Transportation Research Part A 200 (2025) 104659

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Multi-objective resilience-oriented optimisation for the global container shipping network against cascading failures

Yuhao Cao [a], Xuri Xin [a,*], Xinjian Wang [a,b], Jin Wang [a], Zaili Yang [a,*]

[a] *Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, United Kingdom*
[b] *Navigation College, Dalian Maritime University, Dalian 116026, PR China*

A R T I C L E I N F O

Keywords:
Maritime transport
Resilience analysis
Cascading failures
The global container shipping network

A B S T R A C T

Disruptive events at ports (e.g., epidemics, natural hazards and regional conflicts) continuously challenge the stability of cargo flows, leading to cascading failures that significantly undermine the resilience of global shipping networks. To address these challenges, this study proposes a new Multi-objective Stepwise Optimisation (MSO) framework that can aid decision-makers in maintaining resilience against cascading failures. Specifically, this study first formulates multiple objectives aimed at minimising adverse impacts on maritime stakeholders by reducing transit time, alleviating port overload, and preserving the network's structural completeness. Then, to explore ideal load redistribution strategies mitigating the cascading effects, a Stepwise Cascading Mitigation (SCM) model is newly developed. In this model, all feasible target ports are identified, followed by an iterative algorithm applied to determine the equilibrium volumes of load redistributed to each target. An evolutionary procedure is then designed to ensure renewal of diverse solutions and reduce computational complexity. By simulating the entire cascading process, multi-dimensional reductions in shipping network resilience are eventually assessed. Taking the Global Container Shipping Network (GCSN) as a case study, comprehensive experiments, alongside targeted analyses of major international ports, are conducted to validate the effectiveness and superiority of the MSO framework over four benchmarking methods. Sensitivity analysis results further reveal that maintaining appropriate redundancy across the network, combined with the proposed optimal redistribution strategies, can effectively mitigate the adverse impacts of cascading failures on system resilience. Therefore, this study provides stakeholders with adaptable emergency response protocols to alleviate excessive congestion at critical ports, ensuring the timely and reliable movement of goods, thereby proactively protecting the overall robustness and resilience of global supply chains.

1. Introduction

Starting from April 2025, a series of tariff games and the back-and-forth between the superpower economies has led to swings in economic markets globally. With the reconfiguration of the multilateral trading system and the ongoing exchanges between countries over tariff policies, global supply chains are facing the risk of fluctuated costs and increased uncertainties (Chen et al., 2025; Zhang et al., 2025). Predictably, as the turmoil spreads, the resilience of the liner market will be further challenged by the strategic shift in

* Corresponding authors.
E-mail addresses: X.Xin@ljmu.ac.uk (X. Xin), Z.Yang@ljmu.ac.uk (Z. Yang).

https://doi.org/10.1016/j.tra.2025.104659
Received 22 May 2025; Received in revised form 30 July 2025; Accepted 22 August 2025
Available online 29 August 2025
0965-8564/

containerised trade and the increase in landed costs. Along with other disruptions like operational accidents (Cao et al., 2025a; Wang et al., 2025a; Xin et al., 2025b; Yu et al., 2025), public health events (Fan et al., 2023), natural hazards (Wan et al., 2024), geographical conflicts (Ke et al., 2025) and so forth, more dynamic vulnerabilities within the global shipping network may trigger a series of propagation of risks, continuously resulting in inter-systems cascading failures and maritime network reconfiguration (Cao et al., 2025b; Wan et al., 2018; Wan et al., 2024; Zhang et al., 2024). For instance, the recent Red Sea crisis significantly reshaped maritime connectivity, reinforcing the competitiveness of Western Mediterranean hub ports due to their strategic location near the Strait of Gibraltar, while ports dependent on the Suez Canal saw reduced connectivity and increased transportation costs (Bedoya-Maya et al., 2025). Such historical and more current crisis (e.g. COVID-19 pandemic and Russia-Ukraine conflict) highlighted the urgent need to accelerate efforts toward building a resilient global shipping network (Bai et al., 2022; Li et al., 2022; Peng et al., 2024; Poo et al., 2024; Wang et al., 2025b). Understanding how transportation networks adapt, deteriorate, and recover during prolonged disruptive events can provide valuable insights into the patterns of resilience and the critical role of policy interventions in managing network responses and recovery (Li et al., 2023).

Resilience studies have been widely delivered for shipping networks during the past decade, attempting to model disruptive failures and understand the resilience characteristics from multiple perspectives (Li et al., 2022; Liu et al., 2023). For instance, to project the impact of port closures or overloads on a shipping network, simulation-based approaches like deliberate disruptions (Wu et al., 2019; Xin et al., 2025a) and cascading failure models (Bai et al., 2023; Cao et al., 2025b; Xu et al., 2024d) were applied based on Complex Network (CN) theory (Cao et al., 2024). Following this, topology-based, attribute-based and performance-based indicators were developed for resilience measurement and evaluation (Yang et al., 2025; Zhang et al., 2024). Although the coupling application of both simulation and evaluation provides insights into understanding the possible breakdown on the system, it is more than like the post-hoc assessment on disruptive impacts and patterns, lacking practically actable plans for different decision makers when facing disruptions. Therefore, to address these challenges and bridge the gap between assessment and practice, this study proposes a new Multi-objective Stepwise Optimisation (MSO) framework for offering effective short-term responsive strategies (i.e., the load redistribution) to mitigate losses and maintain resilience against cascading failures, and further, supporting long-term investment decisions and system resilience planning. Specifically, effective load redistribution deployments aim to mitigate the effects of cascading failures to a minimal level, balancing interests between different stakeholders (Lu et al., 2024). To this end, this study proposes, for the first time, a Stepwise Cascading Mitigation (SCM) model designed to strike optimal redistribution solutions that align with the priorities of three key stakeholder groups from micro to macro levels. Firstly, for carriers and shippers, the central objective is the safe, timely, and cost-effective delivery of cargo. In the event of disruptions, their preferred redistribution schemes should minimise delays, thus avoiding increased transportation costs for carriers and time-related penalties for shippers. Accordingly, minimising the cost implications for carriers and shippers constitutes the first optimisation objective of the SCM model. Secondly, from the perspective of port operating groups, capacity constraints mean that poorly balanced redistribution can lead to severe overloading at specific ports, resulting in logistical delays, operational inefficiencies, and reputational harm. Thus, the second objective aims to minimise the overloading degree of individual ports, promoting operational continuity and faster recovery. Thirdly, from a broader network perspective, cascading failures threaten the connectivity, resilience, and overall functionality of global shipping systems. Therefore, the third objective seeks to minimise the total number of overloaded ports, thereby containing the propagation of cascading failures and safeguarding the structural integrity and serviceability of the shipping network.

To implement this framework, the SCM model evaluates each redistribution stage iteratively. For a certain redistribution round, all potential redistribution target ports are identified through an elite selection method, and corresponding redistribution scenarios are thoroughly explored. Meanwhile, an improved iterative algorithm is applied to compute the redistribution load volumes among the selected ports within every scenario. The resulting redistribution solutions are then evaluated, with all non-dominated solutions retained. Here, to promote the iteration process and reduce computational cost, an evolutionary procedure is introduced, ensuring the continuous generation of solutions with improved convergence and diversity. Then, among all non-dominated solutions on the Pareto Frontier (PF), this study further employs the Coefficient of Variation-based Technique for Order Preference by Similarity to Ideal Solution (CV-TOPSIS) method to select the most appropriate trade-off solution for actual implementation. If any new ports become overloaded during this process, the SCM model is repeated. Ultimately, the reductions in network resilience are systematically assessed until cascading failure propagation ceases. Given the proven effectiveness and superiority by detailed case studies, the proposed approach provides a comprehensive theoretical framework for managing shipping network resilience, guiding robust protective measures to minimise cascading-failure-induced damages resulting from port disruptions.

The remainder of the study is structured as follows. Section 2 reviews the related work of resilience analysis in shipping networks; Section 3 introduces and describes the proposed MSO framework in detail. Section 4 applies this framework to the Global Container Shipping Network (GCSN) and presents experimental results. Section 5 discusses the implications of the study's findings and offers an outlook for future resilience research in shipping networks. Finally, Section 6 summarises and concludes the study.

2. Overview of resilience analysis in shipping networks

Generally, a comprehensive resilience analysis framework for shipping networks comprises several interconnected components, including network establishment, simulation modelling, resilience indicator evaluation, and decision-making analyses, all designed to collectively assess the impacts of disruptions on the network. Consequently, this section reviews relevant and representative studies focusing on these critical aspects and concludes current research gaps and new contributions.

2.1. Network establishment

Establishing shipping networks is the foundation for the relevant resilience analyses. This process highly relies on the type of input data. To date, two primary datasets, i.e., Automatic Identification System (AIS) data and service routes data, have been widely used to build networks, in conjunction with the CN theory (Xu et al., 2020).

Overall, AIS data is collected from individual ships and provides detailed information on ship specifications and trajectories (Shu et al., 2025), while service route data, sourced from liner shipping companies, records predefined port rotation sequences for entire service routes (Jarumaneeroj et al., 2023). This fundamental difference affects how networks are established. Specifically, AIS data contains voyage logs and needs the aggregation of vast numbers of ship trajectories into network links (Bai et al., 2023). It can cover different types of vessels, allowing for the construction of various shipping networks tailored to specific research objectives, such as container ships (Bai et al., 2023; Xu et al., 2024d; Yap and Yang, 2024), LNG carriers (Xiao et al., 2024; Xu et al., 2025b), and tankers (Si et al., 2025; Su et al., 2025). However, data accessibility and computational complexity often affect the utilisation of AIS data. Obtaining a relatively complete and globally representative AIS dataset over a given period is difficult due to issues such as missing data, data protection policies, and high costs. Furthermore, AIS data typically requires to be pre-proceeded for identifying berthing areas and filtering valid connections before modelling shipping networks (Bai et al., 2023; Liu et al., 2025; Si et al., 2025). By comparison, service route data typically provides structured and aggregated information, including sequences of port calls, sailing times, ship commitments, and route capacity (Cao et al., 2025b; Lu et al., 2024; Xu et al., 2020; Xu et al., 2024c). This dataset is clear, well-organised, and easier to process, often represented as Origin–Destination (O–D) pairs. By extracting relevant ports and aggregating multiple shipping routes, network structures can be directly formed. Therefore, comparing with AIS data, where vessel movements

Table 1
A review of existing representative cascading models applied in shipping networks.

Reference	Adopted data	Cascading failure modelling		Subject	Performance metrics
		Redistribution target selection principles	Redistribution principles of load volume		
(Xu et al., 2022)	Service routes data	• Belonging to the same country with the failed port. • Distance less than the average length of the initial route. • Remaining functional.	• If a failed port is skipped, all loads are equally redistributed to remaining ports. • If a target is selected, all loads are redistributed to the target port.	GLSN	• The giant component size • Efficiency
(Bai et al., 2023)	AIS data	• Accessible in 3 days • Having same port role with the failed port. • Not congested.	• Proportional to each target's capacity.	GLSN	• The giant component size • Efficiency
(Ding et al., 2024)	Service routes data	• Neighbouring ports.	• Proportional to each target's capacity.	The Belt and Road land-sea transport network	• Node retention ratio • Efficiency • The giant component size
(Jiang et al., 2024)	Service routes data	• Neighbouring port with the highest capacity.	• All loads are redistributed to the target port (a single target redistribution).	The 21st-century Maritime Silk Road container shipping network	• The giant component size
(Lu et al., 2024)	Service routes data	• Downstream ports (the NS-LD method). • Downstream cooperative ports (the NS&PCM-LD method).	• Proportional to each target's weighted degree (the NS-LD method). • Proportional to edge weight (the NS-LD method).	The China-Europe liner shipping network	• Node congestion ratio • Node failure ratio • Shipper loss
(Qu et al., 2024)	Service routes data	• Neighbouring ports.	• Proportional to each target's remaining capacity.	The China-U.S. container shipping network	• Node failure ratio • Efficiency
(Xu et al., 2024a)	Service routes data	• Neighbouring ports within a circle of radius L.	• Proportional to each target's degree. • Proportional to each target's distance. • Proportional to each target's remaining capacity. • Proportional to each target's distance and remaining capacity.	GLSN	• Node retention ratio • OD pairs retention ratio • Efficiency
(Xu et al., 2024d)	AIS data	• Closest K ports ($K = 3$)	• Proportional to dynamic route cost to each target.	GCSN	• Node failure numbers • Cosine similarity
(Cao et al., 2025b)	Service routes data	• Neighbouring ports. • Accessible in 5 days. • Not failed and overloaded.	• Proportional to each target's Borda score (the BFRR method). • All loads are redistributed to the target port with the largest Borda score (the DFRR method).	GCSN	• The giant component size • Efficiency • Redundancy

need to be inferred by course and speed, predefined liner shipping routes involve multiple ships operating on regular schedules with known endpoints and a fixed port-to-port calling sequence. The convenience and adaptability enable that service route data is particularly advantageous for examining the macro-structure of Global Liner Shipping Networks (GLSNs) or GCSNs (Xu et al., 2020).

