Resilience modelling and assessment of maritime transportation systems

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SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

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Resilience modelling and assessment of maritime transportation systems

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A thesis submitted to the Nanyang Technological University in partial fulfilment of the requirement for the degree of Doctor of Philosophy

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarized materials, and has not been submitted for a higher degree to any other University or Institution.

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[Yuen Kum Fai]

Authorship Attribution Statement

This thesis contains material from 4 paper(s) published in the following peer-reviewed journal(s) in which I am listed as the first author.

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The contributions of the co-authors are as follows:

- I proposed the initial idea, Associate Professor Yuen provided suggestions, comments, and guidance.
- I developed the simulation and assessment models and conducted all the model analyses.
- The model development had been discussed with Associate Professor Yuen.
- I prepared the manuscript drafts. The manuscript was revised by Associate Professor Yuen.

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Summary

Maritime transportation systems (MTSs) play a crucial role in global trade and economic development by facilitating the movement of goods and commodities across vast distances, thereby connecting producers and consumers worldwide. However, MTSs face disruptions from various sources. To enhance the resilience of MTSs—their ability to cope with these disruptions—this thesis aims to conduct modelling and assessment studies on their resilience.

In terms of research methodology, considering data availability, both data-driven methods and expert opinion extraction are employed. For data that is difficult to obtain, this thesis proposes a novel method to extract expert opinions based on Dempster-Shafer evidence theory and hesitant fuzzy linguistic terms. To establish causal relationships between variables, Bayesian network methods are also investigated. For available data, detailed data cleaning, analysis, and simulation model construction are conducted for different components. Specifically, for shipping networks, a method for detecting port communities based on the Infomap algorithm is proposed.

In the application of this research, the three most critical components of MTSs—waterways, ports, and shipping networks—were selected for analysis. The main contributions of these applications and analyses can be summarized as follows.

Waterway Transportation Channel (WTC) Resilience Study: A discrete-event simulation model is proposed to quantify WTC resilience by collecting Automatic Identification System data from the Yangtze Estuary Deepwater Channel. The model simulates ship operations within this specific waterway, an area currently limited in the literature. Different scenarios, such as ship delay and ship load, are designed to test the system's performance. Based on the analysis of experimental results, several practical suggestions are provided for stakeholders to aid in WTC risk management. By considering ship load, ship delay, and recovery cost, a composite resilience indicator is proposed to help managers design rescue

plans. Using real accident data, different rescue scenarios are proposed and compared, with simulation results demonstrating the effectiveness of the new indicator.

Port Resilience Study: A circular four-stage method is proposed to study port resilience, incorporating a port resilience assessment model using Bayesian networks. This model categorizes resilience strategies into six metrics (robustness, redundancy, visibility, flexibility, agility, recovery) to assess resilience capabilities (readiness and response), aiding port managers in distinguishing the specific functions and effectiveness of different strategies. Major disturbances affecting ports are summarized, with the Shanghai Yangshan Deepwater Port in China used as a case study for quantifying port resilience. Sensitivity analysis validates the model and compares the effects of resilience strategies and metrics on resilience capacities. Forward and backward inferences identify pathways to achieving a resilient port system. Key conclusions from the case study include: natural disasters are major disruptors; automated terminals exhibit higher overall resilience; and strategies enhancing visibility and recovery are crucial for readiness and response, respectively.

Shipping Network Resilience Study: An enhanced disruption simulation model is proposed and a novel research perspective: port communities is introduced. The simulation model integrates cascading failure and recovery mechanisms, incorporates ship behaviour during disruptions, and introduces a temporal dimension to track the network's evolution. Port community-to- community connections provide a clearer and more holistic perspective. Using Infomap algorithm, port communities are identified based on transportation direction, capacity, and geographic proximity, resulting in a decentralized and balanced structure while preserving GCSN's scale-free and small-world properties. Simulations of various disruption scenarios and recovery strategies yielded optimized key parameters and practical recommendations. For instance, the optimal distance threshold for detecting port communities is 300 km. Additionally, weak correlations between alternative port numbers and community size/throughput (0.17, 0.246) underscore the need for geographically balanced distribution and reduced reliance on single ports.

Overall, this thesis presents resilience modelling and assessment studies of key components within MTSs. The findings offer practical recommendations for strengthening the resilience of maritime operations, ensuring the system's capability to withstand and recover from disruptions. Moreover, the research methodology provided in this study demonstrates versatility and applicability across various contexts, offering a valuable framework for future investigations into the resilience of complex transportation networks.

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Lists of Symbols

Symbol	Explanation
sd_r/sd_o	Safe distance between adjacent stationary ships / adjacent ships in normal operation
R	Resilience
$R_{S_L}//R_{S_D}/R_C$	Resilience indicator of ship load/ ship delay/ recovery cost
α/β	Parameters related with ship load/ ship delay
S_L	Ship load
S_D	Ship delay time
CM	Recovery monetary cost
T/t	Simulation time
Δt	Time step in simulation
L	Length of waterway
x	Location
J_t	Sequence of ships at time t
τ	The time that ship spent in the waterway
N/n	Number
C_L	Capacity of the waterway
$\alpha_L/\alpha_{L,d}$	Ship load within the waterway during the normal operation /perturbation
P	Probability of event
$A/B/$C	Event/ Element
F	Causal factors of event
PN	The probability of $Noisy-OR\ model$
l	Leak factors
$WMEAN$	Weighted average
W/ω	Weight set/ weight
Θ	Set of events/ Frame of discernment
E	Evidence
Ø	Empty set
F	Proposition

m	Mass function /basic belief assignment /basic probability assignment
K	Conflicting coefficient
div	Divergence measure
E_d	Deng entropy
Iv	Information volume
S	Linguistic term set
s_α	Linguistic term
$s_{\tilde{\alpha}}$	Virtual linguistic term
k_α	Semantic of linguistic term s_α
Υ	Linguistic scale function
Υ^{-1}	Inverse Linguistic scale function
h_s	Hesitant fuzzy linguistic terms
h_d	Hesitancy degree
$\#h_s$	Number of linguistic terms in h_s
GS	Hesitancy degree of h_s
d	Distance
$\bar{d}$	Average distance
r	Reliability of experts
Dm	The distance metric between two h_s
DM	Distance measure matrix of evidence
$\overline{Iv}$	Average information volume
Sup	Support degree
Crd	Credibility degree
TS	Total support degree
Wav	Weighted average evidence
cw	Weight of the evidences
AI/ai	Assessment indicators set/ assessment indicator
EP/ep	Experts set/ expert
Λ/λ	Predefined weights set of experts/ predefined weight of experts
L/l	Impact level set/ impact level
C/c	Assessment criteria set / assessment criteria

Z^p	Hesitant fuzzy linguistic decision matrix
z_{ij}^c	Converted evidence framework
sm	Similarity measure among the evaluations
sd	Similarity of experts
mw	Modified weight/support degree of experts
$\overline{mw}$	Normalized support degree of expert
G	Graph
N	Nodes in graph
E / e_{ij}	Edges in graph
CO	Community
q/p	Probability
H	Entropy
LR	The average description length of a random walk
A'	Adjacency matrix of graph
F' / f_{ij}	Transportation flow matrix / transportation flow
D' / d_{ij}	Transportation distance matrix / transportation distance
fa_{ij}	The actual transportation flow
fd_{ij}^{A0}	The average daily transportation volume of Ship A on the edge e_{ij}
$\overline{f_{ij}}$	Normalized transportation flow
$\overline{d_{ij}}$	Normalized transportation distance
α'	The tolerance parameter for port capacity
TO_i	The average daily throughput of Port i
$MaxL_i$	The maximum load capacity of Port i
β'	The distance tolerance parameter
v_{ij}^A	The sailing speed of ship between ports
BL	The blocking volume
tr_{ir}^A	The transit time from between ports of ship

Lists of Abbreviation

Abbreviation	Explanation
AC	Actual capacity
AGV	Automated guided vehicle
AIS	Automatic identification system
AI	Artificial Intelligence
ARMG	Rail-mounted gantry crane
BBA	Basic belief assignment
BJS	Belief Jensen-Shannon
BN	Bayesian network
BPA	Basic probability assignment
BV	Boolean variables
BWM	Best-worst method
CPT	Conditional probability tables
DAG	Directed acyclic graph
DCR	Dempster's combination rule
DM	Decision maker
DP	Disturbance phase
DSET	Dempster-Shafer evidence theory
DWT	Deadweight tonnage
GCSN	Global container shipping network
GLSN	Global liner shipping network
GT	Gross tonnage
HFLTS	Hesitant fuzzy linguistic term
IMO	International Maritime Organization
JPD	Joint probability distribution
LB	Lower bound
LC	Lost capacity
LOA	Length overall
IoT	Internet of Things
LSF	Linguistic scale function

LT	Linguistic term
LTS	Linguistic term set
LV	Labelled variables
MSA	Maritime safety administration
MTS	Maritime transportation system
NPT	Node probability tables
NR	Non-resilient
R	Resilient
RsP	Response phase
RyP	Recovery phase
SATD	Ship arrival time distribution
SOP	Stable original phase
SRP	Stable recovery phase
SSD	Ship speed distribution
STD	Ship type distribution
SD	Standard deviation
TEU	Twenty-foot equivalent unit
TNORM	Truncated normal distribution
UB	Upper bound
VTS	Vessel traffic service
WTC	Waterway transportation channel

Chapter 1 Introduction

1.1 Research Background

The maritime transportation system (MTS) is the backbone of the international supply chain, accounting for more than 80% of global merchandise trade by volume. The rapid development of international trade has driven significant growth in the maritime industry over the past fifty years. The total volume of international seaborne trade increased from 2.6 billion tons in 1970 to 12 billion tons in 2022, with an expected growth of 2.4% in 2023 and continued but moderated growth between 2024 and 2028 (UNCTAD, 2023). Various essential elements comprise the MTS, including navigable waterways, ships, ports, and direct and indirect consumers. Among these, ports serve as critical hubs where goods are transferred between different modes of transportation, such as ships, trucks, and trains. This intermodal connectivity enhances the efficiency and effectiveness of the supply chain, enabling the smooth and timely movement of goods across the globe. Waterways are vital infrastructures that facilitate the navigation of ships, providing safe and efficient routes for maritime transport. They are essential for connecting inland areas with coastal regions, thereby extending the reach of maritime trade to landlocked regions and fostering regional economic integration. Ports and navigable waterways respectively form the nodes and links of the maritime shipping network, which is the backbone of international trade. These three elements are the most critical components of the MTS, playing vital roles in the global supply chain, regional and international economic activities, transportation network systems, and employment growth (Hossain et al., 2019).

However, ports, waterway and shipping networks are vulnerable to various disturbances, such as natural disasters (e.g., typhoons and earthquakes), technical issues (e.g., cyber-attacks) and economic or political factors (e.g., financial crisis and policy changes). Given their crucial role in regional and global trade, any disruption can lead to significant economic losses. For instance, Hurricane Ida in 2021 severely disrupted U.S. logistics, resulting in the closure of several ports, including New Orleans, Mobile, Baton Rouge, Pascagoula, and Mississippi. Hurricane Ida's wind and storm surge caused insured losses estimated between $17 billion to $25 billion (Spoerry, 2021). Beyond financial losses, severe disturbances can also result in environmental and social impacts. For example, the Tianjin Port explosion in 2015 not only caused economic losses but also resulted in devastating human casualties, with 165 deaths, 8 missing persons, and 798 injuries (State Council of China, 2016). Additionally, the release of hazardous chemicals during the explosion posed significant environmental risks, such as soil and water contamination, affecting surrounding communities and ecosystems for years. Furthermore, disruptions at certain ports can impact national security and defense, such as the cyberattacks that disrupted operations at oil storage companies in the Amsterdam-Rotterdam-Antwerp oil trading hub (Bush, 2022).

In addition to acute events, long-term disruptions in the MTS can exacerbate environmental degradation. For instance, uncoordinated rerouting of vessels due to port congestion can lead to increased greenhouse gas emissions, which contribute to global climate change (Li et al., 2023). Similarly, delays in container movement may result in the spoilage of perishable goods, leading to waste generation and heightened environmental burdens (Grant et al., 2024). Furthermore, disruptions in the maritime transportation system can significantly impact social well-being by delaying the delivery of essential goods such as medical supplies, food, and energy resources, thereby threatening the livelihoods and safety of vulnerable populations (Lima, 2024).

Since the onset of the global pandemic, COVID-19, new threats have emerged in MTS. For example, prolonged port closures and global supply chain delays resulted in severe shortages of critical goods, including medical equipment and personal protective equipment, highlighting the social vulnerabilities associated with disruptions in maritime systems (Nguyen, et al., 2024). The pandemic emphasized the importance of resilience in not only mitigating economic losses, but also addressing broader environmental and societal challenges that arise in interconnected global systems. In a rapidly changing environment with numerous uncertain threats, resilience plays a crucial role in achieving system sustainability (Wang et al., 2024a). The impact of COVID-19 highlights the need for improved risk management, greater readiness, and enhanced resilience (UNCTAD, 2021). Compared to safety and reliability, resilience focuses more on post-disruption resistance than on pre-emptive prevention (Wang et al., 2023a), serving as an important complement to safety management and reliability engineering. Therefore, developing resilient ports, waterways, and shipping networks is paramount not only to promoting the sustainable development of the MTS but also to safeguarding social stability, environmental health, and the well-being of affected communities. Implementing appropriate resilience strategies is essential to enhancing the resilience of the MTS and minimizing the cascading impacts of disruptions across economic, environmental, and social domains.

1.2 Research Gap and Motivation

Currently, various efforts are undertaken to enhance the resilience of different systems (Esmalian et al., 2022). With widespread and increasing use, resilience no longer simply refers to a return to a stable equilibrium, but rather to the ability of a socio-technical system to maintain a certain way of functioning under the direction of a decision maker or manager (Pan et al., 2022). However, resilience still lacks a commonly accepted definition and has different interpretations when applied to different systems (Gu et al., 2020). These differences raise additional challenges when trying to studying resilience assessment methods and strategies and also provide motivation for research. Given that ports, waterways, and shipping networks are key components of the MTS, my research is segmented into these three distinct parts.

For waterways, resilience research mainly focuses on resilience assessment by relying on influencing factors (Hosseini & Barker, 2016; John et al., 2016) or resilience metrics (Chen et al., 2017; Omer et al., 2012), optimization of recovery strategies (Dui et al., 2021; Baroud et al., 2014), and resilience analysis using statistical data (Knoester et al., 2024; Farhadi et al., 2016). The following research gaps are noted. First, when constructing resilience assessment model, the variables used are usually binary (false or true) (Hosseini & Barker, 2016) or ordinal (Very Low, Low, Medium, High, Very High) (John et al., 2016), which are determined based on expert judgement. Next, when constructing resilience assessment model using resilience metrics, the network nodes or links in the transportation system only possess two states: either operating or failed (Dui et al., 2021; Chen et al., 2017; Baroud et al., 2014). The specific changing trend of systems’ line or node when the disturbance occurs is lacking. Finally, when evaluating rescue/recovery strategies, the monetary cost of options, a very important part in practice, is rarely combined with system performance. With the lack of effective resilience assessment indicators, there are limited guidelines and tools for the system’s stakeholders to design rescue plans or allocate the available and limited resources, such as budget, energy and assets. Without a suitable solution, it is difficult for the system to restore its stable operation as soon as possible and ensure the safety of people and property.

For ports, quantification model and methods for improving strategy-related resilience are rare. The resilient operation of the port requires the implementation of various strategies, but the objective data used to assess the effectiveness of the implementation of different strategies is insufficient. Hence, integrating subjective assessment and objective data into resilience management is essential but yet, rare. In addition, most researchers use absorptive, adaptive, and restorative capabilities as the primary constructs to assess resilience, which are based on the definition: resilience enhances the system's ability to absorb, adapt, and recover from any shocks caused by disruptions (Hossain et al., 2019). Since the system's ability to absorb, adapt, and recover depends on the severity of the disturbance, the same strategy may affect different abilities at different levels of disturbance. The research results from literature (Kammouh et al., 2020; Hossain et al., 2019) show that the Bayesian network model can effectively combine expert judgment and statistics analysis, reflect the mutual relationships of various factors in the compound system, and provide insights to improve the system's performance. It is of interest to study port resilience assessment models using Bayesian networks with a suitable framework. Port is a complex system, and identifying resilience strategies with priorities based on effective assessment model is conducive to resilience management at the port.

For shipping network, complex network theory is a primary approach for studying the resilience. Shipping networks constructed from shipping data enable the use of various topological metrics as key network performance indicators for resilience assessment. However, most resilience assessment studies focus solely on node or link removal strategies within shipping networks, without considering the cascading effects between ports (Xu et al., 2024b; Bai et al., 2023; Wang at el., 2023b). In recent years, cascading effects have garnered increasing attention (Liupeng et al., 2024; Xu et al., 2024b). Nevertheless, recovery mechanisms—a critical aspect of resilience research (Wang et al., 2024a)—have largely been overlooked. Furthermore, many researchers analyse shipping networks from the perspective of individual ports. However, the inherent geographical constraints of maritime networks, coupled with the rise of contemporary regional trade blocs, have driven the regionalization of these networks (Wu et al., 2024). Ports within the same region typically operate under similar policy and regulatory frameworks, encounter comparable social and environmental conditions, and are subject to shared disruptions. For instance, natural disasters such as earthquakes or hurricanes can simultaneously impact multiple ports within a region, leading to widespread operational challenges. Studying port communities, therefore, offers valuable insights for attracting investments, fostering regional capabilities, and enhancing the overall performance of the maritime sector (Gupta & Prakash, 2024). Conducting a resilience analysis of shipping networks from the perspective of port communities, rather than focusing on individual ports, provides a more comprehensive understanding of collective response capabilities in the face of natural disasters, global supply chain disruptions, or pandemics. The interconnectedness within port communities allows them to mitigate the risk of operational paralysis at individual ports by distributing impacts across the network, thereby enhancing the overall resilience of the region. Moreover, compared to port-to-port connections, analysing port community-to-port community connections offers a clearer and more holistic perspective on the Global Container Shipping Network (GCSN). Community detection algorithms can effectively identify and partition groups of tightly connected nodes, revealing the underlying community dynamics within the broader maritime network. However, despite the proposal and application of various community detection algorithms in other types of networks, their application in maritime networks remains conspicuously insufficient. Therefore, it is necessary to construct an enhanced simulation model that considers the recovery mechanism and conduct research from the perspective of port community to port community.

1.3 Research Scope and Aims

The key to enhancing system resilience lies in improving the ability to assess it, necessitating the development of effective assessment methods. Different assessment methods are suitable for different systems. This thesis aims to study effective resilience modelling and assessment methods for waterways, ports, and shipping networks in MTS separately. The detailed research aims are listed in Figure 1.1 and introduced as follows.

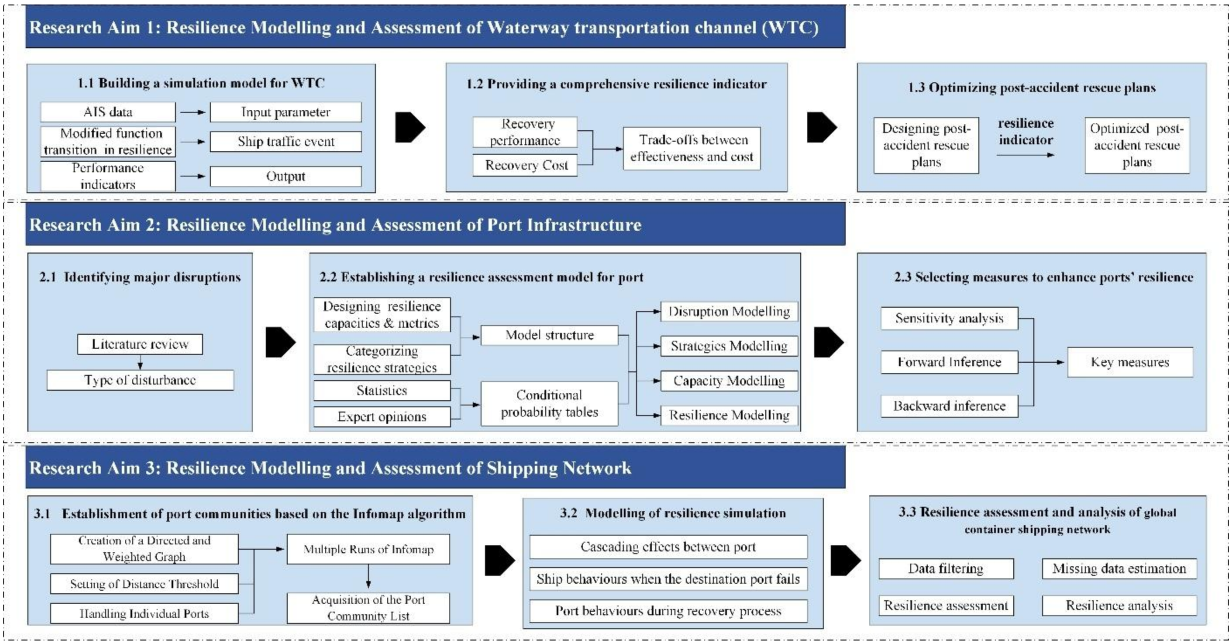


Figure 1.1 Graphical illustration of research framework

For the waterway transportation channel (WTC), the objectives are to assess and analyze WTC resilience through simulation. Specifically, these objectives include: (1) building a discrete-event-based simulation to model the trend of ship movements when encountering different accidents, introducing disruptions at different stages of the resilience recovery cycle; (2) providing a comprehensive resilience indicator to assist managers in developing post-accident rescue plans; and (3) optimizing post-accident rescue plans based on the provided resilience indicator.

Regarding ports as infrastructure, the objective is to develop measures to enhance ports' resilience in coping with risks and uncertainties. In detail, this involves: (1) identifying and categorizing major disruptions affecting port operations through a literature review; (2) developing a port resilience assessment model that considers the relationships among major disruptions, resilience capacities, and resilience strategies. Bayesian networks are used as the modeling method due to their capability to handle causal dependencies between different variables in probabilistic terms, with expert opinions utilized for partial parameter setting due to the lack of objective data; and (3) conducting various experimental analyses to identify key measures that enhance port resilience.

For the shipping network, the objective is to proposes a novel resilience assessment framework, incorporating an enhanced simulation model and analysing resilience from the perspective of port communities. This involves: (1) providing a method for detecting port communities within the shipping network based on the Infomap algorithm. This method aims to optimize the port community structure based on port connections, transportation flow between ports, and geographical proximity; (2) designing an enhanced disruption simulation model to assess the network resilience by integrating cascading failure and recovery mechanisms. The model incorporates detailed ship behaviours in response to disruptions, such as waiting, rerouting, and skipping, while introducing a temporal dimension to track the evolution of the network over time; (3) Analysis of container ship movement data from 2017 to 2023 identified a novel port community structure within the GCSN through the Infomap algorithm. Based on the resilience analysis of the GCSN from the perspective of port communities, key academic insights and practical management recommendations are proposed.

1.4 Organization

Based on the research objectives, this thesis is divided into four progressive modules: theoretical analysis, methods modelling, case application and analysis, and conclusion, spanning seven chapters as shown in Figure 1.2.

In Chapter 1, the background of resilience studies in MTS is introduced, and the major research gaps are identified. Subsequently, the research scope and objectives, which form the core of this report, are presented.

Chapter 2 provides a detailed literature review of resilience research, encompassing five main areas: infrastructure systems resilience, transportation systems resilience, waterway transportation channel resilience, port resilience, and shipping network resilience. The definitions, research directions, and assessment methods for each area are presented, and the respective research gaps are clearly described.

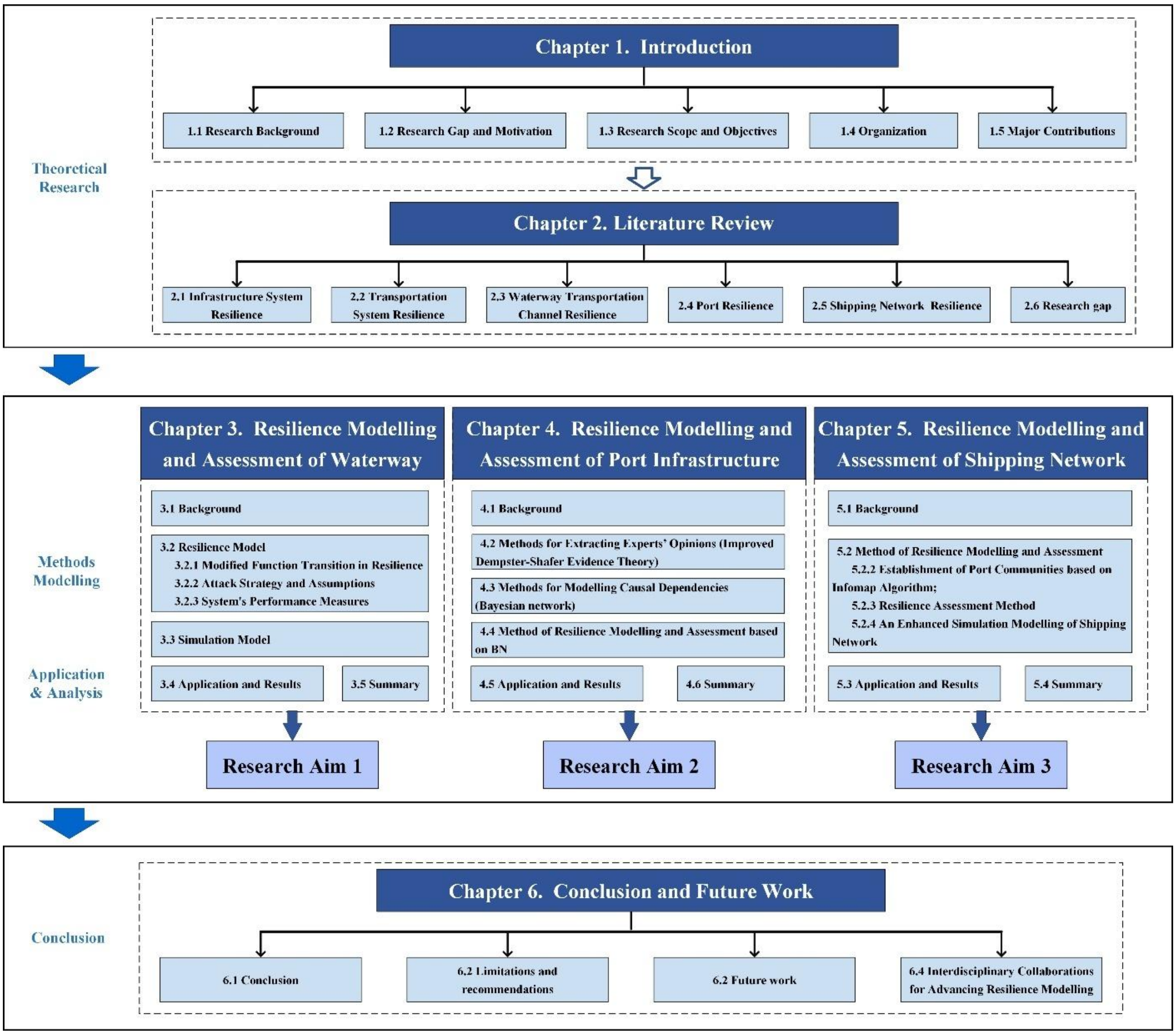


Figure 1.2 Organization of this report

Chapters 3, 4, and 5 address research objectives 1, 2, and 3, respectively.

Chapter 3 analyses the resilience assessment of the of waterway transportation channel by developing a discrete-event-based simulation model, using the Yangtze Estuary Deepwater Channel as a case study.

Chapter 4 examines the resilience assessment of ports by developing a port resilience assessment model using Bayesian networks, with the Shanghai Yangshan Deepwater Port in China serving as a case study.

Chapter 5 presents a data-driven method for assessing shipping network resilience based on port communities, employing the global container shipping network as a case study.

Finally, conclusions and future work are demonstrated in Chapter 6.

1.5 Major Contributions

This thesis builds on existing resilience studies while addressing notable gaps across three key components of the MTS: waterways, ports, and shipping networks. The key contributions of this thesis are summarized below.

(1) Waterway Transportation Channel

Resilience research on WTCs remains underdeveloped compared to other components of the maritime transportation system. Current studies primarily focus on resilience assessment using simplified models or high-level metrics but fail to capture the detailed dynamics of system performance during disruptions. In addition, the proposed resilience index is not comprehensive enough.

This thesis introduces a discrete-event simulation model to capture the dynamic evolution of resilience during disruptions, integrating both system performance metrics and economic factors to support decision-making.

(2) Ports

Quantitative models for strategy-specific resilience assessment remain underdeveloped, often relying on qualitative or subjective evaluations without incorporating objective data. Current frameworks lack consideration of how resilience capacities vary based on disturbance severity, limiting the ability to prioritize strategies under different disruption scenarios. In addition, when objective data is insufficient and expert opinions are needed, issues such as expert uncertainty, ambiguity, and even conflict are often ignored.

This thesis develops a BN-based resilience assessment model, combining expert judgment and statistical analysis to address these limitations. It also provides a structured framework to identify and prioritize key resilience strategies tailored to specific disruptions. To extract experts' opinions, a method based on Dempster-Shafer evidence theory (DSET) and hesitant fuzzy linguistic terms (HFLTSs) is provided.

(3) Shipping Networks

Complex network theory has been widely used to study shipping network resilience, but most studies focus narrowly on node or link removal strategies, neglecting cascading effects and recovery mechanisms. Researchers focus on the port perspective to study resilience, but ignore the regional characteristics of ports, the interdependence of ports within a port community, and the collective response capabilities when dealing with disruptions.

This thesis proposes an enhanced simulation model based on cascading effects and determines the optimized values of key parameters through experimental analysis, providing a valuable reference for future modelling research. Additionally, this study introduces a new research perspective by analysing port failures and resilience enhancement strategies from the viewpoint of port communities. This approach broadens the scope of existing research while offering practical recommendations for improving the resilience of the shipping network.

Consequently, this thesis holds both theoretical and practical significance. The model and methods provided and the academic insights could be generalized to other regions or applied to different types of transportation system.

Chapter 2 Literature Review

This chapter reviews and summarizes the relevant literature on the resilience of MTS, divided into six sub sections: infrastructure system resilience, transportation system resilience, waterway transportation channel resilience, port resilience, shipping network resilience, and a final research gap summary. Excluding the final summary, the concepts in the literature review progress from broad to specific, and the content moves from general to detailed. Given that MTS is fundamentally an infrastructure, Section 2.1 presents an overview of infrastructure resilience research, including the definitions and main modelling methods of resilience, which laying the groundwork for subsequent specific studies. As MTS is essentially a transportation system, Section 2.2 provides a detailed literature review on transportation system resilience. Within this section, Subsection 2.2.1 reviews the primary research directions of transportation systems, and Subsection 2.2.2 focuses on the key aspect of resilience assessment: resilience indicators, which establish a foundation for constructing assessment and quantification models. Sections 2.1 and 2.2 have already presented existing research findings and provided a theoretical foundation for the study of waterway resilience; therefore, a separate literature review specifically for waterways is not included. Section 2.3 reviews major studies on port resilience, including both qualitative and quantitative research. Section 2.4 offers a detailed literature review of the shipping network, including the resilience studies of shipping network and classification method of port communities. Finally, Section 2.5 summarizes the research gaps of each component, which will be addressed in subsequent chapters of this thesis.

2.1 Infrastructure System Resilience

The scope of resilience research is very broad, encompassing areas from ecosystems, engineering to human science. Since MTS is fundamentally a type of infrastructure, this chapter will begin with a brief review of resilience research in the context of infrastructure. The research of infrastructure resilience focuses on various aspects, such as defining resilience, modelling of hazards or threats, modelling of infrastructure systems, and quantifying resilience.

The word resilience stems from Latin word “resiliere,” which means to rebound, or spring back. The first definition of systems resilience was given in 1973 by Holling (1973) when he studied the resilience of ecological systems. Since then, the concept of resilience has been introduced to different disciplines and different definitions of resilience have been developed by researchers in various fields. The concept of resilience engineering was proposed by Hollnagel et al. (2006), that is, the resiliency of a system can be understood as the ability of a system to return to a stable state following a strong perturbation caused by failure, disaster, or attack. An operational definition was proposed by NIAC 2013: infrastructure resilience is the ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event (NIAC, 2013). Reasonable and clear definitions can help policymakers better understand resilience and develop measures. The detailed summary and analysis of resilience's definitions can be seen in Zhou et al. (2019) and Serdar et al. (2022). With widespread and increasing use, resilience no longer simply refers to a return to a stable equilibrium, but rather to the ability of a socio-technical system to maintain a certain way of functioning under the direction of a decision maker or manager (Wang et al., 2024a).

Through a literature review, it was found that resilience is a very broad concept and the functions of resilience include preparing and planning for disruptions (Arango et al., 2023; Tang et al., 2020; National Research Council of USA, 2012), absorbing and adapting to adverse events (Arango et al., 2023; Tang et al., 2020; National Research Council of USA, 2012), resisting and reducing the impact of emergencies (Chen et al., 2022), and recovering quickly from various hazards (Deveci et al., 2023; Chen et al., 2023; Chen et al., 2022). The associated keywords to describe resilience include complex, dynamic, comprehensive, multidimensional, interdisciplinary, and time-phased (Chen et al., 2023; Wang et al., 2023a; Tang et al., 2020).

Based on the summary of resilience definitions, some common themes can be uncovered. 1) System resilience is a dynamic capability and continuous process that changes with the occurrence of disturbances. 2) The meaning of system resilience is multi-layered, which can be divided into different functions or capabilities to cope with these disturbances. A wide variety of evaluation factors are used to characterize resilience, although some of these factors have similar meanings or overlapping relationships (Wang et al., 2023b). These capabilities can be roughly divided into three categories: pre-disruption preparation, such as the ability to anticipate and prepare; post-disruption response capability, such as the ability to adapt and recover; and learning capability throughout the process. 3) The impact of system resilience is multidimensional, including social, economic, technological, environmental, communal, and territorial. 4) Achieving a resilient system requires the cooperation of many parties and processes, such as resilient individuals, systems, networks, and structures.

Resilience assessment of infrastructure systems critically depends upon reliable estimates of hazards (Ganguly et al., 2018). Among various hazards, the modelling of natural disasters is the most common. For example, Souto et al. (2022) construct a flood forecasts model based on rainfall to improve mid-term power system resilience. Bell & Bristow (2022) present a model to simulate marine transport earthquake operational resilience using Graph Model.

The modelling and simulation of compound and interconnected systems are useful in identifying weak spots, preparing and planning countermeasures for system managers (Ganguly et al., 2018). The existing modelling and simulation approaches that are used to model critical infrastructure systems are broadly grouped into four categories (Ouyang, 2014): Network-based approaches, system dynamics-based approaches, agent-based approaches, and empirical approaches. Resilience quantification is closely related to system modelling. For network-based approaches, infrastructures are presented with networks, where nodes denote different critical infrastructure system components, and links denote the physical and relational connections. Methods of network science are roughly grouped into two parts: topology-based and flow-based. The former models the systems only based on their topologies, with the discrete state of each element (represented as a node or link) and generally with two states: normal and failed. For example, Xu and Xu (2024) proposed a two-stage resilience promotion approach for urban rail transit (URT) networks and used the L-space type of topology to map the URT network. In their study, network efficiency is used as the systems' performance indicator, which is the average of node efficiency for all nodes in a network. In this case, resilience is measured by the system performance loss ratio, that is the ratio of time integral of the system performance after the disturbance to the time integral of the original system performance. Flow-based approaches comprise the services or flow made and delivered by the system besides topological information. For example, Wang et al. (2024c) modelled the URT system as a customized two-layer network to distinguish its infrastructure layer and service layer. A new localized measure, i.e., link flow, is suggested to construct the system functionality in attack-repair scenarios. System dynamics-based approaches use a top-down method to manage and analyse complex adaptive systems. For example, Ding et al. (2022) proposed a resilience assessment framework for China's natural gas system under supply shortages by combining the resilience curve and system dynamics model. In their study, demand and satisfaction rate is used as the systems' performance indicator whereas the system's resilience is measured by the performance loss ratio. Agent-based approaches assume the complex behaviour emerges from many individual and relatively simple interactions of autonomous agents. Each agent interacts with the other and its environments using a set of rules, which mimics the way a real counterpart of the same agent would react. For example, Chen et al. (2022) proposed a simulation model to assess the resilience of an urban rail transit network, which offers three travel options for passengers under disturbances. In their study, the demand-impedance indicator is used as the systems' performance indicator, which integrates the network's structure and passenger travel demand jointly. Meanwhile, resilience is measured by the retained performance during the attack and repair processes. Existing empirical approaches rely on historical data and expert experiences. For example, Knoester et al. (2024) provided a new composite indicator to assess the resilience of railway networks using historical traffic realization data in the Netherlands.

Based on the above, the research of infrastructure resilience focuses on defining resilience, modelling of hazards or threats, modelling of infrastructure systems, and quantifying resilience. The concept of resilience is broad and the meaning of resilience is multi-layered, which can be divided into different functions or capabilities to cope with various disturbances. In addition, the differences between systems will also result in significant variations in the definition, modelling, and assessment of resilience.

2.2 Transportation System Resilience

Since MTS is fundamentally a transportation system, this chapter narrows the research scope to transportation systems as infrastructure, specifically summarizing their research directions and quantitative measures.

2.2.1 Research Directions

Various aspects of resilience in transportation system have been studied by researchers to improve resilience, and the main directions in the last decade focus on the following three parts: strategy optimization, factor and structure analysis and resilience assessment.

(1) Strategy Optimization

To help decision makers allocate resources and determine priorities in the restoration activities of damaged facilities, optimization models are often used by researchers (Vugrin et al., 2014). For example, Tao et al. (2024) proposed a network-wide traffic signal optimization model to maximize the resilience of urban road networks. Dui et al. (2021) proposed a method to optimize the residual resilience management of ports and routes in maritime transportation systems and used Copeland method to comprehensively rank the importance of ports and routes. Bocchini and Frangopol (2012) proposed an optimization procedure to allocate funding to the bridges of a transportation network severely damaged by an earthquake. The goal of this optimization is to maximize the network resilience, minimize the time required to reach a target functional level, and minimize the total cost of recovery activities. Pan et al. (2022) studied the optimization of recovery strategies based on their proposed resilience model. Baroud et al. (2014) used heuristic approach to determine the sequence of disrupted links of inland waterway network by considering three metrics: the time to restoration importance, the resilience worth and the total cost of recovery. Faturechi and Miller-Hooks (2014) formulated a bi-level, three-stage, stochastic mathematical program with equilibrium constraints to maximize travel time resilience of roadway networks. With the advancement of data acquisition and storage, data-driven methods have become popular in many areas including the resilience engineering (Zhou et al., 2019). For example, by combining agent-based modelling and reinforcement learning, Verschuur et al. (2020) proposed a methodological framework, to assess the effectiveness of a repair crew allocation strategy and optimize the strategy after an extreme event. Fan et al. (2022) proposed a degree deviation link, an additional strategy to help multiplex network find an optimal strategy to maintain a system's initial ability from a holistic perspective. Zhang et al. (2022) incorporated real-time parallel scheduling of inspection and restoration to maximize the post-earthquake resilience of a highway–bridge network.

(2) Factor and Structure Analysis

As a useful tool to model the causal relationship among several variables, Bayesian networks (BNs) are often used in reliability engineering and can be used to structure the causal relationships among various aspects of resilience. Hosseini and Barker (2016) proposed a resilience model of an inland waterway network from absorptive, adaptive, and restorative capacity perspectives. Tang et al. (2020) proposed a hierarchical BN model to quantitatively evaluate the resilience of urban transportation systems with three layers: function layer, quality layer and factor layer. John et al. (2016) used Bayesian belief networks to model and rank the influencing variables in a seaport system to facilitate resilient port operations. Based on the historical data in Beijing Metro, Yin et al. (2022) established three resilience evaluation models using BN.

In addition to BN, researchers also use other methods to explore system structure and analyse system factors. For example, Liu et al. (2021) proposed a hierarchical resilience enhancement framework for interdependent critical infrastructures based on resilience enhancement strategies. Xu and Chopra (2022a) proposed a spatial–temporal resilience cycle framework to assess the metro infrastructure. Based on performance response function, Xiao et al. (2022) proposed a seismic resilience assessment framework for bidirectional interdependent lifeline networks. Mottahedi et al. (2021) developed a practical framework to estimate the resilience of critical infrastructures by combining expert judgment with fuzzy set theory. Sun et al. (2021) developed an agent-based modelling framework to enable a nuanced modelling on the rapid response-based seismic resilience of critical infrastructures, considering different repair strategies in relation to different phases in the recovery process and different level of damage of the assets. By reviewing the literature and analyzing expert questionnaires, Nickdoost et al. (2024) identify and prioritize multidimensional resilience factors for transportation systems.

(3) Resilience Assessment

For different transportation systems, researchers carry out various resilience assessment methods. For example, Chen et al. (2022) assessed the resilience of subway network with the demand-impedance indicator, and provided several practical suggestions for managing the system under disturbances. Adjetey-Bahun et al. (2016) proposed a simulation-based model for quantifying resilience in mass railway transportation systems. By using part of the Paris railway transportation system, Adjetey-Bahun et al. (2016) tested the impact of a perturbation and crisis management plans during a perturbation on the model's performance indicators. Goldbeck et al. (2019) developed an integrated, dynamic modelling and simulation framework to conduct resilience assessment for interdependent urban infrastructure systems and modelled the optimal response to disruptions using a rolling planning horizon. Nogal et al. (2016) and Nogal and Honfi (2019) proposed a new method to assess traffic network's resilience, and determined the resilience of Cuenca network (Spain) and Luxembourg-Metz traffic network, respectively.

In addition to the three main research directions introduced above, there are also some other directions, such as the comparative evaluation of different resilience measures (Li and Gao, 2022; Balal et al., 2019), resilience analysis based on statistical data (Knoester et al., 2024), and etc.

Among different research directions, resilience assessment is the focus, which is also the basis for strategy optimization. Resilience metrics are the key to assessing resilience and will be introduced in detail in the next section.

2.2.2 Resilience Metrics

According to different definitions of resilience, different dimensions and properties have been proposed by researchers to measure systems' resilience, and multiple metrics and various measurement indicators have been proposed to quantify these dimensions and properties (Poulin and Kane, 2021). However, no widely accepted measurement of resilience is available for transportation systems. In this section, resilience quantification metrics in transportation systems will be summarised and analysed. The performance-based metrics are summarised in Table 2.1.

Table 2.1 Studies on assessing infrastructure system's resilience

Resilience metric	Reference	Object	Performance indicator
Performance loss	Pan et al. (2022)	Transportation Network	Network efficiency
	Zhang et al. (2022)	Highway–bridge networks	Between-city travel time
	Chan & Schofer(2016)	Rail transit System	Lost service days
	Bocchini & Frangopol (2012)	Road networks	Total travel time and distance
	Adjetey-Bahun et al. (2016)	Railway systems	Passenger load and passenger delay
	Chen et al. (2022)	Urban rail transit network	Demand-impedance indicator （passenger trips and travel time）
	Goldbeck et al. (2019)	Interdependent urban infrastructure systems	Quantity and quality of services
	Nogal et al. (2016); Nogal & Honfi (2019)	Traffic network	Cost and stress level
Recovery ratio	Baroud et al. (2014)	Inland waterway network	Time to restoration importance and resilience worth
	Liu et al. (2021)	Critical infrastructures	Weighted sum of the states of users
	Farhadi et al. (2016)	Marine transportation systems	Average vessel dwell time and net vessel transits
Demand ratio	Chen & Miller-Hooks (2012)	Intermodal freight transport network	Transport capacity (the number of shipments)
	Tao et al. (2024)	Urban road networks	Minimum system travel time
	Faturechi & Miller-Hooks (2014)	Roadway network	Total travel time
	Ahmed et al. (2019)	Transportation system with several Connected and Automated Vehicle	Number of trips
	Chen et al. (2017)	Container transportation network	Total satisfied container volume
	Calvert & Snelder (2018)	Road traffic	Link Performance Index for Resilience (ratio of traffic flow to speed)
	Omer et al. (2012)	Maritime transportation systems	tonnage, time and cost
Other	Vugrin et al. (2014)	Transportation networks	System performance and recovery effort

Based on the summary of previous studies, resilience metrics can be divided into three categories: topological metrics, attributes-based metrics, and performance-based metrics. From the perspective of systems' structure, topological metrics are usually constructed on some graph-based properties. The size of giant component and average shortest paths (Hartmann, 2014) are the two most used metrics. In addition to the system's structure, attribute- and performance-based metrics also consider the dynamic characteristics of the system. The difference between them is that the attribute-based metric tries to assess resilience from some specific aspects of resilience (e.g., recovery speed and efficiency (Mojtahedi et al., 2017), while performance-based metric is designed to assess a system's resilience based on its performance over the entire affected period. In general, performance- and attribute-based metrics are both better than topological metrics, and performance-based metrics are the most appropriate method to measure a system's resilience.

In this thesis, performance-based metrics are divided into three categories: performance loss, recovery ratio and demand ratio. The references are summarized in Table 2.1 according to the category, in which the research object and performance indicator are listed. Suffering from external actions or disturbance will cause negative changes or deterioration of the overall system performance (Nogal and Honfi, 2019). Therefore, performance loss is one of the most direct and popular metrics of performance-based metrics, while the performance indicator varies greatly in different systems and studies. In practice, both individual and composite indicators can be used for assessment. Recovery ratio is the ratio of restoration at time t resulting from disruption to function loss caused by previous disruption, which is a kind of time-dependent resilience metric (Zhou et al., 2019). Demand ratio is the ratio of expected demand met by the post-disaster system to the pre-disaster system. In addition to the three widely used resilience metrics, there are also some new metrics. For example, Vugrin et al. (2019) provided a composite resilience measure by considering system performance and recovery effort collectively.

From Table 2.1, it can be concluded that regardless of the type of metric, time and load are the most common performance indicators. These will be utilized in the resilience assessment model for the WTC in Chapter 3.

2.3 Waterway Transportation Channel Resilience

Waterway transportation channels play a crucial role in global maritime transport, serving as essential routes for commercial shipping and international trade. Compared to open seas, restricted waterways present significantly higher risks due to their confined space, complex hydrodynamic conditions, and potential congestion (Li et al., 2023, September). Current research on restricted channels covers various types, including narrow channels (Cho et al., 2021), ice channels (Zhang et al., 2024, June; Xie et al., 2023), dredged coastal entrance channels (Tang et al., 2014), curved bridge channels (Ai et al., 2020), and ship tunnels (Zhang et al., 2023b). These waterways are particularly significant subjects of study due to their navigational challenges and the potential for maritime accidents.

Among the various methods used to analyse such waterways, simulation has emerged as the most widely adopted approach. By replicating real-world navigational conditions, simulations allow researchers to examine factors affecting ship navigation and identify key influences. For example, Ai et al. (2020) used simulations to assess ship passing capacity and determine the minimum distance between bridge-pier surfaces and channel edges in curved bridge channels. Li et al. (2021) studied ship performance in ice channels narrower than a ship's beam through model-scale tests and numerical simulations. Xie et al. (2023) conducted full-scale simulations of brash ice channels using the computational fluid dynamics–discrete element (CFD–DEM) coupling method, revealing that ship-to-ship distance significantly affects the velocity field, dynamic pressure distribution on the hull, and hydrodynamic interaction forces. Zhang et al. (2023b) employed ship simulations to assess the navigational safety of ten-thousand-ton vessels in ship tunnels, finding a positive correlation between coasting length and factors such as tunnel width, water depth, and sectional coefficient. Additionally, simulations are valuable for decision-making. For instance, Tang et al. (2014) developed a simulation-based optimization framework to determine optimal channel dimensions under limited dredging budget constraints.

Another key research focus is traffic simulation based on vessel behavior, which is used for channel risk assessment. For example, Xin et al. (2019) developed a simulation model for ship navigation in the “Xiazhimen” waterway using statistical analysis of AIS data, considering key factors such as speed, location, and time. Similarly, Wang et al. (2020) proposed a traffic simulation to analyze the relationship between various factors and channel risk. Li et al. (2023, September) examined collision risks in a hazardous construction channel through a numerical model of ship collision avoidance. Bogalecka and Dąbrowska (2023) applied the Monte Carlo simulation technique to model shipping accidents and chemical release consequences in global maritime waters.

Overall, by replicating real-world navigational conditions, simulations serve as essential tools for assessing vessel behaviour, evaluating risk factors, and developing strategies to enhance maritime safety and efficiency. While vessel disruption simulation models are not uncommon, most existing studies focus on risk assessment or pre-accident analysis. However, comprehensive resilience studies covering the entire disruption event remain limited. Addressing this gap is the primary innovation of this study.

Research on the resilience of waterway transportation channels is relatively scarce, and it is often approached as a system-level study by researchers. For example, Zohoori et al. (2023) propose an analytical approach to quantify the resilience of narrow waterway systems during disasters. In their study, two metrics: (1) the number of inbound and outbound vessels and (2) total stopped vessel-hours, are used to measure the resilience of a waterway system. They processed AIS data from the Houston Ship Channel to analyse the impact of Hurricane Harvey in August 2017. From the perspective of metrics, key factors such as cost are not considered. Methodologically, their study focuses on data analysis, overlooking critical elements such as specific vessel behaviours and rescue plans. To address these two research gaps, this thesis proposes a more comprehensive evaluation model and a detailed disruption simulation model. Further details can be found in Section 3.

2.4 Port Resilience

Ports are critical and special components of MTS. This section will specifically review the current state of resilience research on ports. It will begin by summarizing main methods used to construct resilience models (Table 2.2), followed by an analysis of the various factors affecting ports (Table 2.3).

