{ij} = \sum_{k=1}^{N} P_k(t) \times T_{ij}(k) = 0.25 \times T_{ij}(1) + 0.5 \times T_{ij}(2) + 0.25 \times T_{ij}(3)$, where $T_{ij}(k)$ represents the repair time of line l_{ij} under k-th level disaster. The repair time of lines in MTS is shown in Table 4.

Table 4 The repair time of lines in MTS

line	$\boldsymbol{T_{ij}(1)}$	$\boldsymbol{T_{ij}(2)}$	$\boldsymbol{T_{ij}(3)}$	$\boldsymbol{T_{ij}}$
$\boldsymbol{l_{12}}$	2.2	2.2	2.2	2.2
$\boldsymbol{l_{13}}$	2.2	2.2	2.2	2.2
$\boldsymbol{l_{24}}$	0	0	0	0

l_{35}	0	0	0	0
l_{45}	2	2.5	2.2	2.3
l_{56}	2	2.5	2.2	2.3
l_{67}	0	0	0	0
l_{6-11}	2.5	2.2	2.2	2.275
l_{78}	2.2	2.2	2.2	2.2
l_{79}	0	0	0	0
l_{9-10}	1.67	2	2.5	2.04
l_{10-14}	2	2.5	2.2	2.3
l_{11-12}	2	2.5	2.2	2.3
l_{12-13}	1.67	2	2.5	2.04
l_{13-14}	2	2.5	2.2	2.3
l_{1-17}	2.5	2.2	2.2	2.275
l_{17-18}	0	0	0	0
l_{18-6}	0	0	0	0
l_{1-19}	2	2.5	2.2	2.3
l_{7-13}	1.67	2	2.5	2.04
l_{7-15}	2.5	2.2	2.2	2.275
l_{15-16}	2.5	2.2	2.2	2.275

For calculation purposes, in the simulation, it is considered that the system flow does not change continuously, but completes the jump when encountering disaster and the repair is completed.

MATLAB is used in this paper to model the MTS and to calculate the resilience of failed lines. The resilience increment of each failed line to the system is obtained as shown in Fig. 9.

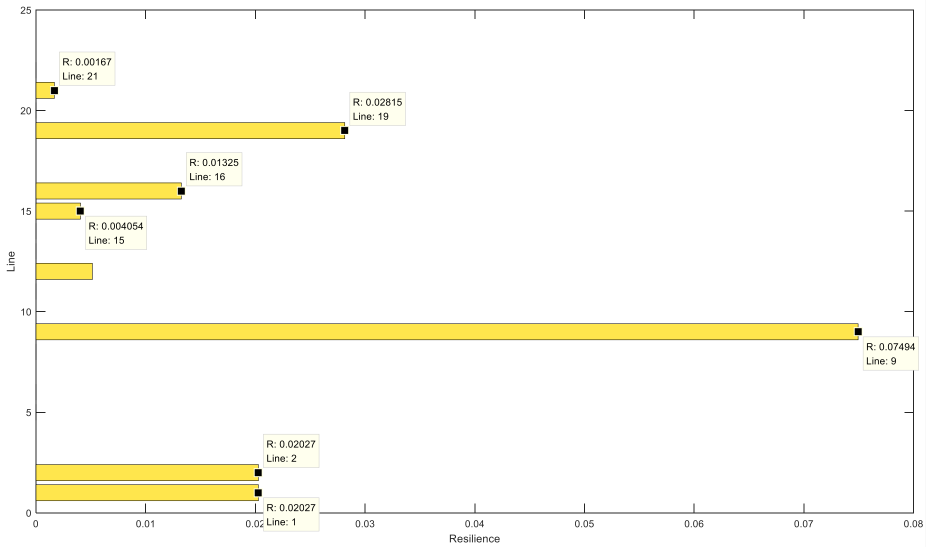

Fig. 9 The resilience increment of each failed line to the system

As can be seen in Fig. 9, some lines have resilience increment of number 0 to the system, because repairing such lines will have no impact on system performance. Some lines have a non-zero resilience increment to the system. The lines are ranked in order of their resilience increment to the system in descending order as line9>line19>line1=line2>line16>line12>line15>line21. It can be seen that line9 has the largest resilience increment value to the system, which is 0.07491, because line9 is in the supply chain from Ningbo to Beirut, and its flow is small compared with the flow of other lines in the supply chain, and its performance change will have a great impact on the flow of this supply chain. Thus line9 has a greater impact on the total flow of the system. Line 19 has the second largest resilience increment value to the system, which is 0.02692, because line19 is in the supply chain from Ningbo to Busan, and this supply chain only contains line19, its performance change will have an impact on the flow of this supply chain. The damage level of line19 is lower than that of line9, its impact on the system performance is smaller than that of line19. Line1 and line2 have the same resilience increment value to the system, i.e., 0.020272. Line1 and line2 are in multiple supply chains, their flows are larger, their changes will have some impact on the system performance; Line21 has the smallest resilience increment value to the system, i.e., 0.00171, indicating that line21 has the smallest resilience increment to the system among the lines whose resilience increment is not 0.