2.2. Simulation modelling

Simulation modelling is a key technique in resilience studies to map the real-world disruptive events with theoretical scenarios to established CN structures, typically falling into two categories: strategic removals (also known as attacks) of nodes (i.e., ports) or links (i.e., shipping routes) within the network (Liu et al., 2023), and the development of rule-based models to simulate the dynamic propagation mechanism of failures (also known as cascading failure modelling) (Cao et al., 2025b).

Within the network structure, the strategic removal of certain components is a relatively straightforward and effective approach to simulating closures or overloads of ports and routes simultaneously. Typically, such “attacks” are performed based on a predetermined percentage of random deletions (as control groups) or specific factors such as degree (Wu et al., 2019), strength, centralities (Bai et al., 2023; Peng et al., 2018), clustering coefficient (Wang et al., 2016; Wu et al., 2019), etc. This approach helps explore the direct coupling impact of multiple failures on both the structural resilience (e.g., topology and connectivity) and functional resilience (e.g., efficiency and vulnerability) of networks. However, the direct removal of nodes or links is inherently a static, one-off treatment, assuming that (1) all failures occur in isolation at ports and thus the propagation mechanisms of failures are overlooked and (2) once one failure occurs in a port and the port will lose its functionality entirely, overlooking the different severity levels of the failure impacts.

In fact, recent literature highlights the dual-edged nature of dynamics and interdependencies within transportation systems, underscoring that while interconnected networks can offer redundancy and alternative pathways to maintain system functionality, they can also propagate disruptions, exacerbating systemic vulnerabilities (Li et al., 2025b). As a result, to investigate how failures propagate within shipping networks and assess the extent of damage they may cause, cascading models have been proposed by researchers as a dynamic modelling approach. Specifically, pioneered by Motter and Lai (2002), cascading failures within physical networks were considered to be triggered by an initial failure and executed by load diversions and movements (theoretically known as load redistribution behaviours), with all nodes constrained by their maximum capacities. When a failure occurs at a port (e.g., due to closures, natural disasters, war, or political events), its cargo load needs to be, partially or fully, redistributed to alternative ports to mitigate risks and maintain schedules (Asghari et al., 2023). If redistributed loads cause overloads (i.e., exceeding the maximum capacity) in alternative ports, severe congestions, operational inefficiencies, or even complete port blockages may happen, ultimately increasing shippers/carriers’ cost (Lu et al., 2024). Therefore, modelling cascading failures serves two key purposes: (1) to explore the propagation mechanism by which disruptions propagate through shipping networks; and (2) to deliver efficient load redistribution strategies mitigating the cascading effects to the least severity. To provide an explicit overview of the state-of-the-art, a review of existing cascading models applied in shipping networks is carried out and the results is presented in Table 1, summarising the relevant studies.

From the review, it is evident that valid load redistribution strategies need to address two key questions: how to select redistribution targets and how to determine the redistributed load volumes to each target. Current studies have attempted to provide solutions by implementing relatively fixed conditions for selection and redistribution. Specifically, one common approach to ensuring economic feasibility is to select targets within an appropriate range, indirectly reflecting considerations of redistribution costs. For instance, Bai et al. (2023), Xu et al. (2024a) and Cao et al. (2025b) imposed fixed time constrains for all redistributions, while Xu et al. (2022) used a varying distance criterion to ensure that alternative targets were no further than the original ones. Moreover, another important strategy for enhancing practical applicability is the selection of neighbouring or downstream ports. In other words, selected targets should be directly connected to the redistributing port, indicating an existing shipping route or trade relationship (Cao et al., 2025b; Ding et al., 2024; Jiang et al., 2024; Lu et al., 2024; Qu et al., 2024; Xu et al., 2024a). Additional strategies, such as ensuring the selected targets remain functional (Bai et al., 2023; Cao et al., 2025b; Xu et al., 2022), belong to the same country (Xu et al., 2022) or serve as a similar function (Bai et al., 2023), are based on different modelling preferences and considerations, further enhancing the realism of models. Once targets are determined, load volumes to be redistributed can be calculated based on the relative proportion of one or more characteristics of the selected targets. These characteristics include weight or capacity (i.e., port size) (Bai et al., 2023; Ding et al., 2024; Qu et al., 2024; Xu et al., 2024a), degree value (Lu et al., 2024; Xu et al., 2024a), distance (Xu et al., 2024a; Xu et al., 2024d), and composite customised feature (Cao et al., 2025b). By executing load redistribution strategies from the initial failed port, the resulted overloaded ports will trigger subsequent rounds of redistribution, thereby leading to the propagation of cascading failures. Based on designed simulation results, cascading failure models can be further used to identify critical sets of ports, where recent advancements have employed *meta*-heuristic optimisation procedures to investigate disruptions that could lead to extensive global congestion propagation (Xu et al., 2025a).

Among these previous studies, such static-assumption-based approaches can reveal the propagation mechanism of cascading failures to a certain extent but are not necessarily the most rational way to guide the transshipment of cargo flows. The strong static assumption reveals a significant gap in existing research on cascading failures, requiring new studies from an optimisation perspective aimed at proactively controlling and mitigating cascading impacts, thereby safeguarding overall network resilience. Therefore, this study aims to achieve such a transition in shipping resilience research by proposing optimised and adaptable redistribution strategies to reduce the damage to the resilience of the shipping network caused by cascading failures.

2.3. Resilience evaluation

After simulating disruptions within shipping networks, another crucial step is to determine effective quantitative indicators to measure resilience. Traditionally, some studies have utilised topological indicators to assess resilience changes before and after disruptions. These indicators include degree (measuring the node connectivity) (Jin et al., 2022; Xiao et al., 2024; Xu et al., 2024e), centralities (including degree centrality, betweenness centrality, closeness centrality, etc., which assess different locational characteristics of nodes) (Liu et al., 2018; Liu et al., 2023), clustering coefficient (measuring the tendency of nodes to cluster together) (Jiang et al., 2024; Xu et al., 2024e), etc. With advancements in the field, more physically meaningful indicators, i.e., offering stronger practical implications, were applied to shipping networks. Examples can be found in Table 1, where two commonly used resilience indicators are the node retention ratio (which is closely related to node failure ratio and giant connected component) and efficiency. At the network level, the node retention ratio measures the number of functional ports remaining in the shipping network after cascading failures, while efficiency quantifies the transmissibility between those surviving ports by calculating the average path length of the network (Bai et al., 2023; Cao et al., 2025b; Ding et al., 2024; Qu et al., 2024; Xu et al., 2024a; Xu et al., 2022). These two indicators are widely deemed as effective measures of structural and functional resilience, respectively. Beyond these, studies also attempted to refine existing indicators by employing methods such as summing discrete values (Qin et al., 2023), averaging sums (Guo et al., 2024; Xu et al., 2023; Xu et al., 2024e), calculating rates of change (Liu et al., 2023; Lu et al., 2024; Wan et al., 2023; Wang et al., 2025b; Xu et al., 2024b), and other statistical approaches (Guo et al., 2024; Guo et al., 2023; Li et al., 2025a; Si et al., 2025).

While the development of resilience assessment indicators in shipping networks is being undertaken, a significant gap remains in lacking an optimisation-based approach for decision-making beyond traditional past-event assessments. By finding the optimal or most compromised solutions (e.g. the PFs) under multiple conflicting or complementary evaluation indicators (i.e., objective functions), the proposed optimisation framework in this study has more practical applicability in real-world decision-making, assisting in resilience maintenance and management in shipping networks.

2.4. Research gaps and contributions

Despite substantial progress in resilience analysis for shipping networks, several critical research gaps persist in the existing literature. Firstly, most current studies predominantly focus on post-event assessments of cascading failure mechanisms and resilience losses, offering limited guidance for actionable strategies during disruptions, thus restricting their applicability for real-time maritime decision-making. To overcome this limitation, this study introduces the proactive MSO framework that transitions from passive evaluation towards optimal, iterative intervention. By simulating cascading failures dynamically and embedding optimised load redistribution strategies, the proposed framework significantly enhances operational decision-making during disruption events, thereby effectively mitigating resilience losses.

Secondly, load redistribution strategies in existing cascading failure studies are typically static, rule-based, and oversimplified, neglecting complex real-world trade-offs and stakeholder diversity. To bridge this critical gap, this research develops the SCM model, leveraging a tri-objective optimisation formulation encompassing transit time, port overloading, and network structural completeness. By adopting elite port selection, an improved Method of Successive Averages (MSA) algorithm, gradient-based evolutionary search for diverse Pareto-optimal solutions, and the CV-TOPSIS method for context-sensitive decision-making, this model ensures redistribution planning is simultaneously operationally feasible and resilient against disruptions.

Lastly, previous resilience-oriented strategies frequently lack empirical validation across realistic, large-scale shipping scenarios, limiting their generalisability and practical relevance. To address this, extensive simulations in the GCSN, involving 21 significant global ports, validate the effectiveness and practical value of the proposed MSO framework. Comparative analyses against four

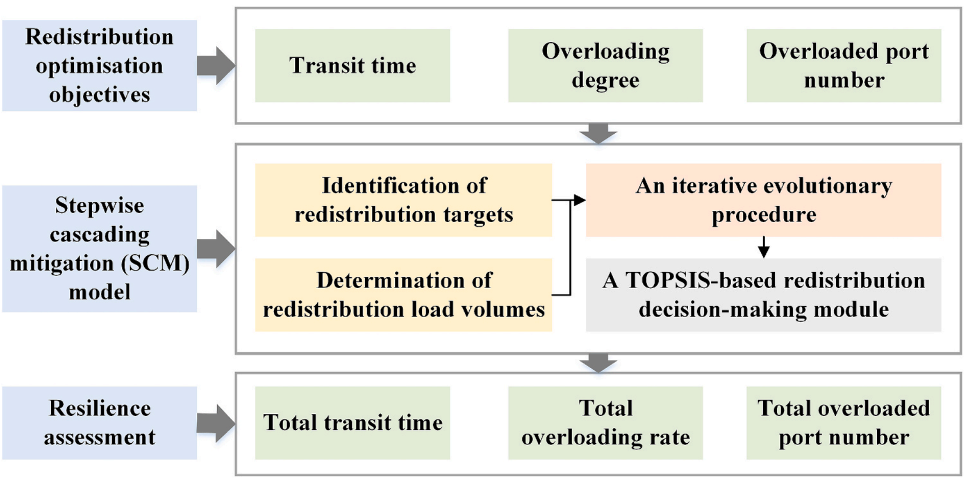


Fig. 1. The overview of the proposed MSO framework.

benchmark methods illustrate the framework's superior capability in reducing excess transit time, maintaining network efficiency, and controlling overloaded ports, thus substantiating its real-world applicability and enhancing industry confidence for resilience planning and emergency response strategies.

