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Resilience Analysis Of The Intra-European Container Shipping Network Against Cascading Failures

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Abstract

This study aims to develop an innovative load redistribution model to systematically assess the resilience of the European container shipping network (ECSN) against the cascading failures. The new model pioneers the examination of the impact of port selection preferences (i.e., evenness, connectivity, betweenness and scale) on load propagation and the systematic assessment of resilience in terms of both connectivity and vulnerability. The thorough analysis and case studies of 172 European ports indicate that the disruptions in Port of Rotterdam would result in the most vulnerable network. For enhancing the resilience of the ECSN, this study suggests two key strategies: implementing the weight-based redistribution rule and maintaining adequate reserve capacity. This work offers valuable insights for port and logistics stakeholders in managing unforeseen risks and in the planning and development of port infrastructure.

Keywords: resilience analysis, European container shipping network, cascading failures

1. Introduction

In the European multimodal transport system, containerisation has revolutionized logistics, allowing seamless transfer across various modes such as ships, trains and trucks. The efficiency and scalability of containerisation have significantly reduced costs, fulfilling the complex demands of Europe's diverse geographical and trade networks (Figueiredo et al., 2023). As the essential component, container shipping networks have become increasingly complex and interconnected, owing to the growth of the trade scale (Wu et al., 2021). However, over the past few years, particularly in the context of the COVID-19 pandemic, this interconnectedness has increased the vulnerability to port closures or congestions. In 2022, the challenges faced by the European container shipping network (ECSN), caused by geopolitical events such as the Russo-Ukrainian War, have highlighted the urgency of the issue (Liu et al., 2023). Therefore, analysing and enhancing the resilience of a shipping network has become an important topic for stakeholders to protect themselves against these uncertain risks and make the operational decisions.

Resilience studies have been extensively conducted across a number of transport and logistics sectors, such as air networks (Zhou et al., 2019a), supply chain networks (Burgos and Ivanov, 2021), shipping networks (Xu et al., 2022). Generally speaking, in transport networks, "resilience" refers to the property to maintain its functionality and quickly recover its ability to operate normally in the face of various disruptions or stresses (e.g., accidents, natural disasters, traffic peaks, or system failures) (Zhou et al., 2019b). Theoretically, the resilience of transport network can be analysed in terms of modularity (Xu et al., 2020), vulnerability (Liu et al., 2018), robustness (Peng et al., 2018), recovery (Fan et al., 2023), etc. However, in shipping networks, since the recovery of ports is affected by unquantifiable human and policy factors, the recovery speed is thereby difficult to be accurately defined by data-driven approaches. Therefore, the existing studies in the relevant literature mainly assess resilience through the analysis of the vulnerability or robustness, i.e. studying the degree of resistance to disruptions or the degree of disruption damage to the network (Zhou et al., 2019b). Furthermore, distinguishing from the traditional resilience analysis based on topological features, dynamic resilience analysis against cascading failures has exhibited more practical implications (Bai et al., 2023). Specifically, Motter and Lai (2002) pioneered to propose a Motter-Lai model, which is the load-capacity based cascading model that takes into account the propagation of loads during

cascading, not just the transfer of failure states. It allows this model to be effectively applied to transport networks. For example, Liu et al. (2022) applied the cascading model on a multiple layer rail network, where the propagation of the load (i.e., passenger) was based on the proportion of the giant connected component (GCC). Cumelles et al. (2021) applied a flow-based cascading model in an air network, with redistributed flow being proportional to the load of the airports. On the one hand, it needs to be acknowledged that both applications did indicate the load transfer behaviour. While on the other hand, they ignored the effect of node characteristics (i.e. preferences) on the cascade process, i.e., the distribution, topology and capacity of ports may affect the choices and decisions made in the cascading process. Thus, these studies are not capable to capture the differences in priorities caused by preferences in reality. In addition, some other studies would remove nodes in a certain proportion to simulate the deliberate attacks to observe changes in the network resilience (Liu et al., 2022). However, this approach would not only neglect the effect of individual port on the resilience of the whole network but would equally ignore the interconnected cascading effects between these removed nodes. Furthermore, focusing on the resilience of shipping network, the GLSN is used to be assessed by (Xu et al., 2022; Bai et al., 2023). Such analytical studies in shipping industry can reflect the resilience and identify the key ports at a global level, while they overlooked the dense distribution of regional ports, e.g., in the European area. This is due to the geographic characteristics and diversity of Europe, the size and status of the European ports are unique in the global freight transport, compared to other mega ports in Asia and actually play an essential role in the European regional intensive transport system. Therefore, a study focusing on the European region would be more reflective of the regional resilience.
Therefore, the aim of this study is to provide a systematic assessment of the resilience of the intra-ECSN. The contributions of this study are threefold. Firstly, a novel load redistribution model is proposed to simulate the propagation of the cascading failures. This novel four-step model based on four redistribution rules pioneers to consider the effect of different characteristics of ports (i.e., evenness, connectivity, betweenness and scale) in the failures' propagation process. Secondly, two metrics named the giant weakly connected component and weighted efficiency are innovatively applied to measure the resilience. This will also be the first time for the resilience assessment of the ECSN considering both direction and weight. Finally, a case study is conducted to analyse the resilience of the entire European region (total of 172 ports). The results of this study will provide a theoretical basis of transport safety for European stakeholders.