Table 2.2 Summary of literature related to port resilience

Research direction	Research context	Literature
Qualitative research	Establishment of frameworks to improve resilience	Mansouri et al., 2010; Nair et al., 2010; Omer et al., 2012; Justice et al., 2016; Almutairi et al., 2019; Duchek, 2019; Vanlaer et al., 2021, Kim et al., 2021
Quantitative research	Modeling resilience using Bayesian networks	Hossain et al., 2019; Hosseini & Barker, 2016; John et al., 2016; Panahi et al., 2022
	Establishment of probabilistic frameworks to assess resilience	Shafieezadeh & Ivey Burden, 2014
	Design of resilience assessment tools based on simulation	Dhanak et al., 2021;
	Ports Resilience Index	León-Mateos et al., 2021; Liu et al., 2023a
	Port meteorological risk assessment	Wang et al., 2024c
	Identification of the relationships between customer needs, risk, and resilience measures	Lam & Bai, 2016

In order to address the challenges triggered by these diverse disturbances and improve or enhance the port resilience, researchers use various methods to analyse the influencing factors and conduct resilience measurement studies. The research methods can be roughly classified into two categories: qualitative and quantitative, which are summarized in Table 2.2 and described in the subsequent sections.

Based on the literature review, the major disturbances of ports as infrastructure are summarized and shown in Table 2.3. From Table 2.3, it can be seen that the disruptions affecting ports are diverse and numerous. These disruptions can generally be categorized into four types: natural factors, technological factors, organizational factors and others. The detailed category will be detailed in Section 4.

Table 2.3 Summary of port disruptions based on literature review

Author	Factors of port disruptions
Mansouri et al. (2010)	Natural disasters, organizational factors, technological factors, human factors
Berle et al. (2011)	Loss of capacity to supply, financial flows, transportation, communication, internal operations or capacity, human resources
Hsieh et al. (2014)	Accessibility (ground access system, travel time, shipping route density), capability (gantry crane capacity, facility supportability, wharf productivity), operational efficiency (Electronic Data Exchange connectivity, turnaround time, labor productivity, berth occupancy rate), industrial cluster/energy supply (investment growth, Free Trade Zones business volume, electric power supply, gas supply)
Lam and Su (2015)	Earthquakes, tsunamis, typhoons, explosions, ship collisions and labor action
Grainger & Achuthan (2014)	Economic, environmental, human, access, network
Lam & Bai (2016)	External risks (Natural disaster, Piracy/terrorism), supply chain risks (congestion in port, port state control, technical downtime, operational risk), internal risks (human resource management, IT system)
Loh & Thai (2016)	Impact or collisions, mechanical failures, external factors, and human factors
Hosseini & Barker (2016)	Natural disasters (e.g., floods, tornados), hazardous material threats (e.g., fires, explosions, liquid spills)
John et al. (2016)	Operational risk, security risk, technical risk, organizational risk, natural risk
Hossain et al., 2019	Natural disasters (hurricanes, drought, storms), cyber-attacks (malware and phishing, denial of services, GPS spoofing and jamming), others (access factors, organizational factors, economic factors)
Hossain et al., 2020	Economic, human, environmental, organizational, technological, and network and access factors.
Vanlaer et al., 2021	Policy, economic, operational impact
Panahi et al., 2021	Covid-19 pandemic
Liu et al., 2023a	Covid-19 pandemic
Wang et al., 2024c	Typhoons, dense fogs, and storm

2.4.1 Qualitative Research

Qualitative approaches focus on defining resilience, identifying causal relationships among factors, thereby establishing resilience frameworks.

The risk Management-based Decision Analysis framework was proposed by Mansouri et al. (2010) to help port stakeholders measure the resilience of port infrastructure systems and make better decisions. The framework consisted of three phases: assessing vulnerabilities, devising resilience strategies, and valuing investment strategies. Nair et al. (2010) proposed a framework to measure port network resilience based on the networkwide resilience model provided by Chen and Miller-Hooks (2012) with the combination of Monte Carlo simulation technique and benders decomposition algorithm, which was applied to the Port of S´winoujs´cie in Poland. Networked Infrastructure Resiliency Assessment framework is proposed by Omer et al. (2012) to evaluate the resiliency of the major Pacific Ocean-facing port networks, consisting of three stages: boundary definition, resiliency assessment process, resiliency scheme identification and evaluation. By reviewing the complex port environment in the US such as the expansion of the Panama Canal, Justice et al. (2016) conceptualized US container ports within a Complex Adaptive Systems framework, characterized by self-organization, to help managers better manage port resilience and hence to achieve sustainability in a complex and uncertain environment. Almutairi et al. (2019) proposed a resilience analysis framework by integrating stakeholder mapping and scenario-based preferences modeling to examine the joint influences of scenarios and stakeholders on priorities. By applying this framework to a container port of Virginia, Almutairi et al. (2019) found that the most robust, highly prioritized initiative is constructing the CIMT terminal. To help organizations achieve organizational resilience in practice, Duchek (2019) conceptualized resilience as a meta-capability and divided the resilience process into three successive phases (anticipation, coping, and adaptation) based on time (before, during, after disturbances). Then, Duchek (2019) assigned important organizational capabilities (knowledge base, resource availability, social resources, and power/responsibility) to each of these phases. Based on the work of Duchek (2019), Vanlaer et al. (2021) refined the port resilience framework from three areas: policy, economics, and operations, which provided port authorities with more detailed resilience measures. Kim et al. (2021) established a framework to measure the port resilience based on the analysis and summary of previous literature and conducted exploratory and confirmatory factor analysis based on samples collected from South Korean port stakeholders.

2.4.2 Quantitative Research

To quantify port resilience, the establishment of probabilistic frameworks is a valuable way. Considering the uncertainties in the process, Shafieezadeh & Ivey Burden (2014) proposed a scenario-based probabilistic framework to assess the resilience of infrastructure systems and studied the seismic resilience of a supposed seaport with realistic settings. The framework included the probabilistic hazard model, repair requirement model, recovery model and operation model. Due to the lack of objective data, expert experience is still the primary source of quantitative data. Based on the questionnaires and interviews with experts from the container liner companies, Lam & Bai (2016) identified the relationship between customer requirements of shipping lines, risks, and resilience measures by developing an original quality function deployment approach.

Bayesian network (BN), excellent for dealing with causal dependencies between different variables in probabilistic terms, has been used widely in the area of resilience and reliability engineering, such as evaluating the resilience of urban transportation systems (Tang et al., 2020) and engineering systems' resilience (Kammouh et al., 2020). In the area of port resilience, John et al. (2016) established a BN-based risk assessment model for seaport disruption, which can be serviced as an analytical tool for implementing resilience strategies. Hosseini & Barker (2016) and Hossain et al. (2019) modelled infrastructure resilience using BN and performed multiple analyses, with the former applying the model to an inland waterway port and the latter applying the model to a deep-water port. Panahi et al. (2022) developed a resilience assessment model for critical infrastructure and analysed the case of ports responding to the impact of the Covid-19 epidemic. The research results from the above literature show that the BN model can effectively reflect the mutual relationships of various factors in the compound system and provide insights to improve the system's performance.

In addition to theoretically quantifying port resilience, researchers have also explored practical tools. León-Mateos et al. (2021) developed and validated a Port Resilience Index to address the challenges of climate change by taking into account all stakeholders associated with seaports. Dhanak et al. (2021) provided a port resilience assessment tool based on the microscopic traffic simulation model to simulate the hybrid multimodal port operations, then applied the model to six ports along the southeast US coastline and showed the impact of Hurricane Matthew in 2016. Liu et al. (2023b) proposed a port resilience index system based on the entropy weight method from a multistakeholder's view. Wang et al. (2024c) proposed a quantitative algorithm to measure the meteorological risk factors of ports.

Based on the above, quantitative research of port resilience is not enough in terms of the number of papers and models, and quantification models and methods for strategy-related resilience are rare. Each model and method have its own applicability and limitations, with data being the main limitation. The port is a complex system, and identifying resilience strategies with priorities based on effective assessment models is conducive to resilience management at the port. However, the objective data used to assess the effectiveness of the implementation of different strategies is insufficient. On the one hand, a port involves the operation of a wide range of equipment. In the case of poor facilities or underdeveloped technology, objective data on some equipment are not available from the port itself due to the lack of monitoring systems. For example, for traditional loading and unloading equipment in port, its real-time bearing operational data are difficult to obtain. On the other hand, the internal operations of a terminal are often confidential for security reasons. It is difficult for the public to access such data. Hence, integrating subjective assessment and objective data into resilience management is essential but yet, rare. The research results from the literature (Kammouh et al., 2020; Tang et al., 2020; Hossain et al., 2019) show that the Bayesian network model can effectively combine expert judgment and statistics analysis, reflect the mutual relationships of various factors in the compound system, and provide insights to improve the system's performance. Therefore, BN is selected as the port resilience modelling approach, which will be introduced in Chapter 5.

2.5 Shipping Network Resilience

This subsection narrows the research scope to the resilience of shipping networks. Based on the literature review above, the study of networks primarily utilizes complex network theory. Therefore, this section will summarize the resilience of shipping networks using complex network theory. Additionally, considering the use of community detection for modelling shipping networks in the later studies, the methods for port community detection in shipping networks will also be summarized.

2.5.1 Resilience Studies of Shipping Network

Through a comprehensive literature review, resilience studies of shipping networks using complex network theory (CNT) can be divided into three primary areas: characterization of network properties, assessment, and optimization, according to the definitions provided by the researchers, as illustrated in Table 1. Resilience is a relatively novel concept within the context of shipping networks; historically, most research has concentrated on other performance metrics, such as connectivity, vulnerability, and robustness (Liu et al., 2024). Nevertheless, these studies offer valuable assessment guidelines pertinent to the investigation of resilience. Additionally, resilience is a comprehensive concept that often encompasses other performance aspects, such as vulnerability and robustness (Wang et al., 2023a). Consequently, Table 1 also includes a summary of notable papers that focus on these alternative performance aspects.

Table 2.4 Summary of literature related to shipping network analysis

Research direction-Level I	Research direction-Level II	Research Method	Investigation subjects	Data	Variables/factors	Reference
Characterization of network properties	Network analysis	CNT	Maritime transportation network	878 global seaports and 1,802 container routes, sourced from CI-online	Degree distribution, degree correlations, etc.	Hu & Zhu (2009)
	Network analysis	CNT; gravity model	Maritime transportation network	The journey details of 16,363 cargo vessels throughout 2007	Mean degree, clustering coefficient, node strength, link weight, etc.	Kaluza et al. (2010)
	Network analysis	CNT; optimization model	Maritime transportation system	Employing “web scraping” to automatically gather data from the Internet	Degree/ closeness/ betweenness centrality, cost	Alderson et al. (2020)
	Port connectivity analysis	CNT; transshipment service removal	Global container liner shipping network	The liner services of the ten major liner companies throughout 2008, sourced from CI-Online	Transportation time and capacity, etc.	Jiang et al. (2015)
	Network analysis	CNT; entropy weight method	The Regional Comprehensive Economic Partnership shipping network	Route data of global top 100 shipping lines from Alphaliner	Degree/proximity/ betweenness/closeness centrality, core-edge	Wang et al. (2024b)
	Resilience analysis	Disruption simulation (continuous node removal); CNT	Maritime silk road shipping network	Shipping data from China’s coastal ports to Europe, Africa, the South China Sea, and the South Pacific, sourced from	Network efficiency; Network and Node Diversity	Yang and Liu (2022)

				Drewry's Container Forecaster in 2019		
Assessment	Vulnerability assessment	CNT; links removal	Global container shipping network	5069 fully cellular container vessels throughout the 2012	Link betweenness, link salience; robustness and flexibility	Viljoen et al. (2016)
	Vulnerability assessment	CNT; attack simulations (links removal)	Shipping network	Liner shipping services data for intra- and extra-regional routes in the U.S., sourced from Containerization International (2012)	Total degree; betweenness centrality, etc.	Calatayud et al. (2017)
	Vulnerability assessment	CNT; joint entropy; multiscale factor	Asia–Europe maritime transportation network	A network with 54 seaports and 112 shipping routes	Neighborhood-/ gravity-based centrality, etc.	Wen et al. (2022)
	Vulnerability assessment	CNT; attack simulations (links removal)	Global container shipping network	Container transport data in 2019 and 2020	Average path length, network efficiency, etc.	Li et al. (2024)
	Robustness assessment	CNT; node removal	Global container shipping network	Ports of call and routes managed by the 25 leading shipping companies at two time points (2004 and 2014)	Network's average degree, clustering coefficient, etc.	Wang et al. (2016)
	Robustness assessment	CNT; attack simulations (continuous node removal)	Global cargo ship transportation networks	Automatic identification system (AIS) data of global cargo ships in 2015	Degree, betweenness centrality and flux	Peng et al. (2018)
	Robustness assessment	CNT; attack simulations (node removal)	Global liner shipping network	World's liner shipping service in 2019, sourced from Alphaliner	Degree, rich-club coefficient; motif centrality	Xu et al. (2023)
	Connectivity assessment	CNT; scenario simulations (adding arctic	Arctic shipping routes; global	Shipping schedules from Q4/2011 to Q3/ 2017	Latitudinal centrality index, degree/closeness/betweenness centrality	Poo et al. (2024)

		shipping routes)	container shipping network			
	Resilience assessment	Simulation (terrorist attacks, etc.); integer programming; Monte Carlo method	Port-hinterland container transportation network	Sweden's Port of Gothenburg and its surrounding hinterland	Proportion of fulfilled container flow relative to overall transport demand; time, cost	Chen et al. (2017)
	Resilience assessment	CNT; node removal (knock-on effect simulation model)	Global liner shipping network	AIS data of container ships from 2018 to 2020	the extent of congestion, etc.	Bai et al. (2023)
	Resilience assessment	CNT; historical and stress-test TC scenarios	Global liner shipping network	Global liner shipping route data for 2015, sourced from Alphaliner	Path redundancy (shipping capacity); ratio of performance maintained to original performance	Xu et al. (2024a)
	Recovery strategies assessment	CNT; node recovery	Shipping lanes in the Pacific Northwest and Northern Indian Ocean regions	Service information of 16 leading container shipping companies worldwide from Oct. to Dec. in 2016	Global network efficiency, recovery cost (port scare and economy)	Wan et al. (2022)
Optimization	Measuring and maximizing resilience	integer L-shaped method; Monte Carlo simulation	A rail-driven intermodal container network within the U.S.	8 nodes representing key cities, 24 single-direction rail arcs, and 22 two-way virtual highway arcs	Estimated share of demand that can be fulfilled following a disaster, along with shipments and time	Miller-Hooks et al. (2012)
	Connectivity optimization	max–min integer optimization	World container shipping network	Service timetables on the webpage during Q4 2015	The largest eigenvalue	Cheung et al. (2020)
	Resilience optimization	Copeland scoring method; CNT	Maritime transportation systems	Sea routes consisting of 23 cities	Capacity (traffic received by the demand node)	Dui et al. (2021)
	Resilience optimization	Borda Count method; CNT; continuous node removal; optimization model	Global maritime transportation network	Data from Maersk Shipping Line for July 2019	Degree centrality, closeness centrality, etc.	Poo et al. (2022)

(1) Characterization of Network Properties

In studies of network properties characterization, researchers primarily use shipping line data to construct a shipping network. Based on this network, various key metrics can be calculated using complex network theory, such as node degree (Hu & Zhu, 2009), clustering coefficient (Kaluza et al., 2010), and closeness centrality (Alderson et al., 2020). These metrics elucidate the characteristics of the shipping network, and different shipping networks exhibit varying values for these metrics. Additionally, altering the network structure, such as by removing nodes or service lines, changes the values of these metrics. By analysing these metrics, researchers can summarize the features of the studied network, providing insights for subsequent studies. For example, Hu and Zhu (2009) analysed the statistical properties of the worldwide maritime transportation network (WMN) using metrics such as degree distribution. Their research revealed that the WMN is a small-world network exhibiting power-law behaviour. Similarly, Kaluza et al. (2010) investigated the maritime networks of different vessel types, discovering that the broader pattern of vessel activities shows a heavy-tailed distribution concerning port connectivity and transported loads, with notable differences between ship types. Yang and Liu (2022) employed transmissibility (network efficiency) and diversity (average number of independent passageways) to assess the resilience of shipping network. They then analysed the resilience characteristics using disruption simulations based on continuous node removal strategies for the shipping network of the Maritime Silk Road.

(2) Assessment

In assessment studies, there is significant overlap with analytical studies; however, pure metric analysis based on shipping networks is insufficient. Instead, various attack strategies or scenario simulations are employed. For example, Chen et al. (2017) used simulations of terrorist attacks, strikes, and natural disasters, along with the Monte Carlo method, to conduct a resilience assessment of the port-hinterland container transportation network. Peng et al. (2018) evaluated the global cargo vessel transportation network's robustness by employing different methods: random attack, and three targeted attacks. Additionally, novel metrics have been introduced. For instance, Wen et al. (2022) conducted a vulnerability assessment by combining three metrics: neighbourhood-based, gravity-based, and iterative refinement centrality. Bai et al. (2023) assessed GLSN resilience from two aspects: static and dynamic. For the former, the maximum segment of connected nodes and the average inverse of the shortest path duration served as metrics. For the latter, they measured congestion levels, modelling based on node removal strategies and a knock-on effect simulation model. Xu et al. (2024a) created a framework to assess GLSN resilience against tropical cyclones through path redundancy assessment, employing stress-test TC scenarios. Considering the redistribution of traffic flow, cascading effects are gradually being applied. For example, Xu et al.(2024b) used massive ship trajectory data to construct a cascading failure model for container shipping networks, while Liupeng et al.(2024) developed a cascading failure vulnerability study on the container shipping network along the 21st Century Maritime Silk Road. Beyond network performance assessment, recovery strategies have also been evaluated. For instance, Wan et al. (2022) evaluated various restoration strategies' efficiencies following disturbances in GLSNs, establishing an innovative risk-oriented resilience framework that considers global network efficiency and recovery cost, where recovery cost is related to port scarcity and economic impact.

(3) Optimization

Building on performance assessment studies, a limited number of optimization studies have been introduced, focusing on enhancing the resilience and efficiency of maritime transportation systems. These models incorporate novel variables, such as time and shipment volumes, to address specific challenges in network optimization. For example, Dui et al. (2021) proposed the concept of residual resilience to identify optimal recovery durations and prioritize disrupted nodes and pathways within maritime transportation systems. Cheung et al. (2021) developed a max-min integer optimization approach to improve network connectivity by analysing the largest eigenvalue and its corresponding eigenvector. Similarly, Poo et al. (2022) employed a multi-centrality assessment to pinpoint vulnerabilities in global shipping hubs and networks. This methodology facilitated the formulation of a model to determine the most resilient maritime paths connecting ports, thereby optimizing overall network resilience.

(4) Summaries

As summarized in Table 2.4, despite conceptual differences among researchers in the study of shipping networks, there are also significant similarities. For example, metrics derived from network topology are commonly employed, and the global container shipping network remains the most popular subject of investigation. Data are primarily collected from liner shipping companies and AIS positions of ships. The novelties in these studies often lie in the research objectives and the development of more meaningful assessment indicators.

Despite advancements in shipping network analysis, several research gaps persist. Most studies rely on port-to-port network modelling, focusing on strategies developed from the individual port perspective. This overlooks the potential of port community-to-port community networks, which offer deeper insights into collective response capabilities and provide a more holistic analysis of network structures. Furthermore, disruption strategies in existing research are predominantly static, evaluating the impact of node or connection removal without accounting for the dynamic redistribution of container flows among ports. Although recent studies have begun addressing cascading effects, recovery mechanisms—a critical element of resilience analysis—remain largely unexplored. To address these gaps, this study develops a cascading failure model for the shipping network that integrates recovery mechanisms. By incorporating port community partitioning, we analyse resilience from the perspective of port communities and propose actionable recommendations to enhance network resilience.

2.5.2 Classification Method of Port Communities

Building on the above, segmenting closely connected ports into port communities, and subsequently analyzing and evaluating these communities, provides a clearer and more holistic understanding of shipping network structures. This approach also offers better insights into collective response capabilities, thereby enhancing network resilience. Consequently, the classification methods of port communities are reviewed and summarized as follows.

Due to the constraints imposed by coastlines, oceans, and the geographical distribution of sea areas on cargo ship navigation, physical geography is a primary determinant shaping the development and structural evolution of the GLSN (Xu et al., 2015). Thus, some researchers would divide ports according to their location. For example, Xu et al. (2015) defined a maritime region as a geographic area served by a group of ports collectively, and established seventeen regions from a geographic perspective. Later, various community detection algorithms are introduced to partition ports, like the Girvan-Newman (GN) algorithm (Girvan & Newman, 2002), which aims to progressively eliminate the edges with the greatest betweenness until the network is segmented into separate communities. To illustrate the geographical diversity of ports within the global maritime network, weighted ego network analysis has been proposed by Liu et al. (2018). In their study, ports were divided into six port communities based on the GN algorithm. Additionally, Newman and Girvan (2004) introduced the concept of modularity to evaluate network partitions' quality. Xu et al. (2020) divided ports of GLSN into seven upper-module port communities using modularity maximization. According to Xu et al. (2020), while this algorithm may overlook some smaller structures, it remains reliable on a larger scale. When the community structure is more complex, the GN algorithm may not be able to identify small or tight communities because the edge betweenness in these communities may be relatively low and not easy to be deleted preferentially. Thus, the Louvain algorithm, a heuristic modularity-based method has been proposed to process large-scale networks (Blondel et al., 2008). It has been employed in various studies, including applications to the GCSN (Zhang et al., 2023a; Jarumaneeroj et al., 2024) and cruise shipping networks (Kanrak & Nguyen, 2022; Ito et al., 2022). Subsequently, an improved version of the Louvain algorithm, known as the Leiden algorithm, was developed to address some of its limitations. The Leiden algorithm offers enhancements in several aspects, such as ensuring community connectivity, improving computational efficiency, and exhibiting strong adaptability. For instance, Kang et al. (2022) employed the Leiden algorithm to analyze the global liner shipping network (GLSN) of the top six liner shipping companies, while Zhang et al. (2024) utilized it to explore the characteristics of the global maritime transport network.

Besides the GN algorithm, another common algorithm is the topological decomposition method. Its core idea is to use the network's topology information to decompose the network into multiple sub-structures or levels to better understand the relationship between the community structure. Common topological decomposition methods include k-core, k-clique and k-truss decomposition. Among them, the k-core decomposition is the simplest and intuitive. It recursively deletes nodes with a degree lower than k, up to the point where the degree of the surviving nodes is at least k subgraphs. To identify bridges and communities within the network, Ducruet and Zaidi (2012) extended the concept of k-core. Their approach involves segregating nodes with either elevated or minimal degrees from the remainder of the network, forming subnetworks where the node connectivity is either no less than k or no greater than k.

k-clique decomposition involves partitioning a network into multiple k-cliques, which are complete subgraphs where each node has connections to all other nodes. Through identifying these k-cliques, the method reveals strongly connected substructures within the network. Based on the k-clique method, the clique percolation method (CPM) was proposed. It not only identifies k-cliques but also connects these k-cliques into larger communities through clique percolation, which links k-cliques that share k-1 nodes. Considering the overlapping community structures of maritime shipping network, Bai et al. (2023) used the CPM algorithm to identify port communities.

The computational complexity of CPM is relatively high, particularly in large-scale networks where finding k-cliques is time-consuming. Additionally, the method is sensitive to the choice of k, with the decomposition results potentially varying significantly with different k values. Therefore, Pan et al. (2019) proposed an eigenvalue decomposition approach to detect port clusters within the international transportation network, achieving a good balance between computational efficiency and clustering accuracy.

However, the studies above have focused on modelling unweighted, non-directional or weighted, non-directional networks. In reality, the GLSN functions as a directed and weighted network, where the direction and weight of edges offer significant insights. Specifically, weighted links indicate the strength of transportation routes between ports, while directed links reflect the balance of transport flows between them. These characteristics are crucial for examining the structural attributes and identifying communities within the GLSN. To overcome this limitation, Wu et al. (2024) developed a directed-weighted GLSN, through which 27 practical relevant port communities are detected using the Infomap method. Infomap is a community detection algorithm based on the idea of compressing a description of a random walk on the network. It uses the flow of information to detect communities by reducing the complexity of a random walk, leveraging the principle that good community structures will allow for shorter descriptions. Infomap is particularly well-suited for directed and weighted networks, making it versatile for various types of complex network. Compared to other algorithms, Infomap is more efficient, is suited for directed and weighted networks, and can detect communities with high resolution. Thus, this method will be employed in this study later.

In fact, various community detection algorithms have been proposed and utilized across numerous networks, including social and communication networks. Beyond the common methods described above, some machine learning techniques have also been applied to maritime networks recently. For instance, Chen et al. (2024) employed an unsupervised learning method called Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to compare the community structures of maritime oil transportation and oil tanker networks. Similarly, Mei et al. (2024) used DBSCAN to conduct structural analysis of the European LNG maritime supply chain network. Moreover, Huang et al. (2024) applied a deep learning method, namely a graph convolutional neural network (GCN) model, to derive network characteristics for community identification. According to the summary by Javed et al. (2018), there is a total of 19 community detection methods, which are classified into two categories: disjoint and overlapping community detection algorithms. However, their application in maritime shipping networks is noticeably lacking based on the above introduction. The inherent geographical constraints of maritime networks, along with the development of contemporary regional trade blocs, contribute to the network's tendency towards regionalization. Therefore, research on maritime communities is currently crucial yet insufficient. As the focus of this study is not on port community detection, the detailed introduction and comparisons of community detection algorithms are not included.

2.6 Research Gaps

In this chapter, a review and summary of the literature on resilience research of MTS is provided, which are divided into four sections, the concepts in the literature review progress from broad (Section 2.1 Infrastructure systems resilience, Section 2.2 Transportation systems resilience) to specific (Section 2.3 Waterway Transportation Channel Resilience, Section 2.4 Port resilience, Section 2.5 Shipping network resilience). Based on the literature review, the research gap of each component can be concluded as follows.

Currently, resilience research on WTC is limited, many researchers try to analyze it from the system level. System level mainly focuses on resilience assessment by relying on influencing factors or resilience metrics, optimization of recovery strategies, and resilience analysis using statistical data. The following research gaps are noted. First, when constructing resilience assessment model, the variables used are usually binary (false or true) or ordinal (Very Low, Low, Medium, High, Very High), which are determined based on expert judgement. Next, when constructing resilience assessment model using resilience metrics, the network nodes or links in the transportation system only possess two states: either operating or failed. The detailed analysis of systems' components and structures, and the specific changing trend of systems' line or node when the disturbance occurs are lacking. There are limited guidelines and tools for the system's stakeholders to design rescue plans or allocate the available and limited resources, such as budget, energy and manner assets. Therefore, for the WTC, the objective is to identify the components and subcomponents of WTC resilience and specify their dependencies. Subsequently, a more detailed simulation model will be constructed to simulate the trends in waterway resilience changes. This will help managers more effectively allocate available and limited resources (such as budget, energy, and manpower) to system components. The detailed introduction of WTC resilience modelling and assessment will be provided in Chapter 3.

Quantitative research on port resilience is still insufficient in both the number of papers and models, and there are even fewer resilience quantification models and methods related to strategies. Each model and method have its own applicability and limitations, with data being the primary limiting factor. Ports are complex systems, and identifying prioritized resilience strategies based on effective evaluation models is beneficial for resilience management. However, there is a lack of objective data to evaluate the effectiveness of different strategies. Therefore, it is necessary to integrate subjective assessments with objective data into resilience management, although this approach is currently rare. Additionally, compared to other methods, Bayesian network models can effectively combine expert judgments and statistical analysis, reflecting the interrelationships among various factors in complex systems and providing insights to improve system performance. Consequently, BN are chosen as the method for port resilience modeling, integrating expert experience with actual statistical data to identify key resilience strategies, which will be introduced in Chapter 4.

For the shipping network, the modelling of the shipping network (e.g., network modelling and port community detection) and the resilience assessment of the shipping network (e.g., more rational simulations of disruptions) have not been thoroughly explored. Current research on shipping networks mainly focuses on port-to-port network modelling and disturbance simulation of node removal. Ports located in the same region often share similar policy environments, exposure to disruptions, and operational characteristics. Analyzing resilience at the community level, rather than focusing on individual ports, allows for a more comprehensive understanding of systemic vulnerabilities and collective response capacities. Additionally, evaluating solely based on node removal strategies often neglects the cascading effects between ports. Although recent studies have begun addressing cascading effects, recovery mechanisms—a critical element of resilience analysis—remain largely unexplored. Thus, this thesis aims to address these gaps by providing a novel resilience assessment model for the shipping network based on port community structures, which will be introduced in Chapter 5.

Chapter 3 Resilience Modelling and Assessment of Waterway Transportation Channels

This chapter aims to address Research Aim 1: resilience modelling and assessment of the waterway transportation channels (WTC). Specifically, WTC resilience will be analysed by introducing disruptions at different stages of the resilience recovery cycle through simulation. A comprehensive resilience indicator, comprising ship load, ship delay, and recovery cost, will be provided to optimize post-accident rescue plans. A discrete-event-based simulation model is developed to quantify WTC resilience. The Yangtze Estuary Deepwater Channel is used as the case study, with the automatic identification system (AIS) data of this channel in 2018 collected and utilized as input parameters for the simulation model. Various scenarios and experiments have been designed to analyse the resilience performance of the WTC under different accident conditions. Based on a real accident case, two rescue plans are designed for comparison, and the results demonstrate the effectiveness of the proposed resilience indicator. Based on the analysis results, several practical suggestions are recommended.

3.1 Background

WTC is an important pillar of the national supply chain and plays an important role in the international supply chain. Due to the long and complex nature of WTC, it is susceptible to be disrupted by man-made and natural disasters. For example, the operation error of ultra-large container carrier "Changci" in March 2021 caused the Suez Canal in Egypt to be blocked for more than a week. Consequently, at least 369 vessels were unable to sail normally, including dozens of container ships, bulk carriers, oil tankers, and liquefied natural gas or liquefied petroleum gas vessels, and more than $14 million has been lost per day of the canal (Lewis et al., 2021). Different from other transportation infrastructures, WTCs usually consist of long and narrow waterways, and the network structure is simpler, which means that when it encounters interference, the selectivity of ships movement is very limited and most ships can only choose to wait. This also means that when WTCs encounter disruptions, the results are more serious. Research on the resilience of WTCs is relatively scarce, and it is often approached as a system-level study by researchers. Research on the resilience assessment of other transportation systems can provide inspiration for the study of WTCs, but it cannot be fully tested for WTCs.

The WTC is highly complex. In addition to ships and the channel itself, there are many auxiliary equipment and facilities, such as buoys, aids to navigation, and the mobile communication base station, that service ships to pass through the channel smoothly.

Figure 3.1 describes how stakeholders interact in the waterway. The Maritime Safety Administration (MSA) monitors the navigation of ships in the channel in real-time (Wang et al., 2021) based on auxiliary equipment and facilities. When a severe disturbance or accident occurs, MSA will respond immediately by contacting the captains of the affected vessel and developing strategies to maintain/modify the system based on the specific circumstances. According to the strategies, MSA may contact the captains of other ships in the waterway to implement the plan since some accidents may affect the ships of the whole waterway. The captain of the ship in trouble will promptly report the damage to the MSA and wait for rescue or take rescue actions by himself according to MSA's instructions. Meanwhile, the crew or passengers on the ship will be notified of the real-time situation. In addition, while receiving the MSA's order, the rescue department will rush to the accident site to carry out maintenance or rescue. They may also keep in touch with MSA and the captains during this process. Shortening the response phase can enhance the effectiveness of waterway safety management.

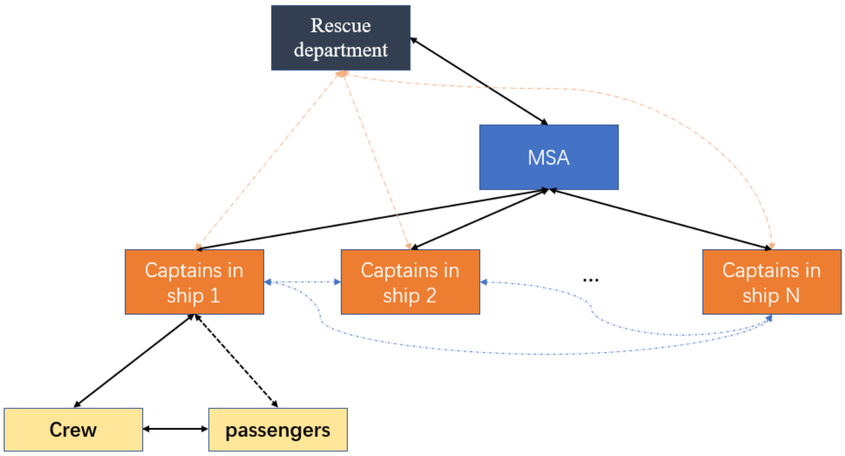


Figure 3.1 Interactions between stakeholders of waterway transportation system

3.2 Resilience Model

3.2.1 Modified Function Transition in Resilience

Based on the paradigm proposed by Henry and Ramirez-Marquez (2012), we propose a modified function transition paradigm in resilience for WTC. The service functions or performance of WTC during the attack (i.e., F(t)) and recovery processes are depicted in Figure 3.2. With the progression of time, the WTC can be divided into 5 stages: (1) stable original phase,

(2) disturbance phase, (3) response phases, (4) recovery phases and (5) stable recovery phases. The phases are discussed in detail below.

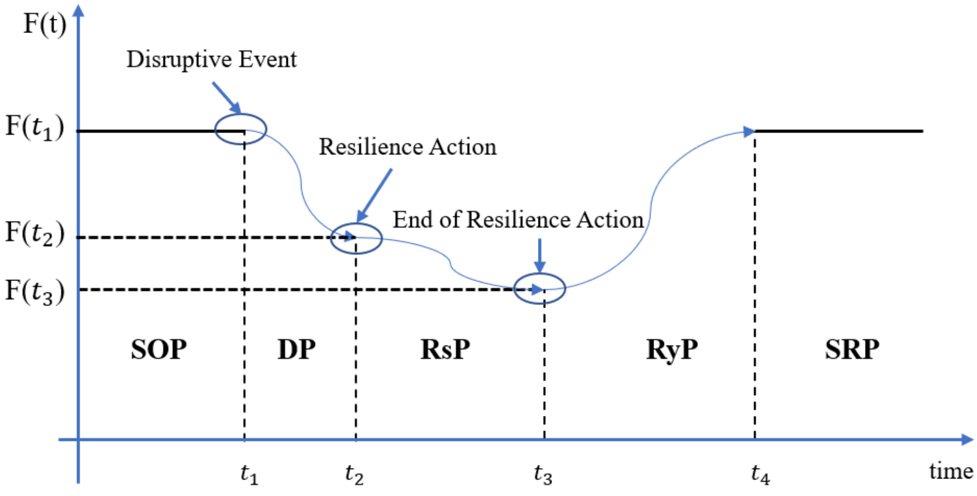


Figure 3.2 Transition of WTC service functions in resilience (Note: SOP= Stable Original Phase, DP= Disturbance Phase, RsP= Response Phase, RyP= Recovery Phase, SRP= Stable Recovery Phase)

(1) Stable Original Phase

Stable original phase is the reliable state of the system before the disturbance occurs.

(2) Disturbance Phase

When disrupted event occurs, the system will enter into the disturbance phase. The system's performance will be reduced according to the severity of the disrupted event. This phase can be instantaneous or long-term. For example, the collision of ships can be instantaneous, while it may take several days for the waterway to freeze.

(3) Response Phase

When the MSA begins to respond, such as formulating an emergency management plan based on the specific information of the accident, that is, when the resilience action occurs, it enters the response phase. Many scholars ignore the response stage (Baroud et al., 2014; Henry and Ramirez-Marquez, 2012), but this stage is essential. This process includes the mutual communication and coordination of various shareholders of organization subsystem and the formulation of plans, as well as the emergency repair personnel rushing to the accident site (if necessary) and launching specific emergency repair operations after the plan is made. In this process, the performance of the channel may continue to decline, for example, when a stranded ship in an accident that has not been moved will continue blocking the channel.

(4) Recovery Phase

When the resilience action is completed, the affected ships in the channel can resume operations, and the WTC enters the recovery phase. At this stage, the affected ships resume their operations one after another. Due to the blockage, the WTC is congested. Therefore, it will take a certain amount of time for each ship to return to its normal driving state.

(5) Stable Recovery Phase

When each ship in the waterway returns to stable navigation conditions, WTC enters stable recovery phase. After the disruption, the SRP state could stabilize at either a higher or lower level.

3.2.2 Attack Strategy and Assumptions

We assume that the channel handled by this model is double unidirectional, which can be simplified to a long and narrow rectangle with the same water depth, width, and speed. When a ship enters the waterway, its direction will not change until it leaves.

In daily operations, the disturbances that lead to WTC failure are mainly random (e.g., natural disasters, equipment failures, human error, etc.). In this study, we assume that the disturbances will cause an instantaneous accident, and the site and time of the accident are random. To simulate the random disturbances, accidents on ship such as ship grounding is selected as the disturbance type. When an accident occurs, ships of the same lane behind the accident site will be affected, and the affected ship can only slow down to a standstill during the response phase or obey MSA's scheduling arrangements during the recovery phase.

Assuming that the ship enters the channel randomly, the parameters such as the type, length, and speed of the ship obey a certain distribution. The relevant distribution function can be obtained by collecting actual data fitting. As our final evaluation is for the whole response phase and recovery phase, it is assumed that all ships are traveling at a constant speed in the waterway before the interference occurs.

In addition, it is assumed that there is a safe distance sd_r between adjacent stationary ships and there is a safe distance sd_o between adjacent ships in normal operation.

3.2.3 System's Performance Measures

We assume that the ships want to leave the waterway as soon as possible. The longer the delay in the waterway, the worse the waterway's service function becomes. Therefore, the first performance measure in this model is the delay of ships when disruptive event occurs.

From the perspective of MSA, ship load is selected as the second performance measure, that is the number of ships in the waterway after destructive events. When an accident occurs, ships may be forced to slow down or stop, so the number of ships gradually increases. It may even exceed the maximum capacity of the channel. As the ships accumulate, the probability of subsequent accidents increases, and the subsequent restoration of the waterway becomes more difficult. In addition, the affected vessels may occupy the position of the port anchorage and affect the normal operation of the ports along the waterway. Therefore, the service function of the waterway will further deteriorate.

For accident vessels, they want to spend as little time and money as possible to get rescued.

Therefore, we define the resilience of WTC in the post-accident period as: the ability to recover rapidly with minimal impact and cost.

We have proposed a new resilience indicator of WTC as follows, which reflects the overall recovery effect of the system under a certain strategy/plan, to evaluate the performance of the recovery strategies.

$$R = (\alpha R_{S_L} * e^{-\beta R_{S_D}})/\gamma R_C \tag{3-1}$$

$$R_{S_L} = \alpha_1 AS_L * (\alpha_2 minS_L) \tag{3-2}$$

$$R_{S_D} = \beta_1 AS_D * \beta_2 maxS_D \tag{3-3}$$

$$R_C = CM/maxCM \tag{3-4}$$

In Eq.(3-1), R is the resilience of WTC, which is related to three performance indicators: resilience indicator of ship load R_{S_L}, resilience indicator of ship delay R_{S_D} and resilience indicator of recovery cost R_C. The value of R_{S_L} is related to the number of vessels in the waterway and reflects the magnitude of the disruption. The value of R_{S_D} is related to the affected time of the waterway and reflects the recovery speed. To make R_{S_D} take values in the interval [0, 1], we use the exponential function for delay time. α and β are parameters related with ship load and ship delay. Extreme and mean values can reflect the impact of system performance from different perspectives. R_{S_L} takes two factors into the consideration: the average ship load AS_L and minimum ship load $minS_L$, α_1 and α_2 are parameters of the two factors; and two main factors are considered for ship delay: average ship delay time AS_D and maximum ship delay time $maxS_D$, β_1 and β_2 are parameters of the two factors. These parameters determine the importance of different indicators and can be obtained based on the focus of the decision makers. R_C is the ratio of recovery monetary cost CM to the maximum recovery monetary cost $maxCM$, which reflects the degree of resource consumption. $maxC$ is the cost of distributing all resources after the accident. γ is the parameter of the R_C.

3.3 Simulation Model

In order to quantify the performance measures, a simulation model based on the assumptions proposed above of WTC is established in this section, and the flow chart of this model is shown in Figure 3.3.

Firstly, the simulation time T and the time step Δt are determined, and the length of the waterway L is set. The simulation time and waterway length should be long enough to obtain sufficient data analysis.

Then the ship traffic characteristics of the waterway such as ship arrival time distribution (SATD), ship speed distribution (SSD) and ship type distribution (STD) should be extracted and used as input parameters for the simulation model, which can be obtained by analysing historical AIS data which provide accurate and reliable information (Wang et al., 2020).

According to the time, this simulation can be divided into three phases: 1) Ship traffic event under normal situation, which represents the stable original phase in Fig.4.2; 2) Ship traffic event after disrupted event, which refers to the disturbance phase and response phase; 3) ship traffic event during recovery, which refers to the recovery phase and stable recovery phase.

(1) Ship Traffic Event under Normal Situation

According to the input distribution parameters, the ships' arrival time, direction, type, speed and etc. can be generated by random sampling. Then, then ship traffic event under normal situation can be generated. If the waterway length is L, the position of ships at the entrance of the waterway is $0/L$, and at the exit is $L/0$. If the arrival time t_i^{in} of ship i, is greater than t, it means that ship i has already entered the waterway at time t.

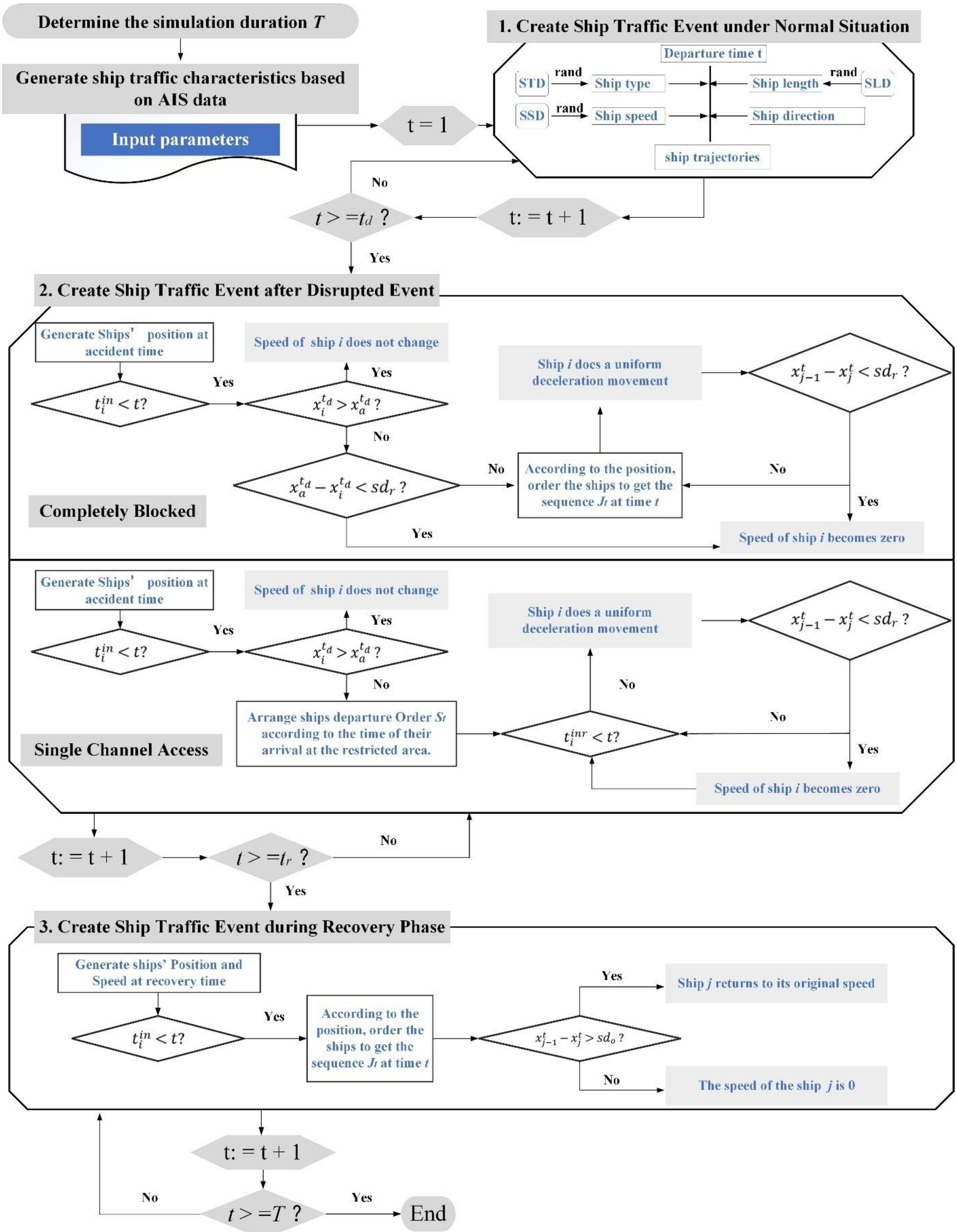


Figure 3.3 Flow chart of simulation model of WTC

(2) Ship Traffic Event after Disrupted Event

When a disrupted event happened at time t_d, the process shall be at phase 2.

According to accident location ${x_a}^{t_d}$ of the disrupted event, the waterway's affected lane is divided into two parts. For ships of the same lane beyond the accident location at time t_d, that is ${x_i}^{t_d} > {x_a}^{t_d}$, they won't be affected by the event and their speed won't change. For ships of the same lane before the accident site, they have to decelerate or stop immediately in case of more collision events, then wait for the arrangement of MSA. In this model, we design two arrangements, one is completely blocked, the other is a single channel access.

a. Completely Blocked

When the waterway is totally blocked, the affected ships of both lanes will have to wait. For simplicity, we assume that the speed of the ship whose distance from the accident location is less than the safe distance at rest, that is $x_a^{t_d} - x_i^{t_d} < sd_r$, is immediately reduced to 0. For ships whose distance from the accident site is greater than sd_r, we sort them by their positions to get the sequence J_t at time t. We assume that the order of their stop positions when they are at rest is the same as sequence J_t. Each ship will make a uniform deceleration movement according to J_t until they reach the stop position. During the process of uniform deceleration, we assume that the speed of the ship whose distance from the previous ship is less than sd_r, that is $x_{j-1}^t - x_j^t < sd_r$, is immediately reduced to 0.

b. Single Channel Access

If the waterway is restricted to single-channel traffic, that is, the ships in both directions near the accident site can only pass via a single channel. The first-come-first-serve (FCFS) principle is used for the narrow waterway channel. The order of ship passage is arranged according to the arrival time of ships at the restricted area. Except for the first ship, the new departure time of all other ships at the restricted area is the accident time plus the accumulation of the time of the previous ships passing through the restricted area. Except for the ships sailing in the restricted area, all other ships will make a constant deceleration movement until they reach a stop position. The rules are the same in the case where the channel is completely blocked.

While the FCFS principle ensures fairness and simplicity in operation, we acknowledge that it may not always be the most efficient policy, particularly when the restricted area is large. In such cases, prioritizing the passage of ships in one direction over the other during constrained periods might be more feasible to minimize delays and additional costs. Although this study does not explicitly analyse such dynamic prioritization strategies, we recognize their potential for future research and practical applications.

(3) Ship Traffic Event during Recovery Phase

When the resilience action is completed, the process turned into phase 3. At this stage, we assume that the rescue work has been completed and the ships affected in the waterway can move on. According to its position at time t, we sequence the ships again to obtain sequence J_t, and we assume that ships will start to sail again according to sequence J_t. For simplicity, we assume that the speed of the ship whose distance from the ship ahead is greater than the safe distance for ships' operation, that is $x_{j-1}^t - x_j^t > sd_o$, is restored immediately, otherwise it remains unchanged. When the speed of all ships returns to normal, the WTC enters stable recovery phase.

It is worth noting that the proposed model is a discrete-event based simulation. In effect, the nature of the proposed model has little difference with queuing theory and Monte Carlo method. The advantage of the proposed model is the corresponding rules constructed for the characteristics of the waterway, such as the waiting rule for ships after an accident, the first-come-first-serve rule for ships when they can only pass through a single channel.

3.4 Application and Results

3.4.1 The Yangtze Estuary Deepwater Channel

Yangtze Estuary Deepwater Channel is used as the case study, which is one of the waterways with the densest ship flow, the most complicated navigation conditions, and the most difficult to manage in the world (Wang et al., 2020). With a total length of about 92km, this channel is the only way for large vessels entering and leaving the main harbour area of Shanghai Port and the main port of the lower reaches of the Yangtze River, and plays an important role in the economic and trade development of China even the world.

The schematic picture of the Yangtze Estuary Deepwater Channel is shown in Figure 3.4, as can be seen from the figure, there are W0, W1, W2, W3, W4, and W5 axis control points in the 12.5m deep water channel of the Yangtze River Estuary from upstream to downstream, which divide the channel into Inner channel, Yuanyuansha channel, Upper channel, Lower channel and Outer channel respectively.

As discussed in Section 2.3, compared to open seas, restricted waterways present significantly higher risks due to their confined space, complex hydrodynamic conditions, and potential congestion. Given these risks, such areas often receive considerable research attention in maritime safety and traffic management studies. Thus, in this thesis, the Yangtze Estuary Deepwater Channel is classified as a restricted area to ensure relevance and applicability in maritime risk assessment. From a practical perspective, this channel exhibits characteristics that justify its classification as a restricted area. It has physical and hydrological limitations, including a fixed depth and navigable width, which restrict ship manoeuvrability, especially for large vessels. Additionally, the waterway is subject to management by the Shanghai Wusong Vessel Traffic Service (VTS) Centre, mandatory pilotage, and traffic separation schemes, all of which impose operational constraints on vessels. Moreover, as the only route for large vessels accessing the main harbour area of Shanghai Port and the lower Yangtze River ports, this channel requires structured traffic control and strict navigational discipline. From a methodological standpoint, defining the entire waterway as a restricted area allows for a simplified yet effective modelling approach, avoiding excessive complexity in simulating ship behaviours under varying navigational conditions. Treating each section separately would necessitate intricate differentiation of risk levels, traffic control measures, and vessel responses, making the analysis unnecessarily complex. This assumption enhances the feasibility of the study while maintaining a reasonable level of accuracy in reflecting real-world constraints.