3. A multi-objective stepwise optimisation (MSO) framework

In this section, an innovative multi-objective stepwise optimisation framework, i.e., the MSO framework, is introduced to simulate load redistribution behaviours and evaluate their impact on the resilience of shipping networks. A comprehensive overview of this framework, along with the associated resilience assessment process, is illustrated in Fig. 1. Specifically, Section 3.1 provides definitions of the network structure and explains the propagation mechanism of cascading failures within shipping networks. To proactively mitigate the cascading effects on system resilience from an optimisation perspective, Section 3.2 introduces three key optimisation objectives. Subsequently, in Section 3.3, the SCM model is developed to simulate the continuous load redistribution process within the network. Finally, to quantitatively assess the resilience losses resulting from cascading failure propagation, Section 3.4 proposes three resilience indicators.

3.1. Definition of cascading failures in shipping networks

Denoting a shipping network as $G = (V, E)$, it consists of a set of nodes $V = \{v_i | i = 1, 2\cdots, N\}$, which represent ports, and a set of links $E = \{e_{ij} | i, j = 1, 2\cdots, N, i \neq j\}$, representing established shipping routes between these ports. Specifically, if port i is directly connected to port j, then $e_{ij} = 1$; otherwise, $e_{ij} = 0$.

Within this directed and weighted network structure, each port-to-port link e_{ij} contains essential information, including its directionality, weight w_{ij} (which represents the cargo volumes from port i to port j and can be obtained from service route data), and travel cost T_{ij} (measured by travel time from port i to port j). Regarding the nodes themselves, their scales are typically characterised by two attributes: weight and capacity. Referring to Motter and Lai (2002), the capacity of a given port i is assumed to be proportional to its weight, as defined by Eq. (1):

$$C_i = \lambda \times W_i \tag{1}$$

where λ is the capacity multiplier, generally with $\lambda \geq 1$. W_i denotes the weight of port i, in practical terms of this study, which refers to the total outbound cargo volume handled by port i, and is calculated as $W_i = \sum_{j \in V, i \neq j} w_{ij} e_{ij}$ (Cao et al., 2025b). In this study, the utilised service route data provides aggregated information for each port-to-port shipping route, including port calling sequences, deployed cargo volumes (measured in TEUs), service frequencies, sailing times between consecutive ports, and basic vessel properties for each route (Jarumaneeroj et al., 2023; Xin et al., 2025a). This data allows us to accurately capture the cargo flow between ports and reflects the real-world cargo-handling and service capacity of each port in the network (Xin and Yang, 2025).

Consequently, if a port experiences a disruption or failure, it is assumed that a proportion β $(0 < \beta \leq 1)$ of that port's load needs to be redistributed to alternative ports, either to mitigate operational risks or to maintain scheduling commitments (Lu et al., 2024). In such a scenario, these alternative ports will utilise their surplus capacity to accommodate the additional loads. However, if the sum of an alternative port's existing load and the newly received load exceeds its maximum capacity, the port becomes overloaded. An overloaded port is considered to operate under constrained conditions, significantly restricting its functionality and rendering it unable

Table 2
The notation list.

Notation	Definition
V	Set of ports
E	Set of links
S	Set of redistributed targets
N	Number of ports
t	The t-th redistribution round within the cascading failure model
τ	Iteration step within the MSA algorithm
$N_o(t)$	Number of overloaded ports at the t-th redistribution round
$\in$	Convergence threshold
λ	Capacity multiplier,$\lambda \geq 1$
β	Failure ratio,$0 < \beta \leq 1$
T_{ij}	Sailing time from port i to port j.
$L_i(t)$	Existing load of port i at the t-th redistribution round
$\Delta L_i(t)$	Redistributed load from port i
C_i	Capacity of port i.
W_i	Weight of port i.
CV_f	Coefficient of variation for the f-th objective function
Z_f^q	Z-score of the f-th objective for the q-th non-dominated solution
I^q	TOPSIS score for the q-th non-dominated solution
ε_{ij}	Decision variable, $\varepsilon_{ij} = 1$ if port j is selected as the redistributed target from port i, 0 otherwise
$\Delta L_{ij}(t)$	Decision variable, redistributed load from port i to port j

to receive further redistributed loads in subsequent rounds (Bai et al., 2023; Cao et al., 2025b). To avoid severe congestions resulting by continuous overloading, any overloaded port needs to further redistribute the cargo exceeding its maximum capacity to other eligible ports. This initiates another round of load redistribution, thus propagating cascading failures throughout the network. Mathematically, the load requiring redistribution from port i at the t-th redistribution round can be expressed as:

$$\Delta L_i(t) = \begin{cases} \beta \times L_i(t) & t = 0 \\ L_i(t) - C_i & t > 0 \end{cases} \tag{2}$$

where $L_i(t)$ represents the existing load of port i at the t-th redistribution round. Initially, before cascading failures occur, the load at port i equals to its original weight, i.e., $L_i(0) = W_i$. Therefore, if port i is the initially disrupted port triggering cascading failures (i.e., at $t = 0$), a proportion β of its load is assumed to be redistributed to other ports. Alternatively, if port i is an overloaded port (i.e., $t > 0$), only the portion of load exceeding its maximum capacity will be further sent out (Cao et al., 2025b; Lu et al., 2024). At each stage of redistribution, the selection of redistributed target is denoted by a variable ε_{ij} where $\varepsilon_{ij} = 1$ indicates that port j is selected as a redistributed target for port i. Correspondingly, the load redistributed from port i to port j at the t-th redistribution round is expressed as $\Delta L_{ij}(t)$.

As a result, for each redistribution round t, this study seeks to identify an optimal trade-off solution incorporating the ideal targets ε^*_{ij} and the corresponding redistributed load volumes $\Delta L^*_{ij}(t)$. This optimal solution aims to minimise additional costs for carriers and shippers, reduce the degree of port overload, and limit overall disruption to network structure and functionality. Following the completion of the entire cascading failure propagation process, the resilience of the shipping network is systematically evaluated.

To facilitate mathematical modelling and clearly focus on developing optimal redistribution solutions, this study assumes that all ports are considered unrecoverable during the propagation of cascading failures (Lu et al., 2024). Additionally, the variables and parameters used within the model are summarised in Table 2 for clarity and reference.

3.2. Multi-objective redistribution optimisation problem

As aforementioned, the optimal redistribution solution aims to balance the interests between different stakeholders. In this study, three objectives are identified to address these different stakeholder concerns, ranging from micro- to macro-level perspectives.

Firstly, carriers and shippers, as direct participants in shipping operations, prioritise the safe and timely delivery of cargo. To ensure the cost-effectiveness, proposed redistribution solutions should minimise delays to cargo arrivals, thereby avoiding increased transportation costs for carriers and additional time-related expenses for shippers. Therefore, the first optimisation objective F_1 in each redistribution step seeks to reduce the transit time for the redistributed load, ultimately lowering any extra costs borne by carriers and shippers:

$$\min F_1(t) = \sum\nolimits_{j \in S} T_{ij} \times \Delta L_{ij}(t) \tag{3}$$

where T_{ij} represents the sailing time from port i to port j.

Then, from the perspective of port operating groups, severe overloading can lead to logistics delays, increased safety and environmental pressures, and diminished port competitiveness. If port j inevitably becomes overloaded after receiving additional loads from port i at the t-th round, i.e., $[L_j(t-1) + \Delta L_{ij}(t)]/C_j > 1$, it is necessary to mitigate this degree of overloading. This ensures avoidance of more severe congestion and facilitates quicker restoration of normal operations. Therefore, for all participated ports at each redistribution, F_2 seeks to minimise the average overloading of them:

$$\min F_2(t) = \left[\sum\nolimits_{j \in S} \frac{L_j(t-1) + \Delta L_{ij}(t)}{C_j} \right] \Big/ \left(\sum\nolimits_{j \in S} \varepsilon_{ij} \right) \tag{4}$$

where $\sum_{j \in S} \varepsilon_{ij}$ indicates the number of ports selecting as the redistributed target.

Furthermore, from a broader network perspective, the most direct indicator of cascade failures' impact is the number of overloading ports. An increase in the number of overloaded ports directly reduces the functionality, structural completeness and overall resilience of the shipping network. Therefore, the third objective F_3 at each round of load redistribution is to minimise the number of overloaded ports:

$$\min F_3(t) = N_o(t) \tag{5}$$

where $N_o(t)$ is defined as the number of overloaded ports at the t-th redistribution round.

In summary, the three-objective function can be expressed as follows:

$$\min F = (F_1, F_2, F_3) \tag{6}$$

subject to the following constrains:

$$\Delta L_i(t) = \sum\nolimits_j \Delta L_{ij}(t),\ \forall i \in V, j \in S, t \in \{0, \mathbb{N}^+\} \tag{7}$$

$$\varepsilon_{ij} = \{0, 1\}, \forall i \in V \tag{8}$$

$$0 \le \Delta L_{ij}(t) \le \Delta L_i(t), \ \forall i, j \in V, t \in \{0, \mathbb{N}^+\} \tag{9}$$

$$L_i(t) \ge W_i, \forall i \in V, \, t \in \{0, \mathbb{N}^+\} \tag{10}$$

where constraint (7) enables the load equilibrium between the redistributing port and redistributed targets. Constraint (8) specifies the values of the binary variable ε_{ij}. If port j is selected as the redistribution target, i.e., $j \in S$, $\varepsilon_{ij} = 1$; otherwise, $\varepsilon_{ij} = 0$. Constraint (9) ensures that the redistributed load from port i to target port j is non-negative and does not exceed the total volume of load that needs to be redistributed from port i. Constraint (10) specifies the limits of $L_i(t)$. The existing load of port i may be dynamic during different redistribution rounds but will not be less than its original level, avoiding over redistribution.

3.3. A stepwise cascading mitigation (SCM) model

As introduced in Section 3.1, cascading failures are typically triggered by an initial port disruption and then propagate to the network by continuously redistributing loads. Reasonable load redistribution strategies can reduce the damage on network resilience against cascading failures and protect stakeholders' interests. To achieve this goal, the SCM model is proposed in this study for simulating redistributions. Specifically, considering diversity and feasibility, Section 3.3.1 develops an elite port selection method to identify all potential targets at each round of redistribution and output corresponding redistribution solutions. Within each solution, Section 3.3.2 applies an equilibrium algorithm to iteratively calculate the redistribution load volumes for each target. Subsequently, to reduce simulation complexity and ensure solution quality, an evolutionary procedure is introduced in Section 3.3.3. Here, the objective values of each redistribution solution will be calculated and compared to progressively retain those optimal and non-dominated solutions. These selected solutions will be finally inputted into Section 3.3.4, where a trade-off solution will be confirmed and utilised for decision-making.

3.3.1. Identification of redistribution targets

As previously outlined in Section 2.2, previous studies often limit redistribution target selection based on factors such as distance, connectivity, capacity, and operational status to ensure both economic feasibility and practical implementation. However, simply selecting the first largest or closest ports may not yield an optimal solution for all stakeholders; instead, a careful balance is essential to maintain both solution diversity and real-world applicability. To address this, this study adopts a more nuanced elite port selection approach.

Specifically, as illustrated in Fig. 2, when an upstream port i becomes disrupted or overloaded at a certain redistribution round, all eligible downstream ports (i.e., if $e_{ij} = 1$, port j is port i's downstream port), excluding those that are already disrupted or overloaded, are ranked according to two criteria: capacity and proximity. That is, downstream ports that are closer to port i (indicated by a virtual closeness in Fig. 2) or have higher capacities (indicated by a larger size) are considered as potential redistribution targets. From each criterion, the top d ports (referred to as "elite ports") are extracted to form a candidate set, resulting in a total size of $d \le D \le 2d$. It is worth noting that, although the GCSN contains hundreds of ports, the number of redistribution candidates considered at each step is localised and limited. In most cases, this candidate set includes no more than 10–20 ports, which substantially reduces the problem size.