2. Methodology

This study adopts a systematic approach to examine cascading failures within the ECSN, initiated by an unexpected disruption of a port in the network. This disruption acts as a catalyst, leading to the selection of neighboring ports for load redistribution, thereby facilitating the propagation of the failure through the network. When the process is finished, the resilience of the whole network will be systematically assessed from the perspectives of connectivity and vulnerability. In this section, the load redistribution model is presented in Section 2.1 and the resilience assessment metrics are introduced in Section 2.2.

2.1. Load redistribution model

In this study, a container shipping network G is a directed and weighted network, nodes are the ports of the network, and links are the directed connections between any two ports. Here, ports and links have their own attributes. Each directed link contains the load L_{ij} and the distance T_{ij} from port i to j. The sum of the load that received by port j is the weight W_j, i.e.,

$$W_j = \sum_{\forall i,j \in G} L_{ij} \tag{1}$$

where W_j also represents the total volume of cargo handled at this port. In the container shipping network, the unit of cargo is expressed as Twenty-foot Equivalent Unit (TEU). For ease of representation, the average sailing time between the two ports is used as a proxy for distance in this study (unit: days).
Referring to the Motter-Lai model (Motter and Lai, 2002) and its application in the road system (Duan et al., 2023), the ports of the shipping network are expected to be constrained by the maximum capacity C, which is proportional to a capacity multiplier λ ($\lambda \geq 1$), i.e.,

$$C_j = \lambda \times W_j \tag{2}$$

Therefore, in the process of cascading failures propagation, the states of ports are classified into three categories (Guo et al., 2023):

- 1) Initial failed, the port experiences an initial disruption. The infrastructure has been broken and loses its function.
- 2) Overloaded, the sum of the redistributed load received by the port and its own load exceeds its capacity.

The infrastructure is not broken but the port loses its function.

- 3) Normal, the port is neither initial failed nor overloaded.

The load redistribution model contains four steps:

- 1) Iteration of all ports as initial failure ports

The load redistribution model of this study starts with an unexpected disruption of a port in the network and ends when no new overloaded port is created (i.e., the weight of initial failed port has been consumed by the network) or no more port is available in the network (i.e., the entire network has collapsed), the process iterates all ports (i.e., all ports go through this process once as initial failed ports).

- 2) Selection of the satisfied and safe neighbor ports

For both the initial failed port and overloaded port, the redistribution targets are their neighbours. Notably, since this network is directed, redistribution targets are restricted to the neighbours directed from the initial failed or overloaded port. This would be consistent with reality as the transport of containers from port i to port j is not necessarily bidirectional. Furthermore, referring to studies (Xu et al., 2022; Bai et al., 2023), this study also sets a time restriction, i.e., only neighbours that are directly connected, not failed or overloaded, and whose transport time is less than the time restriction can be selected. This restriction is intended to enhance the practical implications of this study, as ports that are too far away will make operating costs much higher and uneconomic.