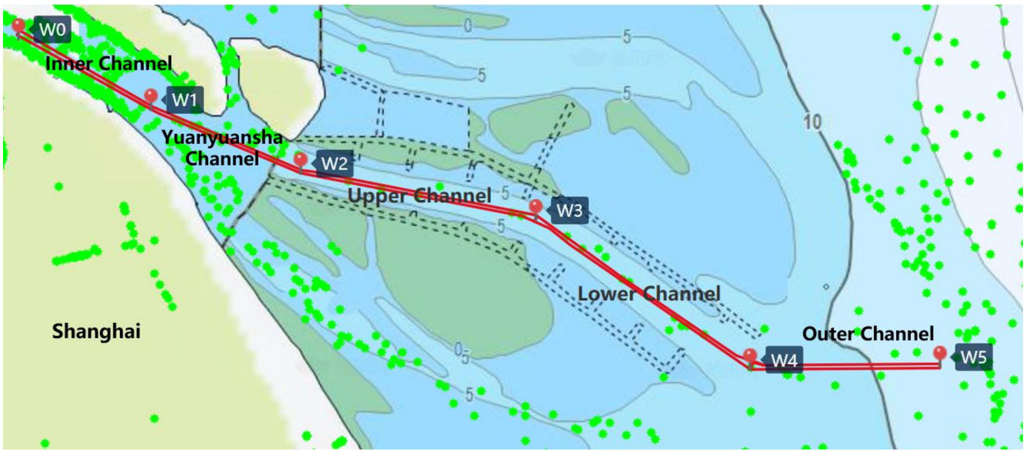
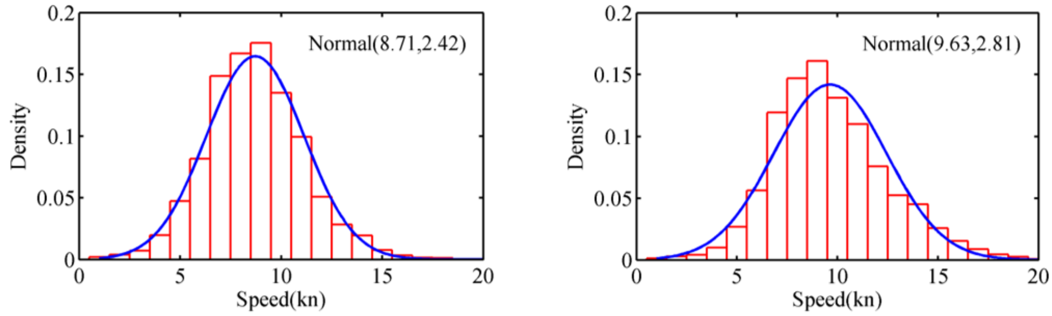


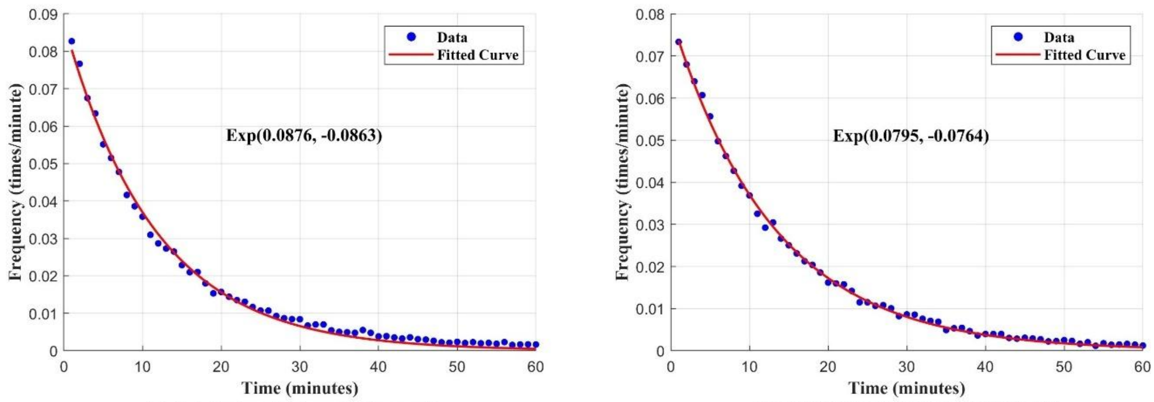
Figure 3.4 Schematic of the Yangtze Estuary Deepwater Channel

The AIS data of this channel in 2018 has been collected from the Shanghai Wusong Vessel Traffic Service (VTS) Centre, which are responsible for channel monitoring. Trough relevant data analysis, ship traffic characteristics of this channel can be extracted and used as input parameters of the simulation model. In order to simplify, we do not consider the influence of ship type, size and other parameters, so we only analyse ships' speed distribution and arrival time distribution, which are shown in Figures 3.5 and 3.6. Inbound and outbound ship in these figures refer to ships entering from the Yangtze River estuary to the upper reaches of the Yangtze River and ships traveling from the upper reaches of the Yangtze River to the estuary, respectively. As we can see, the speed of ships basically obeys normal distribution and the arrival time of ships basically obeys exponential distribution. Accordingly, we use the fitted distribution functions to define ship speed and arrival times in the simulation. As shown in Figure 3.5(a), the average speed of ships entering the waterway is 8.71 knots, with a variance of 2.42. To prevent extreme ship speeds, the upper and lower speed limits are set at 14 knots and 4 knots, respectively, during the simulation. To minimize the impact of random variability, the number of simulation runs is set to 100. Considering real-world conditions, the simulation duration is set to 30 days, as a disrupted waterway typically recovers within a month under normal circumstances. Considering that the average length of ships entering the waterway is 134.63 meters, the safe distance sd_o between adjacent ships in normal operation is set to 300 meters, approximately twice the ship length. The safe distance sd_r between adjacent stationary ships is set to 50 meters. Since stationary ships are not subject to dynamic movements, this shorter distance is sufficient to ensure safety.



(a)distribution of inbound ship speed (b)distribution of outbound ship speed

Figure 3.5 Distributions of ship speed



(a) distribution of inbound ship speed (b) distribution of outbound ship speed

Figure 3.6 Distributions of average time interval

Based on the simulation model established in Section 4.3 and distribution parameters above, the ship traffic event under normal situation is first simulated. The simulation and analysis were conducted using MATLAB, which was chosen for its versatility and strong computational capabilities. All code was implemented directly within the MATLAB environment without reliance on any special toolboxes or external packages. This ensures the approach remains accessible and reproducible for other researchers with basic MATLAB installations. The simulation results are shown in Figure 3.7, as we can see the average number of ships in the WTC under normal operation is about 62, with 31 in both the inbound and outbound directions, and the standard deviation is about10.

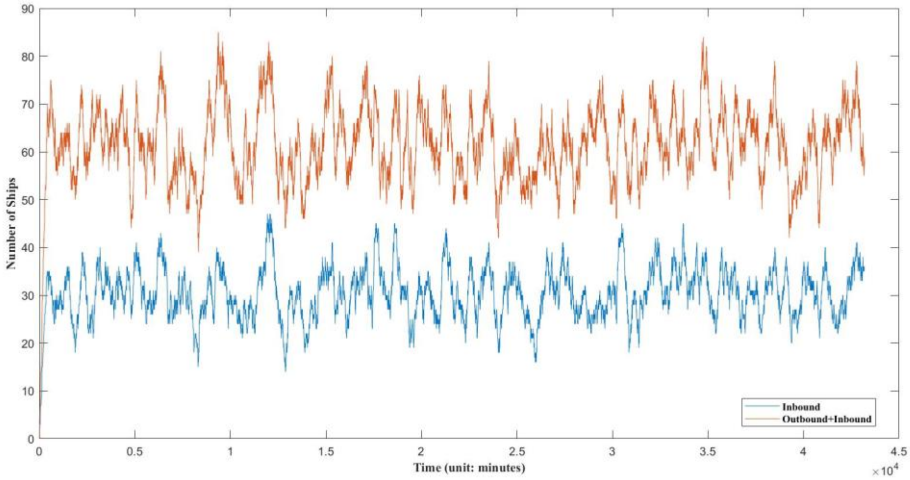


Figure 3.7 Number of ships in the WTC under normal operation

3.4.2 Test of Performance Indicators

3.4.2.1 System's Performance Indicators

Ship delay and ship load are selected as the performance measures in this model, and the corresponding performance indicators calculated in the simulation model are expressed as follows.

The average delay of ships at time t is expressed as follows:

$$AS_D(t) = \frac{\sum_{i=1}^{N_s{}^t}(\tau(t)-\tau_a(t))}{N_s{}^t} \tag{3-5}$$

Where $\tau(t)(\tau_a(t))$ is the time that ship spent in the waterway under normal operation (after accidents) at time t, $N_s{}^t$is the total number of ships affected in the waterway at time t.

When calculating in simulation, t can be expressed as $t = n * \Delta t$, where n is the number related with Δt, so ship average delay can be expressed as follows,

$$AS_D(t) = \frac{\sum_{i=1}^{N}\sum_{i=1}^{N_s{}^i}(\Delta\tau(i))}{N_s{}^i} \tag{3-6}$$

$$\text{Where } \Delta\tau(i) = \begin{cases} 1, & ship\ is\ affected\ at\ the\ i-th\ moment \\ 0, & otherwise \end{cases}$$

The indicator to calculate the ship load S_L of WTC is introduced in Adjetey-Bahun et al. (2016), as shown below.

$$S_L(t) = 1 - \frac{\alpha_{L,d}(t) - \alpha_L(t)}{C_L(t) - \alpha_L(t)} = \frac{C_L(t) - \alpha_{L,d}(t)}{C_L(t) - \alpha_L(t)} \tag{3-7}$$

Where $C_L(t)$ is the capacity of the waterway, i.e., the maximum number of ships that can operate normally in the WTC at time t, $\alpha_{L,d}(t)$ ($\alpha_L(t)$)is the ship load within the waterway during the perturbation (normal operation) at time t.

With the increase of $\alpha_{L,d}(t)$, $S_L(t)$ will decrease. As described above, the waterway performance deteriorates as ships accumulate. Therefore, lower $S_L(t)$ indicates worse channel performance.

The average ship load indicator of the waterway system can be assessed as follows,

$$AS_L = \frac{\int_0^T S_L(t)dt}{T} \tag{3-8}$$

Similarly, T can be expressed as $T = N * \Delta t$, where M is the number related with Δt, so resilience can be expressed as follows,

$$AS_L \approx \frac{\sum_{i=1}^{M} S_L(i)}{T} \tag{3-9}$$

3.4.2.2 Scenarios' Design and Result Analysis

In this section, we will simulate some accidents in this waterway and design three scenarios for analysis. For simplicity, in this section, we only simulate the channel in one direction since both directions have similar effect, that is, the operation of inbound ships is simulated. We designed three distinct scenarios to simulate various attack strategies and evaluate their impact on waterway operations. These scenarios aim to reflect realistic disruptions and highlight different phases of system response and recovery.

(1) Scenario 1: Single Accident

This scenario represents a single accident occurring at a randomly selected location during the Stable Original Phase, which serves as the baseline for normal operations. It illustrates the immediate impact of an isolated disruption and provides a foundation for analysing the system's initial response capabilities.

(2) Scenario 2: Additional Accident During the Response Phase

In this scenario, after a single accident disrupts operations, an additional accident occurs at another randomly selected location during the Response Phase. This simulates a scenario where the system is already engaged in mitigating one disruption, testing its capacity to handle concurrent challenges. The practical significance lies in assessing how overlapping incidents strain the system's resources and response effectiveness.

(3) Scenario 3: Additional Accident During the Recovery Phase

This scenario extends Scenario 1 by introducing a second accident during the Recovery Phase, representing a real-life situation where, as the system attempts to restore normalcy, another disruption occurs. This tests the robustness and adaptability of recovery strategies under compounded stress.

These scenarios reflect practical considerations of real-life disruptions, where multiple incidents can occur in quick succession or overlap with ongoing recovery efforts. By analysing these scenarios, we aim to provide insights into the effectiveness of current response protocols and identify potential areas for improvement in waterway management strategies.

For simplicity, the total time of Disturbance phase and Response phase in every scenario is designed to be 24 hours, in which Disturbance phase is assumed to be instantaneous. The second accident occurred 12 hours after the first accident or first recovery. The length of the waterway is 92km, the coordinate of the entrance and exit of the waterway is set as 0 and 92km respectively. The capacity of the inbound/outbound waterway $C_L(t)$ is set as 200.

The parameters of each scenario are shown in Table 3.1, in which x_a (x_{a2}) is the coordinate of the first (second) accident site, t_a (t_{a2}) is the time of the first (second) accident, t_r (t_{r2}) is the recovery time of the first (second) accident, t_e is the end time of the simulation. It is worth noting that these scenarios are designed to make further comparisons. Therefore, each time parameter is varied to form different scenarios.

Table 3.1 The parameters of three scenarios

Scenario	Coordinate of accident	Time of accident (unit: days/minutes)				
Scenario 1	x_a=50 km	t_a		t_r		t_e
		3/4320		4/5760		10/14400
Scenario 2	x_a=50 km	t_a	t_{a2}	t_r	t_{r2}	t_e
	x_{a2}=30 km	3/4320	3.5/5040	4/5760	4.5/6480	10/14400
Scenario 3		t_a	t_r	t_{a2}	t_{r2}	t_e

	x_a=50 km x_{a2}=75 km	3/4320	4/5760	4.5/6480	5.5/7920	10/14400

Table 3.2 The results of three scenarios

Scenario	AS_L	$minS_L$	N_s	AS_D(unit: minutes)	$minS_D$ (unit: minutes)
Scenario 1	0.78	0.44	133	813	1434
Scenario 2	0.69	0.38	243	751	1428
Scenario 3	0.67	-0.03	351	1260	2589

The simulation results under three scenarios can be seen in Table 3.2 and from Figures 3.8 to 3.13, in which the red dot is the moment when the accident occurred, and the green dot is the moment when the recovery period begins.

(1) Analysis of Ship Load

The simulation results of ship load under the three scenarios can be seen in Figures 3.8, 3.9 and 3.10. From Figure 3.8, we can see that the ship load S_L of the system fluctuates around one under normal conditions. After the accident, it shows a linear downward trend, and after entering the recovery period, it shows a linear upward trend, and the recovery speed is greater than the decay period. In addition, it will not recover immediately after entering the recovery period, and will continue to attenuate for a short time before gradually recovering since it will take the affected ships some time to leave the channel. From Figure 3.9, recurring accidents during the Response phase will result in a continuous reduction of the S_L. After the first accident is fixed, the affected ships between the first accident site and the second accident site will be relieved, thus raising the S_L, while the ships affected by the second accident will continue to be affected at this time until the second accident is fixed. Hence, the S_L curve gradually decreases after increasing. When entering the second recovery period, the S_L increases gradually before stabilizing. From Figure 3.10, recurring accidents during the Recovery phase will aggravate the decrease of S_L even more severely. The recovery curve of the second recovery is obviously steeper than that of the first recovery, and also steeper than that of Scenario 1 and 2. This can be understood as the location of the second accident in Scenario 3 is closer to the channel exit. Therefore, it can be evacuated faster when recovering.

From Figures 3.8 to 3.10 and Table 3.1, we can see that the recurrence of the accident during the Response period does not significantly decrease the ship load, either the minimum ship load $minS_L$ or the average ship load AS_L. The recurrence of the accident during the recovery period causes the previously affected ships to be affected again. Hence, the $minS_L$ and AS_L are decreased. The recurrence of the accident prolongs the time that the waterway is affected. As a result, the time that the ship load is experiencing a low value increase.

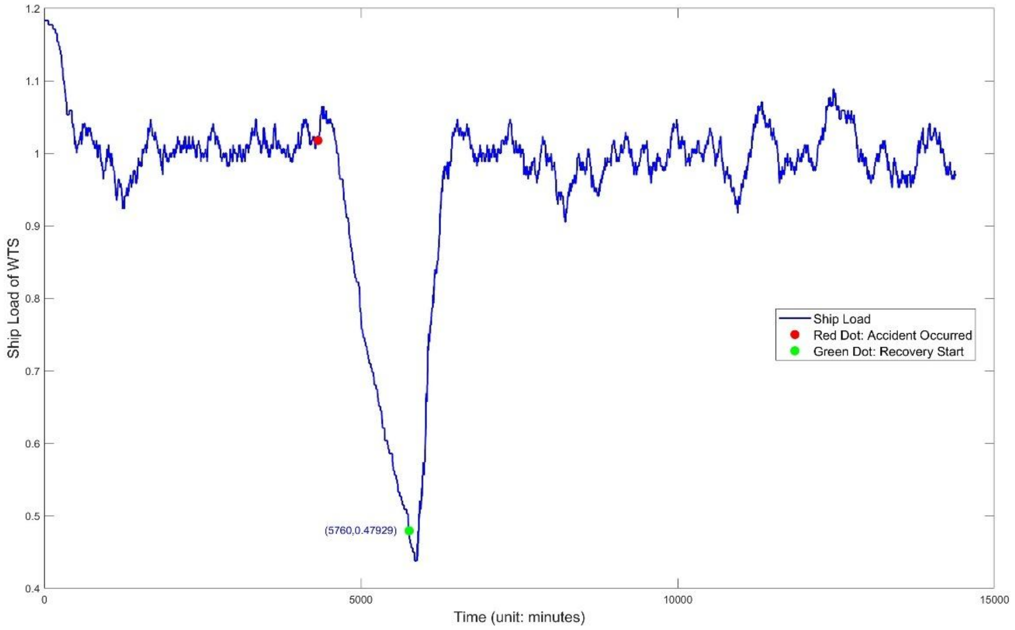


Figure 3.8 Ship load over time in the waterway transportation channel under Scenario 1

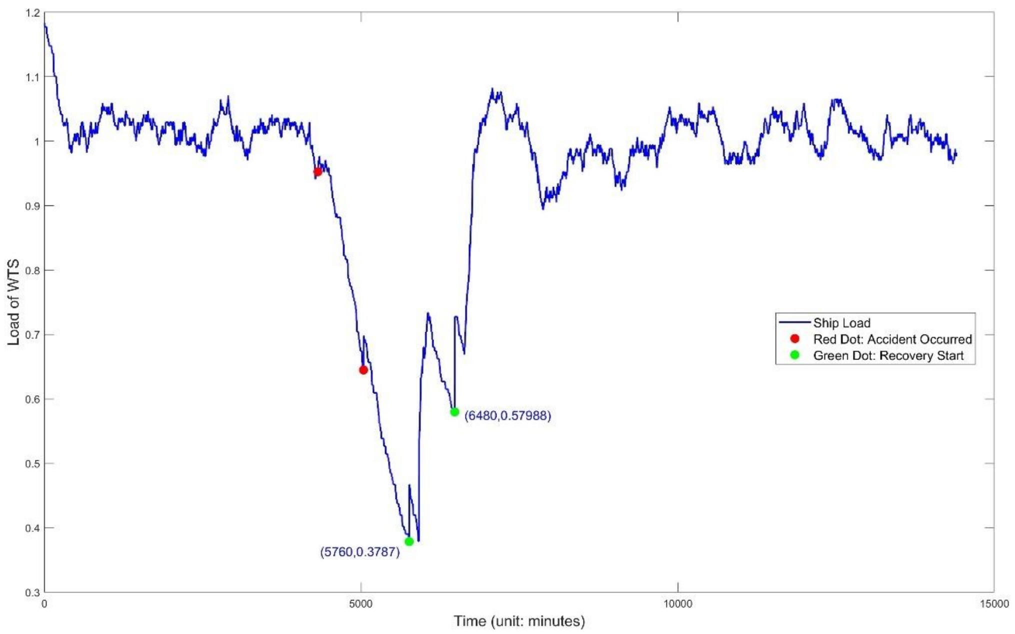


Figure 3.9 Ship load over time in the waterway transportation channel under Scenario 2

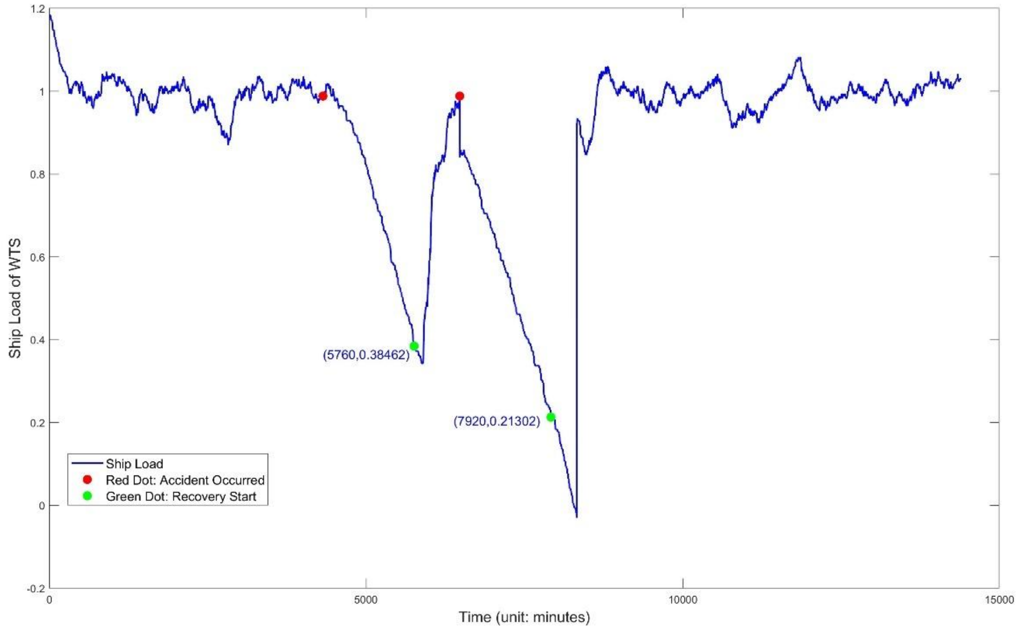


Figure 3.10 Ship load over time in the waterway transportation channel under Scenario 3

(2) Analysis of Ship Average Delay

The simulation results of ship average delay under the three scenarios can be seen in Figures 3.11, 3.12 and 3.13. From Figure 3.11, we can see that the ship average delay AS_D of the system equals to zero under normal conditions. After a single accident occurs, AS_D gradually increases. When entering the recovery phase, the AS_D curve decreases slightly for a while and then stabilizes. This phenomenon of reduced AS_D during the recovery phase is observed across all three scenarios. It can be explained as follows: while the system has not yet fully recovered, newly arriving vessels continue to be affected. These newly arriving vessels experience shorter delay times, but their inclusion increases the total number of affected vessels, thereby reducing the average delay time AS_D per vessel. When there are no new affected ships, the value of AS_D remains the same. From Figure 3.12, recurring accidents during the Response phase will result in a continuous increase of the AS_D. After the first accident is fixed, the affected ships between the first accident site and the second accident site will be removed, thus the AS_D curve declines, while the ships affected by the second accident will continue to be affected until the second accident is fixed, Hence, the AS_D curve gradually increases after decreasing. When entering the second recovery period, the curve drops slightly before stabilizing. From Figure 3.13, recurring accidents during the response phase will exacerbate the increase of AS_D, and the AS_D has increased to 1534 minutes at the second recovery point from 793 minutes at the first recovery point. From Figures 3.11 to 3.13 and Table 3.1, we can see that the recurrence of the accident during the Response period increases the number of affected ships N_s, but do not increase the maximum delay time $maxS_D$ for individual vessels. Due to the increase in N_s, the average ship delay AS_D decreases slightly. The recurrence of the accident during the recovery period causes the previously affected ships to be affected again. Therefore, the $maxS_D$ and AS_D greatly increase. Meanwhile, the time of waterway' full recovery is delayed. As a result, the N_s is greatly increased. The N_s is proportional to the response time.

Based on above analysis, we can conclude that 1) an accident happening again will aggravate the system's performance loss in terms of ship load or ship delay, but would not necessarily cause a change in all indicators. Therefore, it is not appropriate to evaluate system performance by a single performance indicator; 2) The performance loss caused by the recurrence of the accident during the Recovery period is more serious than that during the Response period, since the recurrence of the accident during the recovery period causes the previously affected ships to be affected again; 3) The most significant impact of an accident recurrence is the recovery time. As recovery time is delayed, the number of affected ships increase. Consequently, the ship load will decrease.

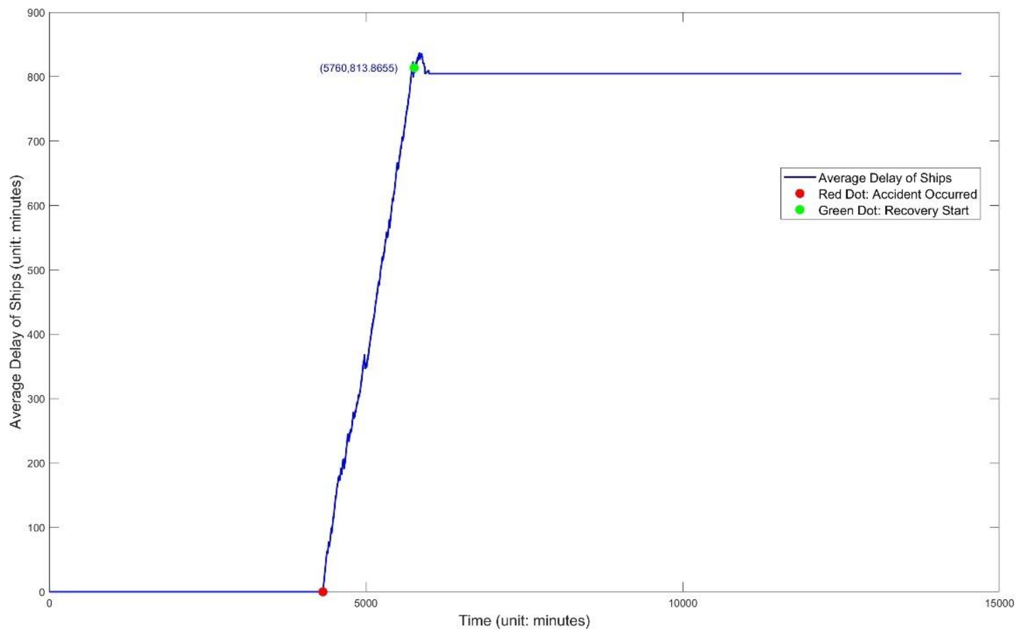


Figure 3.11 Ship average delay over time in the waterway transportation channel under Scenario 1

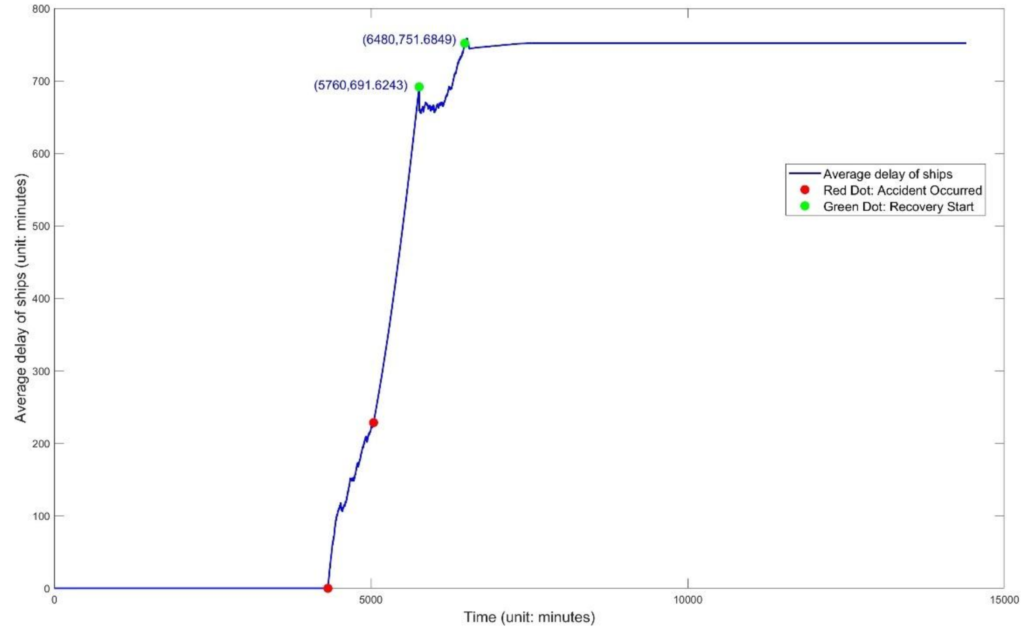


Figure 3.12 Ship average delay over time in the waterway transportation channel under Scenario 2

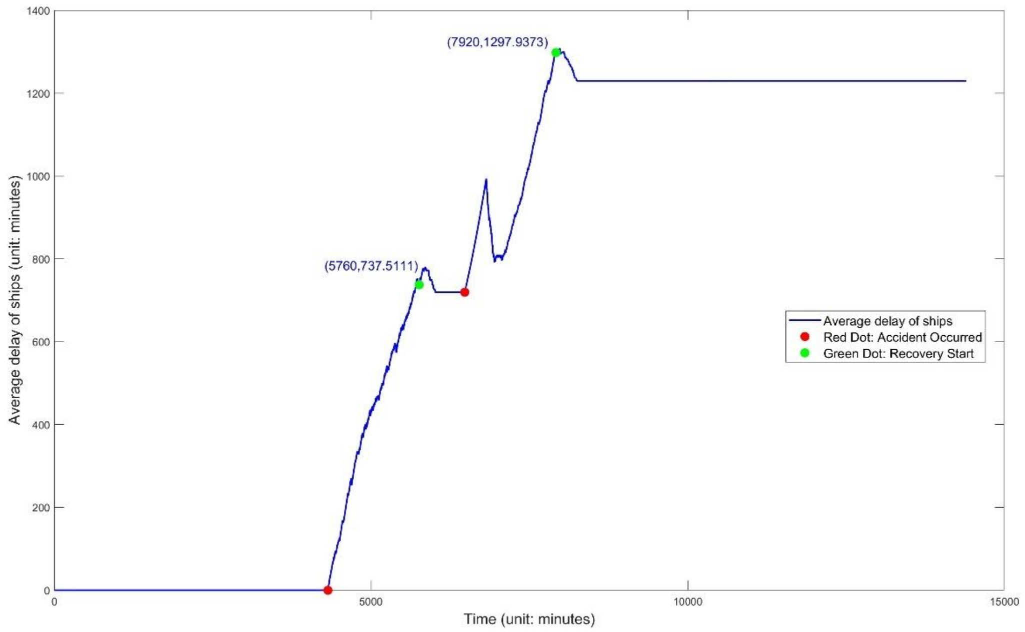


Figure 3.13 Ship average delay over time in the waterway transportation channel under Scenario 3

3.4.3 Test of Rescue Time

Based on Eq.(3-7), we can find that increasing the channel capacity C_L is the way to reduce the S_L as long as $\alpha_{L,d}(t) > \alpha_L(t)$. While the change of C_L has little effect on ship delay $S_D(t)$, since the recovery time is not affected. However, if we decrease $\alpha_{L,d}(t)$ in Eq.(3-7), S_L can be reduced too. $\alpha_{L,d}(t)$ is the accumulation of the number of ships in the waterway, which increases over time. Therefore, one way to reduce both performance indicators is to reduce the response time.

Taking Scenario 1 as an example, it is assumed that in the Response phase the necessary planning time is 2 hours, and the rescue operation time is 22 hours. We explored the impact of rescue time on performance indicators, and the results are shown from Figures 3.14 to 3.16. To clearly compare and highlight the specific impacts of the degree of rescue time reduction on various performance metrics, we chose to use the decreased rescue time as the x-axis rather than the absolute value of rescue time. As the rescue time is reduced, the minimum ship load $minS_L$ and the average ship load AS_L of WTC are gradually increased, in which the growth rate of $\min S_L$ is faster. In addition, the maximum delay time $maxS_D$ and the average ship delay AS_D decrease as the rescue time decreases, in which the growth rate of $maxS_D$ is faster. Therefore, shortening the rescue time is a great way to improve the performance of the WTC from both the perspective of ship and the MSA.

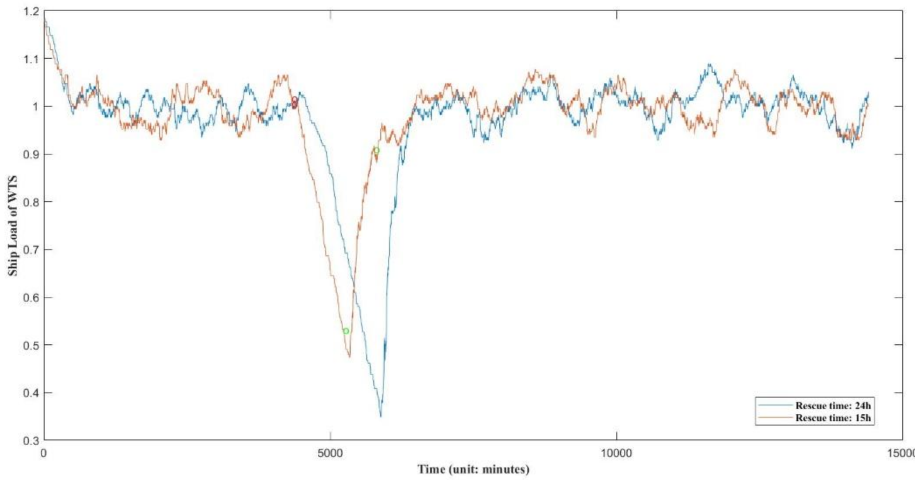


Figure 3.14 Ship load over time in the waterway transportation channels under different rescue time

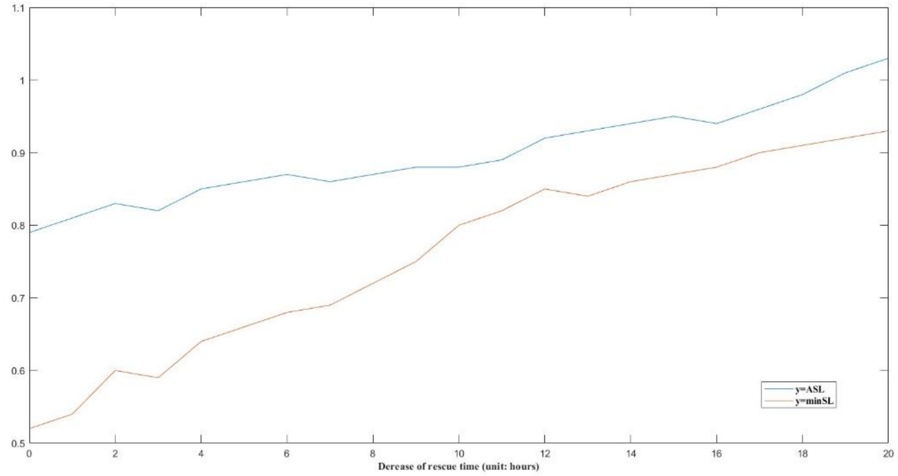


Figure 3.15 Changes in average ship load and minimum ship load when rescue time decreases

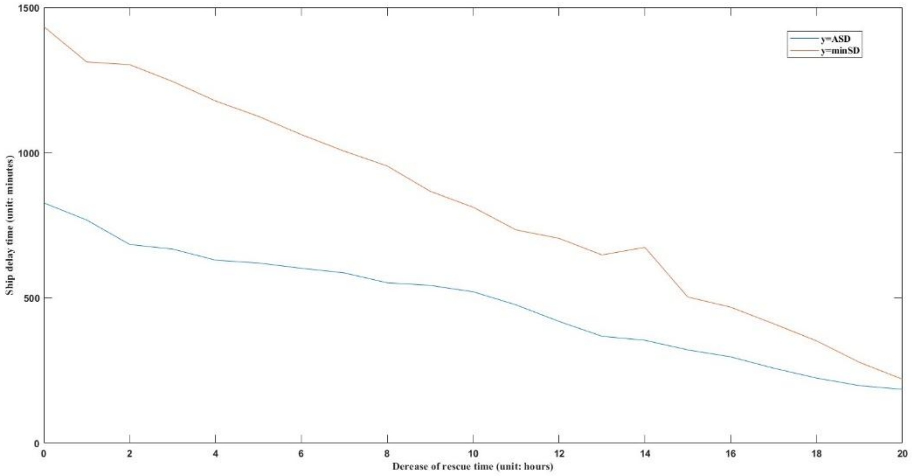


Figure 3.16 Changes in average ship delay and the maximum delay time when rescue time decreases

3.4.4 Test of Rescue Plans

Based on the above, the design of the rescue plan should focus on reducing the rescue time. One way to shorten the rescue time is to allocate more rescue resources, such as rescue ships. If the number of rescued ships increases, the efficiency of rescue can be increased. However, at the same time, it will make the channel more congested and reduce the speed of passing ships.

To analyse the trade-offs, we use a collision accident at the Yangtze Estuary Deepwater Channel as an example. At around 23:00 on December 13, 2020, a container ship "OCEANA" with a capacity of 1740 TEU collided with the container ship "Xinqisheng 69" near the light float

D15 in the North Channel of the Yangtze Estuary Deepwater Channel due to the failure of the main engine. As a result, the "Xinqisheng 69" overturned and sank, and 16 Chinese crew members on the "Xinqisheng 69" were in distress.

After the accident, the Shanghai Wusong VTS dispatched maritime patrol boats to the scene for disposal and coordinated seven vessels, including salvage vessels, tugboats, clean-up vessels, and passing vessels, to participate in the search and rescue. At the same time, Wusong VTS implemented one-way navigation in the channel, conducted point-to-point ship traffic organization, and continued to broadcast safety information. As of December 14, 11 have been rescued (3 of them have no vital signs), and the remaining five people were still being searched.

Based on this, we designed two scenarios for comparison. Scenario 4: A total of 8 ships participated in the rescue. They were responsible for the following tasks: (1) searching and rescue personnel, (2) salvaging containers, (3) hauling accident ships, and (4) cleaning waterways. Each task is performed by two ships, which take 24 hours in total. Scenario 5: 16 ships participated in the rescue. As the number of rescue ships in Scenario 5 is twice that of Scenario 4, the rescue time is assumed to be half that of Scenario 4, i.e., 12 hours. In Scenario 4, the channel is navigable in one direction obeying the first-come-first-serve principle, and the constrained area is one kilometre around the accident site. In Scenario 5, we assume the waterway is completely blocked until it is restored since there are too many rescue ships in the WTC. In both scenarios, the necessary planning time before rescuing is an hour.

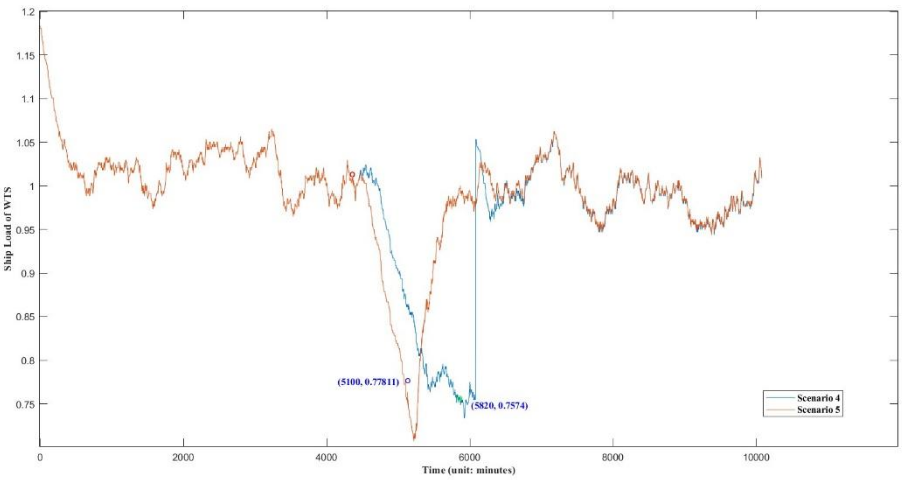


Figure 3.17 Ship load over time in the rescue time under Scenario 4 and 5

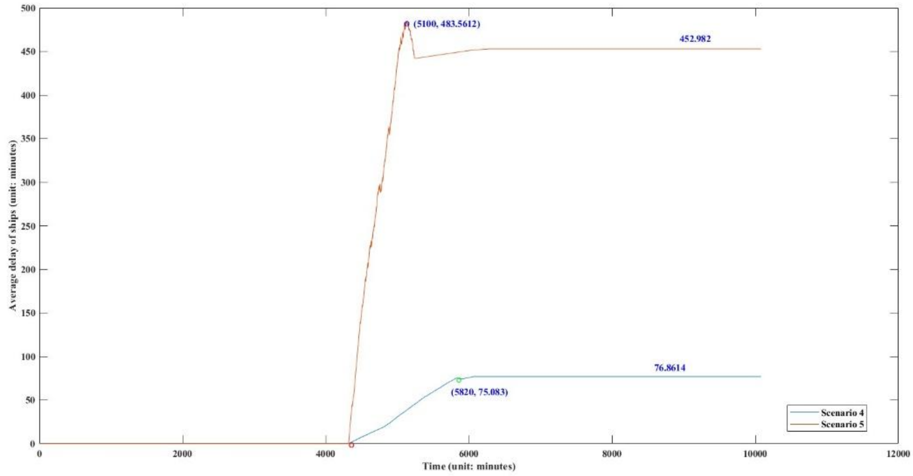


Figure 3.18 Ship average delay time in the waterway transportation channel under Scenario 4 and 5

From Figures 3.17, 3.18 and Table 3.2, we can see that with the number of rescued ships increases, the rescue time decreases, the average ship load and minimum ship load register little change, and the maximum ship delay decreases. However, the average ship delay increases greatly.

Shanghai Port Xingsheng OSRO Co., Ltd. mainly serves emergency missions in Shanghai port area. Based on the Response Expense Tariff of Xingsheng (http://www.xs-osro.com/page16), the cost of Scenario 4 and 5 is estimated in Table 3.3. If we set the value of all parameters to 0.5, the maximum cost is 150,000 dollars, and the unit of time as day, the resilience R can be calculated in Table 3.3, with values of 0.23 and 0.15 for Scenario 4 and 5 respectively. Since the value in scenario 4 is greater than 5, it is more appropriate to choose scenario 4, which is also consistent with the facts.

Based on the above, we can find that reducing the rescue time does not improve all the performance indicators and even increases the average ship delay and recovery cost. Therefore, the resilience indicator R can be used as a tool to judge the effectiveness of rescue plan.

Table 3.3 The results of scenario 4 and 5

Scenario	AS_L	$minS_L$	N_s	AS_D (Unit: minutes)	$maxS_D$ (Unit: minutes)	cost (Unit: US Dollars)	R
Scenario 4	0.84	0.73	1013	77	1185	49666	0.23
Scenario 5	0.85	0.70	176	453	712	73641	0.15

3.4.5 Sensitivity Analyses of Parameters

Based on the resilience assessment model described in Section 3.2.3 (System's Performance Measures), the model incorporates seven parameters: α , β, γ, α_1, α_2, β_1, β_2 . These parameters are associated with the following system components: ship load (R_{S_L}), ship delay (R_{S_D}), the ratio of recovery monetary cost (R_C), average ship load (AS_L), minimum ship load ($minS_L$,), average ship delay time (AS_D), and maximum ship delay time ($minS_L$), respectively. These parameters, are designed to adjust the weighting of different variables based on the decision-maker's preferences. These parameters allow for flexibility in modelling scenarios to better align with specific objectives.

Sensitivity analysis is a critical technique in model evaluation, as it provides insight into how variations in input parameters influence the output of the model. Therefore, a global sensitivity analysis (GSA) employing a parameter sweep method was conducted to assess the sensitivity of these parameters.

The results from Scenario 4 were used as the baseline for this analysis. Each parameter (α , β, γ, α_1, α_2, β_1, β_2) was defined over the range [0.1,1.0], divided into 10 evenly spaced steps. A nested loop structure was implemented to systematically iterate through all possible combinations of these parameters, resulting in a total of 10^7 unique combinations. For each combination, the value of R was computed and stored.

To evaluate the independent effects of each parameter, the stored results were grouped by each parameter, and the mean R-value for each group was calculated. This approach isolates the average effect of a single parameter while accounting for variations in all other parameters. The findings are illustrated in Figure 3.19.

The analysis revealed that γ is the most sensitive parameter. The mean R-value decreases sharply as γ increases, indicating a strong inverse relationship. In contrast, α, $\alpha_1$and α_2 exhibit moderate sensitivity. The mean R-value increases steadily with increases in α, α_1 or α_2. Finally, β , β_1 and β_2 are low-sensitivity parameters, as the mean R-value remains nearly constant regardless of changes in these parameters.

Thus, the most critical factor is cost, followed by the number of ships affected, and finally, delay time.

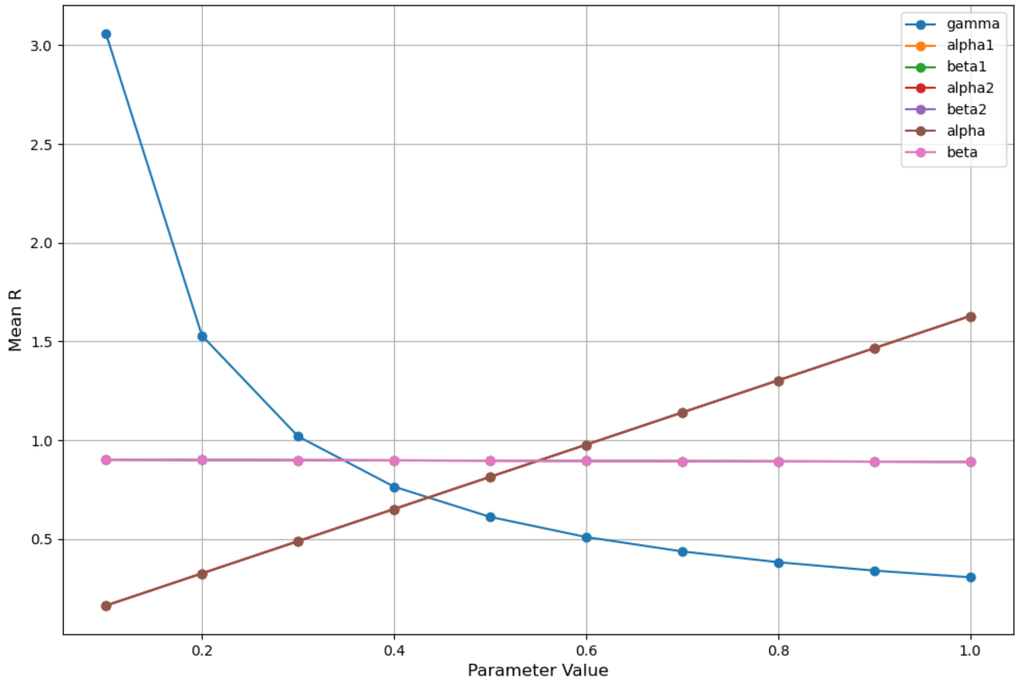


Figure 3.19 The sensitivity analyses result of parameters

3.4.5 Discussions

Research on the resilience of WTCs remains relatively scarce, with most studies treating it as a system-level analysis. From the perspective of metrics, key factors such as costs have often been overlooked. Methodologically, existing studies tend to focus on data analysis, neglecting critical elements such as vessel-specific behaviour under specific disruptions and detailed rescue plans. Although models simulating vessel disruptions are not uncommon, existing research predominantly emphasizes risk assessment or analysis. To explore WTC resilience more comprehensively, this study proposes an enhanced evaluation indicator along with a detailed disruption simulation model.

Using vessel AIS data collected from the Yangtze Estuary Deepwater Channel, we conducted simulations and analyses under various disruption scenarios. However, the limited nature of the current dataset restricts our ability to incorporate further statistical evaluations. In future research, integrating additional statistical analyses could significantly enhance the understanding of vessel distribution characteristics within the WTC. For instance, by collecting more detailed data on ships' movements, models could be developed to assess the impact of disruptions on emissions and energy consumption.

Regarding recovery decision-making following disruptions, future studies could focus on refining disruption and recovery models by incorporating dynamic variables, such as real-time decision-making processes, stakeholder-specific behaviours, and adaptive strategies. Further integration of optimization methods, such as machine learning algorithms or advanced simulation techniques, could support more effective decision-making and resource allocation during disruptions. These enhancements would contribute to the development of a more comprehensive and actionable framework for assessing and improving WTC resilience.

3.5 Summary

In this chapter, we focus on the resilience modelling and quantification of WTCs.

First, a simulation model is proposed to quantify WTC's resilience, which composed of three phases: 1) Ship traffic event under normal situation; 2) Ship traffic event after disrupted event; 3) Ship traffic event during recovery. The Yangtze Estuary Deepwater Channel is taking as the case study, and the AIS data of this channel in 2018 has been collected as the input parameters of the simulation model.

Based on the simulation model, three scenarios are designed for testing, which includes one single accident and two double accidents that occurred in different phases. Ship delay and ship load are selected as the performance indicators. The change of these performance indicators in the WTC when it encounters different accidents are presented and discussed. Based on the result analysis, we can see that an accident happening again will aggravate the decrease of system performance, especially when it happened again during the recovery phase. However, that would not necessarily affect all resilience indicators. Therefore, it is not appropriate to judge a system resilience based on a single performance indicator. The most significant impact of an accident recurrence is the recovery time. Reducing rescue time can improve system performance.

Then, an aggregate resilience assessment indicator for WTC in the post-accident period is developed, which considers ship load, ship delay and recovery. Based on a real accident case, two rescue scenarios are designed for comparisons. The results show that reducing the rescue time does not improve all the performance indicators and the proposed resilience indicator in this study can more accurately judge the effectiveness of rescue plans. After sensitivity analysis, cost is the most important influencing factor. After adjusting the parameters of the factors, decision makers can make decisions based on the most biased factors.