Subsequently, from this candidate set, it is necessary to further form feasible redistribution solutions through systematic permutations. In other words, each redistribution round involves choosing K ports from the candidate set of D ports, generating combinations that can effectively optimise all objectives. Therefore, in this study, a total of $M = 2^D - 1 = \binom{1}{D} + \binom{2}{D} + \cdots + \binom{D}{D}$ potential redistribution combinations exist. Each combination (i.e., solution) m contains a variable set $S^m = \{\varepsilon_{id}^m\}_{d=1}^{D}$, where $\varepsilon_{id}^m = 1$ indicates that port d is selected as a redistribution target from port i. Then, redistribution load volumes to each target are calculated as detailed in Section 3.3.2.

3.3.2. Determination of redistribution load volumes

In this study, the MSA algorithm is applied to determine the load volumes redistributing from overloaded or disrupted ports to selected target ports. As an iterative method, the MSA algorithm is widely adopted in Traffic Assignment (TA) theory to solve User Equilibrium (UE). Essentially, the algorithm progressively converges towards an equilibrium solution by iteratively adjusting travel costs and redistributing flows across paths (Xu et al., 2024d). Referring to its iterative nature, the MSA algorithm is modified in this

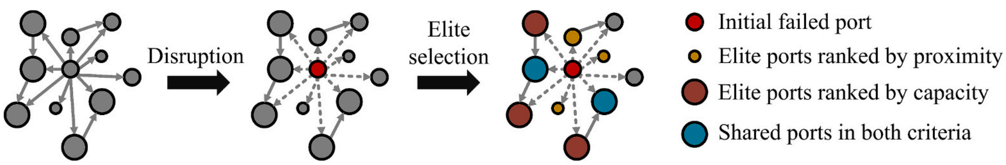


Fig. 2. An illustration of the elite port selection, where shared ports indicates those ports satisfy both criteria.

study for calculating redistribution loads dynamically in shipping networks and embedded into the stepwise optimisation framework without the need to perform large-scale searches.

Specifically, for the m-th redistribution solution, each selected target port d is initially assigned a cost constant δ_{id}^{m}. This constant represents the relative distance cost between port i and port d, and is calculated as:

$$\delta_{id}^{m} = \frac{T_{id}^{m} \times \varepsilon_{id}^{m}}{\sum_{d=1}^{D} (T_{id}^{m} \times \varepsilon_{id}^{m})} \tag{11}$$

Then, the all-or-nothing algorithm is applied, temporarily redistributing the entire load from port i to the target with the smallest nonzero cost constant (i.e., the closest one) at the beginning of iteration process (i.e., $\tau = 0$). At following iteration step τ (i.e., $\tau = \tau + 1$), a dynamic cost function is defined and updated, incorporating both the transfer volume of load and the relative cost constant:

$$Cost_{id}^{m,\tau} = \frac{\Delta L_{id}^{m,\tau-1} \times \varepsilon_{id}^{m}}{W_d} + \delta_{id}^{m} \tag{12}$$

where $\Delta L_{id}^{m,\tau-1}$ denotes the load volumes redistributed from port i to port d within the m-th solution at iteration step $\tau - 1$.

Based on the updated costs, the "interim" redistributed load $\Delta l_{id}^{m,\tau}$ directed to each target port is calculated as follows:

$$\Delta l_{id}^{m,\tau} = \Delta L_i \times P_{id}^{m,\tau} = \Delta L_i \times \frac{\varepsilon_{id}^{m} \times \exp(-0.5 \times Cost_{ik}^{m,\tau})}{\sum_{d=1}^{D} [\varepsilon_{id}^{m} \times \exp(- 0.5 \times Cost_{ik}^{m,\tau})]} \tag{13}$$

where $P_{id}^{m,\tau}$ indicates the redistribution proportion determined by the Logit model (Xu et al., 2024d). Here, the term "interim" (or "auxiliary") is used because the result $\Delta l_{id}^{m,\tau}$ will not be directly used as the final solution. Instead, it serves as an intermediate value intended to be combined with previously accumulated solutions. This reflects the core principle of the MSA algorithm, which calculates a weighted average (commonly using a step size of $1/\tau$) between the current iteration's interim result and the cumulative redistribution outcomes from earlier iterations, producing an updated, formal redistribution solution for the subsequent iteration. Therefore, the "actual" load volume redistributed to each target at iteration step τ is defined in Eq. (14) as follows:

$$\Delta L_{id}^{m,\tau} = \Delta L_{id}^{m,\tau-1} + \frac{1}{\tau} (\Delta l_{id}^{m,\tau} - \Delta L_{id}^{m,\tau-1}) \tag{14}$$

The algorithm continues iterating, recalculating redistribution costs and updating redistributed loads, until convergence is achieved. Here, convergence is determined by the following criterion:

$$\frac{\sqrt{\sum_{d=1}^{D} (\Delta L_{id}^{m,\tau} - \Delta L_{id}^{m,\tau-1})^2}}{\sum_{d=1}^{D} \Delta L_{id}^{m,\tau}} < \epsilon \tag{15}$$

where ϵ is a predefined convergence threshold, typically set to a very small value (e.g., 10^{-5}) (Xu et al., 2024d). Upon convergence, a complete load redistribution solution is finalised, consisting of both selected target ports and the corresponding redistributed load

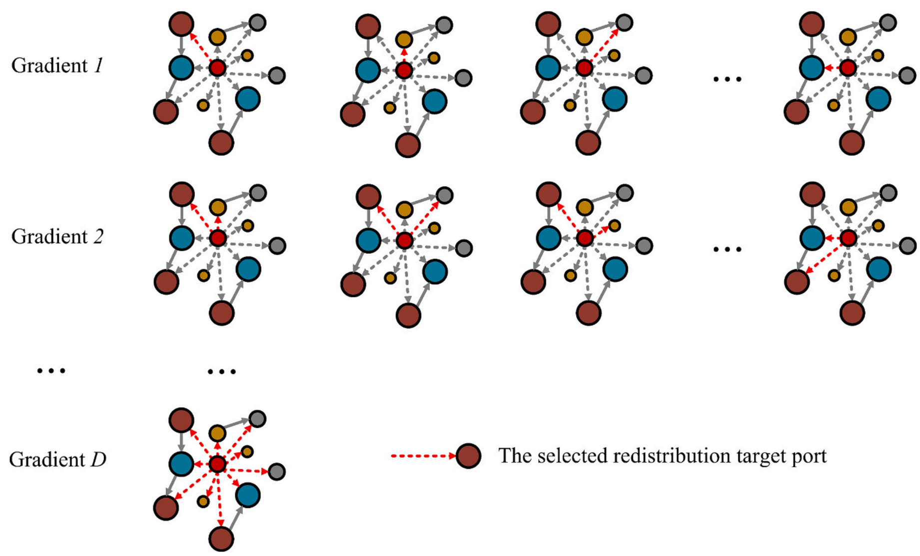


Fig. 3. An illustration of gradients. Note: the red dotted line represents target selection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

volumes.

3.3.3. An iterative evolutionary procedure

Following the modules introduced above, the specifics of each redistribution solution can be clearly determined, including the identity of selected target ports and the volumes of cargo redistributed to each target. However, as the number of candidate ports increases, the potential redistribution combinations rise exponentially, rendering exhaustive enumeration computationally expensive. To overcome this challenge, this study proposes a gradient-based evolutionary procedure.

Specifically, from the total of M redistribution solutions identified in Section 3.3.1, solutions can be categorised into D gradients based on the number of target ports involved. Here, the first gradient comprises solutions involving a single target port, totalling $\binom{1}{D}$ solutions. Similarly, the second gradient comprises solutions with two target ports, totalling $\binom{2}{D}$ solutions. In this manner, the last gradient, i.e., the gradient D, involves all D ports and thus consists of a single solution. For clearer understanding, Fig. 3 illustrates this gradient structure, with each subnetwork representing a redistribution solution, and red dashed arrows indicating the selected redistribution targets.

Starting from Gradient 1 (i.e., the one-port scenarios), redistribution solutions are passed to Section 3.3.2 in order to calculate the redistribution load volumes. Correspondingly, all three objective values for each redistribution solution can be calculated. Subsequently, internal filtering identifies and retains all non-dominated solutions from the current gradient to an external archive. Here, a solution is non-dominated (or Pareto-optimal) if no other solution is strictly better in every objective. Formally, solution S1 dominates solution S2 when S1 is at least as good as S2 in all objectives and strictly better in at least one (for this study, "better" means the objective value is smaller). If neither solution dominates the other, they are both considered non-dominated.

The algorithm then progresses to the next gradient (e.g., two-port scenarios), where a new set of combinations is evaluated. Each solution in this gradient is compared against those already stored in the external archive. If at least one new non-dominated solution is

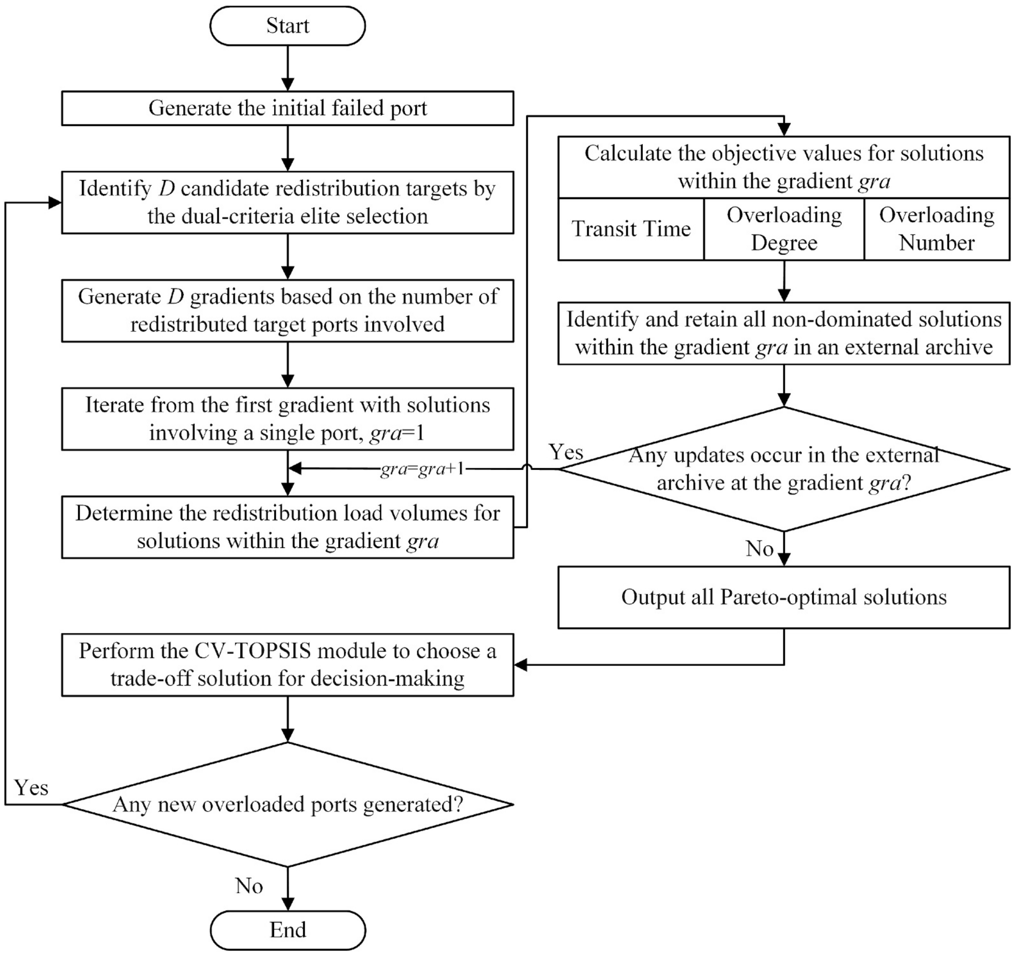


Fig. 4. The flowchart of the SCM model.

added or one dominated solution is excluded from the archive, it is interpreted as an improvement, and the algorithm proceeds to the next gradient. Conversely, if no update occurs, i.e., the archive remains unchanged, the gradient evolutionary procedure is terminated early to avoid unnecessary computation. This convergence criterion ensures that the algorithm explores increasingly complex solutions only when performance gains are still possible.