- 3) Redistribution of the load and record the overloaded ports

The redistributed load depends on the states of the source ports (Guo et al., 2023). For the initial failed ports, the redistributed load is the weight of this port, while for the overloaded ports, the redistributed load is the load in excess of the capacity portion. Then, the load is redistributed to the selected neighbours based on different rules. In this study, we set four types of redistribution rules: average rule, degree (D) based rule, betweenness centrality (BC) based rule and weight-based rule. For the average rule, the redistributed load is equally sent to the selected ports, which can be considered a control group. For the D and BC based rules, the redistributed load is sent to the selected ports according to the proportion of D and BC among all the satisfied neighbors, i.e.,

$$P_{ij}^{D} = \frac{D_j}{\sum_{j \in S} D_j} \tag{3}$$

$$P_{ij}^{BC} = \frac{BC_j}{\sum_{j \in S} BC_j} \tag{4}$$

where P_{ij}^{D} and P_{ij}^{BC} are the proportion of the redistributed load from port i to its neighbour j according to D-based rule and BC-based rule. D_j and BC_j are the degree and betweenness centrality of neighbour j. S is the set of the selected neighbours of port i. Therefore, these two topology-based redistribution rules reflect different preferences. D-based rule redistribute more load to the port which has a larger degree, i.e., the port which have more connections with other ports will have a larger redistribution proportion, this means that such a port will have more options to share the load further. BC-based rule redistributes more load to the port which has a larger betweenness centrality, i.e., the port which has a more important bridging position in the network will have a larger redistribution proportion, this means that such a hub port will be more effective to pass the load further. Similarly, the weight-based rule takes into account the ability and resources of ports to handle cargo. Thus, ports with larger weight (i.e., larger capacity) will have a greater proportion of redistribution P_{ij}^{Weight}, i.e.,

$$P_{ij}^{Weight} = \frac{W_j}{\sum_{j \in S} W_j} \tag{5}$$

Therefore, based on different attitudes of the ports, the redistributed load D_{ij}^{A} from port i to its neighbour j is expressed as:

$$D_{ij}^{A} = \begin{cases} W_i \times P_{ij}^{A},\ port\ i\ is\ initial\ failed \\ (L_i - C_i) \times P_{ij}^{A}, port\ i\ is\ overloaded \end{cases} \tag{6}$$

where A represents four redistribution rules. When port j receives the redistributed load D_{ij}^{A} from port i, its load will be updated to:

$$L_j' = L_j + D_{ij}^{A} \tag{7}$$

If the current load L_j' of port j exceeds its capacity C_j, the state of port j will be updated to overloaded.

- 4) Removal of failed nodes

When the redistribution and iteration of the cascading failures are finished, the network will remove the ports which have the states of initial failed and overloaded, including the ports and their connected links.

2.2. Resilience metrics

After the completion of cascading failures propagation, the giant weakly connected component (GWCC) and efficiency assess the network in the perspectives from connectivity and vulnerability.

- Giant weakly connected component (GWCC)

Generally, GCC is the metric to measure the connectivity and robustness in an undirected network (Liu et al., 2022). Referring to the reality of the logistics network, the transport of cargo from nodes to nodes usually is directed (e.g., goods may be transported from the factory to the warehouse and then distributed from the warehouse to the retail shops, but there is not necessarily a flow of goods directly from the retail shops back to the factory). Therefore, GWCC is adopted to measure the connectivity of the directed network. GWCC is the largest subgraph of the network in which any two nodes are connected at least when the direction of the links is ignored (Newman et al., 2001). By determining the GWCC, an idea of the connectivity of the entire network can be got without considering the link direction. This means that even if the actual shipments are directional, whether the containers can theoretically pass from one port to another can be assessed.

- Weighted efficiency

Furthermore, efficiency also is one of the appropriate metrics to indicate the performance of the network. The definition of efficiency is the average of the inverse of the sum of the shortest paths in the network. As mentioned in Section 2.1, this study uses the sailing time between two ports as the proxy of the distance. As a result, the efficiency in this study is expressed as Eq. 8 (Bai et al., 2023):

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{T_{ij}} \tag{8}$$

where N is the number of the ports in the network.