The model provided in this chapter can be used as the basis for improving system resilience in the future, which allows the involvement of more risk management plans test. Future improvements can be from various aspects, such as the research of stakeholders' specific behaviour or response and the factors that influencing the stakeholders' decision, research on the integration of optimization methods to help stakeholders make the most effective decisions. In addition, integrating additional statistical analyses could significantly enhance the understanding of vessel distribution characteristics within the WTC.

Chapter 4 Resilience Modelling and Assessment of Port Infrastructure

This chapter aims to address research aim 2: resilience modelling and assessment of port infrastructure. A circular four-stage method is proposed to study port resilience. The major disturbances that are currently affecting ports are summarized. Then, a port resilience assessment model using the Bayesian network is proposed, in which various resilience strategies are categorized into different metrics to assess resilience capabilities (i.e., readiness and response capacities). The model is constructed based on expert judgment and statistical analysis. To extract experts' opinions, a method based on Dempster-Shafer evidence theory (DSET) and hesitant fuzzy linguistic terms (HFLTSs) is provided. The Shanghai Yangshan Deepwater Port in China is used as a case study. The results show that natural disasters are major disruptors plaguing ports. The overall resilience of automated terminals is higher than that of non-automated terminals. Strategies to enhance visibility, such as building real-time data management systems and data analysis programs, have the most significant impact on improving ports' readiness. Strategies to enhance recovery such as facility restoration and technology restoration are the most important when improving ports' response capability.

4.1 Background

Ports serve as critical hubs for cargos' conversion and buffering. They are the heart of MTS and play vital roles in the global supply chain, regional and international economic activity, transportation network systems, and job growth (Hossain et al., 2019).

Ports are critical infrastructures and are vulnerable to various disturbances, such as natural disasters (e.g., typhoons and earthquakes), technical issues (e.g., cyber-attacks) and economic or political factors (e.g., financial crisis and policy changes). Since ports are important nodes of MTS and occupy a vital position in regional and global trade, any disruption of the port may lead to huge economic losses. For example, Hurricane Ida in 2021 severely disrupted U.S. logistics, resulting in the closure of several ports, from New Orleans, Mobile, Baton Rouge, Pascagoula to Mississippi. Hurricane Ida's wind and storm surge generated insured losses of $17bn to $25bn, according to AIR Worldwide estimates (Spoerry, 2021). In addition to financial losses, severe disturbance of the port may cause casualties. For example, a total of 165 people were killed, 8 were missing and 798 were injured in the Tianjin Port "8.12" Special Serious Fire and Explosion Accident in the Ruihai Company Dangerous Goods Warehouse in 2015 (State Council of China, 2016). In addition, disruptions in some ports could also affect national security and defence. For example, the loading and unloading at oil storage companies in the Amsterdam-Rotterdam-Antwerp oil trading hub was disrupted by cyberattacks (Bush, 2022).

Since the onset of the global pandemic, COVID-19, new threats have emerged in ports. In a rapidly changing environment with numerous uncertain threats, resilience plays a crucial role in achieving system sustainability (Kim et al., 2021). The impact of COVID-19 highlights the need for better risk management, greater readiness, and resilience (UNCTAD, 2021). Therefore, developing a resilient port system is paramount to promoting the sustainable development of MTS, and implementing appropriate resilience strategies is important to enhance the resilience of ports.

Based on the above, this chapter we aim to develop measures to enhance ports' resilience to cope with risks and uncertainties. A circular four-stage method is proposed to study port resilience, in which a port resilience assessment model using the Bayesian network is proposed. The novelty of this model is that we use six metrics (robustness, redundancy, visibility, flexibility, agility, recovery) to categorize resilience strategies and assess resilience capabilities (readiness and response), which can be employed to facilitate port managers to distinguish different strategies' specific functions and effectiveness and optimize strategy implementation. The framework and parameters of the proposed model are developed based on expert judgment and historical data. To extract experts' opinions, a method based on Dempster-Shafer evidence theory (DSET) and hesitant fuzzy linguistic terms (HFLTSs) is provided. The Shanghai Yangshan Deepwater Port in China is used as the case study to exemplify the quantification of port resilience.

4.2 Methods for Extracting Experts' Opinions

MTS is a complex system composed of multiple interwoven parts, and resilience is a multifaceted concept. Therefore, the available objective data for modelling and assessing the resilience of MTS is often insufficient. For example, port involves the operation of a wide range of equipment. In the case of poor facilities or underdeveloped technology, objective data on some equipment are not available from the port itself due to the lack of monitoring systems. When objective data is insufficient, expert experience serves as a valuable data source. Thus, effective integration of the experience and opinions of experts from different backgrounds for the modelling and assessment of MTS is important.

Information from experts often exhibits significant uncertainty. Common methods for managing this uncertainty in information fusion include DSET, rough set theory, and the maximum entropy approach. Rough set theory is particularly sensitive to the completeness and clarity of relational data, whereas the maximum entropy method relies on establishing appropriate constraints based on prior knowledge. DSET, considered one of the most promising approaches, accommodates diverse data sources and enables the integration of incomplete and conflicting information (Zhou et al., 2022), maintaining an acceptable level of computational complexity when the problem size is manageable. Consequently, this thesis chooses the D-S framework over other fuzzy tools for risk assessment.

To enhance the reliability and robustness of expert-based inputs, we adopted an improved methodological framework that combines improved Dempster–Shafer (D-S) evidence theory with Hesitant Fuzzy Linguistic Term Sets (HFLTSs). This integrated approach offers several advantages: 1) It allows experts to express hesitation and uncertainty through multiple linguistic terms rather than being forced to make a single crisp judgment, thus capturing the natural vagueness in human reasoning; 2) It addresses inconsistencies and conflicts among expert opinions using belief function theory in the D-S framework, which facilitates the fusion of diverse viewpoints without discarding minority perspectives; 3) It supports uncertainty modelling in a mathematically rigorous way, enhancing the credibility of the aggregated expert knowledge.

4.2.1 Preliminaries

4.2.1.1 Dempster-Shafer Evidence Theory

The DSET, an effective method of reasoning, was initially presented by Dempster (1967) and subsequently advanced by Shafer (1976). It can make rigorous estimations and has the ability to combine multi-source evidence under uncertainties. Because of its flexibility and effectiveness in dealing with uncertainty and imprecision information, DSET has been widely applied in various areas of information fusion, for example, obstacle detection, pattern recognition, and so on. The fundamental principles of DSET are outlined as follows.

Definition 4.1 (Frame of Discernment)

Suppose Θ is a set of mutually exclusive and collectively exhaustive events, then the set Θ is named a frame of discernment, denoted as,

$$\Theta = \{E_1, E_2, \dots, E_i, \dots, E_N\} \tag{4-1}$$

Where E_i is the ith event.

The power set of Θ, denoted as 2^Θ, is defined as follows:

$$2^\Theta = \{\emptyset, \{E_1\}, \dots, \{E_N\}, \{E_1, E_2\}, \dots, \{E_1, E_2, \dots, E_i\}, \dots, \Theta\} \tag{4-2}$$

and $\emptyset$ is an empty set. If $F \in 2^\Theta$, F is referred to as a proposition.

Definition 4.2 (Mass function)

For a frame of discernment Θ, a mass function is a mapping m from 2^Θ to [0, 1], formally defined by

$$m: 2^\Theta \rightarrow [0,1] \tag{4-3}$$

which satisfies the following condition:

$$m(\emptyset) = 0 \text{ and } \sum_{F \subseteq 2^\Theta} m(F) = 1 \tag{4-4}$$

In the DSET, a mass function can be also called as a basic belief assignment (BBA) or basic probability assignment (BPA). The parameter $m(F)$ signifies the degree of belief associated with proposition F. If $m(F) > 0$, F is termed a focal element, and the union of all the focal elements is referred to as the core of the mass function.

Definition 4.3 (Belief Function)

For a proposition $F \in \Theta$, the belief function Bel and plausible measure Pl, which can reflect some attributes of the evidence, are defined as follows:

$$Bel(F) = \sum_{B \subseteq F} m(B) \tag{4-5}$$

$$Pl(F) = 1 - Bel(\bar{F}) = \sum_{B \cap F \neq \emptyset} m(B) \tag{4-6}$$

Where $\bar{F} = \Theta - F$.

$Bel(F)$ and $Pl(F)$are the lower and upper bound of the probability assigned to proposition F respectively.

Definition 4.4 (Dempster's Combination Rule)

Suppose there are two arbitrary BBAs m_1 and m_2 on the frame of discernment Θ and these BBAs are independent, Dempster's combination rule, denoted by $m = m_1 \oplus m_2$, which is named as the orthogonal sum, is defined as follows:

$$m_1 \oplus m_2(A) = \begin{cases} \frac{1}{1-K} \sum_{B \cap C = F} m_1(B) m_2(C), & F \neq \emptyset, \\ 0, & F = \emptyset, \end{cases} \tag{4-7}$$

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{4-8}$$

where B and C are also the elements of 2^{Θ}, and K is the conflicting coefficient which presents the conflict between two BBAs. This rule is only applicable to the BBAs with the condition $K < 1$.

For n mass functions, the combination rule is defined as below:

$$(m_1 \oplus m_2 \oplus \dots \oplus m_n)(F) = \begin{cases} \frac{1}{1-K} \sum_{F_1 \cap F_2 \cap \dots \cap F_n = A} m_1(F_1) m_2(F_2) \dots m_{\mathrm{n}}(F_n), & F \neq \emptyset, \\ 0, & F = \emptyset, \end{cases} \tag{4-9}$$

$$K = \sum_{F_1 \cap F_2 \cap \dots \cap F_n = \emptyset} m_1(F_1) m_2(F_2) \dots m_{\mathrm{n}}(F_n) \tag{4-10}$$

where $F_1, F_2, \dots, F_n \subseteq 2^{\Theta}$.

It's important to note that Dempster's combination rule is applicable only to BBAs that satisfy the condition $K < 1$.

4.2.1.2 Existing Partial Conflict Measurement Methods

Although a variety of studies have been conducted using DSET, a main issue arises from the potential counter-intuitive results when contradicting evidences are fused (Zhao et al., 2022; Zhou et al., 2022). The studies solving this issue can be categorized into two perspectives: 1) improving Dempster's combination rule (DCR) and reallocating conflict, and 2) modifying the original evidence before fusion. For the former, Yager (1987) disregarded the entirety of conflicting evidence and allocated evidence of conflict within the universal set; Dubois and Prade (1988) introduced various fusion modes (conjunction, trade-off, and disjunction) to address distinct conflict scenarios (unreliable, unexhaustive, and inconsistent sources); Smets (1990) relaxed Dempster's condition by regarding the mass function as representing the degree of belief that cannot be allocated to any non-vacuous propositions in Ω; Lefèvre and Eloued (2013) provided the Combination With Adapted Conflict methodology to proportionately distribute conflict among all focal elements of evidence via adaptive weighting. Nonetheless, these advancements have faced critique, as some may amplify the uncertainty of evidence or compromise certain desirable properties of the original principles, such as commutativity and associativity (Fei & Deng, 2019; Zhou et al., 2022). In addition, an extended period of time may be required for the adjustment process, which could result in the imprecise allocation of belief mass (Xiao, 2019). Henceforth, numerous scholars have directed their attention towards preprocessing the domain of evidence, a strategy also embraced within this paper. Murphy (2000) introduced the mean method, which employs arithmetic averages of all evidence. This approach was deemed illogical by Yong et al. (2004) due to its failure to consider the associative relationships among multiple sources of evidence. Consequently, Yong et al. (2004) proposed a refined mean approach to address Murphy's deficiency, which computes weighted averages of masses based on evidence disparity. Evidence disparity signifies the extent of conflict or differentiation between pieces of evidence, with greater disparities indicating heightened levels of conflict. Early analyses of divergence measures between conflicting data were predicated on the conflict coefficient K. However, empirical observations reveal no discernible correlation between the value of K and the contradictory nature of two pieces of evidence (Zhang et al., 2014). Subsequently, Jousselme et al. (2001) advocated a distance-centric methodology to articulate the degree of conflict between pieces of evidence, conceptualizing the power set of discernment frames as a 2^N-linear space and each basic belief assignment (BBA) as a multidimensional vector. Zhang et al. (2014) converted the 2^N-dimensional belief assignment vectors into N-dimensional vectors and proposed a novel approach grounded in the cosine theorem. Xiao (2019) later introduced the Belief Jensen-Shannon (BJS) divergence.

Definition 4.5 (BJS Divergence Measure)

Suppose F_i is a proposition in BPA m_1 and m_2, the new divergence measure is defined as:

$$E(m_1||m_2) = \sum_i m_1(F_i) ln \frac{m_1(F_i)}{\frac{1}{2}m_1(F_i)+\frac{1}{2}m_2(F_i)} \tag{4-11}$$

As $E(m_1||m_2)$ is not symmetric, so the symmetric divergence information measure $div(m_1||m_2)$ is proposed as,

$$div(m_1||m_2) = \frac{1}{2}[E(m_1||m_2) + E(m_2||m_1)] \tag{4-12}$$

The BJS divergence is nonnegative, orthogonal, symmetric, and bounded between [0,1], and can show effective results, which can be regarded as the most appropriate method of measuring conflicts between evidence till now, and will be adopted in this thesis.

Deng (2015) advanced a novel belief entropy termed Deng entropy.

Definition 4.6 (Deng Entropy)

Consider proposition F_i in the belief function m, where $|F_i|$ represents the cardinality of set F_i. Deng entropy of set F_i is defined as below,

$$E_d = -\sum_i m(F_i) log \frac{m(F_i)}{2^{|F_i|}-1} \tag{4-13}$$

As the number of hypotheses increases, the Deng entropy of the evidence also increases, indicating that the evidence carries more information. Consequently, when Deng entropy is high, the evidence is expected to receive stronger support from others, playing a crucial role in the final combination. This has been proven by Deng (2015).

To prevent assigning zero weight to the evidence, Yuan et al. (2016) introduced the concept of "information volume" denoted as Iv, which is used to quantify uncertain information instead of Deng entropy in the calculation. The expression for information volume is as follows:

$$Iv = e^{E_d} = e^{-\sum_i m(F_i) log \frac{m(F_i)}{2^{|F_i|}-1}} \tag{4-14}$$

Shang et al. (2021) introduced the Autoencoder-K-Means approach for assessing the evidential credibility in order to discount the evidence. Nevertheless, these discounting techniques overlook the consistency of weight. Additionally, a potential drawback when managing larger amounts of evidence is the risk of encountering combinatorial explosion when calculating the credibility of each individual piece of evidence. Hence, Zhou et al. (2022) introduced a Best-Worst Method (BWM)-derived approach for acquiring optimal evidence discounting weights, incorporating consistency ratios. Their experimentation demonstrates the method's notable benefits in streamlining calculations and enhancing reliability. Nonetheless, prior to applying BWM, it was necessary to ascertain the worst and best BPA using the distance matrix, which is not always available in a real assessment.

4.2.1.3 Hesitant Fuzzy Linguistic Terms

Besides the issue of DSET itself, another problem that needs to be solved in the decision-making is to effectively transfer expert opinions into the D-S framework. This involves allocating BBA to each piece of evidence in the D-S based on expert ratings.

There are many difficulties in extracting expert opinions. First, expressing preferences with a single value can pose challenges for decision makers (DMs) because (1) DMs lack knowledge and information related to the problem due to constraints stemming from limited professional knowledge and experience (Liu et al., 2021); (2) DMs do not have confidence in their own judgments, that is, experts exhibit hesitation when selecting among various terms during the evaluation process (Xiong et al., 2023); (3) DMs usually tend to use language terms to express their preferences (Song et al., 2023). Consequently, Rodriguez et al. (2011) introduced the HFLTS, comprising a range of linguistic terms capable of capturing the diverse preferences of experts. HFLTS has garnered significant interest among scholars due to its potential to effectively handle qualitative decision problems, particularly in group decision-making (Liu & Zhang, 2020). Thus, HFLTS will be employed in this study.

In addition, assigning weight to experts is difficult but important as divergent expert weight assignments can yield distinct consensus outcomes (Liu et al., 2023b). In recent years, two categories of approaches, namely subjective and objective, have been employed to address the issue of setting expert weights. The subjective approach determines expert weights based on the coordinator's subjective preferences. In its simplest form, this may involve assigning equal or varied weights based on factors such as experts' ownership, position, or seniority. In contrast, the objective approach derives expert weights from the objective information present in the decision matrix. For example, the self-management mechanism (Dong et al., 2016). and Bayesian best-worst method (Mohammadi & Rezaei, 2020) are proposed to generate expert weights. In fact, an assessment that combines subjective and objective approaches is more comprehensive. For example, Liu et al. (2021) used expert reliability to modify experts' weight, which will also be used in this study.

Linguistic variables are a concept introduced by Zadeh (1975) as a fundamental component of fuzzy logic and fuzzy set theory. They play a crucial role in representing and handling uncertainty and imprecision in human language and decision-making. In general, the value of a linguistic variables can be represented by a linguistic term set (LTS): $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$, where s_α represents a pre-defined linguistic term (LT), and $(2\tau + 1)$ represents the granularity or number of distinct terms within the set S.

To calculate linguistic information for decision-making, the linguistic scale function (LSF) is employed to assign appropriate semantic values to LTs.

Definition 4.7 (Linguistic Scale Function)

Let $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$ be a predefined LTS and k_α be the semantic of LT s_α. The LSF to translate LT into its corresponding semantic is defined as

$$\Upsilon: s_\alpha \to k_\alpha: [0,1], \alpha = -\tau, \dots, 0, 1, \dots, \tau \tag{4-15}$$

Obviously, LSF Υ is a strictly monotonically increasing function with regard to symbolic index α. The inverse function of Υ exists and is denoted by Υ^{-1}. Similarly, for a virtual LT $s_{\tilde{\alpha}}$, $\tilde{\alpha} \in [-\tau, \tau]$, its semantic value can be calculated by the extended LSF $\tilde{\Upsilon}: s_{\tilde{\alpha}} \to k_{\tilde{\alpha}}: [0,1]$. The inverse function of $\widetilde{\Upsilon}$ is denoted by $\widetilde{\Upsilon}^{-1}$. In this paper, the format of LSF $\Upsilon(s_\alpha) = (\alpha + \tau)/2\tau$ is selected to calculate the semantics of LTs.

Given scenarios in which experts may exhibit uncertainty when conveying their evaluations using linguistic variables, Rodriguez et al. (2011) introduced the concept of HFLTS, denoted by h_s, which is an ordered finite subset of the consecutive LTs of S (Liu et al., 2021).

To enable the calculation of HFLTSs, hesitancy degree and score value are introduced by Liao et al. (2019) for HFLTSs.

Definition 4.8 (Hesitancy Degree)

Let $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$ be a pre-defined LTS and $h_s = \{s_{\varphi_l} | s_{\varphi_l} \in \mathrm{S}, \mathrm{l} = 1, 2, \dots, \#h_s\}$ be an HFLTS on S. The hesitancy degree of h_s, denoted by $h_d(h_s)$, is calculated by:

$$h_d(h_s) = \frac{\#h_s ln\,(\#h_s)}{(2\tau+1) ln\,(2\tau+1)} \tag{4-16}$$

where $\#h_s$ is the number of LTs in HFLTS h_s.

Definition 4.9 (Score Value of HFLTS)

Let $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$ be a pre-defined LTS and $h_s = \{s_{\varphi_l} | s_{\varphi_l} \in \mathrm{S}, \mathrm{l} = 1, 2, \dots, \#h_s\}$ be an HFLTS on S. The score value of h_s, denoted by $GS(h_s)$, is calculated as:

$$GS(h_s) = (1 - h_d(h_s)) \times (\frac{1}{\#h_s} \textstyle\sum_{l=1}^{\#h_s} k_{\emptyset_l}) \tag{4-17}$$

where $h_d(h_s)$ is the hesitancy degree of h_s, $\#h_s$ is the number of LTs in h_s, $k_{\emptyset_l}$ is the semantic value of LT $s_{\emptyset_l}$and can be calculated by the LSF Υ in Definition 1.

Let $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$ be a pre-defined LTS and h_s^1, h_s^2 be two HFLTSs on S. The comparison between h_s^1 and h_s^2 based on their score values is defined as

(1) if $G(h_s^1) = G(h_s^2)$,then $h_s^1 = h_s^2$;

(2) if $G(h_s^1) > G(h_s^2)$,then $h_s^1 \succ h_s^2$;

The distance metric between two HFLTSs h_s^1 and h_s^2 relying on their score values can be computed using the following formula (Liao et al, 2019).

$$Dm(h_s^1, h_s^2) = |\, G(h_s^1) - G(h_s^2)| \tag{4-18}$$

This framework provides a systematic way to handle hesitant, uncertain linguistic information, facilitating decision-making in scenarios where experts may express varying levels of uncertainty using linguistic variables.

4.2.2 Extracting Experts' Opinions based on Dempster-Shafer Evidence Theory and Hesitant Fuzzy Linguistic Terms

Based on the above, a novel method is provided to generate expert group opinions using DSET and HFLTS. The novelty of the proposed method is its thorough consideration of the ambiguity, hesitation, and uncertainty inherent in expert information. This integration effectively addresses the challenges of extracting vague and hesitant expressions from experts and fuses expert consensus on uncertain information, while also mitigating the impact of conflicting evidence.

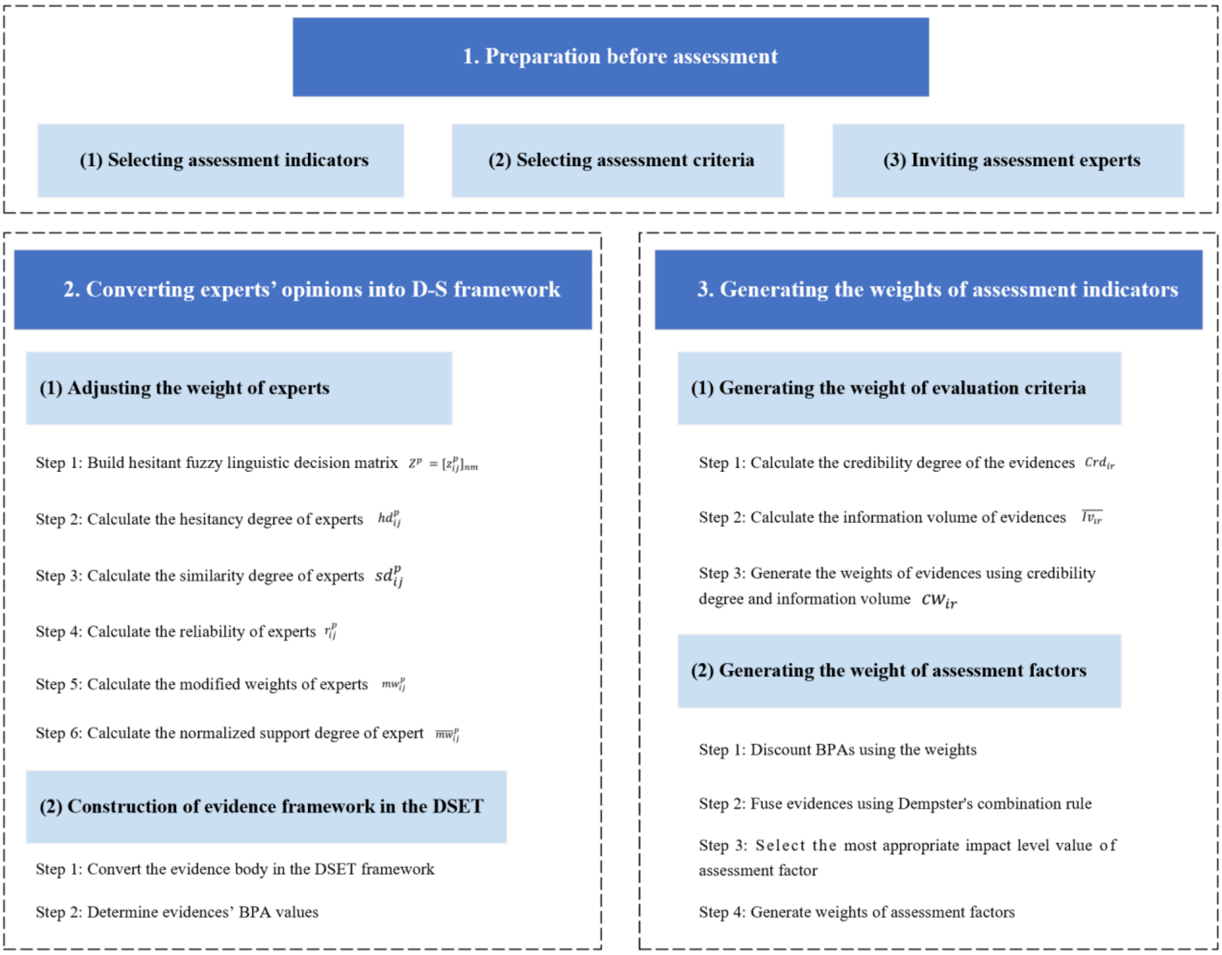


Figure 4.1 Research framework of methods for extracting experts' opinions

The research framework of methods for extracting experts' opinions based on DSET and HFLTS is shown in Figure 4.1. Two crucial parts are involved in this method: converting experts' opinions into D-S framework and generating the weights of assessment indicators using improved DSET, which will be described in detail in the subsequent sections.

4.2.2.1 Converting Experts' Opinions into D-S Framework

As we have selected the assessment indicators $AI = \{ai_1, ai_2, \dots, ai_n\}$. To obtain the weights $W = \{\omega_1, \omega_2, \dots, \omega_n\}$ of assessment indicators, experts $EP = \{ep_1, ep_2, \dots, ep_t\}$ with predefined weights $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_t\}$ are invited to score the impact level $L = \{l_1, l_2, \dots, l_n\}$ of indicators AI using criteria $C = \{c_1, c_2, \dots, c_m\}$.

(1) Adjusting the Weight of Experts

This section discusses the method to effectively transfer expert opinions into the DSET framework. It involves allocating BBA to each piece of evidence in the DSET based on expert ratings. To enhance the objectiveness of the conversion results, expert weights are modified through expert reliability.

Firstly, each expert is invited to employ linguistic expressions to articulate their evaluations of the alternatives based on a predefined LTS denoted as $S = \{s_\alpha | \alpha = -\tau, \dots, 0, \dots, \tau\}$. Subsequently, leveraging their assigned scores, a hesitant fuzzy linguistic decision matrix $Z^p = [z_{ij}^p]_{nm}$ is constructed from the linguistic expressions provided by expert ep_p. Within this matrix, $z_{ij}^p \in HFLTS$ represents the assessment over assessment indicators ai_i on evaluation metrics c_j.

Referring to relevant studies (Liu et al. 2021), the hesitancy degree and the similarity degree of experts are used to calculate expert reliability.

The hesitancy degree hd_{ij}^p of expert ep_p over assessment indicators ai_i on evaluation metrics c_j is calculated as follows.

$$hd_{ij}^p = \frac{\#h_{z_{ij}^p} \ln(\#h_{z_{ij}^p})}{(2\tau+1)\ln(2\tau+1)}, i = 1, 2, \dots, n;\ j = 1, 2, \dots, m;\ p = 1, 2, \dots, t \qquad (4\text{-}19)$$

The similarity of of experts can be derived from the distance between their scorings. That is, the similarity degree sd_{ij}^p of of expert ep_p can be calculated as follows.

$$sm_{ij}^{pq} = 1 - dm(z_{ij}^p, z_{ij}^q), i = 1, 2, \dots, n; j = 1, 2, \dots, m;\ p, q = 1, 2, \dots, t \text{ and } p \neq q \quad (4\text{-}20)$$

$$sd_{ij}^p = \frac{1}{t-1} \sum_{q=1, q\neq p}^{t} sm_{ij}^{pq}, i = 1, 2, \dots, n; j = 1, 2, \dots, m;\ p = 1, 2, \dots, t \qquad (4\text{-}21)$$

where $dm\left(z_{ij}^{p}, z_{ij}^{q}\right)$represents the distance measure between $z_{ij}^{p}$and z_{ij}^{q}; sm_{ij}^{pq}represents the similarity measure among the evaluations of expert ep_p and ep_q for assessment indicator ai_i on evaluation metric c_j.

Then, the reliability of expert ep_p over assessment indicator ai_i on evaluation metric c_j can be calculated as follows.

$$r_{ij}^{p}=\frac{(sd_{ij}^{p}\times(1-hd_{ij}^{p}))^{1/2}}{\sum_{p=1}^{t}(sd_{ij}^{p}\times(1-hd_{ij}^{p}))^{1/2}}, i=1,2,\dots,n;\ \ j=1,2,\dots,m;\ p=1,2,\dots,t \tag{4-22}$$

Thus, the modified weights of experts can be modified as follows through their reliabilities.

$$mw_{ij}^{p}=\frac{\lambda_p}{1+\lambda_p-r_{ij}^{p}}, i=1,2,\dots,n;\ \ j=1,2,\dots,m;\ p=1,2,\dots,t \tag{4-23}$$

For convenience, we normalize mw_{ij}^{p} as.

$$\overline{mw}_{ij}^{p}=\frac{mw_{ij}^{p}}{\sum_{p=1}^{t} mw_{ij}^{p}}, i=1,2,\dots,n;\ \ j=1,2,\dots,m;\ p=1,2,\dots,t \tag{4-24}$$

where $\overline{mw}_{ij}^{p}$ represents the normalized support degree of expert ep_p over assessment indicator a_i on evaluation metric c_j with $0\ \leq\ \overline{mw}_{ij}^{p} \leq\ 1$ and $\sum_{p=1}^{t}\overline{mw}_{ij}^{p}=1$.

(2) Construction of Evidence Framework in the DSET

After we have calculated the modified weights of experts, the evidence framework in the DSET can be generated.

First, the HFLTSs of the hesitant fuzzy linguistic decision matrix $Z^p\ =[z_{ij}^{p}]_{nm}$ can be converted into the evidence body in the DSET evidence framework $F_{ij}=\left\{F_{ij}^{k_{ij}}, k_{ij}=1,2,\dots,K_{ij}\ \right\}$. If one expert's assessment z_{ij}^{p} over assessment indicator ai_i on evaluation metric c_j is the same as another z_{ij}^{q}, it can be combined into one piece of evidence $F_{ij}^{k_{ij}}$.

Once the evidence body is identified in the DSET model, it is necessary to determine their BPA values. The BPA values for focal elements specify the level of support that the current evidence provides for them. Thus, they can be determined based on the degree of support from experts as follows.

$$m\left(F_{ij}^{k_{ij}}\right)=\sum_{p=1,z_{ij}^{p}=F_{ij}^{k_{ij}}}^{t}\overline{mw}_{ij}^{p},\ \ p=1,2,\dots,t;\ k_{ij}=1,2,\dots,K_{ij} \tag{4-25}$$

Based on the evidence body and their BPA values, the evidence framework in the DSET can be constructed as follows: $z_{ij}^{c} = \left\{\left(F_{ij}^{k_{ij}}, m\left(F_{ij}^{k_{ij}}\right)\right), i = 1,2,\dots,n;\ j = 1,2,\dots,m; k_{ij} = 1,2,\dots,K_{ij}\right\}$.

4.2.2.2 Generating the Weights of Assessment Indicators using Improved DSET

(1) Generating the Weight of Evaluation Criteria

As the DSET framework of assessment indicators AI under criteria C has been obtained, the next step is to fuse the information from different evaluation criteria. To overcome the effect of conflicting evidence and optimize the performance of DSET, some techniques are used to modify the weights of BPAs before fusion. The weight is generated from two aspects: credibility degree and information volume. Credibility degree represents the degree of similarity between the scoring values between an evaluation criterion and another. The higher the credibility degree of a criterion's scoring value, the higher the weight should be assigned. Information volume represents the amount of certain data in the evidence set, and the more uncertain information, the smaller the belief entropy, and the lower the weight of the criterion's scoring value.

The detailed calculation steps are as follows.

a. Calculate the Credibility Degree of the Evidences

Step 1-1: Construct distance measure matrix of evidence. The distance measure d_{rq} between the evidences of one assessment indicator from different criteria z_{ir}^{c} $(r = 1,2,\dots,m)$ and z_{iq}^{c} $(q = 1,2,\dots,m)$ can be calculated based on the Belief Jensen-Shannon divergence in Eq.(4-12), where m is the number of criteria; then the distance measure matrix $DM = (d_{rq}^{i})_{m\times m}$ can be constructed as follows:

$$DM_i = \begin{bmatrix} 0 & \dots & d_{1q}^{i} & \cdots & d_{1m}^{i} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ d_{r1}^{i} & \cdots & 0 & \cdots & d_{rm}^{i} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ d_{m1}^{i} & \cdots & d_{mq}^{i} & \cdots & 0 \end{bmatrix} \tag{4-26}$$

Step 1-2: The average evidence distance $\overline{d_{\iota r}}$ of the evidences under criteria r can be calculated by

$$\overline{d_{\iota r}} = \frac{\sum_{q=1}^{m} d_{rq}^{i}}{m-1},\ 1 \ll r \ll m; 1 \le q \ll m \tag{4-27}$$

Step 1-3: The support degree Sup_{ir} of the evidences under criteria r is expressed as

$$Sup_{ir} = \frac{1}{d_{ir}},\ 1 \ll r \ll m \tag{4-28}$$

Step 1-4: The credibility degree Crd_{ir} of the evidences under criteria r is obtained by normalizing the support degree Sup_{ir} as follows:

$$Crd_{ir} = \frac{Sup_{ir}}{\sum_{s=1}^{m} Sup_{is}},\ 1 \ll r \ll m \tag{4-29}$$

b. Calculate the Information Volume of Evidences

Step 2-1: On the basis of the Eq.(4-14), the information volume of evidences under criteria r are calculated.

Step 2-2: the average information volume $\overline{Iv_{ir}}$ of evidences under criteria r are normalized as below,

$$\overline{Iv_{ir}} = \frac{Iv_{ir}}{\sum_{s=1}^{m} Iv_{is}},\ 1 \ll r \ll m \tag{4-30}$$

c. Generate the Weights of Evidences

The weights of evidence can be determined jointly by the product of credibility degree and belief entropy as follow.

Step 3-1: The total support degree TS_{ir} of the evidences under criteria r is obtained by multiplying credibility degree Crd_{ir} and average information volume $\overline{Iv_r}$.

$$TS_{ir} = Crd_{ir} \times \overline{Iv_{ir}}\ ,\ 1 \ll r \ll m \tag{4-31}$$

Step 3-2: The weight cw_{ir} of the evidences on assessment indicator i under criteria r is generated by normalizing the total support degree TS_{ir} as follows:

$$cw_{ir} = \frac{TS_{ir}}{\sum_{s=1}^{m} TS_{is}},\ 1 \ll r \ll m \tag{4-32}$$

(2) Generating the Weight of Assessment Factors

After generating the weights of criteria, the BPAs can be discounted using the weights and fused using Dempster's combination rule. Once the fusing results are identified, the most appropriate impact level value l_i can be selected on account of the value of evidences' belief function.

Then, the weights of each assessment factor can be generated.

$$\omega_i = \frac{l_i}{\sum_{i=1}^{n} l_i}, i = 1, 2, \dots, n \tag{4-33}$$

The weights of assessment factors can be used as the input parameters in the BN model for the modelling of port resilience.

4.3 Bayesian network (BN)

As introduced in the literature review, BN is a reliable tool that specifies causal dependencies between different variables in probabilistic terms, which will be employed in this thesis to model port resilience.

4.3.1 Bayesian Paradigm

Two important components are included in BN, one is the network structure (Figure 4.2), which is a Directed Acyclic Graph (DAG). In DAG, the nodes denote random variables, and the directed edges between the nodes denote the mutual relationship between the nodes (from the parent node to its child node). The other is the conditional probability tables (CPTs) hidden behind the structure, which provides probabilistic relationships among the variables (nodes).

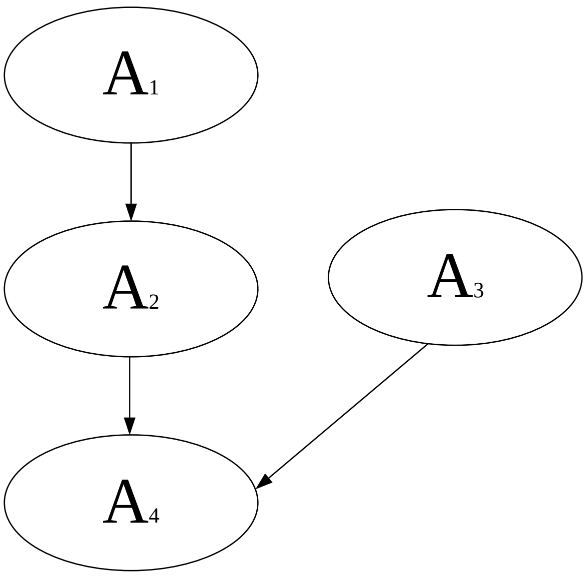


Figure 4.2 A diagram of Bayesian network with four variables

The CPTs are derived from Bayes' rule, which is a mathematical formula to define conditional probability and was proposed by Thomas Bayes (1701–1761) (Salmon, 1970). The mathematical statement of Bayes' rule is shown in Eq. (4-34).

$$P(A,B) = P(A) \times P(B|A) = P(B) \times P(A|B) \tag{4-34}$$

where, $P\ (A,B)$ denotes the probability of event A and B both would happen, $P(A)/\,P(B)$ is the probability of event A or B, $P(B|A)$ or $P(A|B)$ represents the probability of event B given

A or the probability of event A given B. Eq. (4-34) can be modified to Eq. (4-35) by the law of symmetry as follows:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \tag{4-35}$$

where $P(A)$ is the prior probability of A; $P(B)$ is the prior probability that the evidence B itself is true;$P(A|B)$ is the posterior probability of A given the evidence B; and $P(A|B)$ is the probability of the evidence B if hypothesis A is true.

4.3.2 Inference of Bayesian Rule

Based on Bayes' rule, the joint probability distribution (JPD) of a BN comprised of n variables A_1, A_2, A_3 …A_n can be written as follows.

$$P(A_1, A_2, A_3, \ldots, A_n) = \ P(A_1|A_2, A_3, \ldots, A_n)P(A_2|A_3, \ldots, A_n)P(A_{n-1}|A_n)P(A_n) \tag{4-36}$$

Eq. (4-36) can be streamlined as follows:

$$P(A_1, A_2, A_3, \ldots, A_n) = \prod_{i=1}^{n} P(A_i|A_{i+1}, A_{i+2}, \ldots, A_n) = \prod_{i=1}^{n} P(A_i|Parents\ (A_i)) \tag{4-37}$$

For the BN in Figure 4.2, the full JPD can be expressed as follows:

$$P(A_1, A_2, A_3, A_4) = P(A_1)P(A_3)\ P(A_2|A_1)P(A_4|A_3) \tag{4-38}$$

Except for JPD, we are also concerned about computing the marginal distribution of individual nodes in BN, which can be realized by the marginalization process, a distributive operation over combinations (Fenton & Neil, 2019). For example, we can use Eq. (4-39) to calculate the distribution of variable A3 in Figure 4.2.

$$P(A_3) = \sum_{A_1, A_2, A_4} P(A_1)P(A_3)\ P(A_2|A_1)P(A_4|A_3) \tag{4-39}$$

We can further marginalize the global joint probability by marginalizing the local node probability tables (NPTs) and rationalize Eq. (4-40) for Figure 4.2. NPTs are the probability tables of each node, which can be generated manually or realized by eliciting the distribution through related expressions.

$$P(A_3) = (\sum_{A_1} P(A_1)\,(\sum_{A_2} P(A_2|A_1)P(A_1)\,(\sum_{A_4} P(A_4|A_2, A_3)P(A_2)))) \tag{4-40}$$

4.3.3 Techniques to Build Node Probability Tables (NPTs)

For a binary node in BN with n binary parent nodes, we have to determine 2^n parameters, a number that is exponential in the number of parent nodes. To reduce significant computation, two techniques to build NPTs will be introduced in this section and used in the case study.

(1) Noisy-OR Model

The Noisy-OR model was proposed for binary variables by Pearl (1988) and developed to binary leaky Noisy-OR gates by Henrion (1989). In the Noisy-OR, each causal factors F_i represents a cause of event A. The term "noisy" refers to the possibility that some of the causes fail to produce the effect even when they are present. PN_i indicates the probability F_i produces A when it is present and none of the other causes, as shown in Eq.(4-41).

$$PN_i = P\,(A = true|F_i = true, F_j = false;\ \forall\, j \neq i) \tag{4-41}$$

It is generally infeasible in practice to explicitly include all possible causes of an effect, and for this reason, leak factors l is introduced, which are shown in Eq.(4-42).

$$PN_l = P\,(A = true|F_i = false, F_j = false;\ \forall\, j \neq i) \tag{4-42}$$

Based on above, the function of Noisy-OR model for multiple binary variables is shown in Eq.(4-43).

$$NoisyOR(F_1, PN_1, F_2, PN_2, , \dots, F_n, PN_n, , l) \tag{4-43}$$

(2) Weighted Averages

Weighted Averages is another common simple approach to model causal relationships between nodes. As shown in Eq.(4-44), the weighted average of child node is the weighted mean probabilities of all the parent nodes, where i is the number of parent nodes directly connected to the child node and ω_i is the weight associated with the i_{th} parent nodes, which can be calculated based on experts opinions.

$$WMEAN = \sum \omega_i X_i, i = 1,2,\dots,n;\ 0 < \omega_i < 1; \sum \omega_i = 1 \tag{4-44}$$

The various modeling techniques introduced above will be applied in the case study of port resilience, specifically presented in next section.

4.4 Method of Resilience Modelling and Assessment

4.4.1 Method Framework

In this section, a circular four-stage method is provided to study port resilience. The four stages include (1) Identifying major disruptions, (2) Designing resilience capacities, (3) Evaluation and Analysis, and (4) Suggestions and Implementations. Figure 4.3 summarizes the key steps involved in each stage.

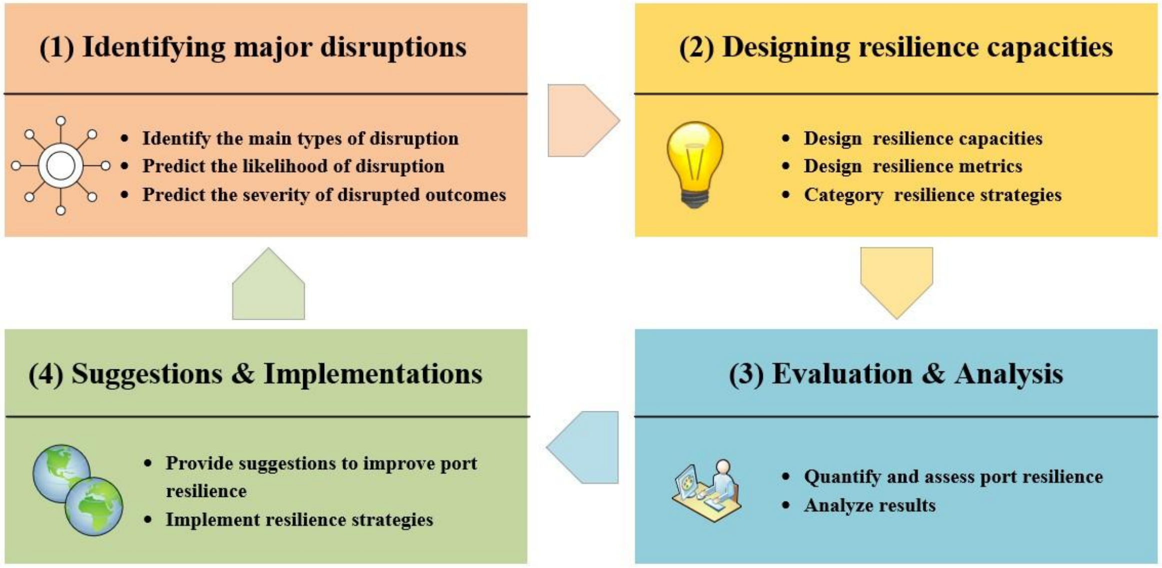


Figure 4.3 The research framework of port resilience

The first phase involves identifying the major types of disruptions that ports may encounter, assessing the likelihood of their occurrence, and predicting the potential severity of their impacts. This stage lays the foundation for subsequent resilience planning by establishing a clear understanding of disruption scenarios relevant to port operations.

The second phase focuses on designing resilience capacities and associated metrics tailored to port systems. This involves structuring resilience capacities into two stages—Preparedness (pre-disturbance) and Response (post-disturbance)—developing quantitative indicators, and categorizing resilience strategies corresponding to each capacity. These serve as measurable objectives for the evaluation phase.

In the third phase, port resilience is evaluated using a BN model, which captures the probabilistic and causal relationships among resilience factors, strategies, and disruption events. Given the limited availability and incompleteness of objective data for many port-related indicators, the BN model integrates both expert elicitation and historical data analysis. To address the inherent ambiguity, hesitation, uncertainty, and possible inconsistency in expert judgments, an enhanced method combining Dempster–Shafer (D-S) evidence theory and Hesitant Fuzzy Linguistic Terms (HFLTSs) is employed for expert opinion extraction and fusion. This approach improves the reliability of qualitative assessments by accommodating hesitation in linguistic evaluations and effectively managing conflicting expert inputs.

The final phase translates analytical findings into actionable recommendations by proposing targeted strategies to enhance port resilience. This includes prioritizing capacity improvements and implementing feasible resilience measures informed by the BN-based evaluation results.

4.4.2 Disruption Identifications

The first step is to identify the main disruptions of ports. As listed in Table 2.2, there are various disruptions existing in ports. Based on the literature and current state of social development, we summarize the current major disturbances that existed in ports into four categories: natural factors, technological factors, organizational factors and others, as shown in Figure 4.4.

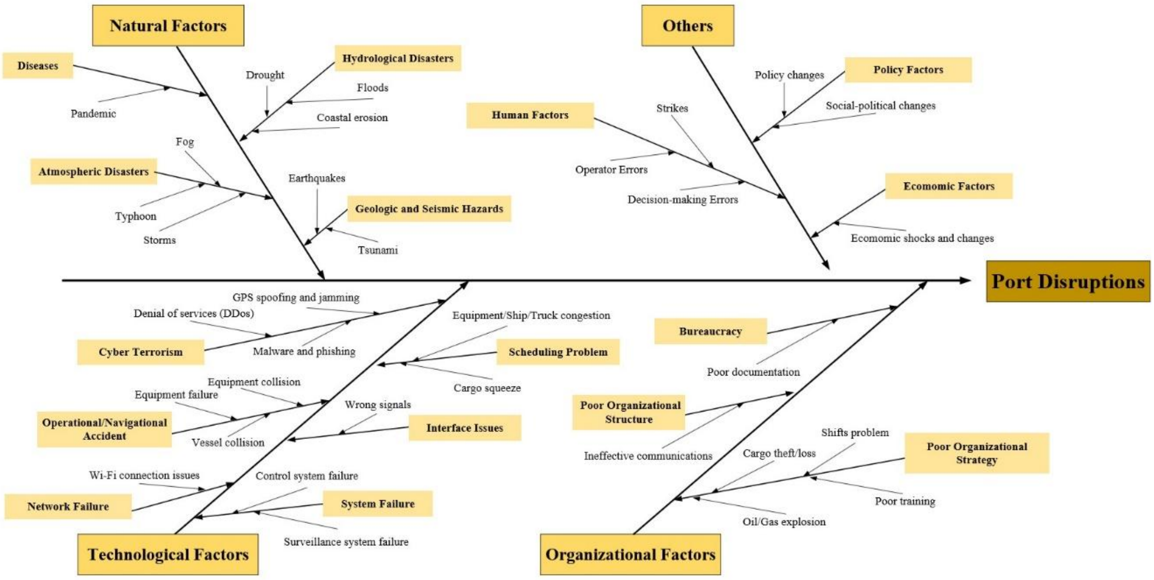


Figure 4.4 The main port disruption factors

Due to differences in geographical locations, social environments, development levels, etc., the types of disturbances suffered by different ports are quite different. For example, ports in earthquake zones will suffer from earthquakes and tsunamis from time to time, while ports in non-seismic zones will not have this concern. In addition, with the development of technology and the change of social background, the disturbances suffered by the same port in different periods are also differential. For example, before 2019, ports had little regard for the impact of COVID-19, but now, the sporadic presence of infected people has been disrupting port operations around the world. Therefore, it is necessary to identify the major disturbances in ports and their probabilities and severities, which is the basis for building resilience strategies. To identify the port's chief disruptions, methods based on expert experience and statistical data analysis can be used.

4.4.3 Resilience Capacity Design

Based on the literature review, the main factors to measure port and infrastructure resilience are summarized and shown in Table 4.1.

Table 4.1 Summary of resilience measures based on the literature

	Literature	Main factors/construct	Sub-factors/resilience strategies
Port resilience	Kim, et al., 2021	Absorptive capability	Robustness, redundancy, visibility
		Adaptive capability	Flexibility, collaboration, agility, information sharing
		Restorative capability	Response, and recovery
	Omer et al., 2012	Vulnerability	Redundancy, diversity, hardening, capacity tolerance, modularity
		Adaptive capability	Resources allocation, preparedness, collaboration, cognitive
	Hosseini & Barker, 2016	Absorptive capability	Backup utility systems, extra cargo handling equipment, storm surge protection, skilled labor and management, communication and coordination, space utilization, maintenance and reliability
		Adaptive capability	Repositioning, mode flexibility (substitution), quick evacuation
		Restorative capability	Budget restoration, resource restoration
	Hossain et al., 2019	Absorptive capability	Strong coastal protection, additional capital equipment, energy infrastructure redundancy, skillful emergency response team, facility redundancy, strong cyber critical infrastructure, management and communication, maintenance, safety management
		Adaptive capability	Alternate routing, timely evacuation, relocation, conservation
		Restorative capability	Facility restoration, manpower (Service) restoration, technology Restoration
	León-Mateos et al., 2021	Governance	Formal and informal regulations, transparency, adaptable management
		Society	Coordinated work, communication among stakeholders, agile internal communication
		Infrastructure and facilities	Digitalization, planning for climate change, operation flexibility
		Operational environment,	Capacity for learning, proactive adaptation strategies, training programs
		Risk management	Culture of risk management, contingency plans, energy independence
Infrastructure resilience	Bruneau et al., 2003	Robustness, redundancy, resourcefulness, rapidity	
	Yazdi et al., 2024	Recoverability, Redundancy, Robustness, Adaptability, etc.	