Through this evolutionary strategy, the optimisation framework effectively balances computational complexity with solution quality, constantly updating to retain new non-dominated solutions and terminating the iteration once no further improvements are found. The approach also aligns closely with industrial practices by exploring feasible solutions within the limited ports context, thus reducing operational costs and minimising disruptions to the resilience of shipping networks.

In the following step, the converged archive containing all Pareto-optimal solutions is passed to a TOPSIS-based decision-making module. A trade-off solution is selected and implemented accordingly. If any ports become overloaded afterwards, new redistribution rounds initiate from these newly overloaded ports, and the SCM model is executed again. For ease of understanding, a flowchart of this process is provided in Fig. 4.

3.3.4. A TOPSIS-based redistribution decision-making module

For each redistribution round, all non-dominated solutions are stored in the converged archive, collectively forming the PF. Although all of these solutions are feasible by achieving a balance across all three optimisation objectives, it still remains necessary to identify a trade-off solution to guide practical decision-making. In this study, the optimisation across three objectives is inherently non-linear, making it essential to systematically evaluate the relative merits of each solution to identify the optimal redistribution scenario. For Multi-Criteria Decision Making (MCDM) problems of this nature, various MCDM methods, such as Analytic Hierarchy Process (AHP) (Ceylan et al., 2023), Evidential Reasoning (ER) (Chang et al., 2021), TOPSIS, etc., offer different decision-making frameworks. Among them, TOPSIS is particularly suitable for this study due to its computational efficiency, ease of implementation, and ability to rank alternatives based on their geometric closeness to an ideal solution. Unlike methods that rely heavily on pairwise comparisons (e.g., AHP) or require subjective preference functions (e.g., ER), TOPSIS provides a straightforward and objective evaluation process. This makes it more appropriate for scenarios in this study, where a large number of alternatives are evaluated using quantitative performance criteria (Ma et al., 2021; Pan et al., 2024).

Before employing the TOPSIS method, a pre-assessment is performed on all Pareto-optimal solutions generated. Here, if the external archive contains only a single non-dominated solution after iterations, this solution is directly selected for redistribution without further evaluation. Conversely, if multiple non-dominated solutions remain, the Coefficient of Variation (CV) for each objective function is calculated first using Eq. (16) (Chen, 2019):

$$CV_f = \frac{\sigma_f}{\mu_f} \tag{16}$$

where $f \in \{F_1, F_2, F_3\}$, σ_f and μ_f denote the standard deviation and mean value of the objective f among all non-dominated solutions, respectively. In this study, the CV measures the dispersion of values for each objective, with higher CV values indicating greater variability. If the CV of a particular objective exceeds a predetermined threshold and significantly surpasses that of the other objectives, this implies substantial variation and notable distinctiveness among solutions. Under such circumstances, for this highly variable objective, the solution with the minimum objective value is directly selected. This approach differs from common practice; here, greater variability in a specific objective highlights the presence of a distinctly advantageous solution (Chen, 2019). For instance, when comparing two non-dominated redistribution solutions, one might substantially reduce costs but slightly increase port overload and disruption levels, while the alternative solution might lower disruptions and overloads but incur significantly higher costs. Choosing the former solution, although potentially introducing minor operational disruptions, would provide considerable practical advantages in overall cost-effectiveness. However, if the CVs of all objectives remain relatively small, indicating limited variability across objectives, the TOPSIS method is subsequently applied as follows.

Initially, assuming a total of Q non-dominated solutions generated by the cascading model, all solutions are normalised to eliminate scale differences between objectives. Here, the Z-score for each objective across Q solutions is calculated for normalisation. For any q-th solution, the Z-score of a given objective f is defined by Eq. (17):

$$Z_f^q = \frac{f^q - \mu_f}{\sigma_f} \tag{17}$$

Thus, the normalised data matrix Z can be expressed as:

$$Z = \begin{bmatrix} Z_{F_1}^1 & Z_{F_2}^1 & Z_{F_3}^1 \\ \cdots & \cdots & \cdots \\ Z_{F_1}^Q & Z_{F_2}^Q & Z_{F_3}^Q \end{bmatrix} \tag{18}$$

Next, the ideal (best) and anti-ideal (worst) solutions for each objective function f, A_f^+ and A_f^-, are determined by identifying minimum and maximum Z-score values, respectively:

$$A_f^+ = \min(Z_f^1, Z_f^2, \cdots, Z_f^q) \tag{19}$$

$$A_f^- = \max(Z_f^1, Z_f^2, \cdots, Z_f^q) \tag{20}$$

To evaluate the proximity of each normalised solution to both the ideal and anti-ideal solutions, the Euclidean distances D^{q+} and D^{q-} are computed:

$$D^{q+} = \sqrt{\sum_f \omega_f \left(Z_f^q - A_f^+\right)^2} \tag{21}$$

$$D^{q-} = \sqrt{\sum_f \omega_f \left(Z_f^q - A_f^-\right)^2} \tag{22}$$

where ω_f indicates the weight assigned to the objective f.

Finally, the TOPSIS score I^q for each solution q is calculated to indicate its relative closeness to the ideal solution:

$$I^q = \frac{D^{q+}}{D^{q+} + D^{q-}} \tag{23}$$

In this study, a smaller value of I^q signifies a better solution, as it is closer to the ideal scenario and farther from worst scenario. Consequently, the solution with the smallest I^q is selected as the optimal trade-off solution for redistribution decisions.

3.4. Resilience assessment

Within the proposed MSO framework, once an initial failure occurs at a port, the SCM model iteratively simulates the propagation of disruptions throughout the shipping network. When this process concludes, the resilience of the network is systematically assessed from three dimensions: economic, functional, and structural.

Firstly, an economic indicator is introduced to quantify additional redistribution costs incurred during cascading failures. In this study, the total Transit Time (TT) for all redistributed cargo loads, represented by the total sailing distance or travel time, is employed as a measure of the economic losses (i.e., reductions in economical resilience) sustained by the network. This indicator is defined by Eq. (24):

$$TT = \sum_t \sum_i \sum_j T_{ij} \times \Delta L_{ij}(t) \tag{24}$$

Secondly, to evaluate the micro-level port vulnerability throughout the redistribution process, this study introduces the total Overloading Rate (OR) as a functional resilience indicator. The OR metric is defined as the cumulative overloading level of all ports involved in the cascading failure propagation. As introduced in Section 3.2, for ports that become overloaded after receiving loads from port i, their average overloading rates are calculated as the average ratio between its exceeded load and its capacity. By summing up all these individual overloading rates, the total OR is then obtained by Eq. (25):

$$OR = \sum_t \sum_i \left[\sum_j \frac{L_j(t-1) + \Delta L_{ij}(t)}{C_j} \Big/ \sum_j \varepsilon_{ij} \right] \tag{25}$$

This indicator provides a direct and interpretable measurement of port-level stress, capturing the compounded effect of load redistribution strategies on local port operations. Along with other metrics focusing on network-wide connectivity or economy, OR reflects the operational feasibility and risk exposure of ports.

Lastly, as previously outlined, load redistributions can lead to multiple ports becoming overloaded, thus impairing their operational capacity and negatively affecting the structural resilience of the network. Therefore, the Number of Overloaded Ports (NOP) is introduced as an indicator to quantify disruptions in network structure and connectivity. Upon completion of the redistribution processes, NOP is computed as the cumulative total of overloaded ports over all redistribution cycles, as expressed in Eq. (26):

$$NOP = \sum_t N_o(t) \tag{26}$$

These three indicators, i.e., TT, OR, and NOP, collectively provide a comprehensive resilience assessment of the shipping network, effectively capturing economic losses, functional risks, and structural disruptions due to cascading failures. Furthermore, it is worth noting that the three resilience indicators introduced above are directly aligned with the optimisation objectives defined in the MSO framework. Specifically, TT corresponds to the objective function F_1, which captures the time- and cost-related implications of redistribution for carriers and shippers. OR reflects the cumulative port-level overload risk and is mathematically equivalent to the summation of F_2 across all redistribution rounds. Similarly, NOP evaluates the overall structural integrity of the network after cascading events and corresponds to the objective F_3. This one-to-one correspondence ensures consistency between optimisation and post-optimisation evaluation, enabling a transparent interpretation of trade-offs and facilitating effective decision support grounded in both model outputs and resilience performance.

4. Results and analyses

In this section, the proposed framework is applied to the GCSN. The utilised datasets are introduced in Section 4.1, following the detailed experimental results.

4.1. Experimental datasets

In this study, the GCSN structure is established to investigate its resilience against cascading failures. To build this network, service route data sourced from the BlueWater Reporting Application Server (https://www.bluewaterreporting.com) are utilised as the input for the proposed framework (Cao et al., 2025b). In total, 45,584 service route records covering the period from 2020 to 2023 are employed to construct the GCSN, which includes 686 ports worldwide.

In practice, the geographical distribution (such as strategic location) and port scale significantly influence the importance of individual ports within the network. Previous studies have demonstrated that disruptions at larger or strategically located ports typically cause greater negative impacts on network resilience, whereas disruptions at smaller or regional service ports have relatively limited effects (Cao et al., 2025b; Lu et al., 2024). This is because, for smaller ports with typically handling relatively less loads, a common risk avoidance approach for them is to temporarily redistribute their loads to nearby major ports, thereby mitigating further disruptions. To facilitate a targeted analysis of those key ports given this background, this study divides the entire network into seven distinct communities based on the modularity partition method proposed by Xu et al. (2020), which considers connectivity patterns between ports. Subsequently, the three largest ports (based on capacity) from each community are selected for detailed analysis, resulting in a set of 21 critical ports, as listed in Table 3. The distribution of ports within the GCSN and their associated community divisions are illustrated in Fig. 5.

4.2. Comparative analysis

In this section, to demonstrate the superiority, the proposed MSO framework is benchmarked against several state-of-the-art cascading failure algorithms, namely the Network Structure Load Redistribution (NSLD) method (Lu et al., 2024), the Breadth-First Redistribution Rule (BFRR) (Cao et al., 2025b), the MSA-based method (Xu et al., 2024d), and the Local Weighted Flow Redistribution Rule (LWFRR) (Bai et al., 2023), all of which build upon the foundational load-capacity model initially proposed by Motter and Lai (2002).

Specifically, the core aim of simulating cascading failures is to devise effective load redistribution strategies capable of mitigating the negative impacts of port disruptions, thereby minimising dynamic disturbances to network resilience. To perform a comparative analysis systematically, each of the 21 selected ports (as identified in Section 4.1) is individually used as an initial point of failure. The cascading failures originating from these ports are simulated using each of the competing algorithms, and three resilience indicators defined in Section 3.4 are calculated to evaluate the extent of damage inflicted upon the network's resilience. Ultimately, each algorithm is executed 21 times, i.e., once for each initial port failure scenario, and the results obtained from these runs are averaged and recorded.

Among the algorithms, a universal hyperparameter termed the capacity multiplier λ (although it may have different names across various studies) is employed to control the maximum capacity assigned to each port. In this comparative analysis, λ is changed from 1.1 to 2.0 to explore how increases in port capacity influence the network's resilience against cascading failures. Additionally, this study incorporates another critical hyperparameter known as the failure ratio β, representing the proportion of cargo load requiring redistribution from the initially disrupted port. To ensure consistency and comparability with previous studies, β is set to 1 for the MSO framework in this analysis, meaning that all cargo loads at the initial failed port are assumed to be fully redistributed.