Notably, as a weighted network, the load on the links reflects the flow level of different waterways. When removing ports and its links due to the disruption or overload, the removal of the links between large ports may lead to the relatively greater influence on the network than the removal of the links between small ports. Therefore, Zhou et al., (2019a) proposed a network disintegration model to improve the applicability of the performance metrics to the weighted network, an example is shown in Figure 1. In the network disintegration model, the weight of the links is represented as the number of the standardised units. For example, if one standardised unit equals to 50,000 TEUs, the weight on the link with 150,000 TEUs between node x and node y is 3. Therefore, the network will be disintegrated according to the weight on the links (Zhou et al., 2021). At each iteration, each link is stripped of one unit weight, the stripped unit weights would form a new subgraph (e.g., the subgraph 1 in Figure 1). The iteration process ends until only links with a weight of 1 unit exist in the original network. The subgraph has the same distribution and number of nodes with the original network. The weight of links on each subgraph is 1. Then, the weighted efficiency of original network is equal to the sum of the efficiency of every subgraph. However, the setting of the value of standardised unit determines the computational accuracy. A very large value can make it difficult to capture the characteristics of some load-small links, and a very small value can increase computational complexity. Therefore, in this study, the load on the links is converted into a logarithmic form, where a logarithmic value of 1 is a normalised unit.

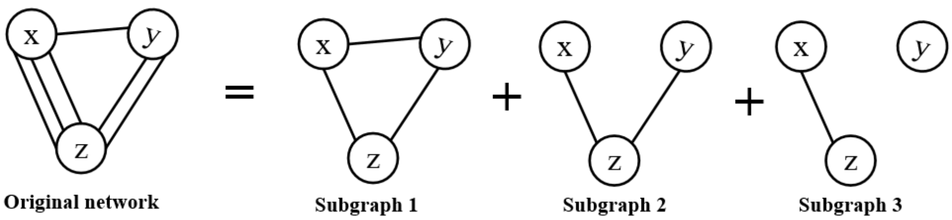

Fig. 1. An example of the network disintegration model.

3. Results

3.1. Data and the European container shipping network

In this study, the ECSN is established based on the data from www.bluewaterreporting.com. The data is presented on a quarterly basis, with each quarter's data containing the port of origin and destination, the mean weekly volume of cargo transported, and the average sailing time on the route. After integrating the data for the four quarters of 2022, as shown in Figure 2, the ECSN contains 172 ports and 913 links. Based on the port weight, the Top 5 ports have been shown in Table 1. It is worth noting that the values of the weights in Table 1 are the average weekly container cargo handled at the corresponding ports within the intra-European region, rather than the total amount of container cargo transported by these ports globally.

Table 1. Top 5 ports based on port weight (unit: TEUs/week).

Port code	Port name	Weight
NLRTM	Rotterdam	474090
BEANR	Antwerp	389070
DEHAM	Hamburger	369303
ESVLC	Valencia	247650
FRLEH	Le Havre	222278

Fig. 2. The European container shipping network.

3.2. Resilience analysis

Based on the proposed load redistribution model in Section 2.1, all ports in the ECSN network are sequentially treated as initial failed ports. This approach enables a thorough exploration of cascading processes under varying scenarios and rules. In this study, to highlight the ports that have a greater effect on the resilience of the ECSN, the capacity multiplier is set to 1.1 (i.e., $\lambda = 1.1$). Since more than 95% of the intra-European container ships in the data of this study have an average sailing time of no more than 5 days, the time restriction is set at 5 days to keep the redistribution targets not too far away. Subsequently, the sizes of GWCC and the efficiency are calculated, as shown in Figure 3 and 4. The x-axis in two figures is the ports of the ECSN. The y-axis in Figure 3 is the size of the GWCC after selecting a port as the initial failed port and completing the whole cascading failures propagation process, and the y-axis in Figure 4 is the efficiency.

In the original network, the size of GWCC is 172 and the efficiency is 0.22. From Figure 3 and 4, it can be found that the failures of most of the ports does not drastically diminish the network's resilience. One statistic shows that with about 90% of ports individually acting as the initial failed ports, the size of GWCC and the efficiency of the entire ECSN have consistently remained above 90% and 70% of the original level. Even for the failures of some large or hub ports in the European region, the entire network does not collapse with a capacity multiplier equal to 1.1. In the realistic shipping network, a reduction in GWCC size to less than 90% of its initial value indicates that about 20 ports in European are failed or overloaded, which seems to be less possible. Therefore, from an overall perspective, this demonstrates that the resilience and robustness of the ECSN stands at a relatively high level.