As can be seen from the simulation results in Fig. 9, resilience relates to the normal flow of line and topology of the supply chain in which the line is located. MTS is the one that consists of multiple maritime supply chains. On the one hand, the flow of supply chain is influenced by the route with the smallest flow. Therefore, the routes with less traffic have a greater impact on the supply chain in which they are located. In the daily repair management of the MTS, managers should be aware that ports with low flow are not necessarily unimportant to the MTS, and that care should be taken to ensure that lines with low flow are kept open. On the other hand, the blockage of the Suez Canal mentioned above is due to the fact that the Suez Canal is a unique route, which is a necessary route that many supply chains must go through, making it vulnerable to disasters. Managers should therefore focus on the location of the shipping route in the MTS.

Assume that the direct loss of all lines is $10,000. Since the indirect losses are in units of cargo volume, in order to sum up with the direct loss, the intermediary of an average of $100,000 per container is introduced. Thus, the fee for indirect losses can be expressed in dollars. The indirect loss of each failed line is shown in Fig. 10.

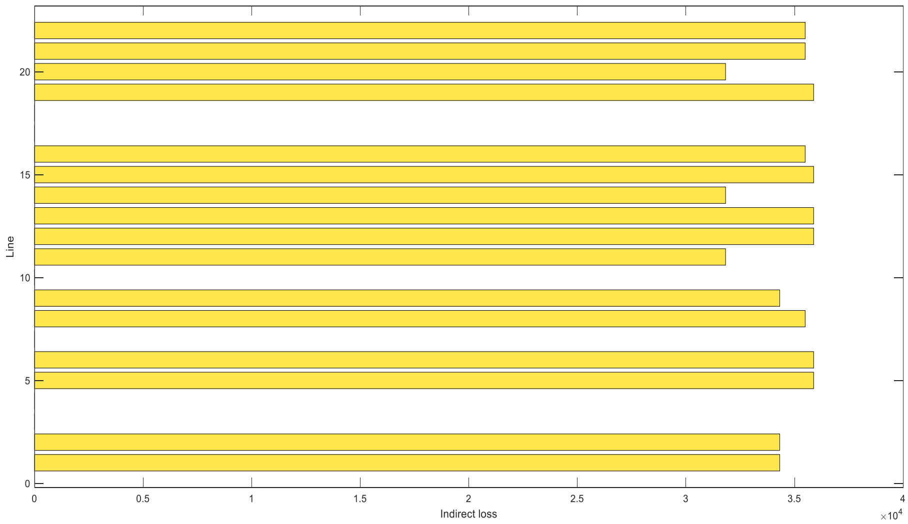

Fig. 10 Indirect losses when repairing only a single line

It can be seen that the indirect losses when repairing only a single line are in the interval of (30000, 40000), as shown in Table 5.

Table 5 The indirect losses when repairing only a single line

line	line1	line2	line5	line6	line8	line9	line11	line12
indirect loss	34320	34320	33680	35880	35490	34320	31824	35880
line	line13	line14	line15	line16	line19	line20	line21	line22
indirect loss	35880	31824	35880	35490	35880	31824	35490	35490

5.1. Repair strategy analysis with repair probability of 1

Assuming that all lines have a repair probability of 1. After knowing the resilience increment of each failed line to the system and indirect loss, repairmen can transform the repair strategy into solving the 0-1 backpack problem. Let the repair time not exceed 10 days, then the repair line set is {line1, line2, line9, line19}. The solved set can ensure that the total resilience increment of the lines to the system reaches the maximum and the total loss is the minimum.

The repair line set has been determined as {line1, line2, line9, line19}. The importance measure of each line in the repair line set is calculated as shown in Fig. 11.