By aggregating these comparative results, Fig. 6 provides a comprehensive illustration of performance differences between the proposed framework and the four alternative algorithms. Clearly, the proposed MSO method consistently outperforms the other algorithms across three indicators and all capacity multipliers, evidentially demonstrating its effectiveness and superiority.

As for these three indicators, all algorithms exhibit a decreasing trend as port capacities increase. This decline is because higher capacities provide greater redundancy, enabling the improved resilience to absorb the redistributed load. Taking the NOP as an instance (Fig. 6 (a)), as a crucial and direct measurement, NOP indicates the degree of structural disruption due to cascading failures. Here, a substantial improvement is noticeable for our proposed method. The NOP values achieved by the MSO framework are

Table 3
Global large-scale ports used for subsequent analyses.

No.	Port Code	Port Name	Community	No.	Port Code	Port Name	Community
1	SGSIN	Singapore	1	12	AUSYD	Sydney	4
2	MYPKG	Klang	1	13	ESVLC	Valencia	5
3	LKCMB	Colombo	1	14	GRPIR	Piraeus	5
4	USSAV	Savannah	2	15	ESBCN	Barcelona	5
5	USCHS	Charleston	2	16	NLRTM	Rotterdam	6
6	USNYC	New York	2	17	BEANR	Antwerp	6
7	MXZLO	Manzanillo	3	18	DEHAM	Hamburg	6
8	PECLL	Callao	3	19	CNSHA	Shanghai	7
9	PAROD	Rodman	3	20	CNNGB	Ningbo	7
10	AUBNE	Brisbane	4	21	HKHKG	Hong Kong	7
11	AUMEL	Melbourne	4				

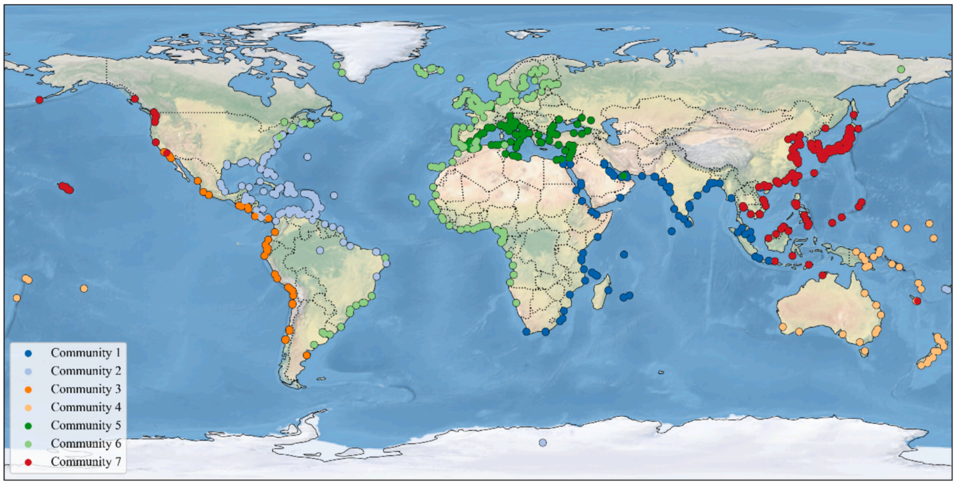


Fig. 5. The distribution of ports and community detection results within the GCSN.

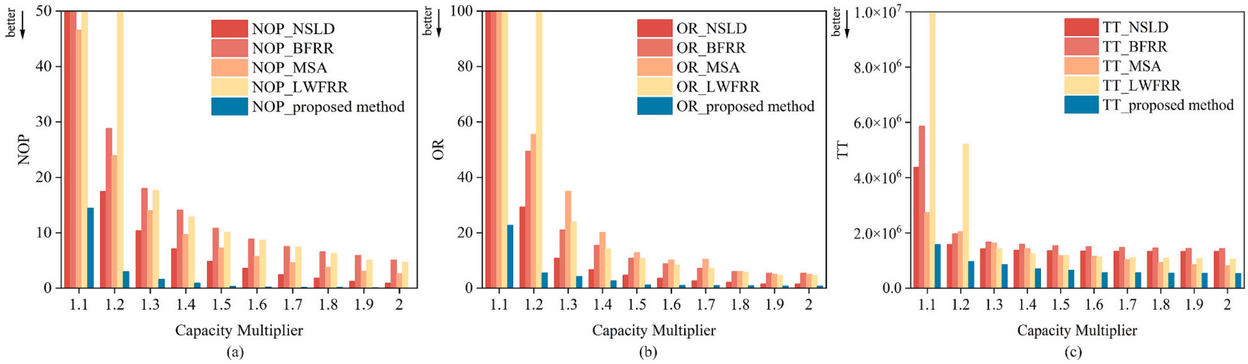


Fig. 6. Comparison of the five cascading failure models.

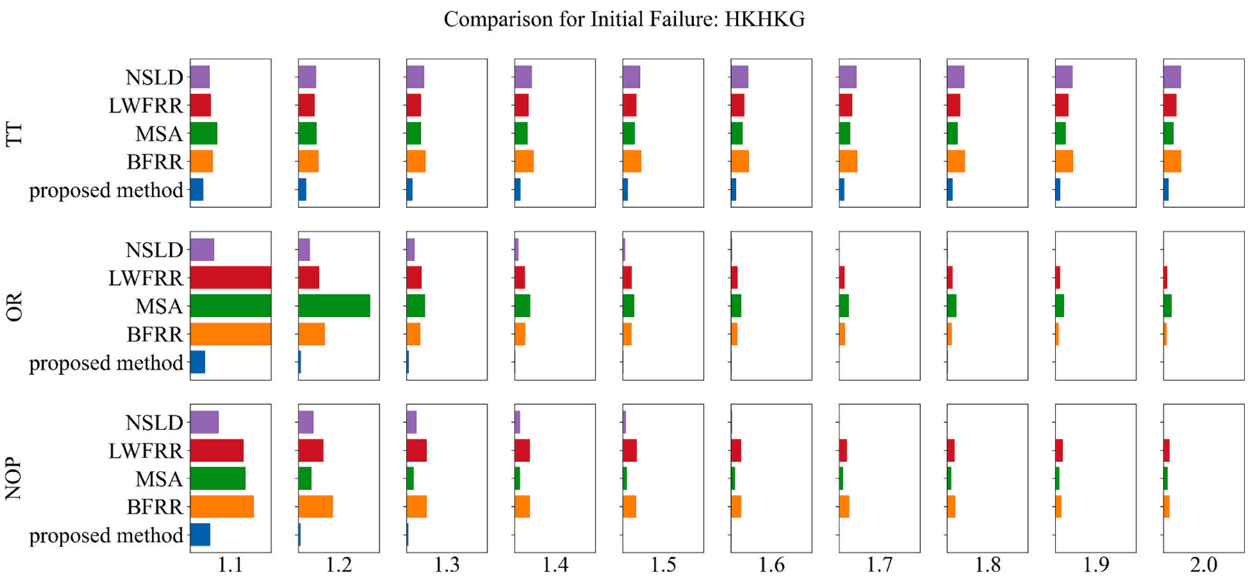


Fig. 7. Comparison of the five cascading failure models (Initial failure scenario: Port of Hong Kong).

consistently much lower than those of other methods, reflecting a significantly more effective load redistribution strategy in mitigating disruptive impacts and maintaining overall resilience within the GCSN.

Similar superiorities are also evident regarding port vulnerability (OR in Fig. 6(b)) and economic effectiveness (TT in Fig. 6(c)), highlighting the practical necessity and applicability of adopting the proposed multi-objective optimisation framework. In fact, a critical advantage of our proposed approach compared to existing methods lies in bridging the gap between theoretical model design and real-world effectiveness. Specifically, instead of relying solely on predetermined theoretical parameters such as network weights, topology, or distance, our optimisation framework explicitly incorporates practical, benefit-oriented considerations. Whereas traditional approaches typically focused exclusively on post-event assessment through simulations and indicator evaluation, this study effectively supplements the previously overlooked aspect of pursuing more optimal load redistribution strategies to proactively mitigate damage and maintain the network resilience. Therefore, this multi-objective optimisation approach is vital for developing resilient port risk-management strategies and promoting greater regional and global synergy among ports.

4.3. Case studies

In this section, two specific ports, Hong Kong (port code: HKHKG) and Hamburg (port code: DEHAM), are selected as detailed case studies to illustrate the redistribution processes and corresponding Pareto-optimal results. Comparative results for these two scenarios are presented in Figs. 7 and 8, respectively.

As two of the busiest world-leading ports, the ports of Hong Kong and Hamburg serve as key gateways in Asia and Europe, respectively. Selecting both representative ports as case studies provides valuable insights into the vulnerabilities and resilience of the GCSN across different regions. As illustrated in Figs. 7 and 8, the proposed MSO framework exhibits exceptional effectiveness in developing valid load redistribution strategies and mitigating the negative impacts of cascading failures in both scenarios. To ensure realism, the specific redistribution processes presented in this section assume a capacity multiplier (λ) of 1.2, implying a 20 % safety redundancy maintained by the GCSN, with the failure ratio (β) kept at 1, meaning that all loads from the initial disrupted port are redistributed. The statistics are presented in Table 4.

The Port of Hong Kong, as one of Asia's busiest container ports, serves as a crucial node connecting southern China and Southeast Asia to global markets. According to the MSO framework, the deployed load redistribution strategies directly result in minor cascading failures, with two ports overloading (NOP = 2), a slight overloading pressure for participated ports (OR = 3.0258), and limited additional costs (TT = 986,661). As illustrated in Fig. 9 (a), the proposed method involves three successive rounds of redistribution from Hong Kong, balancing stakeholder interests at each round. Additionally, Fig. 10 illustrates all non-dominated solutions from each redistribution round forming PFs, from which optimal trade-off solutions are selected to guide the redistribution decisions.

Specifically, at the first round, the nearby ports of Shekou (CNSHK) and Yantian (CNYTN) are chosen as targets to absorb the redistributed load from Hong Kong, becoming overloaded as a consequence. This decision is both practically feasible and strategically sound, given that Shekou and Yantian are geographically proximate to Hong Kong, significantly reducing transit times and transhipment costs. Furthermore, both ports possess substantial container-handling capacities, advanced infrastructure, and extensive shipping routes, making them well-equipped to manage additional loads. Although both ports become overloaded following redistribution, sharing the load between them significantly reduces individual port pressures and mitigates the broader regional disruption compared to single-target redistribution or redistributions involving more smaller ports with limited capacities. In subsequent