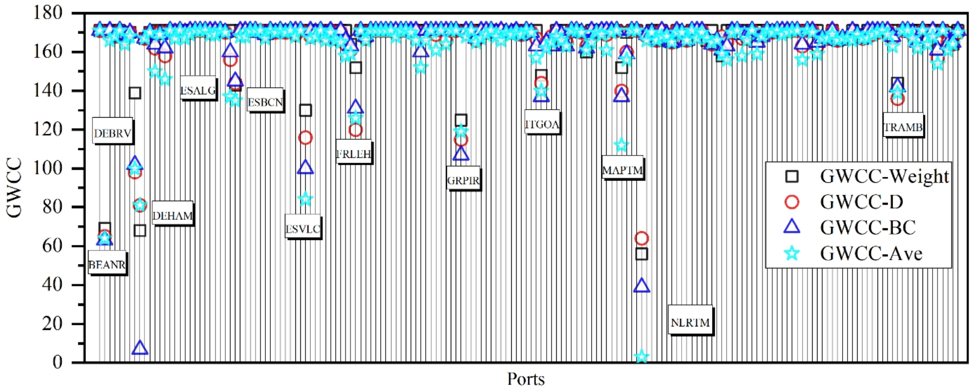

Fig. 3. The GWCC of the European container shipping network.

Specifically, the resilience of the ECSN is vulnerable to be affected by some key ports. The same port has different effects on the ECSN under different redistribution rules. Therefore, in the context of the failures of different ports, the redistribution rules need to be adopted purposefully to mitigate the damage to network resilience. For example, in Figure 3 and 4, the sizes of the GWCC and the efficiency of the network reach their lowest points when the port of Rotterdam (i.e., NLRTM) acts as the initial failed port with the average redistribution rule, with the values of 3 and 0.00026, respectively. In this scenario, although the network has not theoretically collapsed, in reality the only remaining 3 ports in the GWCC can also be approximated as the ECSN no longer functioning. The reason is mainly due to the unique status of the port of Rotterdam. As the port with the largest scale and degree in Europe, the load of the Rotterdam is about 20% higher than the second-ranked port of Antwerp, and even several orders of magnitude higher than most ports. Its failure necessitates a nearly network-wide cargo redistribution, inducing a widespread cascading effect. In particular, when the average rule is adopted, smaller ports will be allocated the same amount of cargo as larger ports, which will cause more small ports to fail. Thus, the failure of the port of Rotterdam based on the average rule will lead to a smaller size of GWCC and efficiency.
Besides Rotterdam, 12 other ports with significant network influence are identified in the Figure 3 and 4. The stakeholders should make the targeted redistribution decisions based on the setting of capacity and the different rules. Generally, the weight-based rule lessens the effect on network resilience, which can be seen in the ports of Antwerp, Bremerhaven, Algeciras, Valencia, Le Havre, Piraeus, Genoa, Tangier-Med, and Ambarli. In fact, this rule is particularly effective for medium-to-large scale ports that are often connected to larger hubs. By proportionally redistributing more load to larger ports, the risk of failure among smaller ports is reduced.

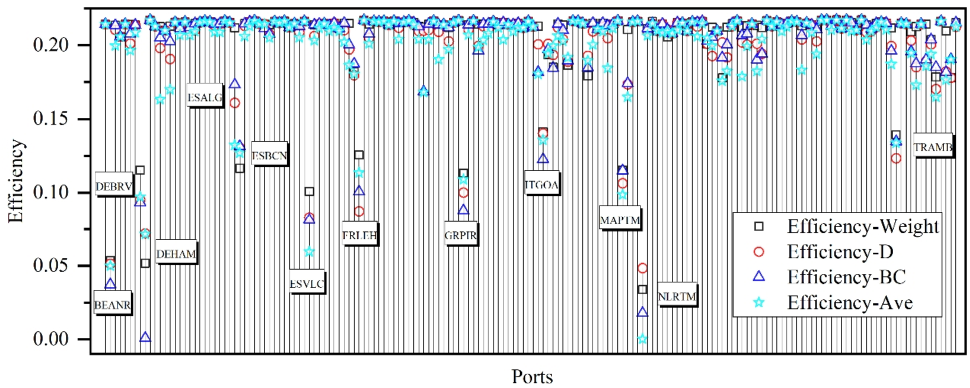

Fig. 4. The efficiency of the European container shipping network.