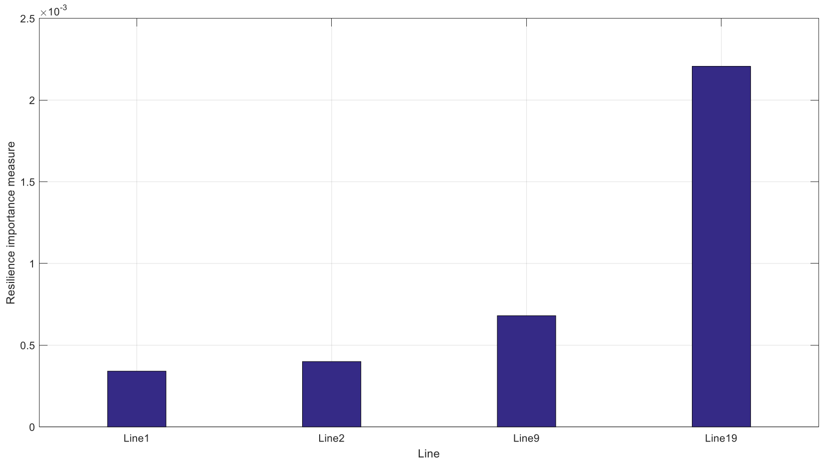

Fig. 11 The resilience importance measure of each line in the set of repair lines

From the results shown in Fig. 11, line 19 has the highest resilience importance measure value, i.e., 0.002206. Line19 is a single line in the network from Ningbo to Busan, which constitutes a supply chain, repairing this line will therefore result in a significant increase in system resilience. Line 9 has the second highest resilience importance measure value 0.000680, the normal flow of line 9 is small in the supply chain from Ningbo to Beirut. Line 9 is severely damaged, so repairing it can make the flow of this supply chain larger, thus making the system resilience larger. The resilience importance measure values of line2 and line1 are 0.000399 and 0.000341, respectively. There are multiple supply chains via line2 and line1, and the flow of these two lines is larger.

Based on the ranking of resilience importance measure value, the repair order of the four lines is to repair line19 first, followed by line9 and line2, and then line1 at last, we denote this order as repair-order-1. The completely opposite repair order of repair-order-1 is called repair-order-2, that is, repair line 1 first, then repair line 2 and 9, and finally repair line 19. In order to verify the superiority of the model proposed in this paper, the change curves of resilience of MTS under repair-order-1 and repair-order-2 are plotted, respectively, as shown in Fig. 12.

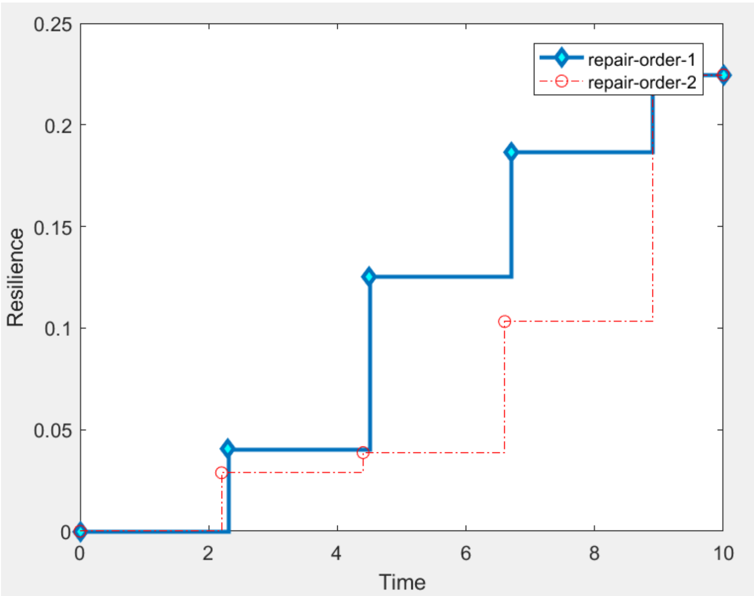

Fig. 12 The change curve of resilience of MTS

By comparing the change curves of resilience of MTS under the two different repair strategies, the resilience under repair-order-1 is greater than that under repair-order-2 at each moment, indicating that repair-order-1 can restore the system resilience to the maximum value faster. Therefore, the model proposed in this paper has its merits.

5.2. Repair strategy analysis with repair probability of not 1

However, in the actual MTS, the repair probability of the line is not 1. Generally, the higher the flow of the line, the worse its ability to automatically recover to normal state, and the higher the probability of needing repair. The smaller the flow of the line, the simpler the line, the better its ability to recover to normal state automatically, and the smaller the repair probability. Set the repair probability of the line as shown in Table 6.

Table 6 The repair probability of failed line

line	line1	line2	line5	line6	line8	line9	line11	line12
indirect loss	0.95	0.95	0.95	0.95	0.8	0.7	0.4	0.7
line	line13	line14	line15	line16	line19	line20	line21	line22
indirect loss	0.5	0.5	0.95	0.7	0.05	0.05	0.05	0.2

The indirect loss and the resilience increment of the failed line remain unchanged. Based on Eqs.

(11) and (12), the repair line set can be obtained as {line 1, line 2, line 9, line 16}. Next, the resilience importance measure of these four lines can be calculated according to Equation (29) as shown in Figure 13.