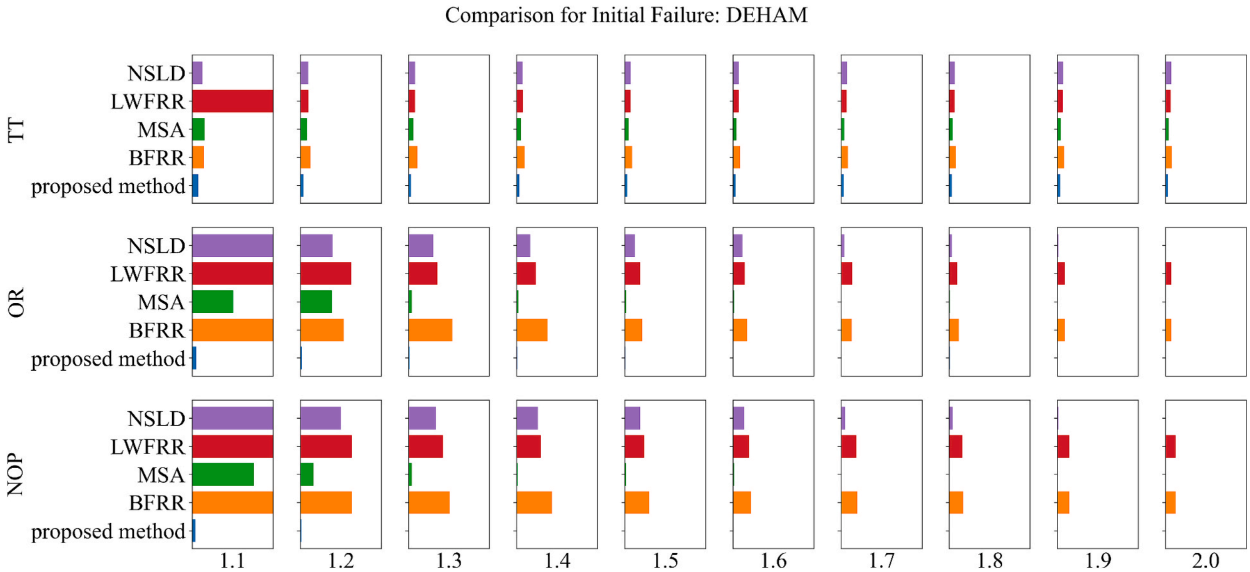
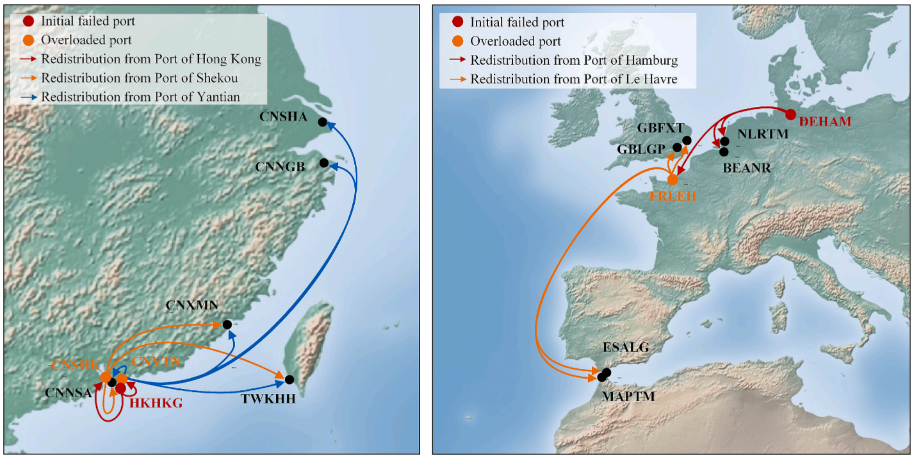


Fig. 8. Comparison of the five cascading failure models (Initial failure scenario: Port of Hamburg).

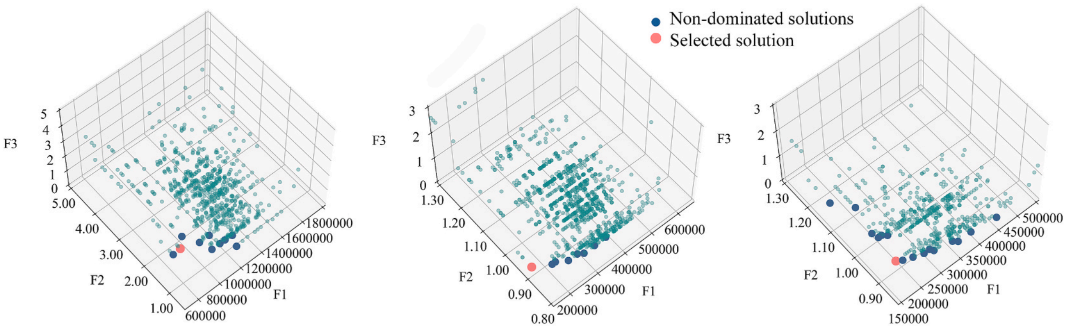
Table 4
The results of the proposed method in two scenarios.

Initial failed port	The start port of redistribution	Number of solutions	Number of non-dominated solutions	The trade-off target solution	F1	F2	F3	NOP	OR	TT
HKHKG	HKHKG	1012	11	CNSHK, CNYTN	619,746	1.1816	2	2	3.0258	986,661
	CNSHK	1022	8	CNNSA, CNXMN, TWKHH	169,058	0.9218	0			
	CNYTN	510	16	CNNGB, CNNSA, CNSHA, CNXMN, TWKHH	197,857	0.9224	0			
DEHAM	DEHAM	511	12	BEANR, FRLEH, NLRTM	334,417	0.9980	1	1	1.8489	382,249
	FRLEH	510	13	ESALG, GBFXT, GBLGP, MAPTM	47,831	0.8509	0			



(a) Cascading failure triggered by Port of Hong Kong (b) Cascading failure triggered by Port of Hamburg

Fig. 9. Detailed redistribution processes originating from the Ports of Hong Kong and Hamburg.

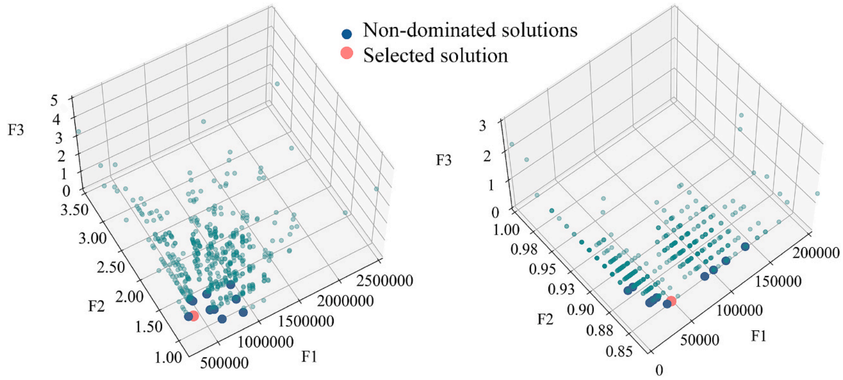


(a) Redistribution solutions from Port of Hong Kong (b) Redistribution solutions from Port of Shekou (c) Redistribution solutions from Port of Yantian

Fig. 10. Pareto-optimal redistribution decisions for the scenario of the Port of Hong Kong.

redistribution rounds, as the remaining loads become smaller, the MSO framework deploys a more dispersed redistribution strategy. For instance, ports including Xiamen (CNXMN), Kaohsiung (TWKHH), Ningbo (CNNGB), and Shanghai (CNSHA) are subsequently utilised as redistribution targets from Yantian, capitalising on their extensive resources to mitigate regional risks and economic losses.

Similarly, a broader and more diversified redistribution approach is observed in the scenario of the failure of the Port of Hamburg (Fig. 9 (b) and Fig. 11). As Germany's largest port, Hamburg serves as a central hub for Northern and Central European markets. Within the dense European container shipping system, the redistribution strategy employed illustrates a careful balance between regional and global risk considerations, alongside optimisation of network resilience and contingency management. The cascading failures originating from Hamburg can be mitigated through two redistribution rounds. Initially, loads from Hamburg are redirected to the nearest



(a) Redistribution solutions from Port of Hamburg (b) Redistribution solutions from Port of Le Havre

Fig. 11. Pareto-optimal redistribution decisions for the scenario of the Port of Hamburg.

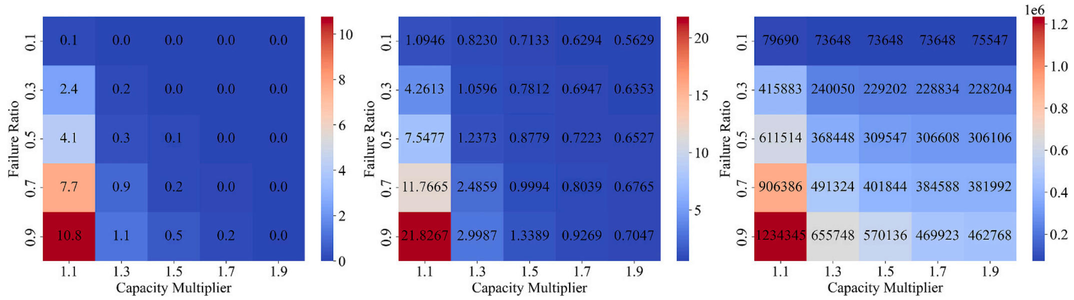
major alternative ports in the North Sea region, i.e., Rotterdam (NLRTM), Antwerp (BEANR), and Le Havre (FRLEH), which share extensive shipping routes and networks with Hamburg and can rapidly absorb cargo flows due to their strategic proximity. This targeted approach promptly limits regional disruptions and effectively balances the three optimisation objectives proposed in this study. Subsequently, to avoid overwhelming these three key ports and creating further logistical bottlenecks within their countries, the second round involves redistributing cargo from Le Havre to additional ports located in the United Kingdom (i.e., the ports of Felixstowe (GBFXT) and London Gateway (GBLGP)) and Southern Europe (i.e., the ports of Algeciras (ESALG) and Tanger Med (MAPTM)). This multi-regional decentralisation strategy reduces the risk of regional congestion, leveraging the diverse capabilities and geographical distribution of European ports. Consequently, this approach significantly decreases operational disruption costs and reduces overall transhipment complexity.

Overall, both case studies demonstrate clearly the reasonableness and reliability of the proposed MSO framework. The redistribution decisions effectively balance risk avoidance and cost efficiency, highlighting the framework's flexibility and capability in real-world emergency response scenarios. By integrating considerations of economy, port capacity, and network connectivity, the proposed approach offers practical guidance to shipping companies, port operators, and policymakers in their efforts to develop effective risk management strategies. Additionally, by promoting decentralisation and regional equilibrium, the MSO framework successfully reduces both the scale and intensity of cascading failure propagation, substantially contributing to the sustained resilience of the GCSN.

4.4. Sensitivity analysis

As discussed in earlier sections, two key hyperparameters, i.e., capacity multiplier and failure ratio, significantly influence the extent of damage cascading failures cause to the resilience of the GCSN. In this study, the capacity multiplier sets the maximum handling capacity of each port within the GCSN, while the failure ratio determines the proportion of cargo load requiring redistribution from the initially disrupted port. Given that the initial load (throughput) at each port is fixed, the capacity multiplier, on the other hand, also effectively controls the redundancy level within the GCSN. In practical terms, this redundancy serves as a safety margin, enabling ports to absorb unexpected cargo flows, such as those resulting from upstream overloaded ports.

Still using the 21 key ports identified in Section 4.1 as individual initial disruption scenarios, a sensitivity analysis is performed by calculating the average values of the three resilience indicators under various combinations of both hyperparameters. Overall, it is expected that increases in network capacity or decreases in the failure ratio would mitigate the impacts of cascading failures, aligning



(a) NOP (b) OR (c) TT

Fig. 12. Average values of the three indicators under different values of capacity multiplier and failure ratio.

closely with the results illustrated in Fig. 12. Specifically, as the capacity multiplier increases from 1.1 to 1.9, the average values of NOP, OR, and TT decrease steadily. Likewise, reductions in the failure ratio, meaning fewer loads require redistribution from the initial disrupted port, significantly alleviate adverse impacts on network resilience.

Moreover, the proposed MSO framework demonstrates effective risk-control protocols. Across these scenarios involving disruptions at 21 major ports, the MSO framework successfully restricts the propagation of cascading failures within acceptable bounds. Even in situations featuring limited port capacities and relatively severe failure ratios, for instance, a capacity multiplier of 1.1 and a failure ratio of 0.9, the average number of overloaded ports remains around 10. While this scenario implies moderate impacts on network efficiency and economic costs, the disruption level remains manageable and notably outperforms similar scenarios previously examined by Lu et al. (2024), Cao et al. (2025b), and Xu et al. (2024a). Furthermore, when sufficient capacity exists within the network (e.g., capacity multipliers exceeding 1.5), cascading failure impacts are nearly fully mitigated through the proposed load redistribution strategies.