Furthermore, the effect of capacity multipliers on network resilience also needs to be further explored. The remaining ports, i.e., the ports of Hamburg, Barcelona and Rotterdam, have a small effect on the network resilience based on the D rule from Figs. 3 and 4. On the one hand, the reason may be that the mega ports like Rotterdam and Hamburg have obtained substantial weights, failing to generate large proportional gaps in the redistribution process. Instead, the D-based rule allows them to redistribute more load to the ports with a larger degree, which are also more capable of further redistributing the load to a larger number of ports, thus reducing the effect on a single port. On the other hand, the potential possibility raised by the values of different capacity multipliers should not be ignored. To specifically discuss the effect of the capacity multipliers, Section 3.3 deliveries the case studies to three critical ports. Capacity multiplier values ranging from 1 to 2 will be iterated to avoid fluctuations caused by the presence of certain specific values. Therefore, in the view of improving overall resilience, it is suggested that large ports should choose appropriate rules to reduce the effect of cascading failures on small-to-medium ports, while small-to-medium ports should appropriately increase their own reserve capacity to avoid closures due to overloading.

3.3. Case study

In Section 3.1 and 3.2, the ports of Rotterdam, Antwerp and Hamburg are not only identified as the most significant in terms of weight within the ECSN, but also as those exerting the most substantial effect on the network's overall resilience. Therefore, Rotterdam, Antwerp and Hamburg ports are selected for in-depth case studies to specifically analyse the role of these ports on network resilience. This analysis involves varying the value of the capacity multiplier, as illustrated in Figs. 5, 6 and 7, respectively. Each figure comprises four dual y-axis subgraphs, representing the results under four redistribution rules. The left y-axis (blue lines) in these subgraphs illustrates the changes in size of the GWCC, while the right y-axis (red lines) depicts the change in efficiency. The x-axis across all subgraphs denotes the values of the capacity multiplier. Taking a view of the three figures collectively, as the capacity multiplier increases, each port shows a consistent upward trend in both the size of GWCC and efficiency under each redistribution rule. This phenomenon aligns with practical expectations, suggesting that augmenting the reserve capacity of ports enhances their ability to handle unforeseen risks, ultimately enhancing the resilience and robustness of the network.

Specifically, in Figs. 5, 6 and 7, although the failures of Rotterdam, Antwerp and Hamburg ports do not theoretically lead to a complete reduction of the sizes of GWCC and efficiency to 0, at small capacity multipliers ($\lambda < 1.06$), the whole network is practically in a state of near collapse. This suggests that when the capacity multiplier of the ECSN is small (i.e., the reserve capacity is small), the network struggles to effectively withstand cascading failures triggered by the disruption of major ports.

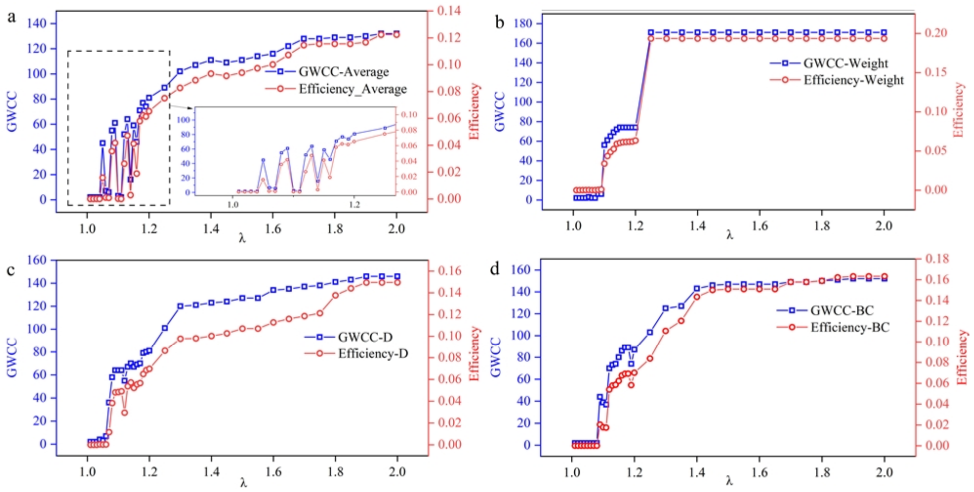

Fig. 5. The effect of 4 redistribution rules on the European container freight network when the port of Rotterdam is the initial failed port, (a) average rule; (b) weight-based rule; (c) D-based rule; (d) BC-based rule.