	Panahi et al., 2022	Absorptive capacity, adaptive/transformative capacities, Recovery capacity, etc.
	Liu et al., 2023a	Port governance efficiency, Smart port, National logistics hub, ICT infrastructure, Digital industrial convergence, Government response to COVID-19 index, Local governance score
	Shirali et al., 2013	Commitment, culture, awareness, opacity, preparedness, flexibility
	Vugrin et al., 2010	Absorptive capability (robustness, redundancy), adaptive capability (contingency, substitutability), restorative capability (resources, procurement)

From Table 4.1, most researchers use absorptive, adaptive, and restorative capabilities as the primary constructs, which are based on the definition: resilience enhances the system's ability to absorb, adapt, and recover from any shocks caused by disruptions (Hossain et al., 2019). Since the system's ability to absorb, adapt, and recover depends on the severity of the disturbance, the same strategy may affect different abilities at different levels of disturbance. For example, the strategy of building an emergency response team can improve absorptive, adaptive, and restorative capabilities in different scenarios. It may be difficult for managers to distinguish each strategy's specific function and effectiveness, which is not conducive to the prioritization and allocation of resources.

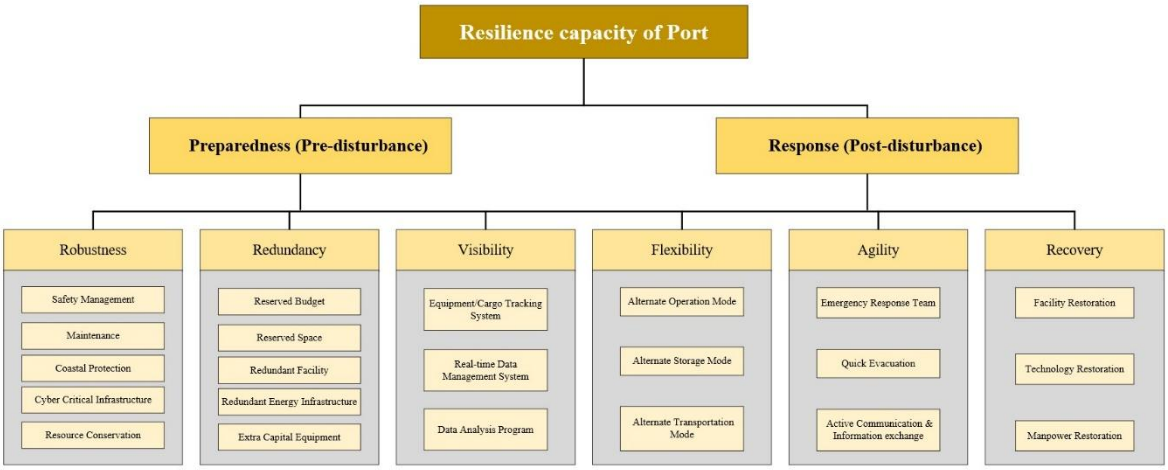


Figure 4.5 The structure of port resilience capacity

To aid strategy formulation and based on previous research, this chapter proposes a new framework model to measure port resilience (Figure 4.5) based on the summaries of resilience definition in Section 2.1. From literature review in Section 2.1, the concept of resilience is broad and the meaning of resilience is multi-layered, which can be divided into different functions or capabilities to cope with various disturbances. Thus, the resilience capability is divided into two parts: readiness(pre-disturbance) and response (post-disturbance) in this chapter. To measure the two capabilities, we propose six metrics: robustness, redundancy, visibility, flexibility, agility, recovery. Then, the common resilience strategies are classified under these metrics.

4.4.3.1 Robustness

Robustness refers to the ability to withstand a given level of stress or demand without suffering degradation or loss of function (Bruneau et al., 2003). In this paper, we group safety management, maintenance, coastal protection, cyber critical infrastructure, resource conservation under robustness, and elaborate them below.

(1) Safety Management

To transfer various hazardous materials with maximum safety (U.S. Coast Guard, 2017), the port must carry out strict safety management in daily operations. The management methods include: 1) formulating detailed management rules and regulations, such as smoking is not permitted inside workspace; 2) providing complete safety equipment and facilities, such as providing operators or laborers with personal protective equipment such as gloves and helmets, and deploying fire extinguishing devices and alarms in functional areas; 3) arranging regular training and workshops for employees to raise their safety awareness (Hossain et al., 2019).

(2) Maintenance

Routine preventive maintenance activities are an important means of strengthening ports' reliability and limiting the potential for major disruptions, including on-time repair scheduling of various equipment and availability of different spare parts (Tsinker, 2004). Maintenance interventions may include equipment maintenance (such as vessel and cranes), facility maintenance (such as channel and pipeline), and slop and sludge disposal (Hossain et al., 2019).

(3) Coastal Protection

Coastal protection refers to measures aimed at protecting the coast against coastline retreat or rising sea level, which is key in dealing with the effects of climate change. Coastal protection can be divided into two types, man-made and natural protection measures. Man-made protection measures include marsh and dune restoration, construction of walls, stone embankments, levees, living shorelines, floodgates, and/or berms. Natural coastal protection measures include the use of plants like mangroves and sea grasses as natural barriers to inundation.

(4) Cyber Critical Infrastructure

Extensive networks are maintained by port to conduct daily operations (Hossain et al., 2019). Different types of cyber-attacks are occurring all over the world today, which can severely impact port databases, transportation, navigation and management systems (Kramek, 2013). The establishment of a highly advanced security system, including dedicated cyber response plans and a competent team of cyber experts, can enhance the robustness of port cyber security.

(5) Resource Conservation

In addition to the resources mentioned above, there are many other resources in the port that need to be protected in normal operations, such as the yards and gates. We refer the strategies that enhance other resources' security as resource conservation, which are substantial in reducing the impact of disturbance. Resource conservation or rationing emphasizes automation and eliminates nonessentials (Hossain et al., 2019). It is a way to avoid additional financial losses during the disruption.

4.4.3.2 Redundancy

Redundancy refers to the extent to which elements, systems, or other units of analysis that are substitutable (Bruneau et al., 2003). We roughly divide the port resources into five categories: budget, space, facility, utility systems and equipment, which are introduced as follows.

(1) Reserved Budget

Budget constraints are the main driver of resilience enhancing investments (Haimes, 2009; Hosseini & Barker, 2016). The availability of budget determines the redundancy of resources such as equipment and facilities before the disturbance occurs, and also determines the recovery capability of affected resources such as damaged equipment and facilities after the disturbance occurs.

(2) Reserved Space

As a goods hub, the port is responsible for the loading, unloading and storage of cargos. Improving space utilization during operation and reserving suitable space can relieve the pressure when goods are backlogged. Additionally, larger operations often have the potential to utilize cargo handling capacity more efficiently, as they are less likely to get stuck in small chunks of unused terminal space (Hosseini & Barker, 2016).

(3) Redundant Facility

In ports, the redundancy of seaside facilities (such as berths and anchorages), landside facilities (such as backup gate and intermodal facilities) and extra terminal provide additional capacity for terminal services (Rice & Trepte, 2012; Hossain et al., 2019). It can be used as a replacement for damaged facilities after a disturbance, thereby reducing the consequences of the disturbance.

(4) Redundant Energy Infrastructure

In order to maintain the long-term and high-intensity operation of various large-scale equipment in the port, redundant energy infrastructure such as power systems and fuel storage are essential. Power system failure is one of the common problems that hinder the normal operation of port facilities (Hosseini & Barker, 2016). Backup power sources, such as backup generators, wind energy, backup solar power, can be used as mitigation measures during power outages at port facilities (Berle et al., 2011).

(5) Extra Capital Equipment

Various operations exist in ports. In addition, the ports' equipment is also diverse. In container terminals, the equipment usually includes container loading and unloading equipment (such as gantry cranes and quay cranes), container transportation equipment (such as trucks or Automated Guided Vehicles (AGVs)), auxiliary equipment (such as dredging equipment, tugs and mooring instruments). When the equipment in operation fails, backup equipment can be deployed to maintain the normal operation of the system.

4.4.3.3 Visibility

Visibility refers to the extent to which actors can observe operations which they consider as being key or useful (Jüttner and Maklan, 2011; Kim, et al., 2021). End-to-end visibility will increase resilience while enhancing efficiency and productivity gains (UNCTAD, 2021). To improve the visibility, the equipment/cargo tracking system, real-time data management system and data analysis program can be constructed.

(1) Equipment/Cargo Tracking System

Building an effective tracking system, such as GPS and RFID, can help operators locate equipment and cargos quickly and track operations accurately, which facilitates clearer scheduling both before and after disruption.

(2) Real-time Data Management System

Real-time data management system, such as electronic data interchange, allows for real-time exchange and processing of data, based on which communication between various cooperative departments can be facilitated.

(3) Data Analysis Program

Port operations involve the collection and processing of large amounts of data. Developing an intelligent data analysis program, that is, using existing data to fit or build various intelligent models, such as machine learning, can facilitate managers to explore potential relationships between various modules. Data analysis programs can give managers a more comprehensive view of the port system, allowing for more accurate predictions before and after disruptions.

4.4.3.4 Flexibility

Flexibility refers to the ability of a system to adapt to the changing requirements of its environment with minimum time and effort (Erol et al., 2010; Kim, Choi, S., & Kim, C., 2021). To achieve flexibility, multiple modes can be deployed to reduce the impact of disruptions on operations by switching modes when managers are aware that disruption is imminent or has occurred. Some of these modes include transportation mode, storage mode, and operation mode.

(1) Alternative Transportation Mode

Alternative transportation mode includes planning for alternative transportation routes and nodes. There are various types of transportation route replacements, such as from waterways to railroads or highways. The replacement of nodes can be based on strategic alliances with nearby ports, so that ships that anchored at the affected ports during the disruption can be redirected to partnering ports.

(2) Alternative Storage Mode

The storage mode of the port facility should also be flexible in order to cope with different types of disturbances. For example, during a storm or hurricane, items such as containers should be relocated on the ground/yard, but during floods, these items should be relocated at heights that floodwaters cannot reach.

(3) Alternative Operation Mode

The alternative operation mode mainly services the work of port employees. For example, when the epidemic occurs, it is difficult for most of the staff to work on-site. Under this circumstance, they can switch to online office, with the flexible change of the corresponding office process.

4.4.3.5 Agility

Agility refers to the ability to rapidly respond to changes (Jain et al., 2008; Kim, et al., 2021).

(1) Emergency Response Team

In order to respond to disruptions rapidly, it is necessary to build an emergency response team, which is an asset to port during disruptions (Touzinsky, 2016). This team is primarily responsible for determining the cause of the disturbance and assess the severity of the accident, notifying the responsible person in a timely manner following a disturbance, and providing appropriate advices for personnel in the affected area of any potential threats and/or initiating necessary counteractive measures. To do this, regular training and workshops should be arranged for the team.

(2) Quick Evacuation

Quick evacuation, the timely transfer of manpower, cargos and facilities from a threatened port to another port or other storage location in the event of port disruption, is an effective strategy to mitigate the potential threats (Hossain et al., 2019).

(3) Active Communication and Information Exchange

Active communication and information exchange before or during the disruption will limit the consequences of a shock (Hossain et al., 2019). This strategy can be divided into two parts: internal communication and external cooperation. Internal communication includes timely notification of various information (such as equipment scheduling, shift information adjustment, etc.), which can promote effective communication between employees and ensure normal operation in the port; external cooperation includes communication with the National Meteorological Administration, shipping agents, regulatory agencies and other relevant agencies, so as to keep abreast of various changes and take precautions in advance.

4.4.3.6 Recovery

Recovery refers to the ability to return to normal operational state rapidly with lower cost and resources (Pettit et al., 2010; Kim, et al. 2021). To achieve recovery, strategies can be deployed in three ways: facility restoration, manpower restoration and technology restoration (Hossain et al., 2019).

(1) Facility Restoration

There are many types of facilities at the ports, including functional sites (such as container yards, anchorages, docks, berths, gate, security zones and transit sheds), equipment (such as gantry cranes, quay cranes and trucks), and buildings (such as office buildings and warehouse). Facility restoration strategies focus on bringing the damaged equipment, sites, and buildings back into operation as soon as possible through methods such as cleaning, repairs, replacements.

(2) Manpower Restoration

Corresponding to the various facilities in the port, the human resources for managing and operating the port facilities, including engineers, operators, technical crews, drivers, labourers and maintenance personnel should be sufficient and capable. Manpower restoration strategies focus on the reestablishment of human-based assistance to restore the normal operation after disruptions (Hossain et al., 2019). For example, this can include readjusting shift schedules and working hours in the event of reduced labour.

(3) Technology Restoration

As ports involve the handling and storing a large amount of cargo and scheduling large number of equipment, the operating technology of the port should be advanced and sophisticated. Therefore, technology restoration, that is, the restoration of technological resources, is a substantial and critical part of the post-disturbance strategy. The main technological resources include system (such as the terminal operating system, equipment management system, the programmable logic controller, navigation systems and surveillance system), network, software platforms, computers.

4.5 Application and Results

In this section, the methodology proposed above and a case study will be used to illustrate the port resilience quantification model. Based on expert experience and historical data, the resilience of automated and non-automated terminals is compared and analyzed.

4.5.1 Case Study

Shanghai Yangshan Deepwater Port, the largest and busiest container port in the world, is chosen to serve as the case study. The Yangshan Port, a key element of the Belt and Road

Initiative, is at the heart of the New Silk Road. Since its establishment in 2005, the port has undergone four expansion phases. Non-automated container terminals were established in the first three phases. At the end of 2017, the fourth phase was completed, which is the largest automated container terminal in the world (ShipHub, 2022). As shown in Figure 4.6, the Yangshan Port is a natural and superb Deepwater port, which is located close to a chain of islands between the mouth of the Yangtze River and the Hangzhou Bay.

Figure 4.6 Shanghai Yangshan Deepwater Port. (Source from Baidu Map)

4.5.2. Threat Identifications

To identify the main disruptions of Yangshan Port, the method that combining DSET and HFLTS will be employed.

As the main disruptions has been summarised in Figure 4.4, which can be used as the assessment indicators $AI = \{ai_1, ai_2, \dots, ai_n\}$. To obtain the weights $W = \{\omega_1, \omega_2, \dots, \omega_n\}$ of assessment indicators, experts $EP = \{ep_1, ep_2, \dots, ep_t\}$ with predefined weights $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_t\}$ are invited to score the impact level $L = \{l_1, l_2, \dots, l_n\}$ of indicators AI using criteria $C = \{c_1, c_2, \dots, c_m\}$. The information of the invited experts is shown in Table 4.2.

Table 4.2 Background information of invited experts

Number of interviewees	Position	Work experience	Familiarity
4	Professor	> 10 years	These professors are familiar with ports' constructions and operations and have published several papers and obtained several projects related to the Yangshan Deepwater Port.

3	Researcher	5-10 years	These researchers are familiar with ports' constructions and operations and have published several papers and participated in several projects related to the Yangshan Deepwater Port.
3	Captain	> 10 years	These captains work on shipping routes around the world and have a great understanding of the Yangshan Deepwater Port.
6	Manager	> 10 years	These managers are working at the major container terminals in China and Singapore. They are familiar with the operations of ports and have a great understanding of the Yangshan Deepwater Port.

After giving the experts the relevant research background and assessment ideas, we invited the experts to evaluate the weight of the summarized disruptions from three assessment criteria: occurrence probability (c_1), severity (c_2), and probability of disruptions being undetected (c_3).

In this study, the evaluated LTS is defined as $\boldsymbol{S}_2$ = { $S_{-2}, S_{-1}, S_0, S_1, S_2$} = {Very Low (VL), Low(L), medium (M), High (h), Very High (VH)}, corresponding to assessment scores ranging from 1 to 5. The detailed questionnaire please review the link ; https://www.wjx.cn/vm/PErWXRM.aspx#. Considering that experts from the industry possess greater practical experience, their opinions are regarded as more significant. Consequently, the predefined weight assigned to industry experts is set to be twice that of academic experts.

Based on the questionnaire, the linguistic expressions used by the 16 experts to describe the assessment indicators are obtained and converted into decision matrices. According to Equations (4-19) to (4-24), the normalized support degree table of experts can be generated from these decision matrices. Subsequently, the experts' opinions are converted into the DSET framework. The weights for each assessment indicator are then generated by fusing information from all three criteria using the techniques provided in Section 4.2.2.2. Finally, the three disruptions with the highest weights in each category are selected and will be introduced as follows.

To demonstrate our specific calculation process, we take the evaluation process of natural factors as a case study and present it in detail as follows.

Based on the questionnaire (https://www.wjx.cn/vm/PErWXRM.aspx#), the linguistic expressions used by the 16 experts to describe the assessment indicators are obtained (Table 4.3). In Table 4.3, e_1 to e_{16} are the experts; c_1 to c_3 denotes the three assessment criteria: occurrence probability (c_1), severity (c_2), and probability of disruptions being undetected (c_3); f_1 to f_9 are the main port natural disruption factors summarized in Figure 4.4: Pandemic (f_1), Earthquakes (f_2), Tsunami (f_3), Coastal erosion (f_4), Drought (f_5), Floods (f_6), Storms (f_7), Fog (f_8), Typhoon/Hurricanes (f_9).

The linguistic expressions in Table 4.3 are converted into decision matrices. According to Equations (4-19) to (4-24), the normalized support degree table of experts can be generated from these decision matrices (Table 4.4).

Table 4. 3 Linguistic expressions provided by experts

	e_1			e_2			e_3			e_4		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	M	Between M and VH	Between M and VH	M	M	M	Between VL and L	Between H and VH	Between H and VH	M	VH	M
f_2	L	Between H and VH	Between H and VH	L	H	H	Between VL and L	Between H and VH	Between H and VH	L	VH	H
f_3	L	M	M	L	M	M	Between VL and L	Between H and VH	Between H and VH	L	H	H
f_4	Between H and VH	Between VL and L	L	M	VL	L	Between L and M	Between L and M	Between VL and L	M	M	M
f_5	VL	H	Between VL and L	VL	H	VL	Between L and M	Between VH and H	Between VL and L	M	Between VH and H	M
f_6	L	L	H	VL	L	L	Between L and M	Between M and H	Between VL and L	L	H	M
f_7	M	H	L	M	H	L	Between L and M	Between L and M	Between L and M	L	M	M
f_8	M	M	H	H	H	M	Between L and M	Between L and M	Between M and H	M	M	M
f_9	M	Between H and VH	H	H	VH	H	Between L and M	Between M and H	Between M and H	M	H	M
	e_5			e_6			e_7			e_8		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	H	H	H	M	Between M and H	Between M and H	M	Between M and H	H	M	Between H and VH	Between H and VH
f_2	L	H	H	L	Between H and VH	Between H and VH	L	Between H and VH	M	L	Between H and VH	Between H and VH
f_3	L	M	M	L	M	M	L	M	M	L	M	M
f_4	L	VL	L	Between H and VH	Between VL and L	L	M	Between VL and L	L	Between H and VH	Between VL and L	L
f_5	L	Between VH and H	VL	L	M	Between VL and L	L	M	Between VL and L	VL	H	Between VL and L
f_6	L	H	L	L	H	L	H	L	L	L	H	M
f_7	L	H	L	L	VL	L	H	VH	M	H	M	L
f_8	L	H	M	Between H and VH	M	H	M	M	H	Between H and VH	M	Between M and H
f_9	L	VH	H	Between H and VH	Between H and VH	H	H	Between H and VH	H	Between H and VH	Between H and VH	Between M and H
	e_9			e_{10}			e_{11}			e_{12}		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	M	Between M and H	Between M and H	M	Between H and VH	H	M	Between H and VH	Between H and VH	L	H	VH
f_2	L	Between H and VH	Between H and VH	L	Between H and VH	M	L	Between H and VH	Between H and VH	L	H	H
f_3	L	M	M	L	M	M	L	M	M	L	M	M
f_4	M	Between VL and L	L	M	Between VL and L	L	Between H and VH	Between VL and L	L	M	VL	L
f_5	VL	M	Between VL and L	Between VL and L	Between VH and H	Between VL and L	M	H	Between VL and L	VL	H	VL
f_6	VL	L	H	VL	L	L	VL	H	L	VL	L	VL
f_7	H	M	L	M	H	L	L	M	L	M	H	L
f_8	M	M	H	M	M	H	Between H and VH	M	Between M and H	H	H	M
f_9	M	Between H and VH	H	H	Between H and VH	H	Between H and VH	Between H and VH	Between M and H	H	VH	H
	e_{13}			e_{14}			e_{15}			e_{16}		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	M	Between H and VH	Between M and H	M	Between M and H	Between M and H	M	H	Between M and H	M	VH	Between M and H
f_2	L	Between H and VH	Between H and VH	L	Between H and VH	H	L	H	H	L	VH	H
f_3	L	M	M	L	M	M	L	M	M	L	H	H
f_4	M	Between VL and L	L	M	Between VL and L	L	M	VL	L	M	M	M
f_5	M	H	L	M	H	L	VL	L	VL	M	H	M

f_6	VL	L	H	VL	L	L	VL	L	VL	L	H	L
f_7	M	M	L	M	H	L	M	L	L	L	M	L
f_8	Between H and VH	M	H	M	M	H	H	H	M	M	M	M
f_9	Between H and VH	Between H and VH	Between H and VH	H	Between H and VH	H	H	VH	H	M	H	M

Table 4. 4 Support degrees of experts

	e_1			e_2			e_3			e_4		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	0.062488	0.062594	0.062585	0.062488	0.062468	0.062463	0.0626	0.062499	0.062507	0.062488	0.062507	0.062463
f_2	0.062495	0.062509	0.062519	0.062495	0.06247	0.062479	0.062568	0.062509	0.062519	0.062495	0.062512	0.062479
f_3	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062568	0.062557	0.062555	0.062495	0.062528	0.062526
f_4	0.062536	0.062504	0.06249	0.062478	0.062468	0.06249	0.062553	0.06253	0.062564	0.062478	0.062532	0.06253
f_5	0.062494	0.062468	0.062508	0.062494	0.062468	0.062474	0.062525	0.062591	0.062508	0.062506	0.062591	0.062531
f_6	0.062491	0.062489	0.062536	0.062491	0.062489	0.062478	0.062532	0.062534	0.062541	0.062491	0.062511	0.062499
f_7	0.062486	0.062488	0.062492	0.062486	0.062488	0.062492	0.062537	0.062552	0.062536	0.0625	0.062481	0.062531
f_8	0.062479	0.062488	0.062496	0.062493	0.062515	0.062489	0.062554	0.062572	0.062532	0.062479	0.062488	0.062489
f_9	0.062487	0.062505	0.062484	0.062481	0.062495	0.062484	0.062562	0.062542	0.062544	0.062487	0.062467	0.062502
	e_5			e_6			e_7			e_8		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	0.062534	0.062463	0.062475	0.062488	0.06251	0.062503	0.062488	0.06251	0.062475	0.062488	0.062499	0.062507
f_2	0.062495	0.06247	0.062479	0.062495	0.062509	0.062519	0.062495	0.062509	0.062506	0.062495	0.062509	0.062519
f_3	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492
f_4	0.062519	0.062468	0.06249	0.062536	0.062504	0.06249	0.062478	0.062504	0.06249	0.062536	0.062504	0.06249
f_5	0.062485	0.062591	0.062474	0.062485	0.062468	0.062508	0.062485	0.062468	0.062508	0.062494	0.062468	0.062508
f_6	0.062491	0.062511	0.062478	0.062491	0.062511	0.062478	0.062597	0.062489	0.062478	0.062491	0.062511	0.062499
f_7	0.0625	0.062488	0.062492	0.0625	0.062576	0.062492	0.06252	0.062541	0.062531	0.06252	0.062481	0.062492
f_8	0.062521	0.062515	0.062489	0.062523	0.062488	0.062496	0.062479	0.062488	0.062496	0.062523	0.062488	0.062532
f_9	0.06253	0.062495	0.062484	0.062517	0.062505	0.062484	0.062481	0.062505	0.062484	0.062517	0.062505	0.062544
	e_9			e_{10}			e_{11}			e_{12}		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	0.062488	0.06251	0.062503	0.062488	0.062499	0.062475	0.062488	0.062499	0.062507	0.062527	0.062463	0.062526
f_2	0.062495	0.062509	0.062519	0.062495	0.062509	0.062506	0.062495	0.062509	0.062519	0.062495	0.06247	0.062479
f_3	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492
f_4	0.062478	0.062504	0.06249	0.062478	0.062504	0.06249	0.062536	0.062504	0.06249	0.062478	0.062468	0.06249
f_5	0.062494	0.062468	0.062508	0.062529	0.062591	0.062508	0.062506	0.062468	0.062508	0.062494	0.062468	0.062474
f_6	0.062491	0.062489	0.062536	0.062491	0.062489	0.062478	0.062491	0.062511	0.062478	0.062491	0.062489	0.062515
f_7	0.06252	0.062481	0.062492	0.062486	0.062488	0.062492	0.0625	0.062481	0.062492	0.062486	0.062488	0.062492
f_8	0.062479	0.062488	0.062496	0.062479	0.062488	0.062496	0.062523	0.062488	0.062532	0.062493	0.062515	0.062489
f_9	0.062487	0.062505	0.062484	0.062481	0.062505	0.062484	0.062517	0.062505	0.062544	0.062481	0.062495	0.062484
	e_{13}			e_{14}			e_{15}			e_{16}		
	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3	c_1	c_2	c_3
f_1	0.062488	0.062499	0.062503	0.062488	0.06251	0.062503	0.062488	0.062463	0.062503	0.062488	0.062507	0.062503
f_2	0.062495	0.062509	0.062519	0.062495	0.062509	0.062479	0.062495	0.06247	0.062479	0.062495	0.062512	0.062479
f_3	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062491	0.062492	0.062495	0.062528	0.062526
f_4	0.062478	0.062504	0.06249	0.062478	0.062504	0.06249	0.062478	0.062468	0.06249	0.062478	0.062532	0.06253
f_5	0.062506	0.062468	0.062488	0.062506	0.062468	0.062488	0.062494	0.062491	0.062474	0.062506	0.062468	0.062531
f_6	0.062491	0.062489	0.062536	0.062491	0.062489	0.062478	0.062491	0.062489	0.062515	0.062491	0.062511	0.062478
f_7	0.062486	0.062481	0.062492	0.062486	0.062488	0.062492	0.062486	0.062518	0.062492	0.0625	0.062481	0.062492
f_8	0.062523	0.062488	0.062496	0.062479	0.062488	0.062496	0.062493	0.062515	0.062489	0.062479	0.062488	0.062489
f_9	0.062517	0.062505	0.062528	0.062481	0.062505	0.062484	0.062481	0.062495	0.062484	0.062487	0.062467	0.062502

Subsequently, the experts' opinions are converted into the DSET framework. The weights for each assessment indicator are then generated (Table 4.5) by fusing information from all three criteria using the techniques provided in Section 4.2.2.2.

Table 4. 5 The assessment results of natural factors

Indicators	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
Impact level	M	0	0	L	L	L	L	M	H
Normalized Weight	0.166667	0	0	0.111111	0.111111	0.111111	0.111111	0.166667	0.222222

Finally, among natural factors, Pandemic (f_1), Fog (f_8), and Typhoon/Hurricanes (f_9) are identified as the primary disruptions. These disruptions will be introduced in detail in next sections. The values of Earthquakes (f_2) and Tsunami (f_3) are 0 due to significant discrepancies in evaluation results under different criteria, which prevented the derivation of a unified result. Upon further investigation, it was found that experts consider earthquakes and tsunamis to be low-probability but highly impactful disruptions for Yangshan Port. Consequently, the substantial differences in evaluation outcomes based on the two criteria— occurrence probability (c_1) and severity (c_2) —resulted in the inability to achieve a final integrated assessment outcome.

(1) Natural Factors

Pandemic, fog, and typhoon are the main natural factors selected by experts, which will be introduced below based on the relevant literature and data.

The COVID 19 pandemic that broke out at the end of 2019 caused untold disruption for the container port industry in the first half of 2020 (LLOHP, 2021). Despite the post-pandemic era, ports are still affected by it. At present, the ports in Europe and the United States are seriously congested, causing delays in the global supply chain and serious problems of stranded empty containers. At the same time, the shortage of empty containers in Chinese ports, including Yangshan Port, has continued. In the worst case, the shortage of empty containers in seaborne imports reached 2 million TEUs (CWT, 2021). In addition, China's measures to control the pandemic are very strict. If port personnel were tested positive, the whole port may have to close immediately.

The fog season in Yangshan Port and the surrounding waters mostly occurs from April to June, and the fog conditions in the whole area are relatively serious, with an average of 42 days of fog conditions per year (Chen, 2021). The reduced visibility brings inconvenience to the operation of port equipment, the moving of trucks, ship lookout, and navigation positioning. In addition, when the fog is severe, truck rear-end collisions on the Donghai Bridge occur frequently (Sea steward, 2019).

Typhoons have always been a major factor affecting port operations. The average number of typhoons in Shanghai is twice a year, with a maximum of four, mainly in July-August, and more than 50% of the typhoons in the sea area have a wind force of 8 or above (China Ports, 2022). Terminals have to suspend services as typhoon approaches, causing a large number of ships to stay at the anchorage, and further forming a congestion situation. When the typhoon is severe, accidents such as the anchoring of ships, the water entering the stern, the tilting of the hull, and even the destruction of the submarine cable may occur, thereby affecting the operation of the port.

(2) Technological Factors

Equipment failure, ship collision, and truck congestion are the main technological factors selected by experts, which will be introduced below based on the relevant literature and data.

A container terminal is a place with dense equipment and facilities. Taking the fourth phase of Yangshan as an example, there are 130 AGVs operating in the terminal, as well as numerous quay cranes, rail-mounted gantry cranes (ARMGs), and other machinery. Their value is estimated at USD 2 billion (ShipHub, 2022). Therefore, the disturbance caused by equipment failure is one of the common port disturbances. According to the internal statistical data of Yangshan Port, the number of equipment failure of ARMGs per day is 7.5, resulting in problems such as the height mismatch of pick-and-place containers and excessive shaking.

Due to the special geographical location of Yangshan Port, in addition to human factors and ship factors that generally lead to ship collision accidents, environmental factors may be one of the biggest factors in the waters of Yangshan Port: strong winds and heavy rain caused by tropical cyclones, extra-tropical cyclones, and cold waves are likely to cause large container ships to collide (Yuan, 2004), and the increase in traffic flow will also increase the occurrence of ship collisions.

As shown in Figure 4.6, the Donghai Bridge is the only route that connects the Yangshan port to the economic hinterland of the Yangtze River Delta and other places in China. With the gradual increase in the throughput of the Yangshan Port, the traffic capacity requirements of the Donghai Bridge are also increasing. At present, the tidal effect of traffic flow of the Donghai Bridge is apparent and the congestion is serious during peak hours, which can cause port congestion and further delays in port loading or pick-up schedules.

(3) Organizational and Other Factors

Based on questionnaire statistics, in Yangshan Port, poor training, shifts problem, and ineffective communications are the main organizational factors, human, policy, and economic factors are the other main factors.

4.5.3 Resilience Quantification

This section will introduce the detailed modeling of factors in BN. AgenaRisk software is used to model and simulate the BN. The structure of the model (as shown in Figures 4.7 and 4.8) is divided into four parts: a. Disruption Modelling; b. Strategies Modelling; c. Modelling for Actual Capacity, Lost Capacity and Recovered Capacity of Ports; and d. Total Resilience Modelling. For part (a), Section 4.4.2 (Disruption Identification) introduces the categories of disruptions, while Section 4.5.2 (Threat Identification) identifies the primary disruptions under each category. Therefore, the primary disruption factors are associated with disruption categories, and the disruption categories are connected to the total disruption. For part (b), Section 4.4.3 (Resilience Capacity Design) has elaborated on resilience and its corresponding strategies in detail. Specifically, Figure 4.5 (Structure of Port Resilience Capacity) illustrates resilience and its corresponding strategies. Thus, the primary strategy factors are linked to resilience capacity. For part (c), the actual port capacity, lost capacity, and recovery capacity are connected to specific port resilience capacities and disruptions. For part (d), the overall port resilience is associated with the actual port capacity, lost capacity, and recovery capacity, thereby establishing a connection among them. The mathematical modelling of each part will be elaborated upon in the respective subsections below.

4.5.3.1 Disruption Modelling

For each main disruption, we use Boolean Variables (BV) to model their probability of occurrence. BVs are binary discrete variables such as True/False and Yes/No, which can represent variables' positive and negative outcomes. For instance, if we know that the probability of occurrence of equipment failure in Yangshan Port is 20%, then the value of equipment failure in the "Yes" state can be set to 20%, and the value in the "No" state can be set to 80%. Similarly, if we know that the average frequency of fog in Yangshan Port every rear is 11.51%, then the value of fog in the "Yes" state and "No" state can be set to 11.51% and 88.49% respectively. The probability of disturbances related to natural and technological factors is mainly based on historical data statistics, while the disturbances related to organizational and other factors are mainly based on expert experience. Since the automated terminal (Phase IV) and non-automated terminal (Phase I, II and III) are in the same port, we assume that they are suffering the same disruptions.

It can be reasonably assumed that each disruption happens independently of the others. They are capable of causing damage in separation and they do not interfere in each other's ability to cause impact. Disasters can also occur even if none of the main disruptions is active. Therefore, we can use Noisy-OR model to model disruptions of each category (see Eqs. (4-45)–(4-48)).

$$P(\textit{Natural Factors}) = \textit{NoisyOR}\ (\textit{Pandemic}, 0.15, \textit{Fog}, 0.1, \textit{Typhoon}, 0.1, 0.1) \tag{4-45}$$

$$P(\textit{Technological Factors})$$

$$=\textit{NoisyOR}\ (\textit{Equipment Failure}, 0.2, \textit{Ship Collision}, 0.05, \textit{Truck Congestion}, 0.1, 0.1) \tag{4-46}$$

$$P(\textit{Organizational Factors})$$

=NoisyOR (Poor training, 0.05, Shifts Problem, 0.05, Ineffective Communications, 0.1, 0.05) (4-47)

P(Others)=NoisyOR (Human Factors, 0.15, Policy Factors, 0.1, Economic Factors, 0.1, 0.1) (4-48)

The total disturbance probability of the four categories can be integrated by the weighted averaging method. The weight of each category can be obtained using the questionnaire (link of the questionnaire: https://www.wjx.cn/vm/wFw8wxk.aspx). Labeled Variables (LV) are used to model disturbances' impact, which can have several discrete states.

As shown in Figures 4.7 and 4.8, natural disasters are major disruptors plaguing ports.

4.5.3.2 Strategies Modelling

For strategies, we also use BV to model their probabilities of success after implementation. The value of the success probability of each strategy is derived based on expert experience using the improved DSET. For instance, in Figure 4.7, the values of the safety management variable are 87.34% for True and 12.66% for False, which means that there is an 87.34% probability that the safety management of the automated terminal (Phase IV) can be successfully implemented, and a 12.66% probability of failure. In Figure 4.8, the values of the safety management variable are 73.42% for True and 26.58% for False. This means that compared with the automated terminal, operations in the non-automated terminal (Phase I, II, and III) are less standard. Hence, the implementation of safety management strategies is less successful.

The capability of each metric can be integrated by the weighted averaging method. The weight of each strategy is calculated based on its capability to enhance their corresponding resilience metrics, which is derived based on expert experience and modeled by LV.

The total capability of readiness and response can also be integrated by the weighted averaging method. The weight of each metric is calculated based on its capability to enhance readiness or response, which is derived based on expert experience and modeled by LV.

4.5.3.3 Actual Capacity, Lost Capacity and Recovered Capacity of Ports

In 2021, the container throughput of the Yangshan Port exceeds 22 million TEUs and the Phase IV is close to 6 million, of which the maximum day and night throughput of the Phase I, Phase III and Phase IV terminals reached 25775, 36481.75, and 25,488 TEUs respectively. Therefore, a truncated normal distribution (TNORM) is used to model the port's actual capacity (AC) per day, which is a modified form of a normally distributed random variable by constraining its lower bound, upper bound or both.

Based on the partial statistics of the port, the AC of the automated terminal (Phase IV) and non-automated terminal (Phase I, II and III) are set as follows,

$$\textit{Actual capacity of automated terminal}$$
$$\sim TNORM\ (\mu = 1640,\ \sigma^2 = 1 * 10^7, LB = 0, UB = 25000) \qquad (4\text{-}49)$$

$$\textit{Actual capacity of non-automated terminal}$$
$$\sim TNORM(\mu = 4380,\ \sigma^2 = 1 * 10^7, LB = 0, UB = 80000) \qquad (4\text{-}50)$$

In this model, the lost capacity (LC) depends on three aspects: the disruption, the AC of port, and readiness. When a disruption occurs, if the readiness is strong enough (state is True) to absorb the shock of the disruption without implementing any response measures, the LC is set to zero; otherwise (state is False), the mean value of LC is set as the product of disruption and AC. The LC of automated terminal and non-automated terminal are set as follows,

$$\textit{Lost capacity of automated terminal}$$
$$\sim TNORM\ (\mu = Disruption * AC, \sigma^2 = 1 * 10^7, LB = 0, UB = 20000) \quad (4\text{-}51)$$

$$\textit{Lost capacity of non-automated terminal}$$
$$\sim TNORM(\mu = \mathrm{Disruption} * \mathrm{AC}, \sigma^2 = 1 * 10^7, LB = 0, UB = 70000) \quad (4\text{-}52)$$

The recovered capacity (RC) depends on two aspects: LC and response. We assume that if the response is successful (state is True), port infrastructure will recover its lost capacity with a certain proportion; otherwise (state is False), the value of RC is 0. The TNORM is used to model the recover proportion as follows,

$$\textit{Recover proportion} \sim TNORM(\mu = 0.8,\ \sigma^2 = 0.01, LB = 0.1, UB = 1) \quad (4\text{-}53)$$

For the baseline model in Figures 4.7 and 4.8, we set the recover proportion as 0.8.

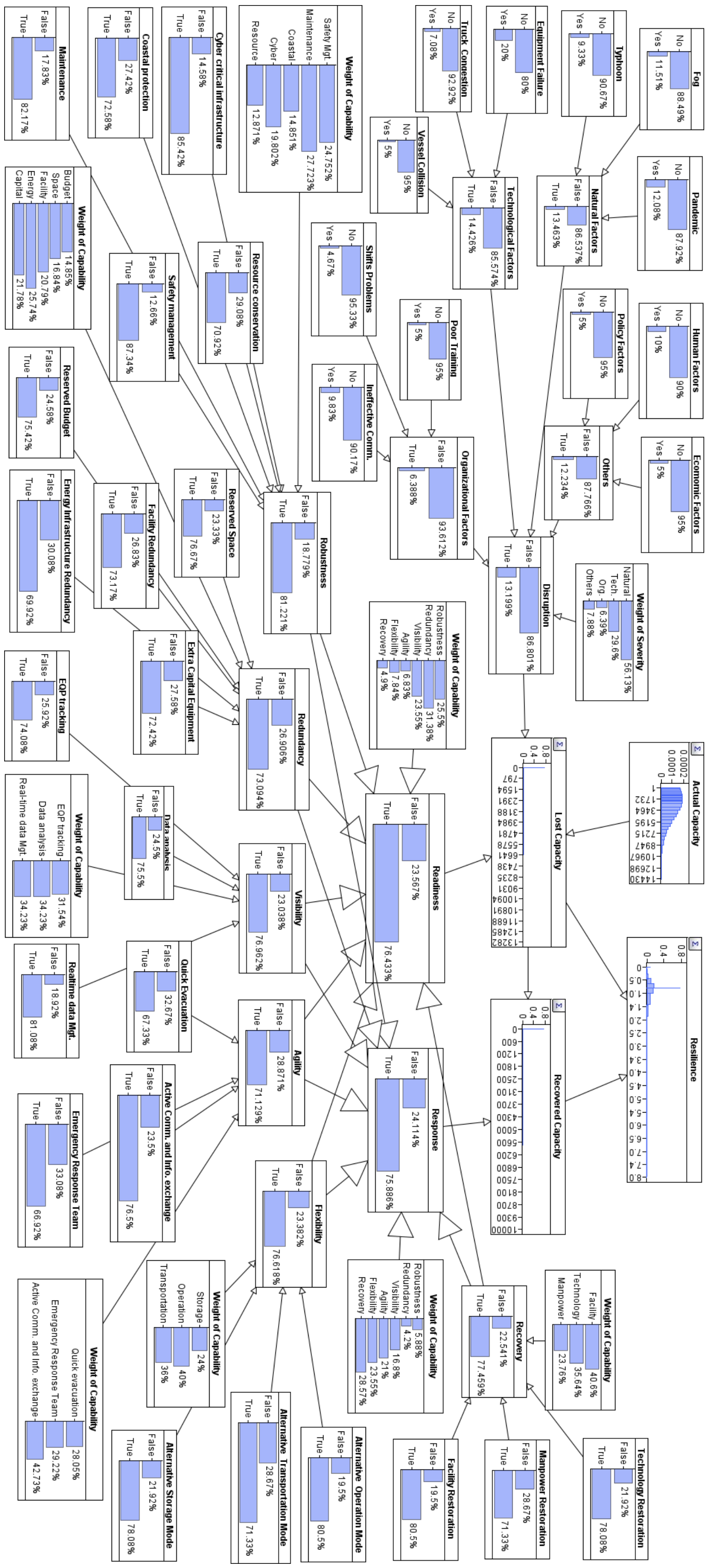


Figure 4.7 Baseline resilience assessment model of the automated container terminal

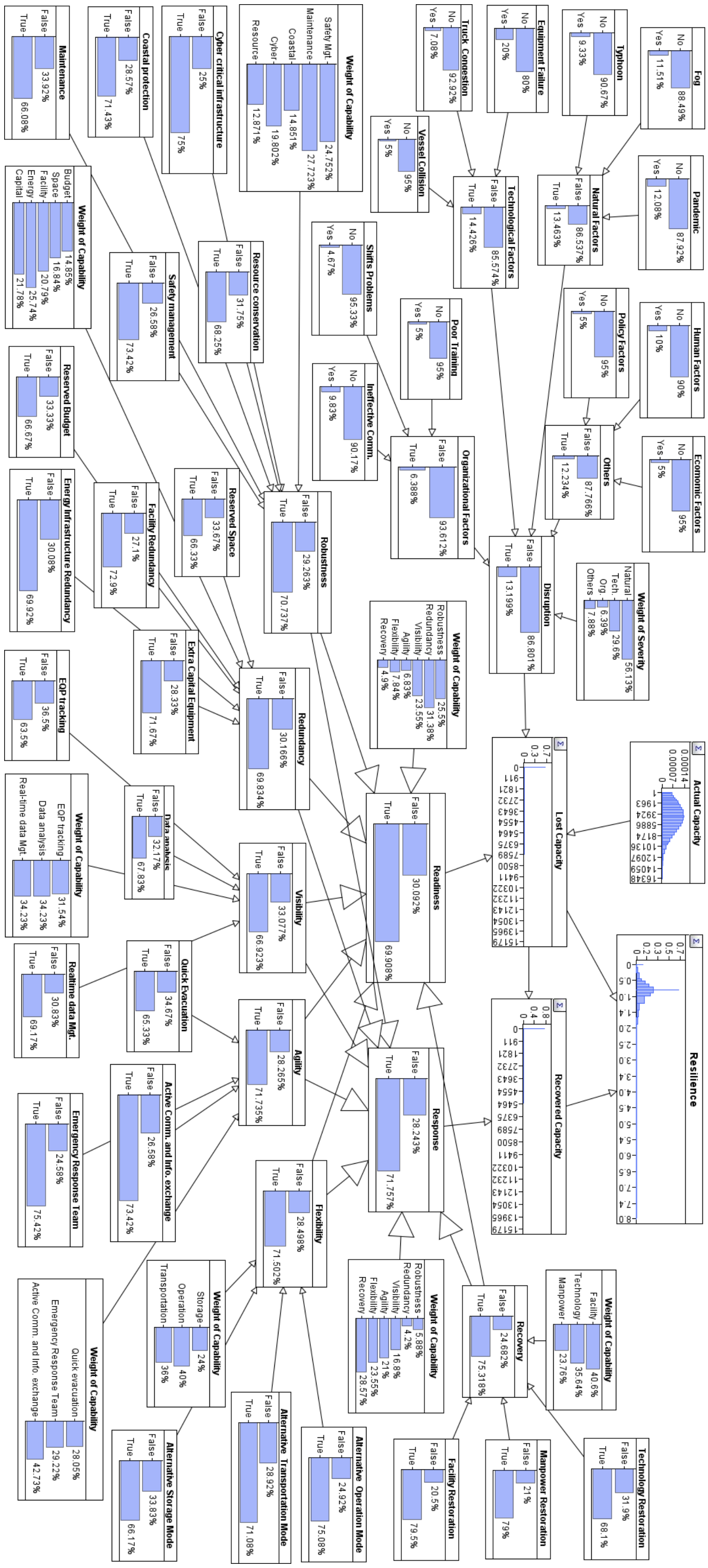


Figure 4.8 Baseline resilience assessment model of the non-automated container terminal

4.5.3.4 Resilience

Based on the literature review, various indicators have been proposed to calculate the system resilience. In this model, we use recovery ratio to calculate the port resilience, that is the ratio of recovered capacity to lost capacity. When LC is 0, we set the port resilience to 0.8; otherwise, the resilience is equal to the value of RC divided by LC. Based on this calculation, the expected resilience of automated terminal and non-automated terminal is 0.73 and 0.69.

4.5.4 Results Analysis

4.5.4.1 Sensitivity Inference

Sensitivity analysis helps to discover the relative importance of different indicators in arriving at diagnosis and hence in choosing options (Henrion,1989). To explore the impact of the resilience strategies on the resilience capacity, sensitivity analysis is conducted on readiness and response as target nodes concerning its causal factors (strategies and metrics).

The analysis results are displayed in tornado graphs, in which the length of the bars corresponding to each sensitive node indicates the degree of influence of the corresponding node on the target node.

Sensitivity analysis of readiness capacity with respect to resilience strategies of the automated container terminal is used as an example. The Tornado graph (Figure 4.9) illustrates the influence of various parameters by showing how the probability changes when each parameter transitions between its states (True/False). From the Figure 4.9, Realtime Data Management, Data Analysis, and EQP Tracking are the most influential parameters. When $P_{(\text{Realtime Data Mgt.=True})}$, the probability of $P_{(\text{Readiness=False})}$ decreases from the baseline value of 0.092 to 0.083. Conversely, if $P_{(\text{Realtime Data Mgt.=False})}$, the probability increases significantly to 0.137. This demonstrates that real-time data management is the most critical factor influencing readiness. Enabling data analysis ($P_{(\text{Data Analysis=True})}$ reduces the probability of $P_{(\text{Readiness=False})}$ to 0.080. Disabling data analysis ($P_{(\text{Data Analysis=False})}$) increases the probability to 0.133. This indicates that effective data analysis is essential for maintaining readiness. If $P_{(\text{EQP Tracking=True})}$ the probability of $P_{(\text{Readiness=False})}$ decreases to 0.085. If $P_{(\text{EQP Tracking=False})}$, the probability increases to 0.129. Thus, equipment tracking emerges as another key parameter for readiness.

Parameters such as Facility Restoration, Alternative Operation Mode, and Active Communication and Info Exchange exhibit moderate influence. For example,

$P_{(\text{Facility Restoration=True})}$ reduces $P_{(\text{Readiness=False})}$ to 0.085, while $P_{(\text{Facility Restoration=False})}$) increases it to 0.124.

Parameters such as Reserved Budget and Coastal Protection have a comparatively smaller impact. For example, $P_{(\text{Coastal Protection=True})}$ reduces $P_{(\text{Readiness=False})}$ to 0.088, while $P_{(\text{Coastal Protection=False})}$) increases it to 0.106.