Practically, these findings also underscore the critical importance of maintaining adequate safety redundancy and effective risk management practices. For policymakers and port authorities, ensuring continuous port redundancy of at least 10 % above regular throughput levels is essential for preventing severe port congestion and overload conditions. As suggested by (Zhao et al., 2024a), such timely governmental intervention and strategic policies can considerably mitigate the negative impacts on global supply chains and economic activities. Likewise, for shipping companies and port operators, adopting robust load redistribution strategies represents a crucial measure for avoiding substantial economic losses and reducing pressure on neighbouring ports.

5. Discussions

The findings of this study underscore the multifaceted superiorities of the proposed MSO framework in addressing cascading failure propagation within the GCSN. By integrating theoretical modelling, optimisation algorithms, and practical decision-making techniques, this research furnishes new insights into both the academic study of shipping resilience and the operational strategies of the maritime industry, especially benefiting the real-world management and maintenance of resilience in global shipping networks. Below, four key aspects are discussed accordingly: the theoretical significance of the method, the practical importance of the results, the industry value of the findings, and the outlook for shipping network resilience studies.

(1) Theoretical significance of the proposed framework

A principal theoretical contribution of this study lies in its introduction of the MSO framework that shifts from conducting post-event simulations to delivering proactive resilience maintenance strategies. Beyond traditional cascading failure models that predominantly concentrate on post-hoc assessments of propagation mechanisms, the key objective of our MSO approach is to actively optimise load redistribution at each step of propagation. This dynamic emphasis advances theories on complex network resilience by incorporating real-world constraints, economic considerations, and port capacity limitations.

More detailed, the SCM model's four-module design provides further theoretical depth. As described in Section 3.3, the redistribution target selection module introduces a novel approach to systematically generalise a broad set of potential redistribution targets into multiple feasible combinations through a selective permutation strategy. Concurrently, the improved MSA algorithm iteratively calculates optimal redistribution loads for each decision scenario, effectively capturing the evolving interplay between economic costs, port capacities, and overall network efficiency. As a result, both diversity and convergence among redistribution solutions are robustly assured.

In the context of shipping networks, the number of redistribution targets significantly influences risk propagation and simulation complexity. Previous research has indicated that overly dispersed redistribution strategies may engage numerous smaller ports with limited redundancy, thereby exacerbating disruption propagation (Cao et al., 2025b). To address this, the SCM model progressively and systematically generates diverse, non-dominated solutions using the evolutionary gradient approach. Specifically, non-dominated solutions are sequentially identified, beginning with those involving fewer ports and gradually progressing to solutions involving more ports. By embedding these advanced multi-objective optimisation principles, this study refines cascading failure models into a comprehensive, integrative, and Pareto-optimal approach that closely reflects real operational complexities.

Furthermore, while traditional scalarisation methods could combine the three objectives into a single function, this study retains the multi-objective optimisation framework followed by the decision-making process (TOPSIS) to preserve trade-offs among stakeholder-driven priorities. This separation ensures solution diversity, avoids premature weight assignments, and enables more flexible, interpretable and context-aware decision support after optimisation.

(2) Practical importance of the results

Beyond its theoretical appeal, the MSO framework also exhibits high practical relevance. Simulation results, as shown in Fig. 6, demonstrate that the proposed load redistribution solutions substantially outperform standard methods in maintaining network resilience. Even under stringent conditions in Fig. 12, including those with limited port capacity (i.e., low redundancy, $\lambda = 1.1$) and high-intensity disruptions (e.g., nearly complete port shutdowns, $\beta = 0.9$), the model effectively curtails the number of overloaded ports (less than 2 % of global ports on average), controls overloading rates for ports, and limits total transit time. In practice, such robust performance indicates that a carefully managed redistribution plan, informed by data on port proximity, ship capacity, and route connectivity, can rapidly stabilise network operations.

In particular, this stepwise design allows stakeholders to enact rapid, favourable decisions at critical moments accordingly, mitigating the risk of large-scale cascading failures with reduced calculation complexity. Unlike traditional one-time global optimisation, the framework formulates the multi-objective optimisation task at each round (or step), identifying the most appropriate redistribution scheme and observing its impact on the network. This "step-by-step" nature is closer to the operation of the actual transport system, where each port is a relatively independent entity and dynamically adapts the strategy based on the current state of the network and the most up-to-date congestion, pursuing minimal disruptions to its benefits, the downstream ports and the resilience of the network. As a result, the decision path for each step of optimisation and redistribution is traceable and interpretable. This is important for real port operators and policy makers and helps to translate the model results directly into actionable emergency management strategies, even interfacing with real-time decision support systems. For example, feedback can be obtained immediately after the completion of the current round of redistribution and the next round of optimisation can be carried out accordingly, allowing the model to be embedded into the emergency response process in real time.

Case studies of major ports, including Hong Kong and Hamburg, also highlight and validate the robust and effective nature of this adaptive framework. Instead of shifting all pressure to the nearest mega-hub or simply utilising all possible targets, the MSO framework promotes decentralised redistribution across a set of optimally selected ports, where load redistributions occur in smaller, better-controlled increments, fewer ports become critically overloaded, and cascading disruptions across regions are less severe. Eventually, the structural and functional integrity of the wider network is thereby preserved. This aspect of the model is especially useful for ports in regions with uneven infrastructure development, where carefully managing limited capacity is essential to maintaining operational continuity.

(3) Industry value and real-world applications

As introduced in Section 1, the increasing uncertainties and those occurred events within global supply chains, ranging from global pandemics, climate changes to regional conflicts, have proven that the impact of localised disruptions can quickly propagate across continents. In such an environment, the ability to pre-emptively plan for cascading failures and implement real-time, multi-objective redistribution strategies is essential for a range of maritime stakeholders, including port authorities, shipping lines, logistics service providers, and policymakers.

Specifically, at a micro level, the OR serves as a critical indicator of port vulnerability and demonstrates the effectiveness of the proposed strategy in mitigating localised pressures. As shown in Figs. 6 and 12, the proposed method consistently maintains lower overloading rates across failure scenarios, where the OR values are at most around 1/5 of those produced by other benchmarks, confirming its advantage and capability in preserving functional resilience for individual ports. Nevertheless, as illustrated by the numerical results in Fig. 12, ports within the GCSN are strongly encouraged to implement protective cooperation and infrastructure investment strategies aimed at maintaining a minimum redundancy level of 10 %, and ideally reaching 30 % redundancy. This level of redundancy enables ports to absorb redistributed cargo more effectively, thereby preventing the majority of disruptions from escalating into catastrophic failures. This strategic direction is also supported by previous studies, which have highlighted the critical role of infrastructure redundancy and inter-port cooperation in enhancing network-wide resilience and reliability. These works reaffirm the value of strategic co-opetition, i.e., a balance of cooperation and competition, among ports as a means to collectively withstand and recover from disruptive events in maritime transport systems (Asadabadi and Miller-Hooks, 2018, 2020).

Shipping companies and vessel operators can use the model to identify optimal contingency routing when ports are disrupted, thereby avoiding excessive delays, penalties, or loss of cargo value. As the framework considers economic, structural, and functional objectives in parallel, it aligns well with commercial imperatives to maintain service levels while minimising costs and reputational damage. For instance, in the Hong Kong scenario ($\lambda = 1.2$), our method reduces TT by over 50 % compared to the LWFRR benchmark and only leads to 2 overloaded ports compared with the MSA of 13 and the NSLD of 15. Furthermore, strategic alliances, encouraged by governmental incentives or subsidies, have also been recognized as effective mechanisms to enhance port resilience against extreme weather and operational disruptions (Zhao et al., 2024b). Given this, the output of the model offers guidance to coordinate inter-port collaborations and pre-arranged redistribution agreements, allowing for swifter responses when disruptions do occur.

At a broader network scale, the indicator NOP serves as another key resilience indicator and also reflects the model's effectiveness in avoiding widespread congestion. As visualised in Figs. 6–8 and reported in Table 4, our method achieves an average 90 % reduction in NOP across 21 selected port scenarios. Moreover, Fig. 12 confirms that, even under limited redundancy and high disruption intensity, no more than 2 % of GCSN ports are affected. This highlights the model's robustness and scalability under stress conditions.

Beyond such immediate operational gains, the framework complements governmental and regional logistics strategies, such as reducing over-reliance on a small number of major hub ports. By identifying viable alternative routes and optimising cargo redistribution volumes, the MSO model contributes to policy objectives such as modal diversification and the promotion of secondary ports. Ultimately, the integration of this framework into digital port management systems or maritime decision support tools could significantly enhance the maritime sector's capacity to respond to future global challenges. Its data-driven, optimisation-centred design marks a shift from reactive crisis response to proactive resilience management in the maritime domain.

(4) Outlook for shipping network resilience research

Whilst the proposed framework offers a robust basis for managing cascading failures, several avenues for future research remain open. On the one hand, there is scope to integrate port recovery dynamics within the modelling. Many ports, once overloaded, gradually regain functionality through overtime shifts, temporary yard expansions, or alliances with inland logistics hubs.

Incorporating these recovery times and strategies could offer a more detailed depiction of post-failure network evolution.

On the other hand, multimodal transitions, such as rerouting cargo to rail or trucking networks, deserve deeper exploration. Complex disruptions often prompt rerouting strategies that go beyond maritime modes alone, implying that a unified model spanning maritime, rail, and inland waterway systems might more comprehensively capture the cascading behaviour of global supply chains. In this manner, the fundamental concepts introduced in this study, the multi-objective, stepwise, and Pareto-oriented optimisation, could be extended to emergent risks and multimodal supply chain management.

6. Conclusion

In light of the increasing occurrence of cascading failures in global shipping networks, establishing an integrated framework for proactive resilience planning is vital to maintain the stability of international shipping systems and supply chains. To minimise such cascading disruptions, this study proposes the MSO framework aimed at guiding stakeholders within shipping networks to effectively withstand unexpected port failures and maintain the overall resilience. By defining three objectives, economic efficiency, functionality, and structural completeness, the proposed SCM model ensures that loads from disrupted ports are effectively redistributed to suitable alternative ports, keeping cost, congestion and connectivity issues within manageable limits. To explicitly quantify the impacts of port disruptions, three resilience metrics are introduced and applied, and the GCSN structure is established. Specifically, the findings of this study can be summarised as follows:

1) In comparative analyses involving 21 major global ports, the proposed framework consistently outperforms existing methods by significantly reducing the number of overloaded ports, controlling port overloading degrees, and limiting additional transit times.
2) Detailed case studies focusing on the ports of Hong Kong and Hamburg further illustrate the redistribution processes and practical effectiveness of the approach.
3) Sensitivity analyses examining variations in the network's capacity multiplier and failure ratio suggest that maintaining adequate redundancy (at least additional 10 % safety backup) and employing optimal redistribution strategies substantially reduce the severity and reach of cascading failures.
4) The framework's demonstrated capability to mitigate congestion at key ports and prevent severe regional bottlenecks provides valuable guidance for port authorities, shipping companies, and policymakers. Ensuring suitable capacity margins alongside flexible redistribution strategies can significantly enhance resilience, enabling robust emergency responses and safeguarding global supply-chain stability.

While the proposed MSO framework generates high-quality load redistribution strategies, this study represents a new solution to leveraging optimisation techniques for proactive resilience management. Future research is recommended to use this study as a benchmark for developing more comprehensive, multi-dimensional resilience-maintenance and protection solutions across a broader context. Furthermore, advancements in emerging technologies such as Artificial Intelligence, Digital Twins, and multi-source data fusion present significant opportunities for deeper and broader insights. Integrating these technologies will substantially enrich resilience studies of shipping networks, enabling decision-makers to manage maritime transport risks and response strategies in a more scientifically robust manner.

CRediT authorship contribution statement

Yuhao Cao: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Xuri Xin:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Xinjian Wang:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Jin Wang:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Zaili Yang:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was funded by a European Research Council project under the European Union's Horizon 2020 research and innovation programme (TRUST CoG 2019 864724). The authors also gratefully acknowledge support from the China Scholarship Council under grant number 202308060322.

Data availability

Data will be made available on request.

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