Taking the port of Rotterdam as an example, with the increase of the capacity multipliers to 1.1, 1.07 and 1.09, the network resilience receives the first significant increment under different redistribution rules, as shown in Fig. 5. These three turning points can be considered as the minimum capacity multipliers required by the ports of the network, which allows part of them to begin demonstrating resilience to cascading failures. Differently, the average rule, despite the first resilience increase at the capacity multiplier equal to 1.05, the resilience of the network is widely fluctuating in the range of 1.05 and 1.14, dropping to its lowest level several times. Therefore, the minimum capacity multipliers of the average rule should be set to 1.14. Then, all four redistribution rules experience the continuous upward trends and reach at the relatively stable levels. The second turning points, indicating the capacity multipliers at which the network becomes resilient to cascading failures, are approximately 1.7 for the average rule, 1.25 for the weight-based rule, 1.3 for the D-based rule, and 1.4 for the BC-based rule. Notably, across all these three large ports, the weight-based rule (i.e., Fig. 5 (b), Fig. 6 (b), Fig. 7 (b)) clearly stabilise at the highest level of resilience among the four redistribution rules, i.e., having the highest GWCC size and efficiency. Therefore, weight-based rule may be assumed to be a more ideal redistribution strategy for these three ports. Such a strategy not only avoids excessively high-capacity multipliers, which could escalate construction costs for the ports, but also maintains resilience and robustness in response to risks and disruptions.

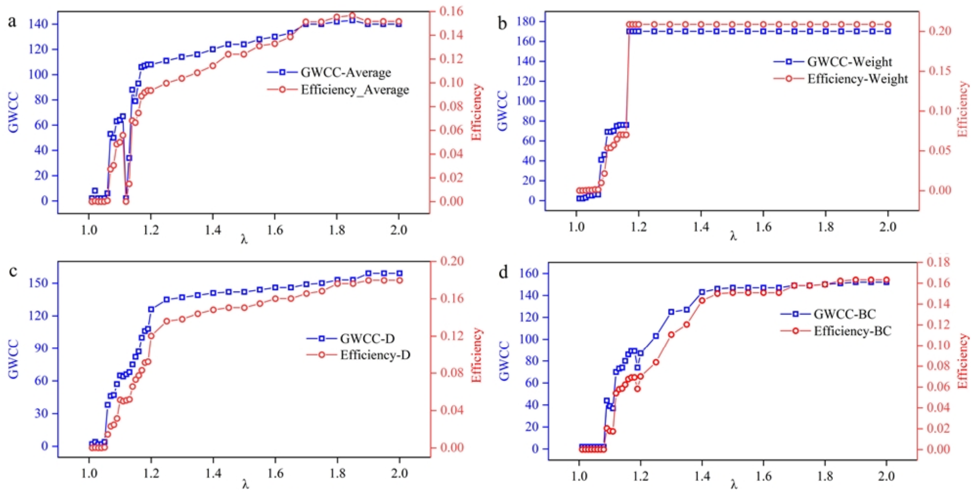

Fig. 6. The effect of 4 redistribution rules on the European container freight network when the port of Antwerp is the initial failed port, (a) average rule; (b) weight-based rule; (c) D-based rule; (d) BC-based rule.

Furthermore, two noteworthy phenomena can be observed in the resilience of the network before arriving at the stable level, i.e., the slight drop and the sudden change in the upward phase. Theoretically, the expected resilience of the entire network should continue to increase with the improvement of the reserve capacity. In practice, however, as the multi-objective cascading process, the small capacity multiplier may make it possible for overloaded ports to have no available neighbour (i.e., not overloaded and failed) presence. At this point, the entire network may be divided into multiple independent subgraphs and the load from the initial failed port is not fully absorbed by the entire network. With the increase of the capacity multiplier, the proportion of the redistributed load to a certain port remains constant. When the capacity multiplier reaches a certain threshold, the port may no longer be overloaded after receiving this redistributed load, enabling the continuation of the cascading process through this port. Although this might temporarily increase the number of overloaded ports (evidenced by the slight drops in GWCC size and efficiency), it effectively reduces undistributed cargo, thereby minimizing economic losses. Similarly, the phenomenon of the sudden changes can be also attributed to the contribution of key ports' capacity above a certain threshold, which makes the propagation path of the load change. During the cascading process, when the capacity multiplier remains within a certain range, even some large ports can be vulnerable to the cascading effect and thus overloaded. However, once the capacity multiplier surpasses a threshold, this allows these ports to be able to maintain their functionality when receiving the redistributed load. This threshold is also called marginal tolerance referred to the study of Duan et al. (2023). The reason is that due to the capacity gap between large and small ports, a slight increase in the capacity multiplier of the large ports can significantly boost their actual capacity, which is even greater than the combined capacities of many smaller ports. Therefore, when large ports transition from being overloaded to functional, they prevent the load from being redistributed to connected smaller ports. This shift is manifested as a sudden and noticeable change in both the size and efficiency of the GWCC, marking a critical juncture in enhancing network resilience.