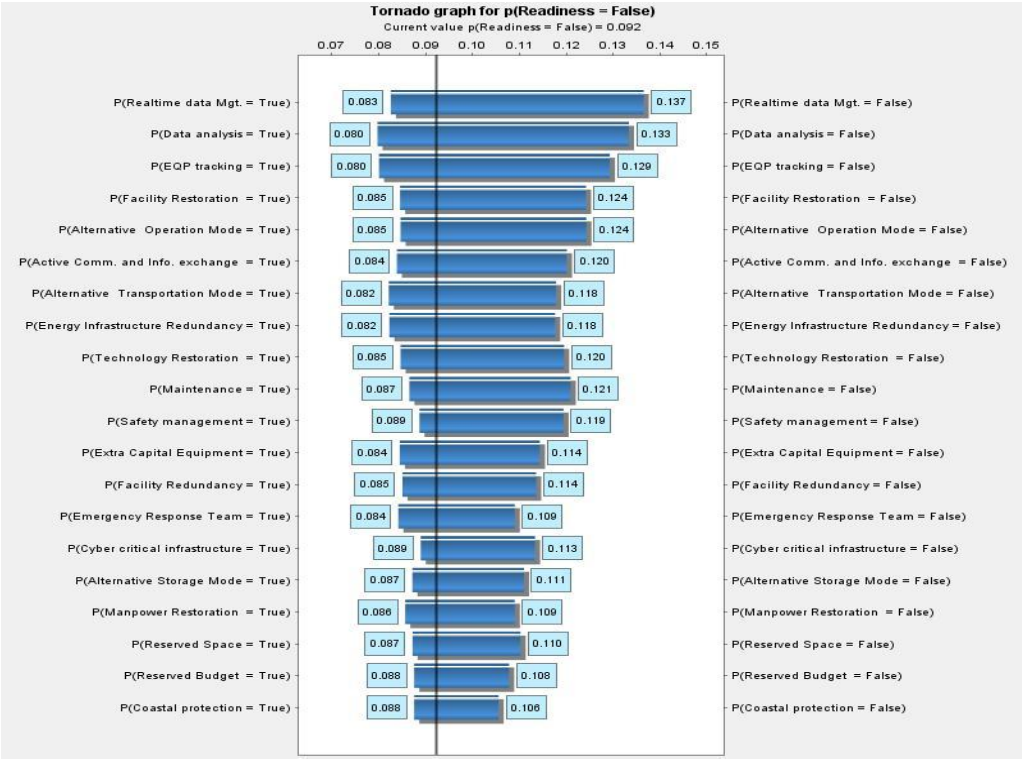


Figure 4.9 Sensitivity analysis of readiness capacity with respect to resilience strategies of the automated container terminal

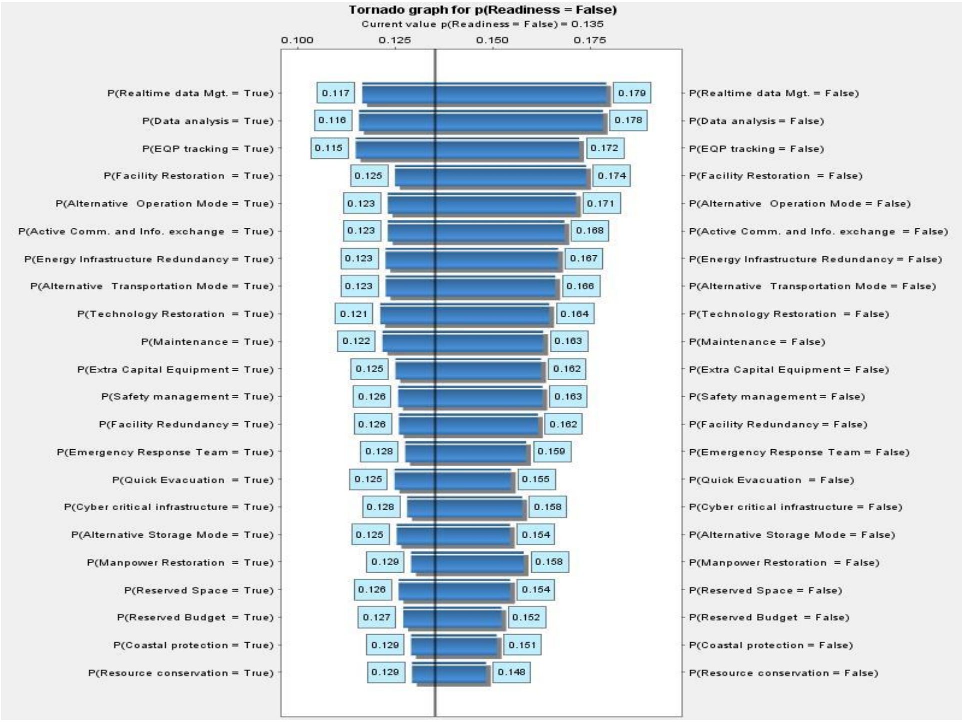


Figure 4.10 Sensitivity analysis of readiness capacity with respect to resilience strategies of the non-automated container terminal

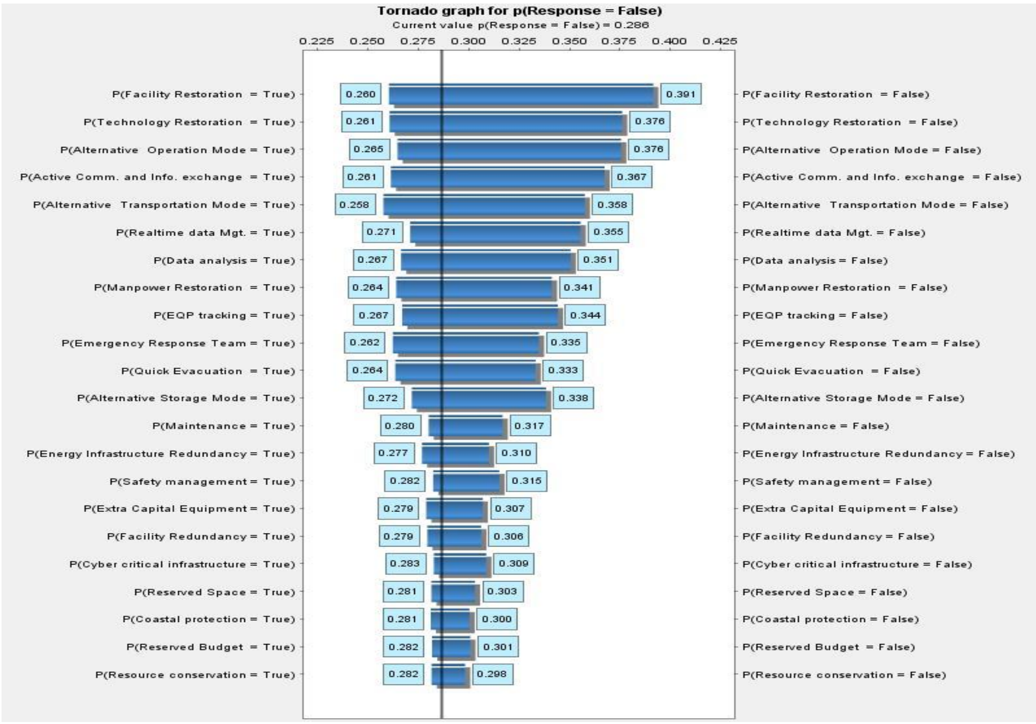


Figure 4.11 Sensitivity analysis of response capacity with respect to resilience strategies of the automated container terminal

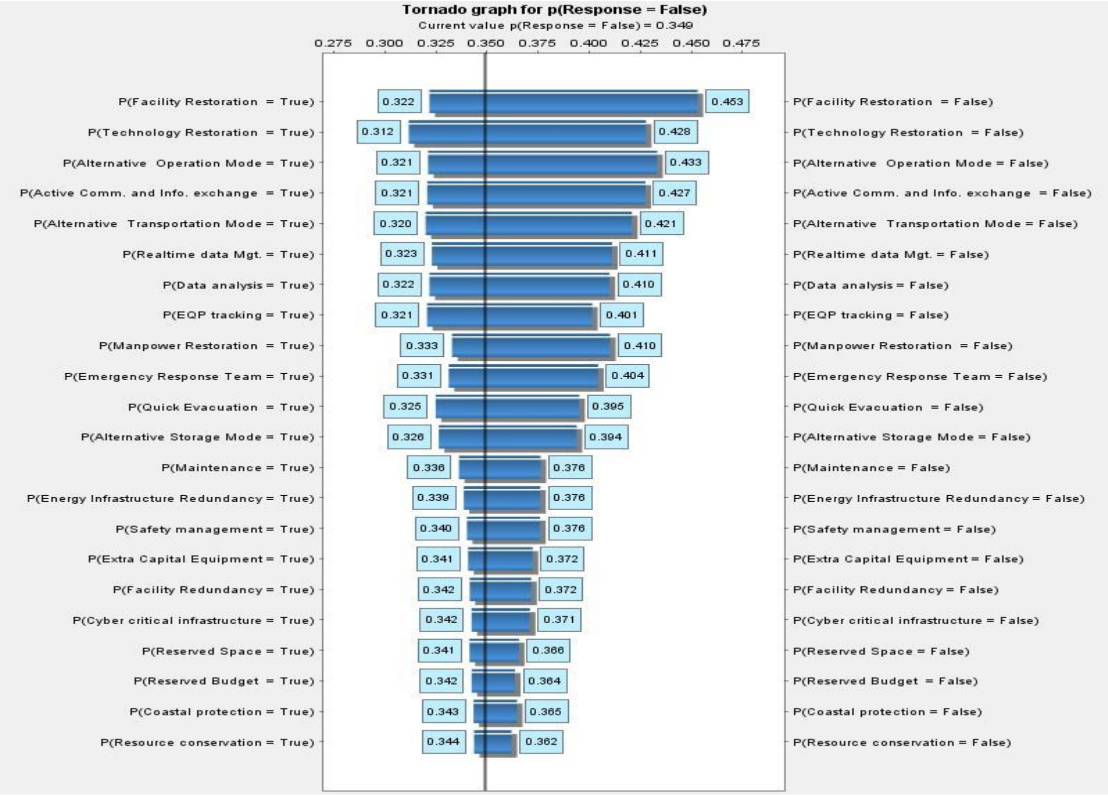


Figure 4.12 Sensitivity analysis of response capacity with respect to resilience strategies of the non-automated container terminal

From Figures 4.9 to 4.12, for both the automated and non-automated container terminals, real-time data management system has the highest impact on readiness capacity. On the other hand, facility restoration has the highest impact on response capacity.

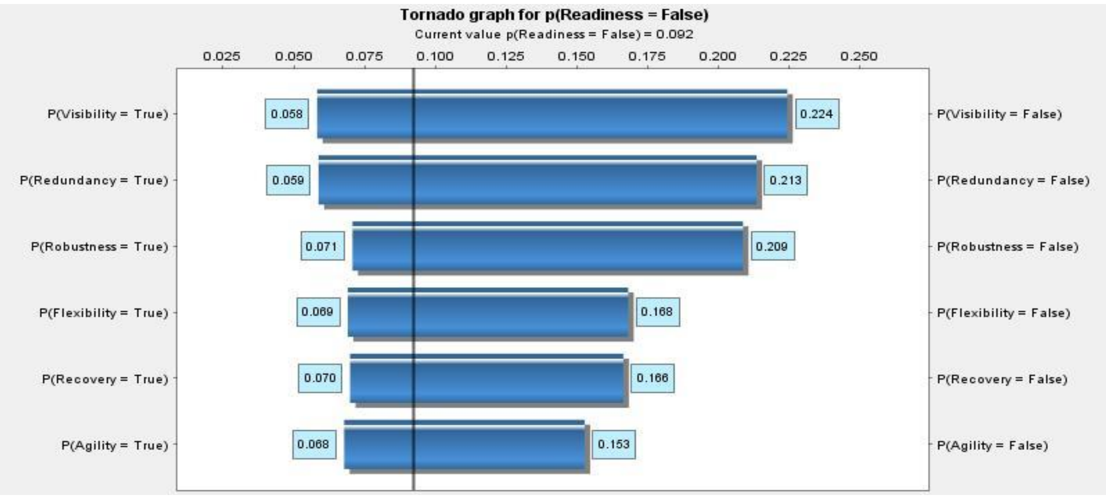


Figure 4.13 Sensitivity analysis of readiness capacity with respect to resilience metrics of the automated container terminal

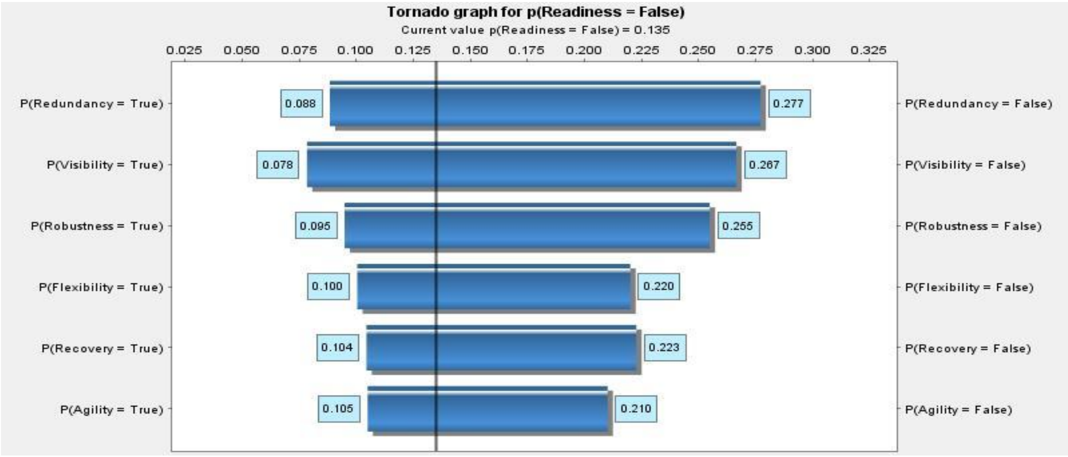


Figure 4.14 Sensitivity analysis of readiness capacity with respect to resilience metrics of the non-automated container terminal

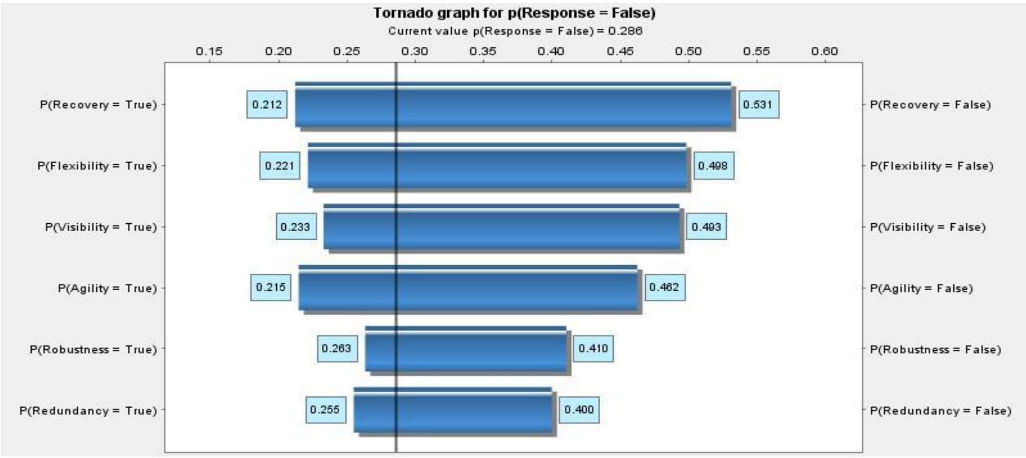


Figure 4.15 Sensitivity analysis of response capacity with respect to resilience metrics of the automated container terminal

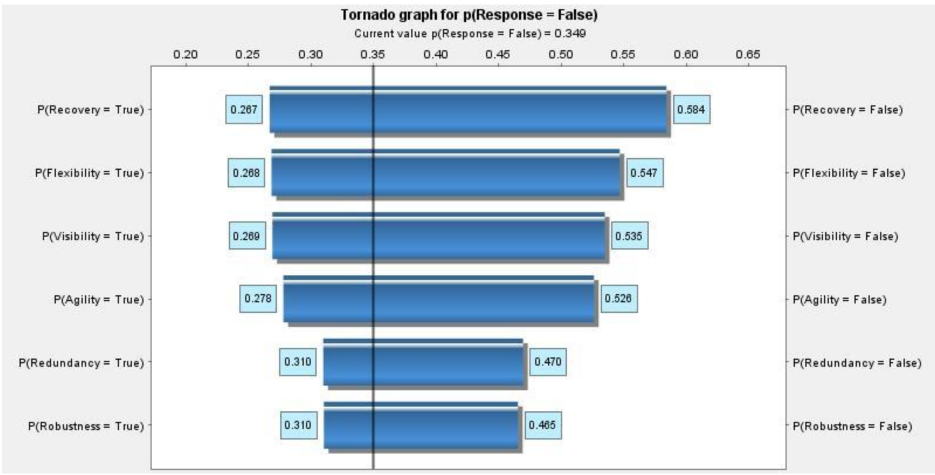


Figure 4.16 Sensitivity analysis of response capacity with respect to resilience metrics of the non-automated container terminal

From Figures 4.13 to 4.16, recovery is the most influential indicator of response whether it is for automated or non-automated container terminals. In terms of readiness, visibility is the most influential metric for the automated container terminal whereas redundancy is the most influential metric for the non-automated container terminal.

The findings of the sensitivity analyses underscore the critical factors influencing port readiness and recovery, providing a robust basis for guiding operational strategies and informing evidence-based policy interventions. These insights highlight tailored approaches to enhance the resilience of both automated and non-automated container terminals, addressing their unique operational characteristics and vulnerabilities.

(1) Prioritizing visibility for Enhanced Readiness for Automated Container Terminals

The sensitivity analyses reveal that parameters such as real-time data management systems, data analysis programs, and equipment tracking systems are pivotal in improving the readiness of automated container terminals. These findings have several implications.

For automated terminals, port managers should prioritize the deployment of state-of-the-art digital tools that enable enhanced operational visibility, predictive analytics, and data-driven decision-making. These tools not only mitigate the risk of disruptions but also optimize operational efficiency and asset utilization. In addition, policymakers should facilitate the adoption of advanced technologies through fiscal measures such as grants, tax incentives, and research funding. Additionally, fostering partnerships between academia, technology providers, and port operators could accelerate the development of innovative automation solutions. Furthermore, the establishment of standardized protocols for data management and sharing would enable seamless interoperability across ports, thereby improving supply chain visibility and enhancing global trade competitiveness.

(2) Balancing Redundancy and Visibility for Non-Automated Terminals

For non-automated terminals, the analyses emphasize the dual importance of enhancing both redundancy and visibility to improve operational readiness. Strategies to achieve these objectives include the development of redundant infrastructure, policy-driven support for infrastructure modernization, and bridging the digital divide.

Managers should invest in resilient energy systems, such as backup power supplies and renewable energy technologies, to safeguard operations during disruptions. Redundancy in critical infrastructure ensures continuity of operations, particularly in terminals with limited automation. Policymakers should implement targeted programs to upgrade the infrastructure of non-automated terminals, particularly those in developing regions. Funding mechanisms and regulatory frameworks that mandate minimum redundancy standards could play a pivotal role in ensuring equitable resilience across global port networks. Digital transformation in non-automated terminals is essential to address visibility gaps. Policies should focus on supporting digitalization initiatives through technical assistance and capacity-building programs.

(3) Enhancing Recovery Strategies for both Automated and Non-Automated Terminals

Facility restoration and technology restoration emerge as critical parameters for improving recovery capabilities in both terminal types. The implications for management and policy-making are as follows.

Managers should institutionalize recovery plans or protocols that include clearly defined processes for rapid infrastructure restoration, IT system recovery, and resource mobilization. Regular drills and simulations can ensure operational readiness during crises. Governments should establish streamlined regulatory procedures for emergency operations, including expedited permitting processes for infrastructure repairs and technology replacement. Such measures would facilitate faster recovery and reduce economic losses. Policies should encourage multi-stakeholder collaboration to develop coordinated recovery frameworks. Collaborative efforts between ports, logistics providers, and government agencies can enhance resource sharing and improve recovery efficiency.

(4) Integrated Resilience Strategies Across Terminal Types

The analyses emphasize the need for a holistic approach that integrates readiness and recovery strategies. For both automated and non-automated terminals, the following actions are recommended.

Port managers should develop and implement resilience frameworks that combine visibility, redundancy, and recovery strategies. These frameworks should be underpinned by risk assessments, employee training, and periodic evaluations of contingency plans. Policymakers should foster cross-sectoral partnerships to pool resources and knowledge, ensuring that resilience strategies are well-coordinated and scalable across regional and national levels. Establishing quantifiable metrics to evaluate port readiness and recovery performance can guide continuous improvement and provide benchmarks for global competitiveness.

4.5.4.2 Forward Inference

Forward inference is a cause-to-effect analysis in which the marginal distribution of ancestor nodes measures their influence on connected descendant nodes. By inputting the prior probability values of each root nodes as evidence, and the probability of Resilience = True can be obtained as evaluation outcomes.

Based on the results of sensitivity analysis, three different disruptive scenarios are designed.

- Scenario 1: The situation where the real-time data management system is not successful (False state)
- Scenario 2: The condition that facility restoration is not successful
- Scenario 3: The condition that both real-time data management system and facility restoration are not successful.

Comparative scenarios among different capacities are shown in Table 4.6, and the forward inference analysis for scenario 1, 2, 3 is illustrated in Figures 4.17 and 4.18. For results, Scenarios 1, 2 and 3 decrease expected resilience of the automated container terminal from 0.726 to 0.691, 0.701 and 0.660, respectively, and decrease expected resilience of the non-automated container terminal from 0.692 to 0.657, 0.661 and 0.621, respectively. It means that all of these strategies are important in enhancing port resilience.

Table 4.6 Analyzed output of forward inference analysis

Scenario	Real-time data management system	Facility restoration	Readiness (%)	Response (%)	Lost capacity	Recovered capacity	Expected Resilience
The automated container terminal							
Base Case	——	——	90.763	71.365	255.71	0.109	0.726
1	False	——	86.345	64.451	381.98	0.098	0.691
2	——	False	87.578	60.85	344.43	0.093	0.701
3	False	False	82.415	54.006	492.56	0.082	0.660
The non-automated container terminal							
Base Case	——	——	86.475	65.064	399.77	0.099	0.692
1	False	——	82.098	58.881	529.44	0.090	0.657
2	——	False	82.613	54.701	514.59	0.084	0.661
3	False	False	77.661	48.71	652.69	0.075	0.621

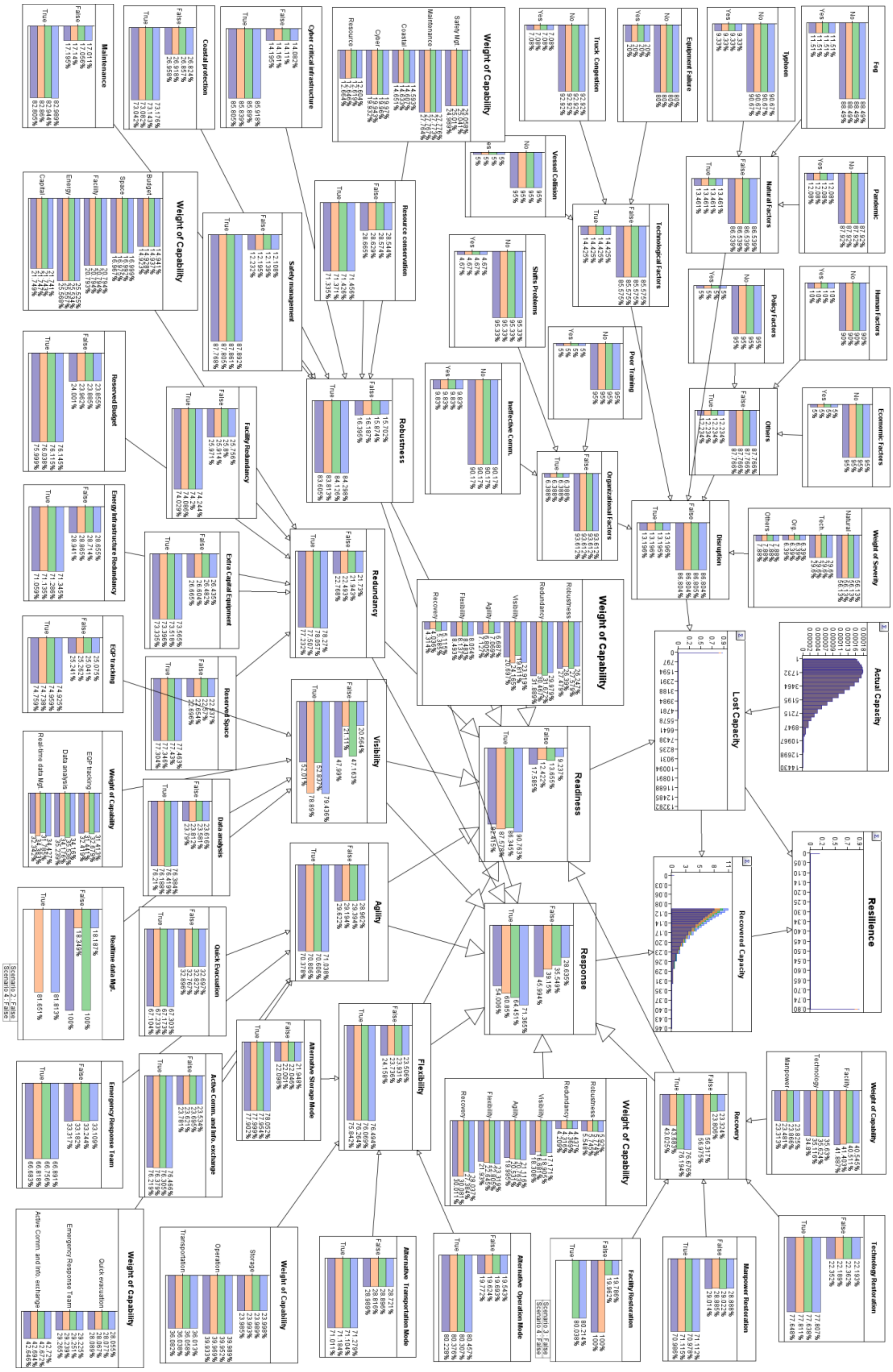


Figure 4.17 Forward inference analysis of BN for measuring port resilience of the automated container terminal

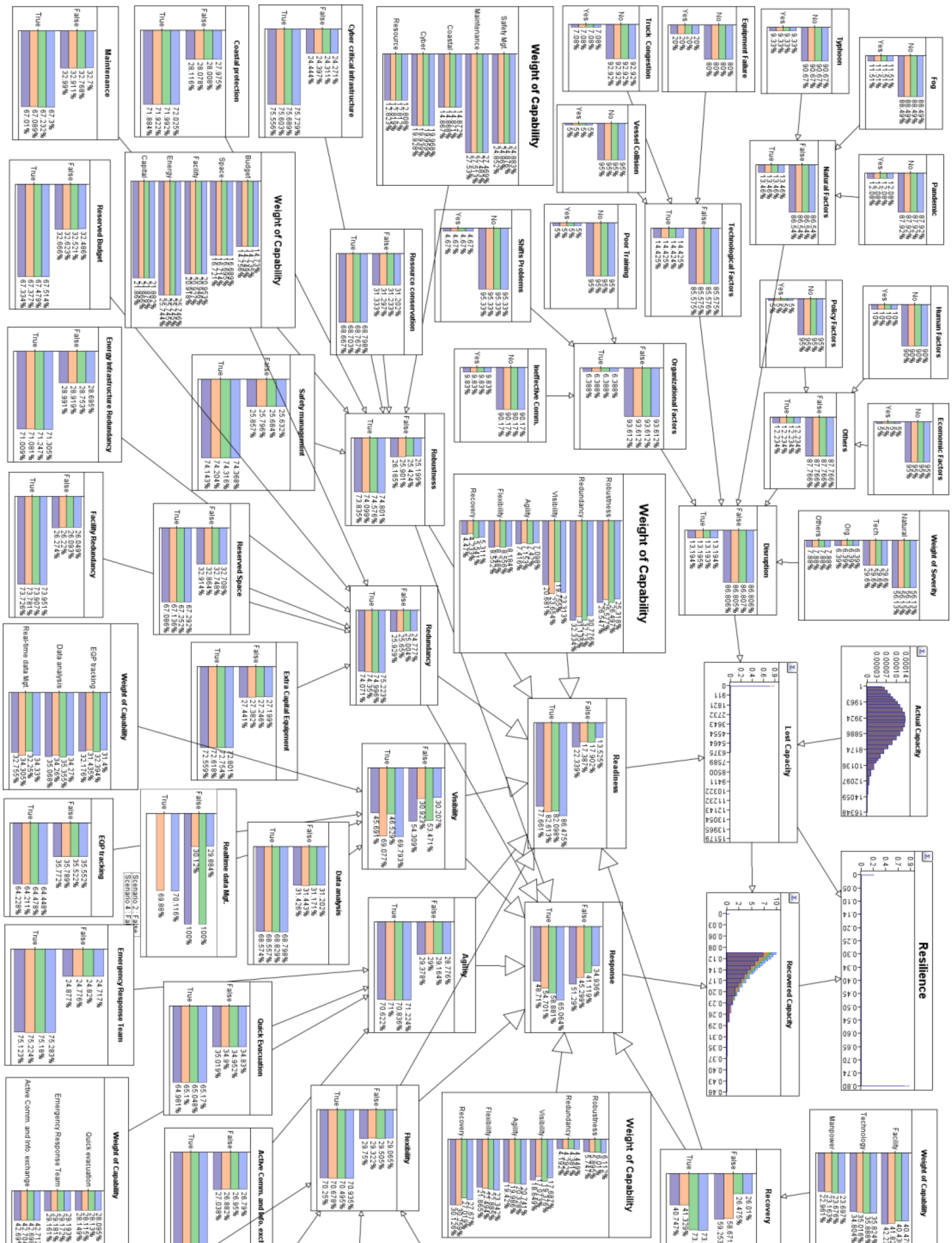


Figure 4.18 Forward inference analysis of BN for measuring port resilience of the non-automated container terminal

4.5.4.3 Backward Inference

Backward inference performs abductive reasoning regarding posterior probability of variables.

As shown in Figures 4.19 and 4.20 by setting the resilience value of the automated container terminal to 0.8, 0.85 and 0.9, the response capacity should increase to 78.58% to 97.651% and 99.63% and the readiness capacity should increase to 100%, 0% and 0%; by setting the resilience value of the non-automated container terminal to 0.7, 0.75 and 0.8, the response capacity should increase to 98.554% to 99.095% and 75.177% and the readiness capacity should increase to 100%, 0% and 0%. It means for both the automated and non-automated container terminals, improving their resilience is not easy, which requires holistic improvement.

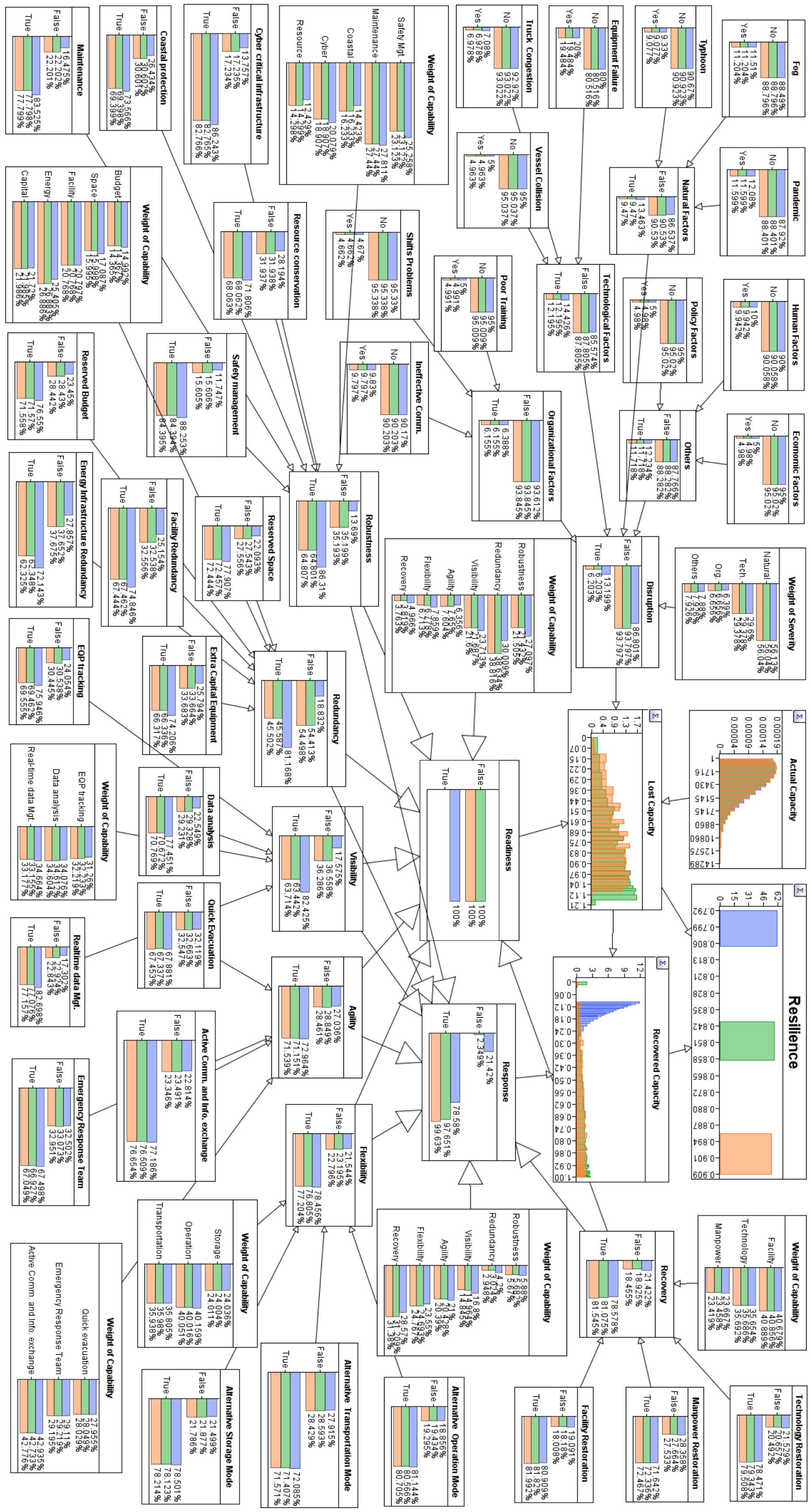


Figure 4.19 Backward inference analysis of BN for measuring port resilience of the automated container terminal

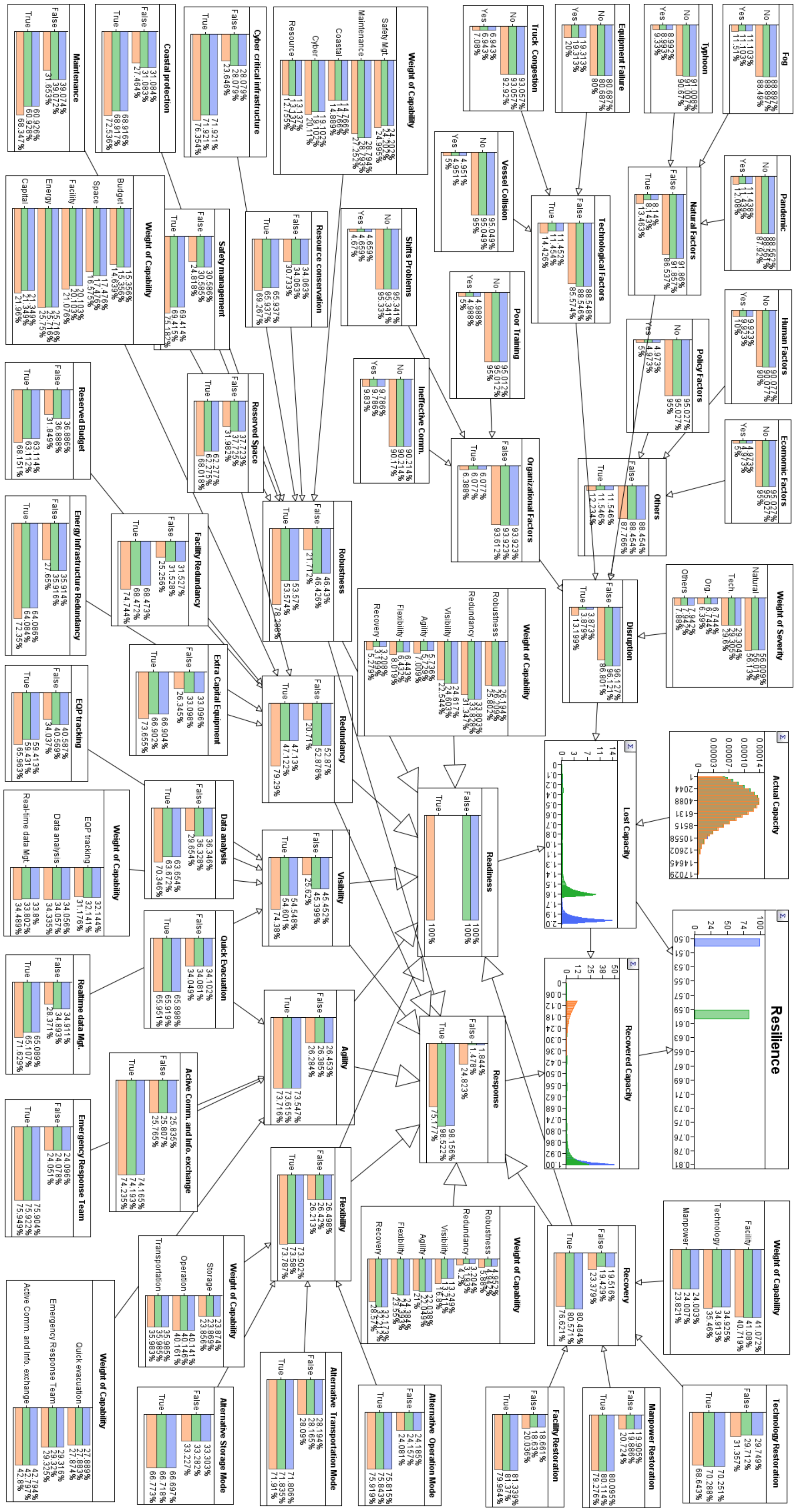


Figure 4.20 Backward inference analysis of BN for measuring port resilience of the non-automated container terminal

4.5.5 Discussions

Ports are critical infrastructure systems that are highly vulnerable to various disruptions. This study aims to model and assess port resilience to identify key measures for enhancing their robustness. A four-stage iterative approach is proposed to examine port resilience, including identifying critical disruptions, designing resilience capacities, constructing a BN-based assessment model, and offering recommendations. The assessment model primarily focuses on three components: disruption modelling, strategy modelling, resilience capacity modelling. The advantages and limitations of each model approach are discussed below

4.5.5.1 Disruption Modelling

In the disruption modelling process, major disruption types are first categorized, and key disruptions within each category are identified. Using expert knowledge and statistical data, the occurrence probabilities and severity weights for each disruption are determined, ultimately resulting in the aggregated probabilities of disruption variables. To extract expert opinions effectively, a method based on DSET and HFLTS is employed. This method addresses uncertainties and conflicts among experts, providing a framework for systematically incorporating expert insights.

While expert opinions are invaluable in addressing complex issues such as port resilience modelling, particularly when empirical data is scarce, there are several potential biases and limitations inherent in relying on subjective assessments. These challenges, if not properly managed, may undermine the accuracy and reliability of the proposed framework. Below, key limitations and biases are discussed.

(1) Subjectivity and Cognitive Biases

Experts' judgments are inherently influenced by their personal experiences, preferences, and cognitive biases, such as the anchoring bias. Experts may disproportionately rely on initial information or their past experiences, which can skew their assessments of disruption probabilities or strategy effectiveness.

(2) Limited Representativeness of Expert Panels

The composition of expert panels plays a critical role in the quality of assessments. If the panel lacks diversity in expertise, geographic representation, or industry backgrounds, the judgments may not capture the full spectrum of disruptions or resilience strategies relevant to a port system. A narrow panel risks producing assessments that are overly specialized or context-specific, reducing generalizability.

(3) Uncertainty in Quantifying Probabilities and Severity

Experts are often required to provide numerical estimates for variables such as disruption probabilities and severity weights, which can be inherently uncertain. Differences in interpretation or a lack of clear guidelines may lead to inconsistencies, making the aggregated results less reliable. Furthermore, experts may struggle to provide precise estimates for rare or unprecedented events, leading to underestimation or overestimation of critical disruptions.

(4) Conflict among Experts

Disagreements among experts are common, especially when their professional experiences or disciplines differ. While the study proposed methods such as DSET to address these conflicts, such techniques cannot fully eliminate contradictions or guarantee consensus. Persistent disagreements may reduce the robustness of the aggregated assessments.

In addition, the methodology described in the study calculates an overall disruption probability by combining the probabilities and severity weights of specific disruptions using a weighted averaging approach. This aggregated disruption variable, in combination with resilience capabilities, is then used to determine the overall resilience of the port. While this approach simplifies the analysis and provides a general measure of resilience, it introduces a significant limitation by failing to differentiate how different types of disruptions impact resilience and require distinct resilience strategies.

Resilience strategies and their effectiveness are highly sensitive to the specific nature of the disruption being addressed. Different disruption types may demand distinct preparedness and response capabilities, leading to variation in outcomes. For example, physical disruptions such as earthquakes, typhoons, or equipment failures are often sudden, highly impactful, and localized. Strategies focusing on infrastructure hardening (e.g., reinforced terminals, flood-resistant designs) and emergency response plans may emerge as the most critical. Operational disruptions are often caused by human factors or system breakdowns, and they may persist for varying durations. Strategies aimed at redundancy (e.g., alternative workforces, backup equipment) and real-time monitoring systems may show higher effectiveness.

By differentiating between disruption types, accounting for interdependencies, and linking tailored strategies to specific scenarios, the methodology can be made significantly more robust, adaptable, and applicable to real-world port operations in the future.

4.5.5.2 Strategy Modelling

For strategy modeling, various resilience strategies are categorized into distinct indicators to evaluate resilience capacities (i.e., preparedness and response capabilities). A hierarchical classification model is developed to facilitate the identification of critical resilience capacities and strategies. The methodology for modeling the probabilities of success for resilience strategies and integrating metrics through weighted averaging has notable strengths, such as simplicity. However, there are several limitations and potential weaknesses associated with this approach. These limitations may impact the comprehensiveness, robustness, and accuracy of the results. Below, the key issues are discussed.

(1) Strategies may not be Comprehensive

In this study, we rely on literature search as the primary source for identifying resilience strategies. While literature reviews provide a strong foundation by consolidating knowledge from existing studies, they have inherent drawbacks that could lead to the exclusion of newer, innovative strategies.

(2) Simplistic Weighted Averaging Method

The integration of metrics and strategies through a weighted averaging method introduces several limitations. First, weighted averaging assumes a linear relationship between metrics and their impact on resilience, which may oversimplify complex, nonlinear interactions. For example, the combined effect of two strategies might not be additive but instead synergistic or diminishing. In addition, weighted averaging does not account for contextual factors that could influence the relative importance of each strategy. For instance, the importance of safety management might vary depending on the port's size, operational complexity, or specific disruption scenarios.

(3) Lack of Dynamic Feedback Mechanisms

The methodology treats readiness and response metrics as static and separate components, aggregated through a weighted sum. However, in real-world scenarios, readiness and response are often interdependent. For example, improved readiness (e.g., better training or infrastructure) can directly enhance response capabilities during a disruption. In addition, the model does not account for how strategies or metrics evolve over time in response to new disruptions or lessons learned, which limits its ability to adapt to changing conditions.

4.5.5.3 Resilience Modelling

In the modeling of resilience capacity, the relationships between disruptions, preparedness, and response capabilities are taken into account to model the actual AC, LC, and RC of ports. These interdependencies are further integrated to compute the final resilience value. AC is obtained by fitting the actual operation data of the port, LC depends on the disruption, AC, and readiness, and RC depends on LC and response.

The methodology is applied to a case study of the Yangshan Deepwater Port in Shanghai, China. Sensitivity analysis, forward inference, and backward inference are conducted to identify key strategies that influence port resilience. However, focusing solely on Yangshan Deepwater Port means the findings and identified strategies are heavily influenced by the specific characteristics, operational environment, and challenges faced by this port. Other ports with different levels of automation, sizes, geographic locations, or infrastructure designs may face entirely different challenges and require alternative strategies.

4.6 Summary

This chapter proposes a circular four-stage method to study port resilience. The major disturbances that are currently affecting ports are summarized. Resilience strategies ascribed to the six metrics are introduced in detail. A port resilience assessment model using the Bayesian network is proposed. The model is constructed based on expert judgment and statistics analysis, and the Shanghai Yangshan Deepwater Port in China is used as a case study. Sensitivity analysis provides validation and detailed comparations of the effect of resilience strategies and metrics on resilience capacities. Forward and backward inferences identify different pathways to achieve a resilient port system.

Three conclusions of the case study can be concluded as follows.

1) Natural disasters are major disruptors plaguing ports; 2) The overall resilience of automated terminals is higher than that of non-automated terminals; 3) All of these resilience strategies are important in enhancing port resilience. However, strategies to enhance visibility such as building real-time data management systems are the most important in terms of improving the readiness of ports; strategies to enhance recovery such as facility restoration are the most important to improve the response of ports.

The study of this chapter enriches the quantification model of port resilience and provides suggestions for decision-making and planning in constructing resilient port systems from implementing proper strategies. The proposed approach and model can be used to quantify the resilience of any other port infrastructure with appropriate modification.

Chapter 5 Resilience Modelling and Assessment of Shipping Network

This chapter aims to address research aim 3: resilience modelling and assessment of shipping network. A port community detection method of the shipping network is provided. This method is based on the Infomap algorithm and considers transportation directions, capacity, and distance between ports. An enhanced disruption simulation model is proposed to assess the resilience of the shipping network. This simulation model integrates cascading failure and recovery mechanisms, incorporates ship behaviour during disruptions, and introduces a temporal dimension to track the network's evolution. The global container shipping network (GCSN) is used as the case study, and the container ship movement data from 2017 to 2023 is collected for data analysis. Port community-to- community connections provide a clearer and more holistic perspective. Using Infomap algorithm, port communities are detected, resulting in a decentralized and balanced structure while preserving GCSN's scale-free and small-world properties. Simulations of various disruption scenarios and recovery strategies yielded optimized key parameters and practical recommendations. For instance, the optimal distance threshold for detecting port communities is 300 km. Additionally, weak correlations between alternative port numbers and community size/throughput (0.17, 0.246) underscore the need for geographically balanced distribution and reduced reliance on single ports.

5.1 Background

Container transportation, as the predominant mode of maritime transport, serves as a cornerstone of the global supply chain (Li at el., 2024b). To support container shipping, the global container shipping network (GCSN) has emerged, significantly impacting the global economy (Zhou & Yuen, 2024). Simultaneously, numerous disruptions, such as the port congestion and extreme weather, have disturbed the maritime transportation system (Li at el., 2024a). For example, the Suez Canal was blocked due to an accident on March 23, 2021, causing an estimated daily trade loss of approximately £7 billion (Fan et al., 2023). In response to these disruptions, resilience—the ability to prepare for and respond to disturbances—has garnered the attention of researchers (Wang at el., 2024a; Wang at el., 2023a). For instance, Xu et al. (2024a) devised a framework to evaluate the global liner shipping network (GLSN)'s resilience against tropical cyclones. Wang et al. (2022) performed a resilience evaluation of waterway transportation systems by integrating system performance and recovery expenses to deal with ship collisions.

Currently, complex network theory is a primary approach for studying the resilience of shipping networks. Shipping networks constructed from shipping data enable the use of various topological metrics, such as node degree (Hu & Zhu, 2009), clustering coefficient (Kaluza et al., 2010), and closeness centrality (Alderson et al., 2020), as key network performance indicators for resilience assessment. However, most resilience assessment studies focus solely on node or link removal strategies within shipping networks, without considering the cascading effects between ports (Xu et al., 2024b; Bai et al., 2023; Wang at el., 2023b). In recent years, cascading effects have garnered increasing attention (Liupeng et al., 2024; Xu et al., 2024b). Nevertheless, recovery mechanisms—a critical aspect of resilience research (Wang et al., 2024a; Wang et al., 2024c)—have largely been overlooked. Furthermore, many researchers analyse shipping networks from the perspective of individual ports. However, the inherent geographical constraints of maritime networks, coupled with the rise of contemporary regional trade blocs, have driven the regionalization of these networks (Wu et al., 2024). Ports within the same region typically operate under similar policy and regulatory frameworks, encounter comparable social and environmental conditions, and are subject to shared disruptions. For instance, natural disasters such as earthquakes or hurricanes can simultaneously impact multiple ports within a region, leading to widespread operational challenges. Studying port communities, therefore, offers valuable insights for attracting investments, fostering regional capabilities, and enhancing the overall performance of the maritime sector (Gupta & Prakash, 2024). Conducting a resilience analysis of shipping networks from the perspective of port communities, rather than focusing on individual ports, provides a more comprehensive understanding of collective response capabilities in the face of natural disasters, global supply chain disruptions, or pandemics. The interconnectedness within port communities allows them to mitigate the risk of operational paralysis at individual ports by distributing impacts across the network, thereby enhancing the overall resilience of the region. Moreover, compared to port-to-port connections, analysing port community-to-port community connections offers a clearer and more holistic perspective on the shipping network. Community detection algorithms can effectively identify and partition groups of tightly connected nodes, revealing the underlying community dynamics within the broader maritime network. However, despite the proposal and application of various community detection algorithms in other types of networks, their application in maritime networks remains conspicuously insufficient.

To address these challenges, this study proposes a data-driven approach to assess shipping network resilience. It incorporates cascading failure and recovery mechanisms and emphasizes port community analysis. The key contributions are as follows: 1) Based on the Infomap algorithm, considering transportation direction, capacity, and distances between ports, a method for detecting port communities within the shipping network is proposed. This method aims to optimize the port community structure based on port connections, transportation flow between ports, and geographical proximity. 2) An enhanced disruption simulation model is designed to assess the resilience of the shipping network by integrating cascading failure and recovery mechanisms. The model incorporates detailed ship behaviours in response to disruptions, such as waiting, rerouting, and skipping, while introducing a temporal dimension to track the evolution of the shipping network over time. 3) Analysis of container ship movement data from 2017 to 2023 identified a novel port community structure within the GCSN through the Infomap algorithm. This structure retains the scale-free and small-world properties of the GCSN while becoming more decentralized and balanced, and offers a clearer and more holistic perspective for resilience analysis. Based on the resilience analysis of the GCSN from the perspective of port communities, key academic insights and practical management recommendations are proposed.

5.2 Method of Resilience Modelling and Assessment

Based on the summaries in Section 2.4, we find that the modelling of shipping network (e.g., network modelling and port community detection) and the resilience assessment of shipping network (e.g., more rational simulations of disruptions in shipping network) have not been explored in depth. Thus, this chapter aims to solve the gap and provide a novel cascading failure model for GCSN and analyse its resilience from the perspective of port community.

5.2.1 Research Framework

Figure 5.1 illustrates the research framework developed in this study. The first step involves detecting port communities within the shipping network to enable resilience assessments from a port community perspective. Ports located in the same region often share similar policy environments, exposure to disruptions, and operational characteristics. Analysing resilience at the community level, rather than focusing on individual ports, allows for a more comprehensive understanding of systemic vulnerabilities and collective response capacities. The Infomap algorithm is employed for community detection due to its suitability for identifying flow-based structures in directed and weighted networks, which aligns with the characteristics of maritime transport systems. Compared to other methods, Infomap offers better scalability and accuracy in representing real-world traffic patterns, making it well-suited for large-scale network analysis (see Section 5.2.1). A directed and weighted network topology is then constructed (Section 5.2.2) to accurately represent the structure and interactions within the GCSN, forming the basis for community detection (Section 5.2.3), resilience assessment (Section 5.3), and simulation modelling (Section 5.4).