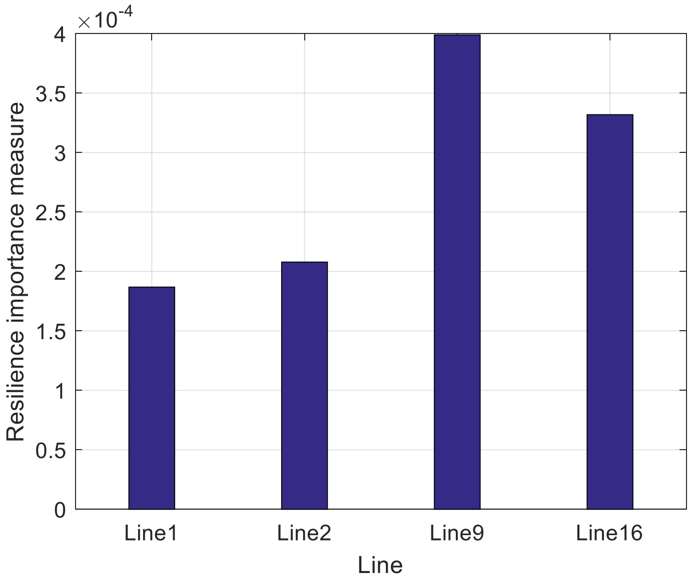

Fig. 13 The resilience importance measure of each line in the set of repair lines

From Figure 13, we can see that the resilience importance measure values of line1, line2, line9, and line16 are 0.00018687, 0.00020789, 0.000399, and 0.00033188, respectively. we can determine the repair order is to repair line9 first, Line16 second, line2 third, and line1 last. We call this repair strategy repair-order-3. The repair-order-3 is different from repair-order-1 because the repair probability of the two cases is different. The repair-order-3 considers the repair probability of the line and is closer to reality. Therefore, in the actual MTS repair management, the repair probability should be focused on. First repair line1, second repair line2, third repair line16, and finally repair line9, this repair order is exactly opposite to repair order3, and is called repair-order-4. The change curve of system resilience with time is determined under repair-order-3 and repair-order-4, as shown in Figure 14.

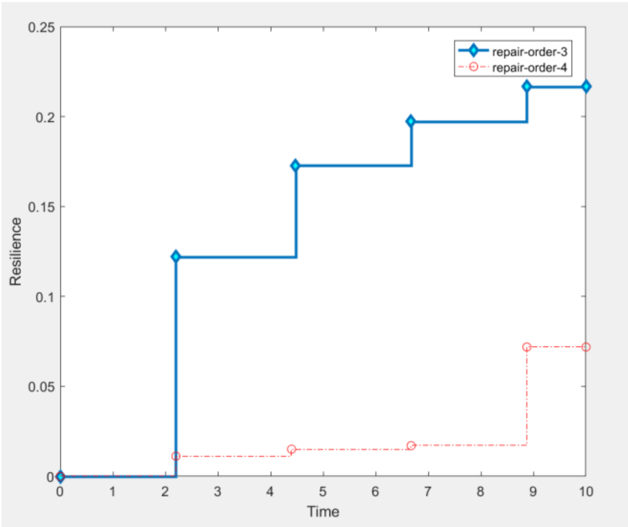

Fig.14 The change curve of system resilience of MTS

By comparing the change curves of resilience of MTS under repair-order-3 and repair-order-4, the resilience under repair-order-3 is greater than that under repair-order-4 at each moment, indicating that repair-order-3 can restore the system resilience to the maximum value faster. Therefore, the model proposed in this paper has its merits.

6. Conclusions and future work

With the development of international trade and economic globalization, the MTS has become increasingly complex. A small disaster may cause a fatal result on the MTS with huge economic losses. This paper analyzed the impact of disasters on MTS, using the Suez Canal "Century of Congestion" as an example. The line state is considered as multi-state, and the impact of the changes of a single line state on the system performance when a disaster occurs was studied. The resilience model and resilience importance measure model were proposed to determine the system recovery strategy for a given failed line set.

The study provides repair strategies of MTS with limited resources and limited time, which can maximize system resilience at minimal loss and within a limited time period. The study helps to identify critical routes in MTS and provides useful insights for the repair management of the routes. Besides, the findings of the paper can be used to analyze the resilience of MTS under multi-level disasters such as deliberate attacks and natural disasters, providing ideas for improving the resilience of MTS.

This paper only classified the disaster levels in a general way and did not provide a clear and specific description of the disaster level. In future work, the classification of disaster levels can be considered, and the impact of other factors on the flow of MTS can be investigated.

Compliance with Ethical Standards

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Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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