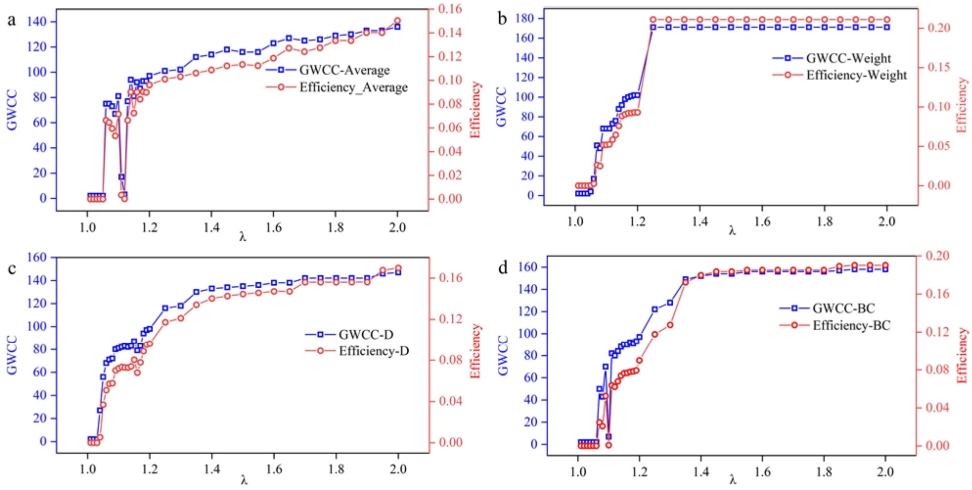

Fig. 7. The effect of 4 redistribution rules on the European container freight network when the port of Hamburg is the initial failed port, (a) average rule; (b) weight-based rule; (c) D-based rule; (d) BC-based rule.

Therefore, the findings of this study underscore that, in the case of major port failures, a weight-based redistribution rule proves more efficacious in preserving the resilience of the network. Focusing on the three ports with the largest container throughputs in Europe, Rotterdam, Antwerp and Hamburg ports, the minimum required capacity multipliers (i.e., the first turning point) of the network are 1.1, 1.08 and 1.06, respectively. While the marginal tolerance (i.e., the second turning point) of the network are 1.25, 1.25 and 1.17, respectively. These results imply that constructing ports with capacities below these minimum values would render the network susceptible to risks. Accordingly, the study recommends that the baseline construction standard should ensure each port's capacity is at least 1.1 times higher than its cargo handling volume. While greater port capacity can increase its resilience at an overall level, exceeding the marginal tolerance too much may result in high construction costs and wasted resources. Therefore, a balanced and optimal range for capacity multipliers is proposed to be between 1.25 and 1.3. This range is selected for several reasons. Firstly, a capacity multiplier of 1.25 is theoretically sufficient for the ECSN to withstand cascading failures, even when the largest ports are the initial points of failure. Secondly, a slight increase beyond this value would prevent significant economic cost escalation while providing additional flexibility. Finally, the upper limit of 1.3 has cross-corroborated by other studies (Bai et al., 2023; Cumlles et al., 2021) as a value that enhances network reliability.

4. Conclusion

Nowadays, subject to a variety of unknown risks, resilience analysis has become a pivotal factor in the design, construction, and risk management strategies of shipping networks. This study proposes a novel load redistribution model to specifically simulate the propagation of the cascading failures in the ECSN. By implementing four distinct redistribution rules, the model elucidates the varying effects of different strategic preferences on network resilience. Then, the resilience of 172 European ports is systematically assessed from the perspectives of the size of GWCC and the weighted efficiency. For cascading failures caused by large ports, the weight-based rule can pass the load out more efficiently and economically. For smaller ports, the appropriate increases of their reserve capacity could help improve risk resistance. Crucially, the study recommends that the capacity of ports within the ECSN should be set between 1.25 and 1.3 times their standard load, which theoretically enables the network to withstand disruption or closure of critical ports and in practice avoids raising economic costs.

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