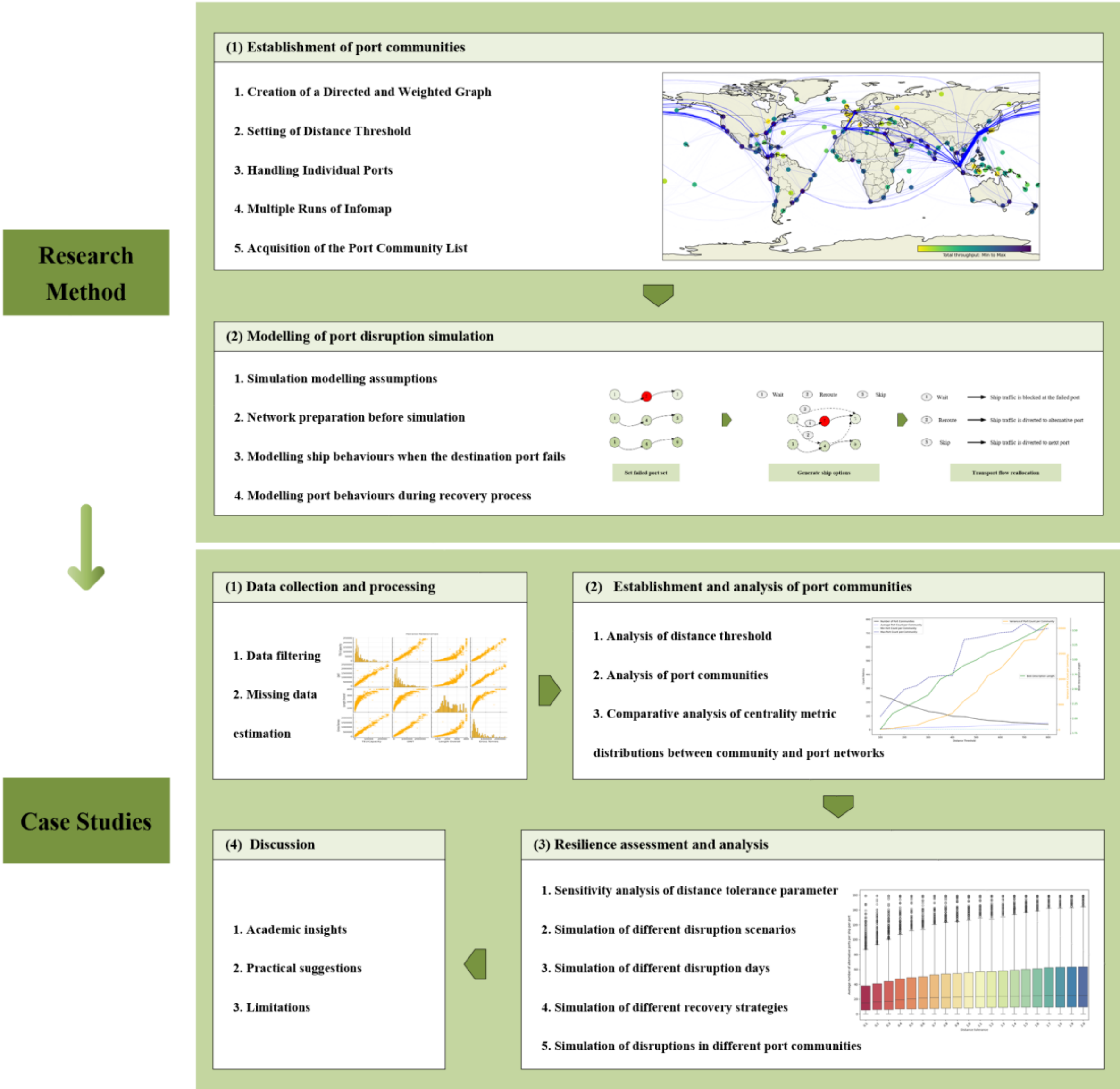


Figure 5.1 The developed research framework

The resilience assessment methodology, introduced in Section 3.3, emphasizes traffic flow within the shipping network to better capture the dynamic impacts of port disruptions compared to traditional topology-based metrics. The core of the methodology is the disruption simulation modelling detailed in Section 3.4, including assumptions (Section 3.4.1), simulation network preparation (Section 3.4.2), ship behaviour during port failures (Section 3.4.3), and recovery processes (Section 3.4.4). This method integrates ship behaviour (e.g., rerouting, waiting, skipping) and models both failure propagation and recovery processes over time. This provides a realistic and dynamic basis for evaluating the resilience of the shipping network under various disruption scenarios. Finally, case studies encompassing data collection, port community detection, resilience assessment, and analysis will be presented in Section 4.

5.2.2 Establishment of Port Communities based on Infomap Algorithm

Based on the introduction in Section 2.5, analysing the shipping network resilience through port communities is beneficial, as the network tends towards regionalization and the network of port community-to-port community connections offers a clearer and more holistic perspective. Currently, numerous community detection algorithms exist, each with distinct characteristics and application scenarios. However, no single algorithm performs optimally across all types of networks (Javed et al., 2018). The choice of algorithm, therefore, largely depends on the specific characteristics of the network under study and the intended downstream analysis. In our case, we aim to analyse network resilience from the perspective of port communities to provide a clearer and more holistic approach for enhancing network resilience. Therefore, we seek to model the GSCN as a directed and weighted network, with non-overlapping port communities that capture container movement flows while preserving the network's essential structure.

Thus, we have selected the Infomap algorithm because it is particularly well-suited to the detection of flow-based communities in directed and weighted networks compared to other community detection algorithms introduced in literature review. Additionally, Infomap has been shown to perform efficiently on large-scale networks, such as the GSCN, where computational feasibility and scalability are critical factors.

5.2.2.1 Infomap Algorithm

Infomap leverages the concept of information theory, specifically the minimum description length principle, to partition the network into communities (Rosvall & Bergstrom, 2008). It operates by simulating a random walk on the network and encoding the path taken by the walker using two-level Huffman coding. The objective is to identify a division of the network that minimizes the average encoding length of an infinitely long random walk, thereby efficiently condensing the data required to characterize the path.

Infomap employs the concept of encoding a random walk on a network. Suppose we have a network represented by a graph $G = < N, E >$, where N represents the collection of nodes and E denotes the set of edges. A random walk on this graph can be encoded in two steps.

(1) Within-Module Description Length:

Each community CO_i is assigned a unique codeword. Within each community, nodes are further encoded relative to the community structure. The probability p_{ij} of moving from node i to node j within the same community is used to determine the code length.

(2) Between-Module Description Length:

When the random walker transitions between communities, a new codeword is assigned to the new community. The probability of moving from community CO_i to community CO_j is considered.

The average description length LR of a random walk can be expressed as:

$$LR = qH(Q) + \sum_{i=1}^{m} p_i H(P_i) \tag{5-1}$$

Where, q is the probability of switching between communities, $H(Q)$ is the entropy of the community-level codebook, p_i is the probability of entering community CO_i, $H(P_i)$ is the entropy of the codebook for community CO_i, m is the number of communities.

The entropy H for a probability distribution P_i is given by

$$H(P) = \sum_i p_i log p_i \tag{5-2}$$

5.2.2.2 Port Network Topology Construction

The network topology of the shipping network should be constructed in preparation for conducting community detection algorithms.

The shipping network can be constructed as graph $G = < N, E, A', F', D' >$, where $N = \{N_P\}$ denotes the set of ports, $E = \{E_P\}$ represents the directed links set. The adjacency matrix A' for graph G is presented in Eq. (5-3).

$$A' = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & & a_{2N} \\ \vdots & & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix} \tag{5-3}$$

Where, N represents the total number of ports in the shipping network. a_{ij} can be denoted as Eq. (5-4).

$$a_{ij} = \begin{cases} 1, & if \text{ port } i\ is\ pointed\ to\ j \\ 0, & otherwise \end{cases} \tag{5-4}$$

The transportation flow matrix of each link is symbolised as F' (see Eq. (5-5)).

$$F' = \begin{bmatrix} f_{11} & f_{12} & \dots & f_{1N} \\ f_{21} & f_{22} & & f_{2N} \\ \vdots & & \ddots & \vdots \\ f_{N1} & f_{N2} & \cdots & f_{NN} \end{bmatrix} \tag{5-5}$$

The variable f_{ij} represents the transportation volume T_{ij} on edge e_{ij} per unit time in the GCSN.

The transportation length of each link within the shipping network is defined as D' (see Eq. (5-6)).

$$D' = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1N} \\ d_{21} & d_{22} & & d_{2N} \\ \vdots & & \ddots & \vdots \\ d_{N1} & d_{N2} & \cdots & d_{NN} \end{bmatrix} \tag{5-6}$$

The variable d_{ij} represents the distance between ports N_i and N_j in the shipping network.

5.2.2.3 Port community construction

The specific steps for detecting port communities using the Infomap algorithm are detailed as follows:

(1) Creation of a Directed and Weighted Graph

Initially, a directed graph is constructed based on the movement data of ships between ports as described in section 5.2.2.2. Ports serve as nodes, and edges represent transportation activities between these ports. The weight of the edges is determined by the volume of transportation (Twenty-foot equivalent unit (TEU) capacity) and the geographical distances between the ports. Due to the difficulty in obtaining actual shipping routes for each pair of ports, this study assumes that transport distances between ports correspond to their geographical distances. The geographical coordinates of the ports serve as the basis for computing these distances. Both transport flow and distances are standardized. Using the standardized values of transport flow and distance, the weight of each edge is computed as Eq. (5-7) and then incorporated into the directed graph, transforming it into a weighted and directed graph.

$$w_{ij} = \overline{f_{ij}} * (1 - \overline{d_{ij}}) \tag{5-7}$$

Where w_{ij} is weight of port N_i to port N_j, $\overline{f_{ij}}$ is normalized flow transported from N_i to N_j, $\overline{d_{ij}}$ is normalized distance between N_i and N_j.

(2) Setting of Distance Threshold

As the objective of this study includes not only detecting port structures but also constructing a simpler shipping network, super large port communities are not considered. Distance is a key factor impacting the division of communities. Therefore, a distance threshold (e.g., 300 km) is established. A connection is added to the Infomap model for each pair of nodes (ports) only if the distance between them is less than or equal to this threshold.

(3) Handling Individual Ports

It is ensured that each node is assigned to a specific community. Unassigned nodes are allocated to the community associated with the nearest assigned node.

(4) Multiple Runs of Infomap

Infomap is a community detection algorithm based on information theory that uses random walks to identify community structures within the network. Due to the inherent randomness in the initial state and path selection of random walks, Infomap is run multiple times (e.g., 100 times) to ensure the reliability of the results. The detailed algorithm steps are as follows:

a. Initialization: Initialize the network with each node being its own community.

b. Local Moving: Iteratively move nodes to neighbouring communities to achieve a lower description length.

c. Merging: Combine communities to form super-communities and repeat the local moving step on the super-communities.

d. Optimization: Continue the process iteratively until no further reduction in description length is possible.

e. Acquisition of the Port Community List: The description lengths of each run are compared, and the partitioning result with the shortest description length is selected as the optimal partition.

Based on the description above, an Infomap algorithm-based port community detection method is provided. This method aims to optimize the port community structure based on port connections, transportation flow between ports, and geographical proximity.

5.2.3 Resilience Assessment Method of Shipping Network

The common method to assess the network's performance is to compare topology structure-based metrics by changing the structure of network, which is called static assessment by Bai et al. (2023). However, when a port fails, ships destined for that port can choose to reroute to an alternative port or bypass it altogether to continue cargo transportation within the network. Therefore, an assessment based solely on the network structure may not be entirely accurate. For the dynamic assessment, congestion was used as the metric, modelled based on node removal strategies and a knock-on effect simulation model (Bai et al., 2023). However, in their model, rerouting of every ship is allowed in the shipping network, which is not realistic. Given that traffic flow is a critical indicator of network performance, this study selects network traffic as the metric for evaluation. Scholars often assume that the slower the decline in performance metrics after a disturbance, the more resilient the system is (Wang et al., 2023b). Thus, the resilience of shipping network is determined as the ratio of the actual network transport flow to the normal network transport flow. In addition, in the subsequent resilience analysis, the network's topological structure will also be examined.

Based on the constructed port network topology $G = < N, E, A', F', D' >$, in Section 5.2.2.2, in which F is the transportation flow matrix of each edge.

Thus, the resilience of the shipping network is calculated as shown below.

$$R = \frac{\sum_{i \in N} \sum_{j \in N} fa_{ij}}{\sum_{i \in N} \sum_{j \in N} f_{ij}} \tag{5-8}$$

Where fa_{ij} is the actual transportation flow from port i to j in a day.

5.2.4 An Enhanced Simulation Modelling of Shipping Network

Although this study aims to examine resilience from the perspective of port communities, ship behaviour occurs between ports. Therefore, when conducting simulation experiments, we consider ports as nodes to construct a shipping network.

5.2.4.1 Simulation Modelling Assumptions

Disruptions are typically sudden, leaving ports with insufficient time to implement countermeasures or prevent the occurrence of the disaster. Therefore, we assume that a port becomes immediately inoperative upon encountering a disruption (Xu, et al., 2024b). The failure of the destination port will impact vessels scheduled to arrive at the failed port. In scenarios where certain ships are impacted, carriers have the option to switch operational ports based on actual conditions. However, altering routes and ports incurs additional costs, and some vessels do not have alternative port options. For example, ultra-large vessels find it challenging to operate in smaller ports due to their high berth requirements. Consequently, in reality, not all carriers may choose this option. Therefore, we assume that vessels have three options: wait, reroute to an alternative port, or skip the port (Xu, et al., 2024b; Xu, et al., 2022b). Waiting refers to vessels remaining near the failed port, postponing loading and unloading until the port resumes operations. Rerouting involves seeking an alternative port near the failed one to handle the cargo initially intended for the disrupted port. Skipping, on the other hand, means bypassing the failed port entirely and processing the intended cargo at the next scheduled port. An alternative port must meet three conditions: it cannot be a failed port, it must be in the same country as the failed port, and the distance from the departure port to the alternative port should not significantly exceed the distance from the departure port to the failed port (Xu, et al., 2022b).

Due to the failure of a port, ships choosing to wait accumulate at the failed port, leading to a backlog in its handling capacity. Meanwhile, vessels that reroute or skip the failed port transfer their cargo volumes to other ports, potentially causing congestion. When the incoming volume at these alternative ports exceeds their maximum processing capacities, these ports may also experience failure, resulting in an overflow of vessel traffic (Liupeng et al., 2024; Xu, et al., 2024b; Xu, et al., 2022b). Consequently, when one port in the network fails, a cascading effect occurs over time, affecting the entire network.

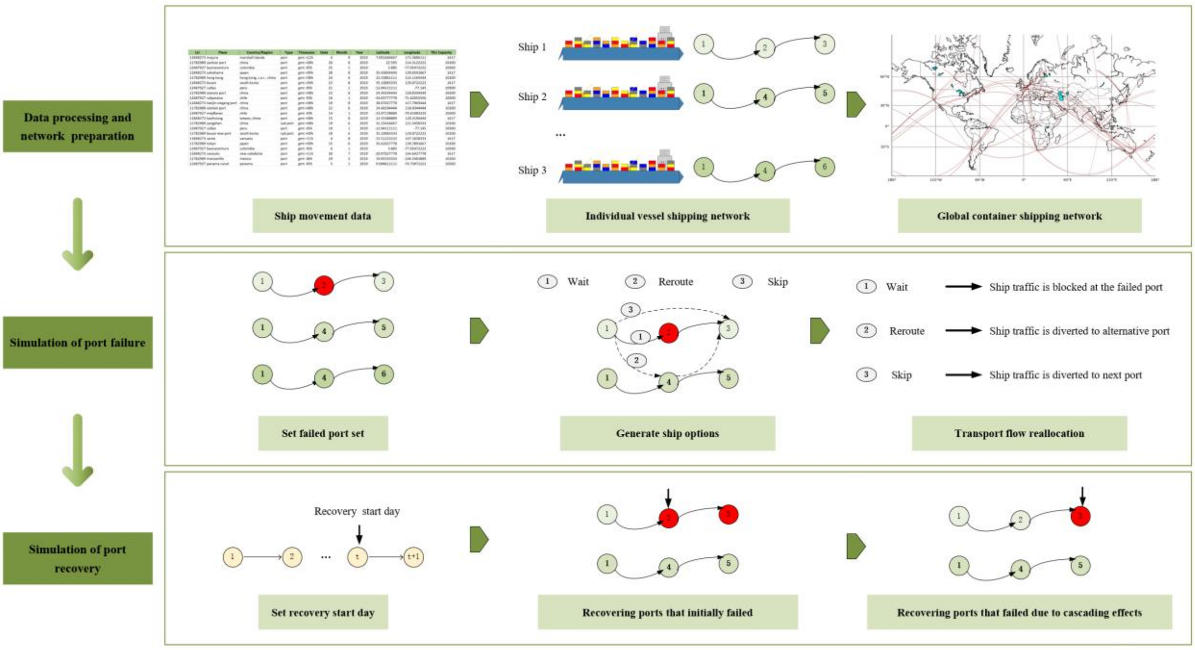


Figure 5.2 The developed simulation framework for port disruption

After a certain period of disruption, port operations begin to recover. Considering that recovery is not an immediate process, it is assumed that during the initial phase of recovery, the operational capacity of the port gradually increases until it fully recovers, after which it operates at a capacity above the normal rate to handle the backlog of blocked ships. A port is considered fully recovered only after it has cleared the accumulated backlog.

Based on these assumptions, the developed simulation framework is shown in Figure 5.2.

5.2.4.2 Network Preparation before Simulation

First, as shown in Figure 5.2, we collect vessel movement data and, for each vessel, construct a time-ordered weighted directed transport network. In this network, ports serve as nodes, and connections between ports are represented as directed edges. For example, if Ship A departs from Port i to Port j, the inbound volume to Port j is f_{ij}^{A0} and upon departing from Port j to another port k, the outbound volume from Port j is f_{jk}^{A0}. The throughput of a port represents the sum of the input and output volumes of all ships passing through that port. Dividing each port's throughput by the total operational days of all ships in the network gives the average daily throughput. If the average daily throughput of Port i is $TO_i(0)$, the maximum load capacity of Port i is defined as $MaxL_i$ = (1 + α') $TO_i(0)$, where α' represents the tolerance parameter for port capacity. By dividing the total transportation volume of Ship A from Port i to Port j by the total operational days of all ships, we obtain the average daily transportation volume of Ship A on the directed edge e_{ij}, denoted as fd_{ij}^{A0}, which also represents the transportation volume of Ship A on edge e_{ij} on Day 0. Dividing this by the edge's distance d_{ij} gives the operational speed of Ship A on the directed edge v_{ij}^{A}. Thus, the adjacency matrix, daily transportation flow matrix, and speed matrix are established for each ship, which can be used as the transportation network for Day 0. By aggregating the transportation networks of all vessels, we obtain the transportation network of the entire container shipping system.

5.2.4.3 Modelling Ship Behaviours when the Destination Port Fails

The simulation begins on Day 1. If Ship A encounters a failed port on Day t, it can wait, reroute, or skip the port, with assigned probabilities for each action.

- In the case where Ship A chooses to wait. If the average daily transportation volume from the previous Port i to the failed Port f is fd_{if}^{At}, the average daily transportation volume from Port f to the next Port j is fd_{fj}^{At}. Thus, Ship A's blocking volume at the failed Port f on Day t is calculated as $BL_{Af}^{t} = fd_{if}^{At} + fd_{fj}^{At}$, in which $fd_{if}^{At} = fd_{if}^{At-1}$, $fd_{fj}^{At} = fd_{fj}^{At-1}$. Since Ship A is stalled at the failed Port f, subsequent transport operations are also halted. Therefore, Ship A's blocking volume in the entire transportation network B_{A}^{t} is equal to the sum of the transport volumes of Ship A within its own network.

- In the case where Ship A chooses to reroute. It first checks if there is an available alternative port for the failed Port f. If there is no available alternative port, Ship A chooses to skip. If multiple alternative ports are available, one is randomly selected. From assumptions, an alternative port must cannot be a failed port and must be in the same country as the failed port. In addition, the distance from the departure port to the alternative port d_{ir} should not significantly exceed the distance from the departure port to the failed port d_{if}. A distance tolerance parameter β' is used here, ensuring $d_{ir} \leq (1+\beta')d_{ij}$. After rerouting, the average daily transportation volume of Ship A from the previous port to the failed port becomes zero, no blockage will generate. However, the transportation volume of Ship A from the failed port to the next port will be blocked during this period. Thus, the blocking volume of Ship A at the failed Port f on Day t is $BL_{Af}^{t} = fd_{fj}^{At}$. Calculating the transit time from Port i to the alternative Port r, that is, dividing the distance from Port i to the alternative Port r by the original speed of Ship A from Port i to the failed Port f, denoted as $tr_{ir}^{A} = d_{ir}/v_{if}^{A}$, and rounding up gives the travel days, denoted as $tr_{ir}^{A'}$. 1) If $tr_{ir}^{A'} = 1$, the blocking volume of Ship A at the network on Day t is only the outbound volume $BL_{A}^{t} = fd_{fj}^{At} = fd_{fj}^{At-1}$, and the intended transportation volume for Port j is transferred to Port r on Day t. Thus, the daily transport volume of Ship A from Port i to Port r on Day t will be the original volume plus the volume initially intended for Port f, denoted as $fd_{ir}^{At} = fd_{if}^{At-1} + fd_{ir}^{At-1}$. 2) If $tr_{ir}^{A'} > 1$, the transport volume that Ship A intends to deliver to the failed Port f cannot be redirected to Port r immediately, a delay of $|tr_{ir}^{A'} - 1|$ days is required. During the delay period, the blocking volume of Ship A at the network on Day t is $B_{A}^{t} = fd_{fj}^{At}$. The average daily transport volume of Ship A at Port r on Day t is $fd_{ir}^{At} = fd_{ir}^{At-1}$. After $|tr_{ir}^{A'} - 1|$ days, the average daily transport volume of Ship A from Port i to Port r will be the original volume plus the volume initially intended for Port f, denoted as $fd_{ir}^{A|t+tr_{ir}^{A'}-1|} = fd_{if}^{At} + fd_{ir}^{A|t+tr_{ir}^{A'}-2|}$, and the blocking volume of Ship A at the network will become zero.

- In the case where Ship A chooses to skip. Since vessel A chooses to skip the port, it has no impact on other ports in its own network except the next Port j. The intended transportation volume for Port f is transferred to Port j. Thus, the daily transport volume of Ship A from Port i to Port j on Day t will be the original volume plus the volume initially intended for Port f, denoted as $fd_{ij}^{At} = fd_{if}^{At-1} + fd_{ij}^{At-1}$. The blocking volume of Ship A at the failed Port f on Day t is the outbound volume $BL_{Af}^{t} = fd_{fj}^{At}$. Considering that after skipping a port, the traffic originally destined for the failed port is redirected to a new port, incurring additional costs, this portion of traffic is still regarded as blocked within the network. Therefore, the blockage it causes in the entire network BL_A^t on Day t is the sum of inbound and outbound traffic $BL_A^t = fd_{if}^{At-1} + fd_{fj}^{At}$.

On each Day t, we record the actual operational volume of each port, which is the sum of input and output volumes for all ships passing through it. If a port's actual operational volume exceeds its maximum capacity, that is $TO_i(\mathrm{t}) > MaxL_i$, it is also marked as failed. The failed port list on Day t includes all newly failed ports, merging them with the failed port list from Day $t-1$.

5.2.4.4 Modelling Port Behaviours during Recovery Process

When the recovery day $t_R$is reached ($t \geq t_R$), the recovery process begins. Recovery is assumed to be gradual, with proportional coefficients determining daily recovery volumes that increase as recovery progresses. During this process, the accumulated congestion at each failed port decreases incrementally. Once all accumulated congestion is cleared, the port resumes normal operations without generating additional blocked traffic.

The simulation concludes only when the cumulative blocking volumes at all ports are reduced to zero, and no ports remain in a failed state.

This section establishes a comprehensive framework to address gaps in shipping network modelling and resilience assessment. The framework includes: 1) the establishment of port communities using the Infomap algorithm; 2) resilience assessment of the GCSN; and 3) an enhanced disruption simulation model incorporating cascading failure and recovery mechanisms. The subsequent section presents case studies conducted using the proposed model and methods.

5.3 Application and Results

Based on the methodology proposed in Section 5.2, this section will systematically examine the resilience of the GCSN through a structured analysis. It begins with data collection and processing to establish the foundational dataset, followed by the detection and analysis of port communities within the GCSN. Subsequently, resilience assessments are conducted through simulations under various disruption scenarios, exploring the impacts of disruption duration, recovery strategies, and port community-specific failures. Finally, the findings are synthesized to provide academic insights.

5.3.1 Data Collection and Processing

Ship movement records between ports were collected from Seasearcher (Shipping and Maritime Intelligence - Lloyd's List Intelligence, seasearcher.com). First, container ships with an operational status of "alive" were selected, resulting in a total of 5,625 ships. Their movement data from January 1, 2017, to December 13, 2023, were compiled. The dataset was then filtered by removing records associated with berths or anchorage activities, leaving 5,544 ships with more than 3 million movement records. Additionally, records where the destination port was the same as the departure port were excluded.

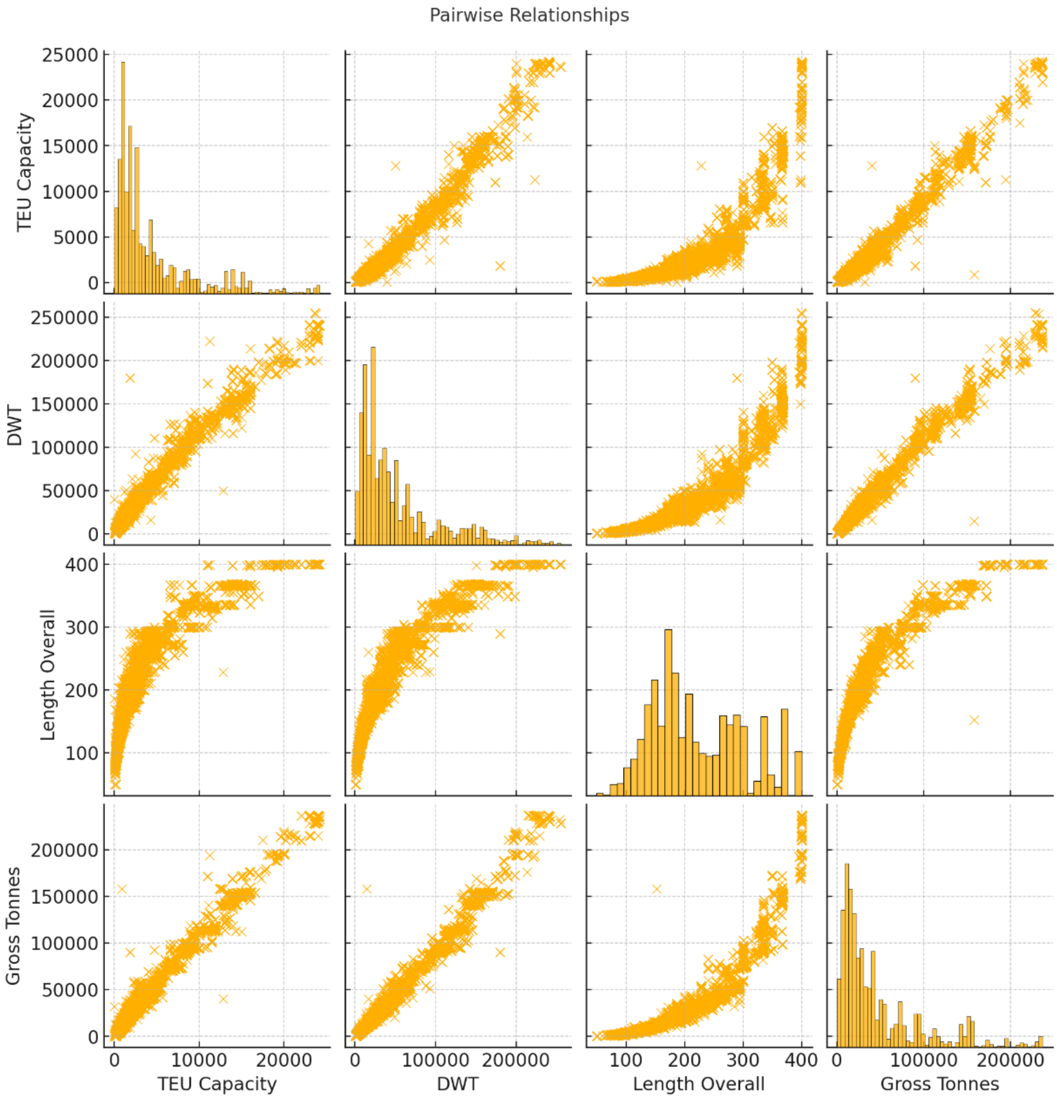


Figure 5.3 Pairwise relationships of container ship factors

Since exact container loading or unloading data were unavailable, the traffic flow between ports was assumed to correspond to each ship's TEU capacity. For ships with missing TEU capacity data, we examined the correlation between TEU capacity and other vessel attributes, including deadweight tonnage (DWT), length overall (LOA), and gross tonnage (GT). Pairwise correlations (Figure 5.3) revealed strong relationships, with TEU capacity correlating with DWT, LOA, and GT at 0.985, 0.889, and 0.991, respectively. This indicates that as TEU capacity increases, these attributes also tend to increase.

Given the nonlinear relationships among some variables and the presence of missing feature values, we employed a Random Forest model for imputation. Random Forest was chosen for its ability to handle nonlinear relationships and incomplete data. The model demonstrated excellent predictive performance, with R-squared values of 0.9994 and 0.9931 for the training and test datasets, respectively.

In Seasearcher, the subports and main ports are listed separately, for example, Yangshan and Shanghai Port. There are a total of 1720 main ports and 210 subports in the dataset. Table 5.1 shows the 20 leading ports with the greatest node degrees in GCSN.

Table 5.1 Top 20 ports with the greatest node degrees in the GCSN

No.	Place	Country/Region	Total Degree	Out-Degree	In-Degree	Type
1	Singapore	Singapore	648	316	332	Port
2	Rotterdam	Netherlands	641	332	309	Port
3	Antwerpen	Belgium	533	284	249	Port
4	Shanghai	China	533	224	309	Port
5	Qianwan	China	461	189	272	Sub Port
6	Port Klang (Pelabuhan Klang)	Malaysia	425	193	232	Port
7	Beilun	China	418	189	229	Sub Port
8	Busan New Port	South Korea	415	200	215	Sub Port
9	Hong Kong	Hong Kong, S.A.R., China	405	180	225	Port
10	Tanger Med	Morocco	403	206	197	Port
11	Busan	South Korea	393	194	199	Port
12	Algeciras	Spain	393	209	184	Port
13	Nansha Port	China	386	181	205	Sub Port
14	Tanjung Pelepas	Malaysia	385	190	195	Port
15	Kaohsiung	Taiwan, China	357	164	193	Port
16	Yantian Port	China	353	161	192	Port
17	Hamburg	Germany	353	179	174	Port
18	Yangshan	China	351	151	200	Sub Port
19	Valencia	Spain	340	156	184	Port
20	Bremerhaven	Germany	330	168	162	Port

The throughput of each port is calculated separately, with the capacities of subports aggregated into their respective main ports. Based on these calculations, each port's total throughput is determined. Table 5.2 presents both the calculated and actual throughput rankings in 2023 of the world's top ten container ports. Although the specific rankings differ, seven of the top ten ports in our calculation align with those in the actual rankings.

While the estimated throughput does not perfectly reflect reality, the ranking remains broadly aligned with real-world trends. This is because, under normal circumstances, ships with larger TEU capacities tend to transport higher cargo volumes. In our resilience analysis, we primarily consider the ratio of traffic flow changes rather than absolute throughput values. Therefore, despite its limitations, this TEU-based approach is still suitable for estimating throughput in the context of this study.

We recognize that this assumption does not fully capture real-world traffic flow dynamics, as it does not account for factors such as vessel load factors, scheduling variations, or operational constraints. For future studies involving specific transport volumes, if actual data remains unavailable, adjustment coefficients could be introduced based on comparisons between real and estimated data. This would help refine the analysis and enhance its practical accuracy.

Table 5.2 The ranking of the world's top ten container ports by calculated throughput and the actual throughput in 2023

Ranking by calculated throughput	Place	Country/Region	Actual throughput ranking in 2023	Place	Country/Region
1	Singapore	Singapore	1	Shanghai	China
2	Shanghai	China	2	Singapore	Singapore
3	Ningbo-Zhoushan	China	3	Ningbo-Zhoushan	China
4	Shenzhen	China	4	Shenzhen	China
5	Busan	South Korea	5	Qingdao	China
6	Hong Kong	Hong Kong, S.A.R., China	6	Guangzhou	China
7	Qingdao	China	7	Busan	South Korea
8	Port Klang (Pelabuhan Klang)	Malaysia	8	Tianjing	China
9	Rotterdam	Netherlands	9	Hong Kong	Hong Kong, S.A.R., China
10	Kaohsiung	Taiwan, China	10	Jebel Ali	United Arab Emirates

The throughput heatmap is depicted in Figure 5.4. The provided heatmap visualization represents the spatial distribution and concentration of container port throughput across the globe. This analysis utilizes kernel density estimation to effectively highlight regions with high throughput volumes. From Figure 5.4, we can observe that East Asia, Europe, and North America are the high throughput concentration regions. East Asia, particularly the coasts of China, Japan, and South Korea indicates the most significant concentration of port throughput. This region is known for its major global trade hubs, including the ports of Shanghai, Hong Kong, and Busan. In Europe, notable throughput concentrations are observed in the North Sea ports, such as Rotterdam and Hamburg. Additionally, the Mediterranean ports, including Valencia and Genoa, show substantial throughput activity. The eastern and western coasts of North America display significant throughput concentrations, with key ports like Los Angeles, Long Beach, and New York/New Jersey being prominent. Besides the high throughput concentration regions, Southeast Asia and Middle East demonstrate the moderate throughput concentration regions. For Southeast Asia, ports in Singapore, Malaysia, and Indonesia exhibit moderate throughput levels, supporting the region's role as a critical node in global maritime trade. For Middle East, the United Arab Emirates (Dubai) and Saudi Arabia, serving as vital gateways for international trade routes. In addition, ports in South America and Africa generally show lower throughput concentrations compared to other regions. However, key ports such as Santos (Brazil) and Durban (South Africa) still play essential roles in regional trade.

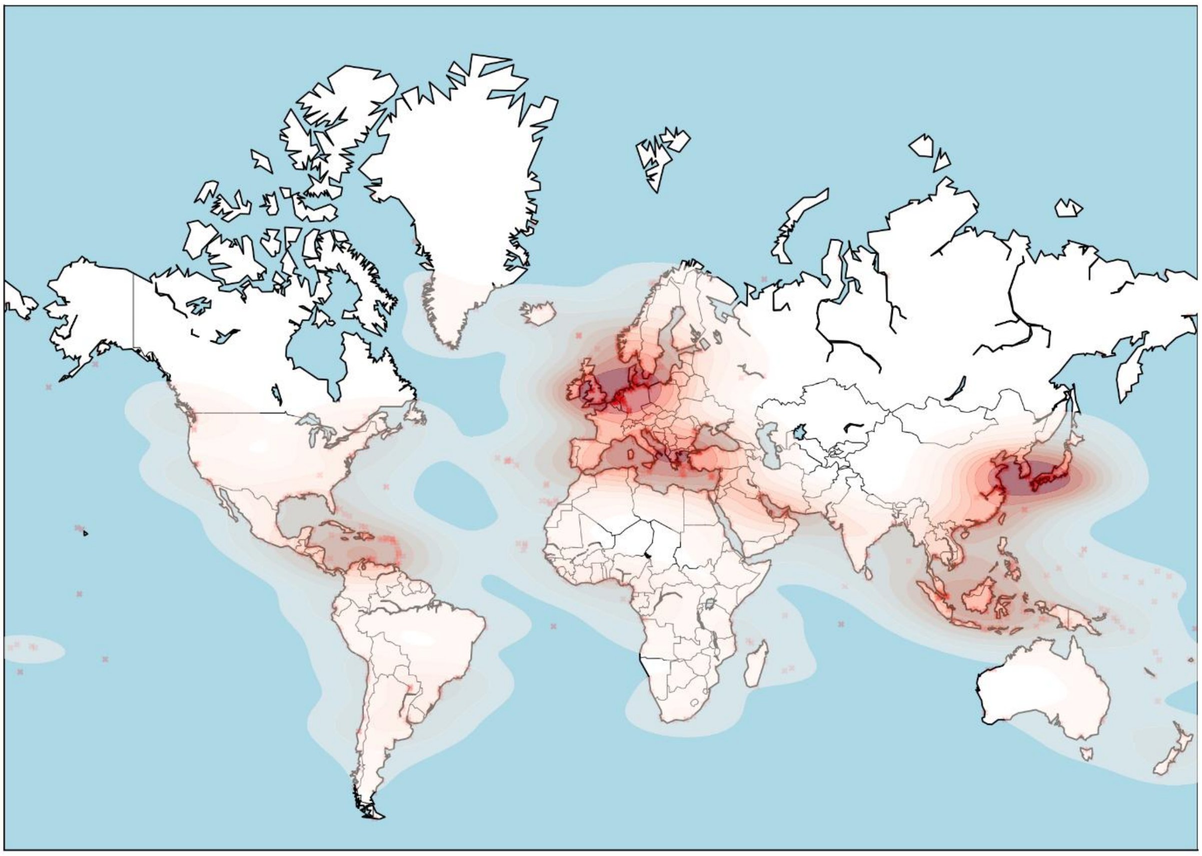


Figure 5.4 Global container ports throughput heatmap

5.3.2 Establishment and Analysis of Port Communities

5.3.2.1 Analysis and Determination of Distance Threshold

As introduced in Methodology section, the distance threshold is a critical parameter used to detect port communities by determining whether ports should be grouped into the same community. Thus, before the establishment of port communities, experiments regarding the distance threshold are added.

By changing the distance threshold, the metric changes related to the port community are detected, and the results are shown in Figure 5.5.

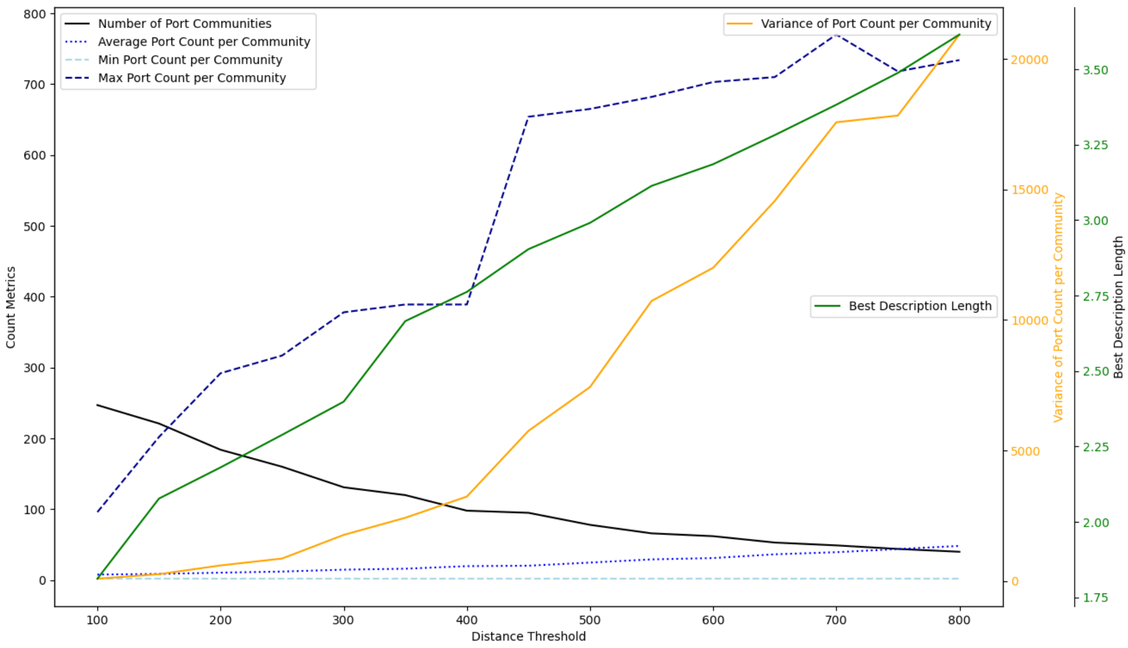


Figure 5.5 Analysis of Port community metrics across varying distance thresholds

Examining the left vertical axis first, we observe that the number of port communities (black solid line) gradually decreases with increasing distance thresholds. Meanwhile, the average port count per community (blue dashed line) shows a gradual upward trend, and the maximum port count per community (dark blue dashed line) rises sharply. However, the minimum port count per community (light blue dashed line) remains constant at 2. This indicates that as the distance threshold increases, the range within which ports merge into communities expands, causing previously separate communities to consolidate. Consequently, both the maximum and average port counts per community increase, while the total number of communities decreases. The consistency of the minimum port count per community suggests that increasing the distance threshold does not facilitate merging for ports that are inherently difficult to consolidate. On the right vertical axis, as the distance threshold increases, both the variance in port count per community (orange solid line) and the best description length (green solid line) continue to rise.

This pattern suggests an increasing disparity in port count distribution within communities and a growing complexity required to effectively describe the community structure.

From Figure 5.5, as the distance threshold increases to 300 from 100, the number of port communities decreases significantly. This indicates that smaller port communities are progressively merging into larger communities within this range. However, beyond a threshold of 300, the rate of decrease in community count slows, suggesting that further increases in the threshold have a diminishing effect on community count reduction. Therefore, selecting 300 as the threshold allows for a reduction in the number of communities while avoiding the excessive merging that could occur with a higher threshold. At this threshold, the average port count per community shows a steady upward trend, indicating that communities are growing in size while the number of ports within each community becomes more balanced. This threshold ensures that community sizes remain moderate, preventing the formation of overly large or excessively small communities. With a threshold of 300, the maximum port count per community also rises noticeably but does not exhibit the sharp increases seen at higher thresholds. This suggests that community sizes remain manageable at 300, avoiding the creation of exceptionally large communities, which supports the stability of data analysis and model performance. On the right vertical axis, the variance in port count and the best description length show stable growth around a threshold of 300. This indicates that at this threshold, the variance in port distribution within communities remains moderate, and the descriptive complexity is within a reasonable range, achieving a balance between data accuracy and complexity. In summary, selecting a distance threshold of 300 provides an optimal balance among reducing community count, maintaining moderate community sizes, and controlling descriptive complexity.

From a practical perspective, the choice of a 300 km threshold is well-supported by real-world port groupings. For example, in many well-known port clusters, such as those along the Northern Range in Europe or China’s eastern seaboard, the distance between neighbouring ports typically does not exceed 300 km. This threshold reflects the natural geographical and operational cohesion of these ports, making it a suitable parameter for defining port communities in our analysis.

Therefore, based on experimental observations and also on practical considerations of port clustering, the threshold distance is set to 300 km.

5.3.2.2 Analysis of Port Communities

Using the methods provided in Section 5.2.2.3 and setting the threshold distance to 300 km, a total of 131 port communities are detected in GCSN (shown in Figure 5.6), and the List of Top 30 port communities is summarized in Table 5.2 (For full list of port communities, please refer to Appendix B.). In Figure 5.6, the port with the largest throughput is selected as the representative port in each port community, and the location of the representative port is drawn on the map as the location of the community. The larger the community's throughput, the larger the shape of the representative port. The larger the community size, that is, the higher the throughput, the darker the colour. In Table 5.3, we rank the port communities according to their throughput ratios, list the representative ports of the communities and the regions where the representative ports are located, as well as the number of ports and throughput ratios of the port communities.

Table 5.3 List of Top 30 port communities

Community Order	Representative port	Country/Region	Type	Number of ports	Throughput ratio
1	Yangshan	China	Sub Port	185	26.16%
2	Tanger Med	Morocco	Port	213	9.78%
3	Rotterdam	Netherlands	Port	378	9.42%
4	Singapore	Singapore	Port	43	8.42%
5	Busan New Port	South Korea	Sub Port	127	7.94%
6	Jebel Ali	United Arab Emirates	Port	46	3.41%
7	Panama Canal	Panama	Port	15	2.66%
8	Port Said East	Egypt	Sub Port	42	2.37%
9	Savannah	U.S.A.	Port	15	2.02%
10	Santos	Brazil	Port	11	1.95%
11	Port Newark	U.S.A.	Sub Port	19	1.82%
12	Jawaharlal Nehru (Nhava Sheva)	India	Port	9	1.50%
13	Jeddah	Saudi Arabia	Port	5	1.36%
14	Cartagena Port	Colombia	Port	50	1.21%
15	Cai Mep	Vietnam	Port	19	1.21%
16	Colombo	Sri Lanka	Port	7	1.19%
17	Laem Chabang	Thailand	Port	10	1.04%
18	Los Angeles	U.S.A.	Port	12	1.01%
19	Tanjung Priok	Indonesia	Port	45	0.89%
20	Manzanillo	Mexico	Port	4	0.84%
21	Lome	Togo	Port	9	0.83%
22	Seattle	U.S.A.	Port	23	0.76%
23	Port Botany	Australia	Port	8	0.56%
24	Oakland	U.S.A.	Port	7	0.49%
25	Montevideo	Uruguay	Port	13	0.47%
26	Callao	Peru	Port	4	0.46%
27	Manila	Philippines	Port	7	0.45%
28	Port Melbourne	Australia	Port	7	0.40%
29	Cape Town	South Africa	Port	8	0.39%
30	Karachi	Pakistan	Port	2	0.39%

Ports along the coast of China and partial ports of Vietnam ranks first with 185 ports and a significant throughput ratio of 26.16%, which constitutes the largest port community in terms of throughout in the world. Community 1 uses Yangshan of Shanghai port as the representative port and represent the regions of East Asia. Followed by Tanger Med in Morocco and Rotterdam in Netherlands, contributing 9.78% and 9.42% to the total throughput and representing Mediterranean and Europe regions, respectively. Next, Southeast Asia region, with the Singapore port as the representative port, has only 43 ports with an 8.42% throughput ratio, highlighting its critical role in global maritime trade. The fifth largest port community consists of ports in Japan, South Korea and parts of Russia ports, with Busan New Port in South Korea serving as the leading hub, representing the Northeast Asia region. The total throughput of the top five port communities accounts for more than 60%.

The remaining port communities also play an important role in world shipping, represented by some prominent ports, but the throughput proportion of the port areas is less than 3.5%. Such as the Jebel Ali, UAE (46 ports, 3.41%), Panama Canal, Panama (15 ports, 2.66%), and Port Said East, Egypt (42 ports, 2.37%), each serving as key nodes in their respective regions.

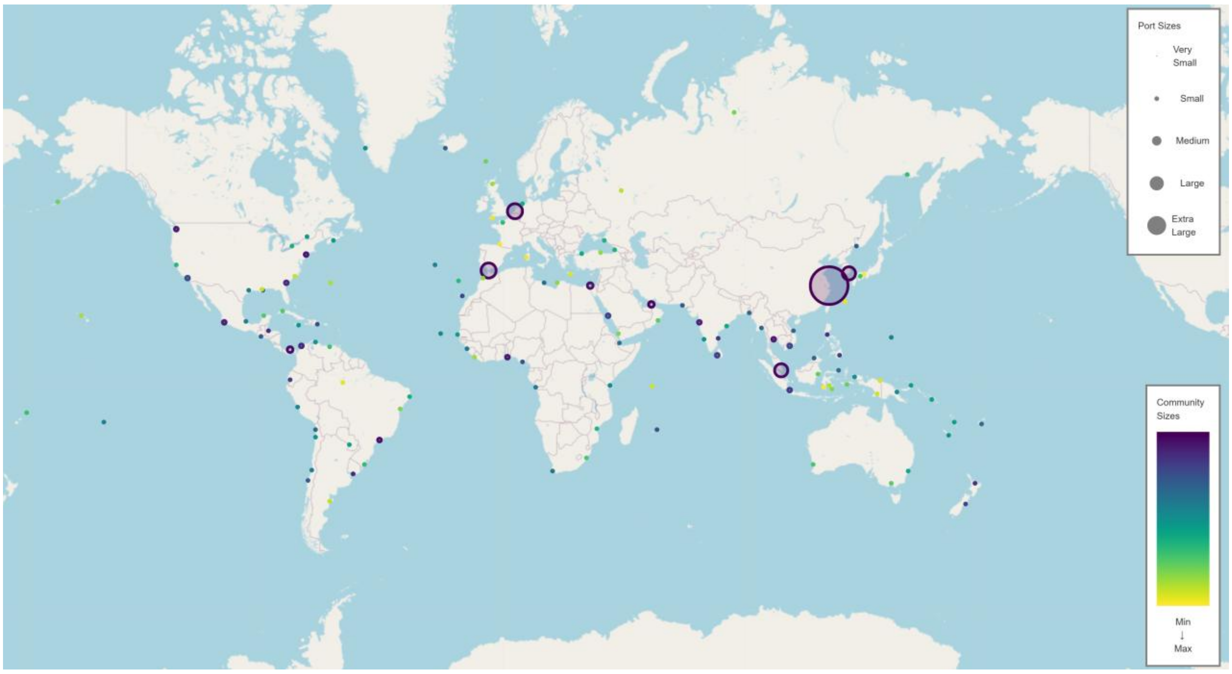


Figure 5.6 Port communities in the GCSN

The directed-weighted GCSN based on port communities is shown in Figure 5.7. Similarly, we select the port with the maximum throughput within each port community to represent the community in the diagram. The higher the throughput of a port community, the deeper the colour of the representative port. The transportation volume between port communities is indicated by the lines connecting the representative ports; the larger the transportation volume, the thicker the line. From the Fig.5, it can be observed that the most closely connected regions are East Asia and Northeast Asia, East Asia and Southeast Asia, and the Mediterranean and Europe.

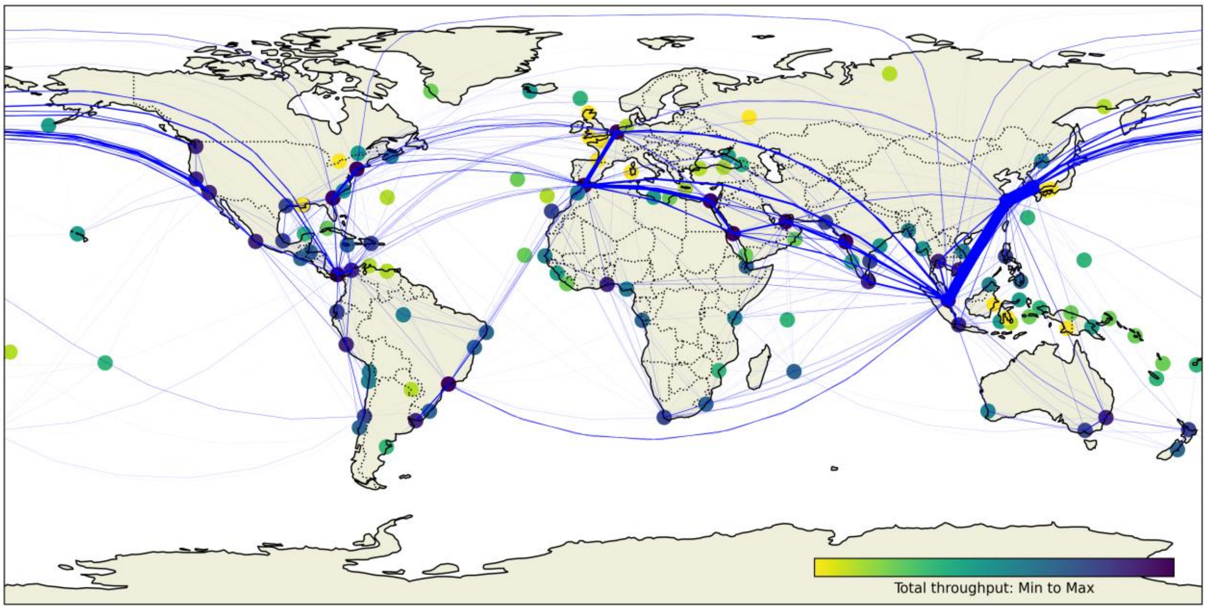


Figure 5.7 Directed-weighted GCSN based on port communities

5.3.2.3 Comparative Analysis of Centrality Metric Distributions between Community and Port Networks

Centrality-based coefficients are fundamental in network analysis as they reflect various aspects of network structure and characteristics. To can examine whether the port community-to-community network preserves the structural and functional characteristics of the original port-to-port network, we compared the distributions of six widely used centrality-based coefficients: Degree Centrality, Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, PageRank, and Clustering Coefficient, as shown in Figure 5.8.

Degree Centrality quantifies the number of direct connections a node has, providing insights into the local connectivity and the node's immediate influence within the network. It helps to identify highly connected nodes that serve as local hubs.

Betweenness Centrality measures the extent to which a node lies on the shortest paths between other nodes, reflecting its role as a bridge or connector within the network. Nodes with high betweenness centrality often facilitate communication and information flow.

Closeness Centrality evaluates the average shortest path from a node to all other nodes, indicating how efficiently a node can access the entire network. Nodes with high closeness centrality are typically well-positioned to disseminate information quickly.

Eigenvector Centrality captures a node's influence by considering not only the number of connections but also the importance of those connections. It highlights nodes connected to other influential nodes, emphasizing global rather than local influence.

PageRank is a variant of eigenvector centrality that incorporates a probability-based approach to assess the relative importance of nodes. Originally developed for web page ranking, it is particularly useful in networks where influence propagates hierarchically.

Clustering Coefficient assesses the tendency of a node's neighbors to form tightly-knit clusters, offering insights into the network's local cohesiveness. It is a measure of how interconnected a node's immediate neighborhood is.

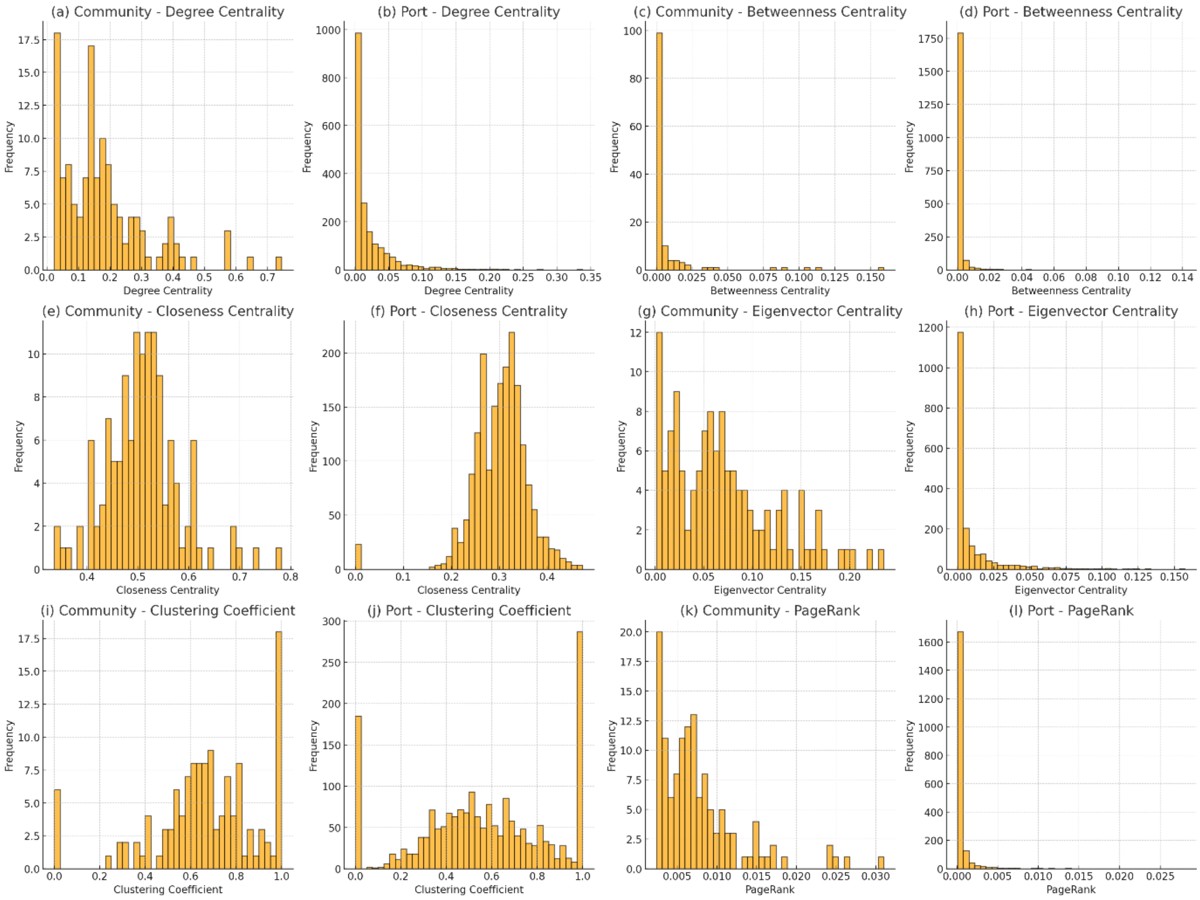


Figure 5.8 Distribution of centrality-based coefficients in port community network and individual port network

From Figure 5.8, some similarities as well as some differences of centrality metric distributions between community and port networks can be observed, the detailed analysis are as follows.

(1) Similarities

a. Centrality Characteristics

In both networks, Degree Centrality, Betweenness Centrality, and PageRank metrics exhibit right-skewed distributions, meaning that most nodes have relatively low values, while only a few nodes exhibit high centrality. This indicates that both community and port networks contain “key nodes” that play significant roles in connectivity and bridging, while the majority of nodes have comparatively limited roles.

Closeness Centrality shows a relatively concentrated distribution in both networks, suggesting that many nodes have moderately short average path lengths, especially for commonly connected nodes. This reflects a high level of accessibility between nodes within both networks.

b. Clustered Structures

In both networks, the Clustering Coefficient exhibits a bimodal distribution or certain dispersion, indicating that both community and port networks contain both high-clustering nodes (closely connected to their neighbours, forming local "groups") and low-clustering nodes (with fewer local connections). This suggests that both networks contain tightly connected local substructures.

c. Structural Centrality (Eigenvector Centrality)

Both networks display a right-skewed distribution for Eigenvector Centrality, suggesting that a few “high-influence” nodes are highly connected and are also linked to other highly connected nodes. This structure implies the presence of “core nodes” in both networks that play prominent roles in the overall structure.

(2) Differences

a. Polarization in Centrality Distribution

In the Port Network, Degree Centrality and Betweenness Centrality distributions are more extreme, with the majority of nodes having minimal connectivity or bridging roles, while a few nodes dominate network weight. This suggests a more hierarchical structure in the port network, relying on a few hub ports to maintain primary flow.

In contrast, Community Network metrics are more evenly distributed, indicating a more balanced distribution of node roles, with multiple nodes potentially playing significant bridging roles. This reflects a more decentralized network suited for providing broad, distributed connectivity.

b. Differences in Accessibility (Closeness Centrality)

The Community Network exhibits a higher overall Closeness Centrality distribution, indicating that average path lengths between nodes are shorter, and the network is more densely connected. This is typical of community networks, which generally contain more cross-links, resulting in higher accessibility between nodes.

In the Port Network, Closeness Centrality values are lower and more concentrated within a narrow range, indicating a more layered network with a clear separation between accessible hubs and peripheral nodes. This structure suggests that if critical nodes fail, network-wide accessibility would be significantly impacted.

c. Differences in PageRank Distribution

In the Community Network, PageRank distribution is relatively uniform, with more nodes exhibiting significant PageRank values, indicating a more even spread of connectivity among nodes and relatively decentralized importance.

In the Port Network, PageRank values are highly concentrated around a few nodes, while most nodes hold very low importance. This suggests a strong hierarchical structure in the port network, heavily reliant on a few central “hub” nodes, likely due to the logistic needs of port networks, where efficient organization of traffic flows around key hubs is crucial.

d. Cluster Structure in Clustering Coefficient

The Community Network exhibits a more dispersed distribution in Clustering Coefficient, with many nodes achieving moderate to high values. This implies that the community network likely contains numerous small “group structures,” with closely connected nodes forming local clusters.

In contrast, the Port Network displays a more polarized Clustering Coefficient distribution, with peaks at both low and high values. This indicates that while some ports are tightly connected within clusters, others remain isolated. This pattern may result from the hierarchical and geographically constrained nature of port networks, where major ports form dense connections, while others serve as peripheral nodes.

In summary, both the Community and Port networks exhibit scale-free and small-world properties, such as the presence of key nodes and the existence of clustered structures, they differ significantly in their centrality patterns and structural organization. The community network is generally more decentralized and balanced, with a more even spread of roles among nodes, resulting in a robust, distributed network. Conversely, the port network is characterized by strong centralization and a hierarchical structure, relying heavily on a few critical nodes for primary connectivity. This configuration implies high efficiency but potentially higher vulnerability to failures in key nodes.

Different researchers apply various algorithms to detect port communities for distinct purposes. Our objective is to detect a port community network that maintains the original properties while also offering a clearer and more holistic perspective on analysing the structure of the GSCN. The analysis above confirms that we have achieved this.

Following the construction of port communities, the subsequent section focuses on conducting resilience analysis using the proposed disruption simulation model.

5.3.3 Resilience Assessment and Analysis

Resilience represents a system's capacity to prepare for, respond to, and recover from various disruptions (Wang et al., 2023a; Wang et al., 2024a). Utilizing the proposed simulation model, this study examines different disruption scenarios, durations, and recovery strategies. Furthermore, from the perspective of port communities, the failure of ports within different port clusters is analysed. These simulations aim to offer actionable insights and strategic recommendations for enhancing and effectively managing the resilience of the GCSN.

5.3.3.1 Sensitivity Analysis of Distance Tolerance Parameter

Before conducting formal simulation modelling, it is essential to determine the key parameters. Some of these parameters can be obtained from previous research; for instance, Xu et al. (2022b) suggested that a port capacity tolerance parameter (α') of 0.2 is most suitable. However, other parameters, such as the distance tolerance parameter (β') for alternative ports, have not been addressed in the existing literature. Here, we will first perform a sensitivity analysis of the distance tolerance parameter before establishing its value.

Specifically, we will sequentially set the distance tolerance parameter from 0.1 to 2, with intervals of 0.1. For each case, we will calculate the average number of alternative ports corresponding to all vessels at each port, resulting in the distribution illustrated in Figure 5.9. Under this experiment, we assume that every port is operating normally.

From Figure 5.9, as the distance tolerance parameter (x-axis) gradually increases from 0.1 to 2.0, both the median and interquartile range in the box plot increase correspondingly. This indicates that with a larger distance tolerance parameter, the average number of alternative ports available per ship also grows, along with a greater variation in the number of alternative ports among different ships. Under each distance tolerance condition, there are numerous outliers, and both the number and extent of these outliers increase as the distance tolerance parameter rises. These outliers likely represent specific ships that have significantly more alternative ports than the average within a given tolerance range. The symmetry of each box and whisker plot suggests no marked skewness in the data, indicating that the distribution of alternative port numbers per ship is approximately symmetric under different distance tolerance parameters. Notably, while the median and variability steadily increases as the distance tolerance parameter ranges from 0.1 to 2.0, the rate of increase slows beyond a certain threshold, suggesting a possible saturation effect. This could imply that beyond a certain distance threshold, additional ports may not significantly increase the pool of suitable substitutes. When the distance tolerance parameter reaches 0.8, the rate of increase in the median drops to below 0.03. Consequently, we set the distance tolerance parameter at 0.8.

In addition, we analysed the correlation between throughput and the number of alternative ports. We found that the relationship between the number of alternative ports and throughput is weak for both individual ports and port communities, with correlation coefficients of 0.079 and 0.246, respectively. Similarly, the relationship between the growth rate of alternative port numbers and throughput is also weak, with correlation coefficients of −0.00047 and 0.240, respectively. This suggests that higher-throughput ports or port communities do not necessarily have a larger number of alternative ports. Likewise, port communities with a large number of ports do not necessarily have more alternative ports, as the correlation coefficients are only 0.17 and 0.18, respectively, for the relationships between (1) the number of alternative ports and the port counts within the port community, and (2) the growth rate of alternative port numbers and the port counts within the port community.

Ports with a large number of alternative ports are primarily located in China, Indonesia, Japan, the U.S.A., and the U.K. With an increase in the distance threshold, ports experiencing a rapid increase in alternative port numbers are mainly situated in China, Indonesia, Japan, the U.S.A., and Norway. These ports generally do not have high throughput but are surrounded by a substantial number of potential alternative ports.

High-throughput ports, such as Singapore, Yangshan Port, Hong Kong, and Busan New Port, show only a small increase in the number of alternative ports. These ports are typically located at key global trade hubs, where the availability of substitutes is limited; however, they already have a sufficient number of alternative ports within a relatively small distance range. Low-throughput ports, such as Bayah and Atapupu in Indonesia, experience a significant increase in alternative port numbers as the distance tolerance increases, possibly due to their location in regions with a dense distribution of alternative ports.

In summaries, higher-throughput ports or port communities do not necessarily have a greater number of alternative ports. Similarly, port communities with a large number of ports do not inherently possess more alternative ports. Instead, the availability of alternative ports is more influenced by regional port density and geographic distribution than by size or throughput. This underscores the importance of maintaining a geographically balanced distribution and avoiding over-reliance on a single port.

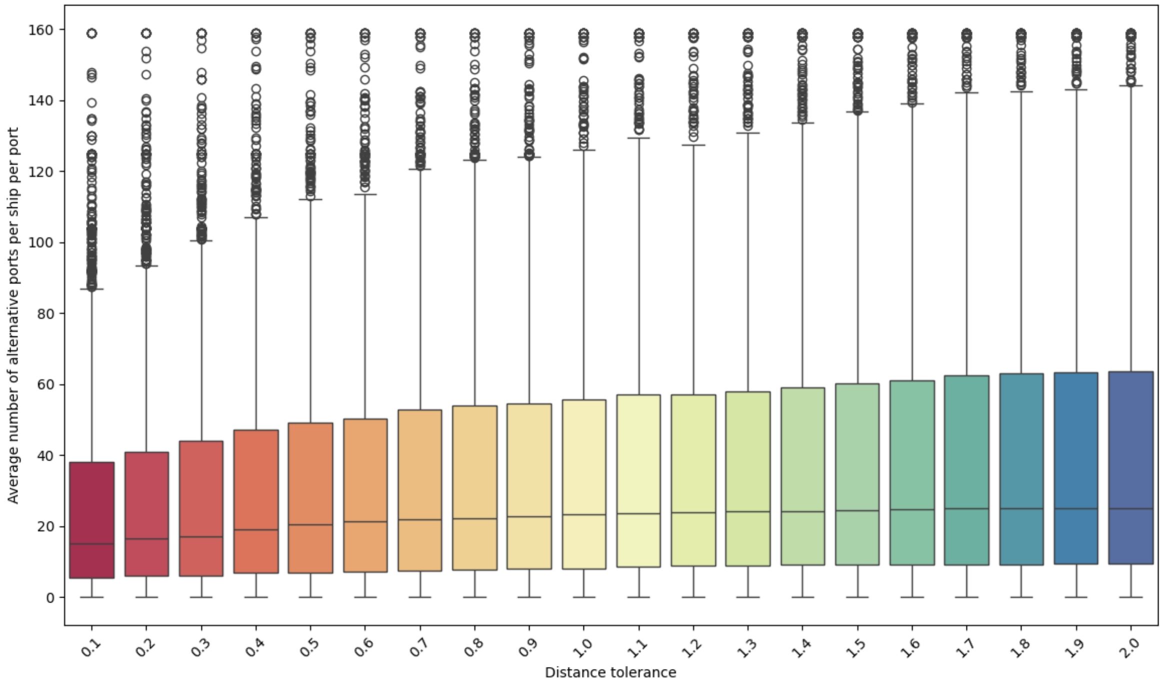


Figure 5.9 Distribution of average number of alternative ports per ship per port across specified distance tolerance

5.3.3.2 Simulation of Different Disruption Scenarios

Disruptions at ports can occur in various forms. From the observed cases, these disruptions can be divided into two types: first, failure of a single port within a port community, as seen in the Meishan Port Area of Ningbo-Zhoushan Port, which suspended operations on August 11, 2021, due to a confirmed COVID-19 case. Operations resumed after a 14-day lockdown (CCTV News Client, 2021). The second type involves the failure of multiple ports, such as during Typhoon Bebinca's landfall in Shanghai on September 16, 2024, which impacted many ports in the Yangtze River Delta region, including Shanghai Port, Ningbo-Zhoushan Port, and Nantong Port (Beijing News, 2024). We will simulate these two scenarios (failure of single port and failure of multiple ports) using the simulation model provided in this study.

For subsequent comparisons, we set the disruption duration and recovery ratios as the same. The recovery starts on the 6th day, with recovery ratios of 0.5, 0.8, and 1.0 on the 1st, 2nd, and 3rd recovery days, respectively, and 1.2 for the 4th day and beyond. The waiting probability and rerouting probability are both set to 0.3, while the skipping probability is set to 0.4. Furthermore, we assume that the initially failed ports are the first to resume operations. Once these ports have recovered and no longer generate additional processing demands on other ports affected by the cascading effect, these failed ports due to cascading effects may begin their recovery.

For the simulation of failure of single port, Yangshan (Sub Port) port is selected as the initially failed port. For the failure of multiple ports, Nanjing, Nantong, Ningbo, Shanghai, Yangzhou, Zhenjiang, Zhoushan, Beilun (Sub Port), Meishan (Sub Port), and Yangshan (Sub Port) ports are selected, which are the main ports located in the Yangtze River Delta region. The results are shown in Figure 5.10.

In Figure 5.10 (a), the number of failed ports is initially zero on day 0. From the first day, port failures are triggered, and the number of failed ports begins to increase over time. The failure count of the single-port failure scenario continues to rise until day 4, while the failure count of the multiple-port failure scenario continues to rise until day 6, when the recovery process starts. Because the ports' operational capacity has not been fully restored, the number of failed ports also does not change during initial recovery period. Starting from day 9, the number of failed ports of both scenarios begin to show a declining trend. As the recovery process progresses, the rate of decrease accelerates. Eventually, the single-port failure scenario fully recovers by day 15, while the multiple-port failure scenario achieves complete recovery by day 18. Although the total disruption duration for both scenarios is relatively similar, the number of failed ports differs significantly. The multiple-port failure scenario results in a number of failed ports that is 4.6

times greater than that in the single-port failure scenario. This highlights the much larger scale of impact caused by multiple-port failures compared to single-port failures.

Similarly, in Figure 5.10 (b), the overall trend in resilience values is similar for both single-port and multiple-port failure scenarios. However, the impact of multiple-port failures is significantly greater than that of single-port failures. In the multiple-port failure scenario, the resilience value drops more sharply and to a much lower level compared to the single-port scenario. Furthermore, even after the recovery process begins, the resilience value continues to decline temporarily. This is because the failed ports are not fully restored, and their reduced capacity still impacts the transportation of traffic within the network. This demonstrates that the incomplete recovery of ports can continue to affect the network's overall resilience until full functionality is achieved.

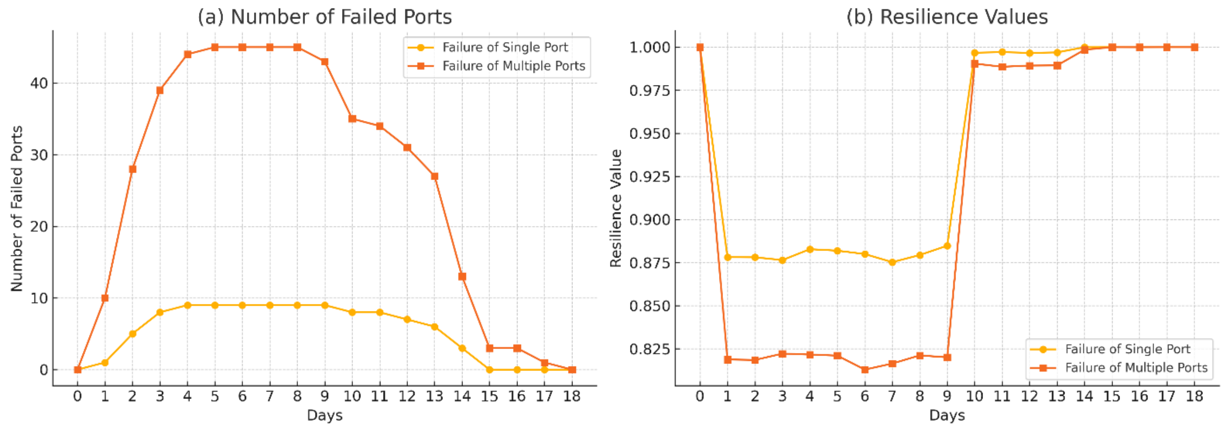


Figure 5.10 Simulation results of different disruption scenarios

In the multi-port failure scenario, the total number of failed ports exceeds 40, presenting significant challenges for analysing individual ports effectively. In such cases, adopting the perspective of port communities offers a novel and effective approach for analysis.

From the perspective of port communities, the distribution of failed ports under different disruption scenarios is analysed, as shown in Figure 5.11. In both scenarios, the ports most affected belong to the same port community (Port Community 1; the composition of each port community can be found in Appendix B). Ports that fail due to cascading effects are primarily those serving as alternative ports. In the single-port failure scenario, the impact is relatively limited. Apart from causing failures within the affected port community itself, it only leads to additional failures in Port Community 5. However, in the multiple-port failure scenario, a total of eight port communities are affected. These include port communities adjacent to the failed ports as well as those that are geographically distant but closely connected to the failed port communities. Ports that fail due to cascading effects not only fail as alternative ports but also fail as the next stop in the route for ships bypassing the disrupted ports.

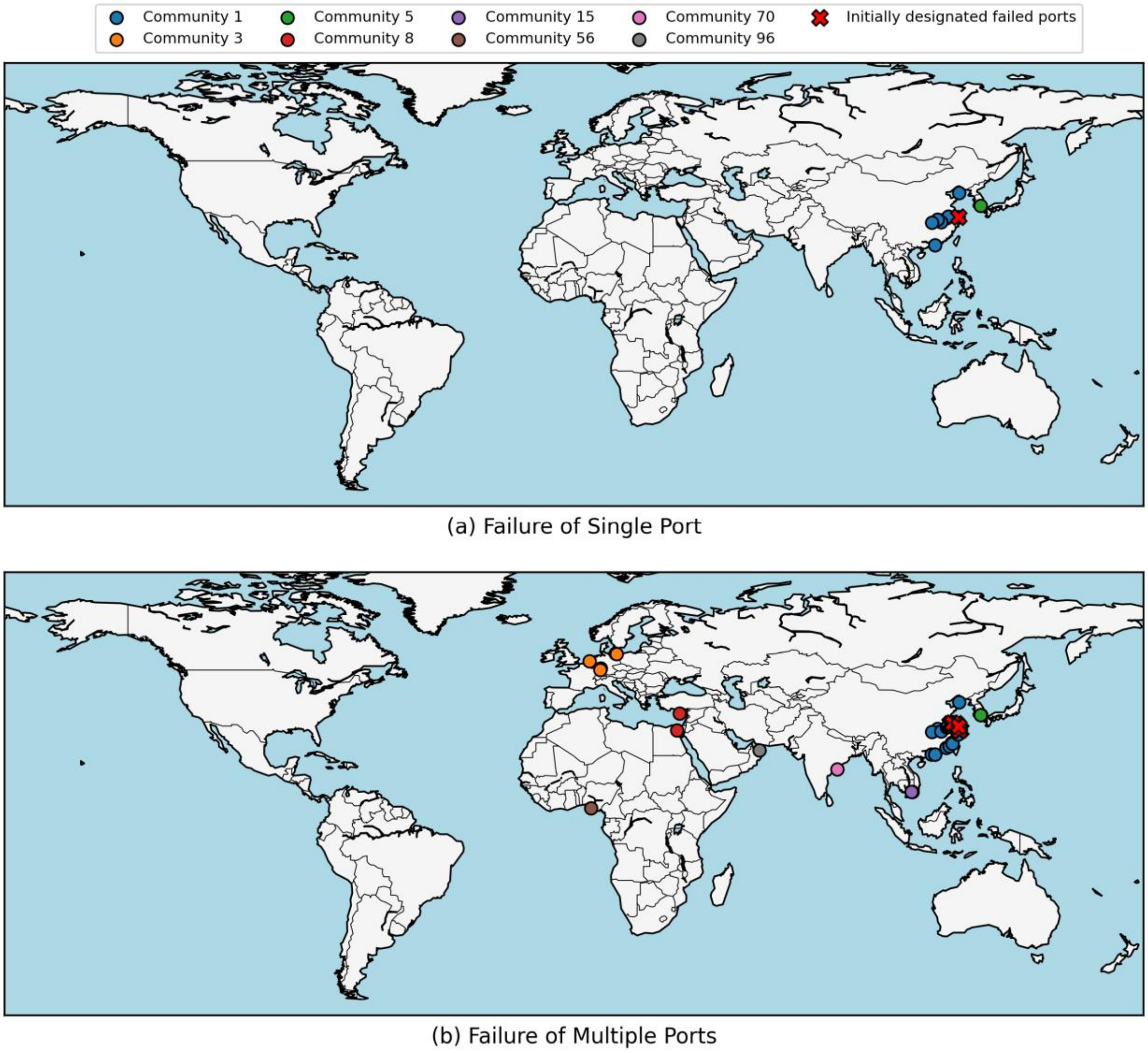


Figure 5.11 Distribution of failed ports under different disruption scenarios

From the perspective of port communities, the daily accumulated blockage distribution of failed ports under different disruption scenarios is analysed, as shown in Figure 5.12. To facilitate comparison, different vertical axes are used. The blockage caused by failed ports within their own port communities is significantly greater than that in other port communities. Therefore, a separate vertical axis (primary Y-axis) is used for the failed port's own community, while another axis (secondary Y-axis) is used for other affected port communities.

The results indicate significant variations in the blockage levels across different port communities. Notably, the timing of when different port communities begin to experience blockage varies, as does the recovery time (the point at which cumulative blockage ceases to grow). Even after some port communities have fully recovered, the cumulative blockage in subsequently affected port communities continues to grow. As a result, port communities affected later experience relatively smaller congestion but also take longer to complete recovery.

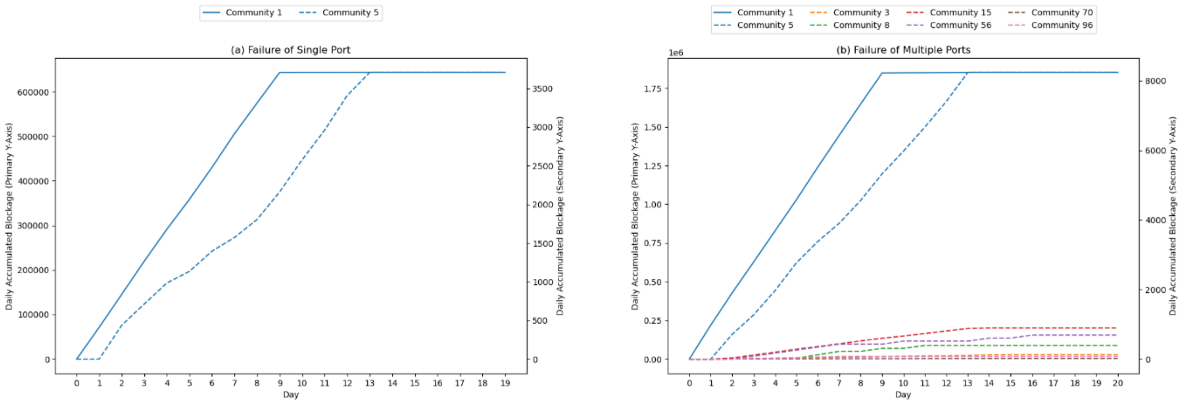


Figure 5.12 Daily accumulated blockage of port communities under different disruption scenarios

5.3.3.3 Simulation of Different Disruption Days

Based on the multiple-port disruption scenario described above, we set different recovery start times to explore the impact of disruption duration on the network. The results are shown in Figure 5.13. As the disruption duration increases, the recovery time also extends. The recovery start time is nearly linearly related to the overall disruption duration. However, the number of maximum affected ports and the minimum resilience value do not show significant changes, suggesting a threshold effect in network robustness. Longer disruptions lead to slower stabilization across the network, emphasizing the importance of prompt recovery actions.

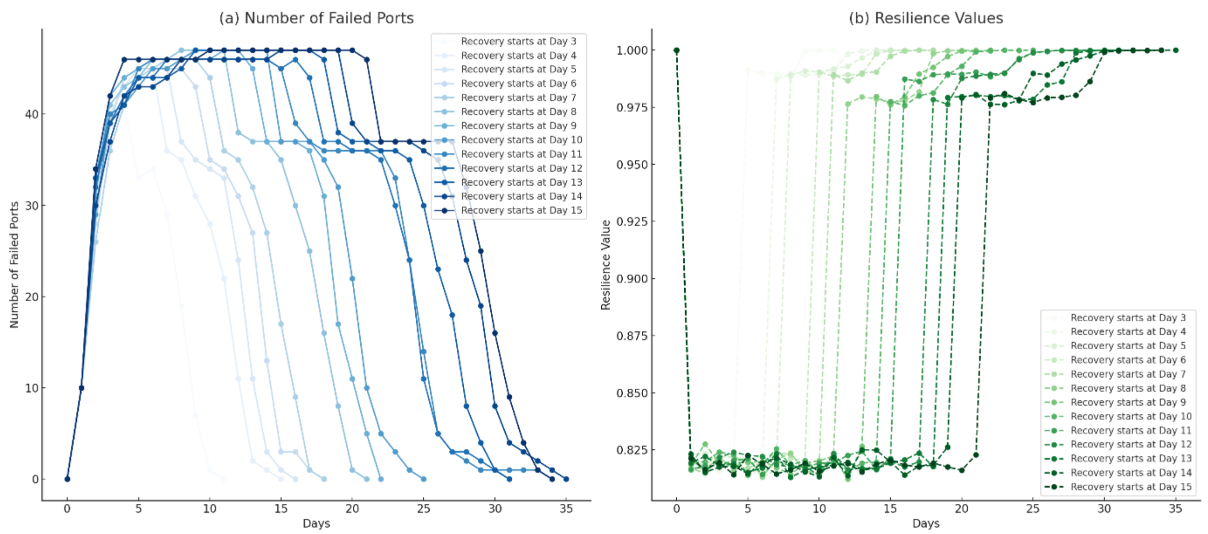


Figure 5.13 Simulation results of different disruption durations

5.3.3.4 Simulation of Different Recovery Strategies

Based on the multiple-port disruption scenario described above, we set different port recovery sequences to explore the impact of recovery strategies on the network. The results are shown in Figure 5.14. The failed ports are categorized into two types: initially designated failed ports and those that failed due to cascading effects. In simultaneous recovery, all failed ports are recovered simultaneously at the beginning of the recovery process. In separate recovery, the initially designated failed ports are recovered first, and the recovery of other failed ports begins only after the initially designated ports are fully restored.

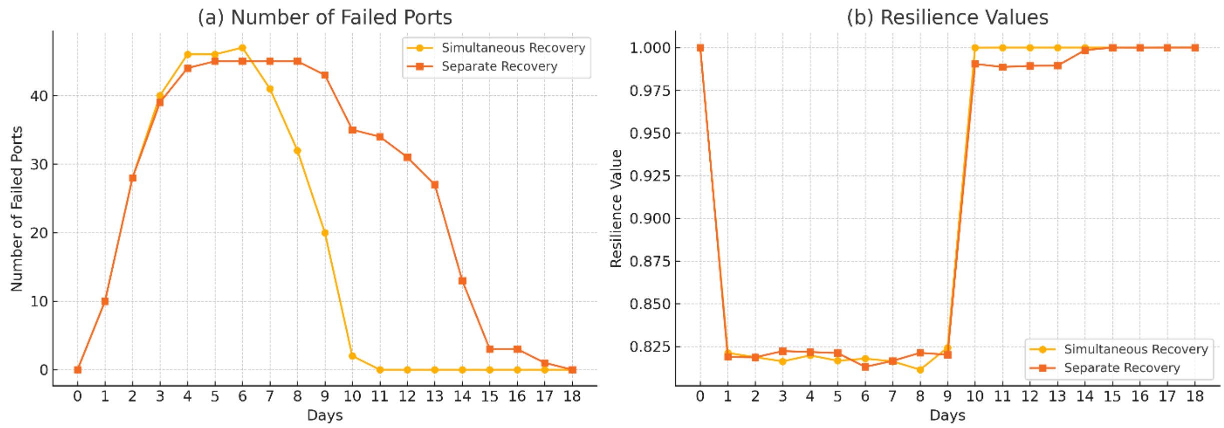


Figure 5.14 Simulation results of different recovery strategies

From Figure 5.14, the simultaneous recovery strategy significantly shortens the overall recovery time. However, the number of affected ports and the minimum resilience value do not show significant differences between the two strategies. It means that separate recovery will prolong total downtime but have little effect on the disruption severity in terms of the maximum daily traffic blockage and failed ports.

5.3.3.5 Simulation of Disruptions in Different Port Communities

Based on the setup of the multiple-port disruption scenario described above, we examined the impact of port communities on the network by simulating port failures in different port communities. Specifically, three ports were randomly selected to fail within each port community. For port communities with fewer than three ports, the entire community was set to fail. At the experiments, we compared three metrics: Max failed port count, Min resilience value, and Disruption days. The results are shown in Figure 5.15. In Figure 5.15, the port communities are arranged in ascending order based on the maximum number of failed ports (The numbers for port communities on the horizontal axis are not related to the community order mentioned earlier.). It can be observed that there is a positive correlation between Max failed port count and

Disruption days, while Min resilience value shows a weaker correlation with the other two metrics. It indicates that network blockage is not only related to the number of failed ports but is also significantly influenced by port throughput.

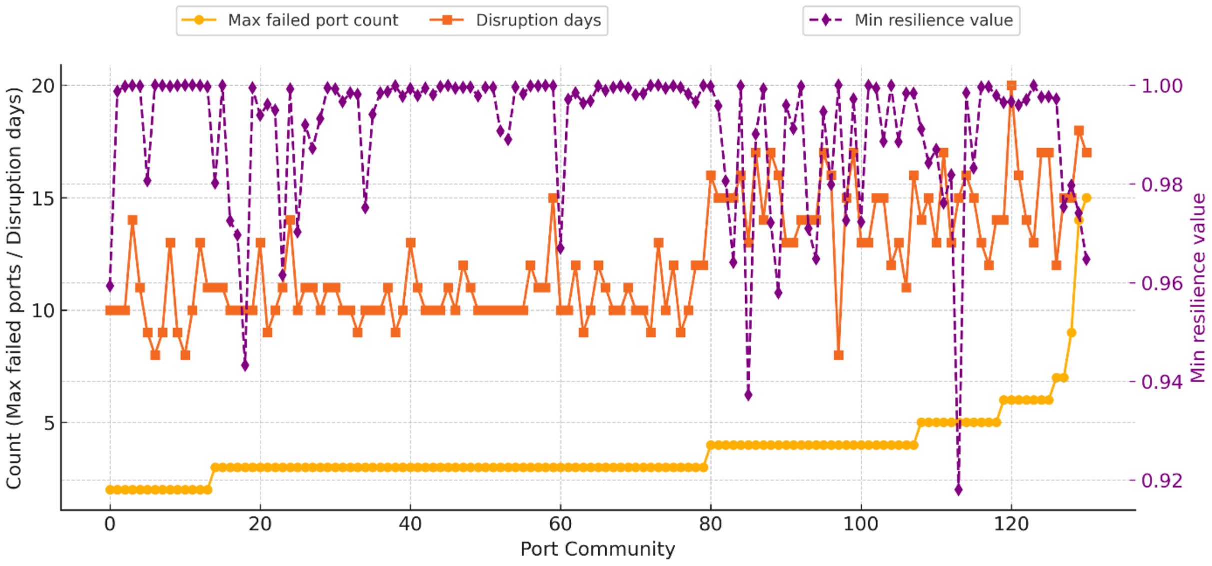


Figure 5.15 Key metrics distribution of port failures across different port communities

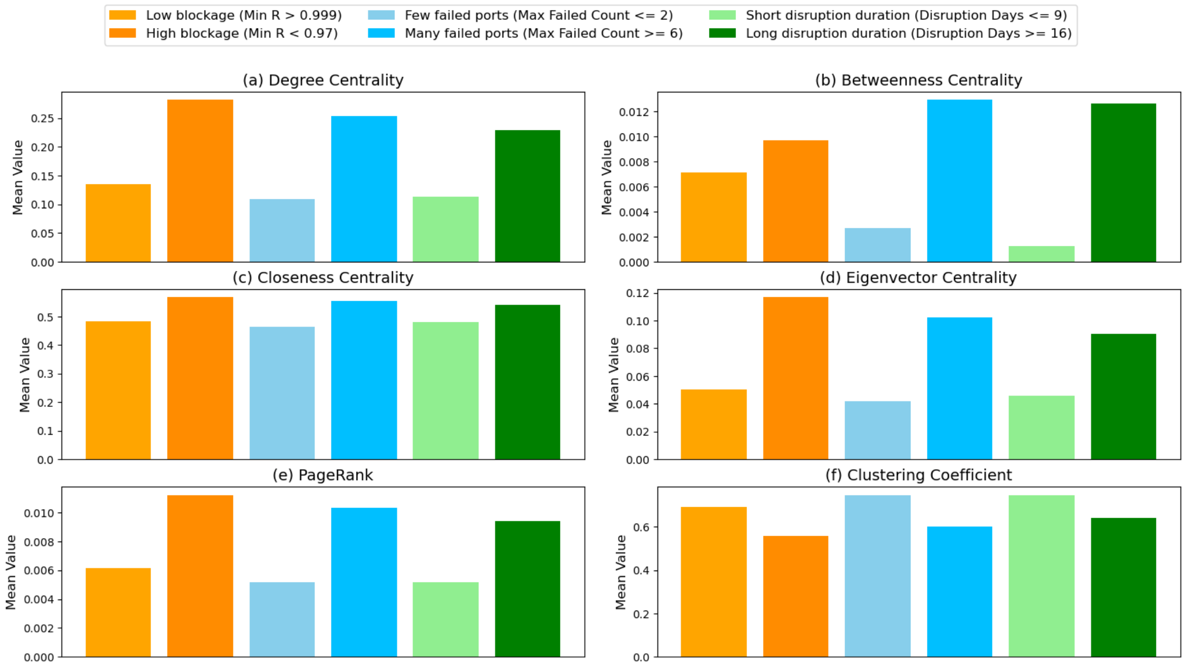


Figure 5.16 Comparison of centrality indices among different types of port communities

In addition, we found no significant relationship between these metrics and the centrality indices of each port community. Therefore, port and port community resilience remain a complex issue involving multiple factors, making it difficult to measure using a single metric. In the following analysis, we classify port communities into six types based on these key metrics (High blockage (Min R < 0.97), Low blockage (Min R > 0.999), Few failed ports (Max Failed Count <= 2), Many failed ports (Max Failed Count >= 6), Short disruption duration (Disruption Days <= 9), Long disruption duration (Disruption Days >= 16)) to examine their relationships with centrality indices (degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, PageRank, and clustering coefficient). The results are shown in Figure 5.16.

Key Observations are as follows.

(1) Degree Centrality: High blockage, many failed ports, and long disruption duration are associated with higher degree centrality values, suggesting a stronger structural role in the network, which could contribute to more severe disruptions.

(2) Betweenness Centrality: Communities with many failed ports and long disruption duration have higher betweenness centrality, indicating that these ports act as critical intermediaries in the network. The high centrality values in such communities suggest that failures in these nodes can lead to cascading effects and more severe disruptions.

(3) Closeness Centrality: Closeness centrality shows minimal variation across all categories, suggesting that it does not significantly influence the extent or outcomes of disruptions within the network.

(4) Eigenvector Centrality: High blockage, many failed ports, and long disruption duration are associated with the highest eigenvector centrality values, highlighting the influence of these port communities in connecting with other highly connected nodes.

(5) PageRank: Similar to eigenvector centrality, PageRank values are higher for high blockage, many failed ports, and long disruption duration, indicating their importance within the broader network.

(6) Clustering Coefficient: The clustering coefficient values are fairly consistent across all categories, with slightly higher values observed for short disruption durations and few failed ports, suggesting these communities are more tightly interconnected.

Overall, the degree centrality, betweenness centrality, eigenvector centrality, and PageRank of port communities have a significant impact on disruptions. Generally, the higher these indices, the greater the resulting disruption. Among them, degree centrality and PageRank have a relatively balanced influence on three disruption metrics (traffic blockage, number of failed ports, and disruption duration). Betweenness centrality primarily affects disruption duration, while eigenvector centrality mainly influences traffic blockage. In contrast, closeness centrality and clustering coefficient have relatively minor impacts on disruptions.

5.3.4 Discussions

(1) Detecting Port Community using the Infomap Algorithm

Distance threshold is a critical parameter for detecting port communities, which directly impacts how ports are grouped into communities. Increasing this threshold results in fewer, larger communities. From our experiments, 300 km is the optimal threshold. First, it ensures a balance between reducing the number of communities and maintaining manageable community sizes. In addition, it avoids excessive merging that could distort analytical clarity or create impractically large communities.

The GCSN demonstrates typical scale-free and small-world properties, characterized by the following features: 1) a few highly connected hubs that serve as central nodes within the network; 2) a limited number of crucial intermediary nodes that facilitate the flow of traffic across the network; and 3) generally well-connected nodes exhibiting varying degrees of local clustering, which indicates the presence of both tightly-knit communities and less cohesive structures within the overall network. After categorizing these ports into port communities, the port community network can maintain this property while become more decentralized and balanced.

The findings regarding distance thresholds and community detection are not only relevant to the GCSN but could also be generalized to shipping networks in other geographic regions or applied to networks with distinct characteristics, such as inland shipping systems, river transport networks, or even intermodal logistics chains. The principle of using a scale-free, small-world framework for identifying optimal community structures can be adapted to understand regional variations in port connectivity or to identify clusters in less dense networks where alternative ports are scarcer. For instance, the 300 km threshold might need adjustment based on regional port density or the scale of the network. This approach could also guide decision-makers in developing targeted strategies for network management and optimization in other maritime or non-maritime transportation systems.

(2) The Impact of Distance Tolerance on the Number of Alternative Ports

As the distance tolerance parameter (β') increases, both the median and interquartile range of the number of alternative ports increase. This indicates that larger values of tolerance parameter allow ships to access a broader range of alternative ports, albeit with diminishing returns beyond a certain threshold. At $\beta' = 0.8$, the rate of increase in the median number of alternative ports reduces to below 0.03. This suggests a saturation point, where increasing β' further yields minimal additional alternatives. Outliers increase as β' grows, indicating that specific ships have disproportionately more alternative ports.

Correlation coefficients indicate a weak relationship between throughput and the number or growth of alternative ports. Larger port communities or higher-throughput ports do not necessarily have more alternative ports. Instead, the availability of alternative ports is more influenced by regional port density and geographic distribution than by size or throughput. This underscores the importance of maintaining a geographically balanced distribution and avoiding over-reliance on a single port.

The findings can be generalized to other regions by emphasizing the importance of regional port density and geographic distribution as key factors in ensuring network resilience. For example, in regions with uneven port distribution, such as isolated island nations or areas with limited coastline, these insights can inform the development of new port infrastructure to create a more balanced network. Additionally, the principles outlined here can apply to inland shipping networks, where alternative ports may be fewer and further apart, requiring a strategic approach to ensure redundancy and resilience.

In multimodal transportation systems, where goods transfer between shipping, rail, and road networks, the same principles can guide the placement and design of intermodal hubs. Creating a geographically distributed network of hubs can minimize the risk of bottlenecks and over-reliance on a single node, ensuring more effective traffic flow in the event of disruptions. The findings are also applicable to emerging or rapidly growing shipping networks, where planners can proactively establish geographically balanced port networks to support future growth while reducing vulnerabilities.

(3) Analysing Disruption Scenarios/Durations/Recovery Strategies

From the comparison between single-port failure and multiple-port failure, we can see that with the increase of failed ports, the affected ports and regions increase dramatically. In comparison, the increase in disruption time is much smaller. Cascading failures amplify network-wide congestion, especially in alternative and next-route ports. Blockages and recovery timelines vary across port communities. The ports in their own port community are the most affected.

From the perspective of recovery start time, as disruption duration increases, recovery times extend linearly. The number of affected ports and minimum resilience values remain consistent, suggesting a threshold effect in network robustness. Longer disruptions lead to slower stabilization across the network, emphasizing the importance of prompt recovery actions.

From the perspective of recovery strategies, simultaneous recovery can significantly shorten overall recovery time by addressing all failed ports at once, separate recovery will prolong total downtime but have little effect on the disruption severity in terms of the maximum daily traffic blockage and failed ports. While simultaneous recovery is faster, logistical constraints in real-world scenarios may favour sequential strategies.

The disruption analysis provides a framework for assessing network vulnerability and designing recovery strategies, which could be generalized to other regions or applied to different types of shipping networks. In regions with high traffic density or strategic chokepoints (e.g., the Strait of Malacca or the Panama Canal), these findings can help optimize contingency planning and port recovery prioritization. Similarly, the principles of simultaneous vs. sequential recovery could be adapted to inland networks, including riverine or canal-based transport systems, where disruptions at key nodes could disproportionately affect traffic flow. This approach could also be extended to other sectors, such as rail or road networks, offering insights into how cascading failures propagate and how recovery timelines impact broader network stability.

(4) Comparative Analysis of Disruptions across Port Communities

By simulating port failures in different port communities, we found that the maximum number of failed ports is positively correlated with disruption duration. Larger failures require longer recovery times. In addition, minimum resilience value shows a weaker relationship with the other two metrics, indicating that traffic blockage is influenced by additional factors such as port throughput and network role.

The centrality indices of each port community show no significant correlation with disruption metrics such as disruption duration, the number of failed ports, and network blockage traffic. Therefore, the resilience of ports and port communities remains a complex issue involving multiple factors, making it difficult to measure using a single metric. However, through the classification of port communities, some valuable insights have been uncovered. Generally, the higher degree centrality, betweenness centrality, eigenvector centrality, and PageRank of port communities, the greater the resulting disruption. In contrast, closeness centrality and clustering coefficient have relatively minor impacts on disruptions.

The insights gained from the comparative analysis of disruptions could be used to evaluate the resilience of other regional networks or applied to different types of shipping networks, such as short-sea shipping or inland waterway systems. For example, the identification of high-centrality nodes as disruption-prone hubs could help policymakers prioritize investments in infrastructure upgrades or redundancy planning for ports playing pivotal roles in the network. Additionally, these findings could be useful for designing hybrid shipping systems where disruptions at maritime hubs directly impact rail and road freight systems, helping to identify critical nodes and mitigate cascading failures. This approach could also support the development of global contingency models, ensuring the lessons learned in one network can inform resilience strategies in others.

(5) Resilience assessment

In this thesis, resilience is quantified as the ratio of actual transported flow after disruption to the normal transportation flow within the network. Thus, the resilience of the network is predominantly influenced by several key factors.

First, the duration of disruption at the affected port plays a critical role. In the model, a disrupted port completely loses its operational functionality, preventing cargo from being loaded or unloaded. As the disruption persists, cargo backlogs intensify, prolonging recovery time, as demonstrated in Figure 5.13(b). Additionally, extended disruptions lead to an increase in the number of waiting vessels, further delaying the restoration of normal network operations.

Second, vessel behavioural responses during disruption significantly impact resilience. Following a disruption, vessels can adopt one of three strategies: (1) waiting at the disrupted port, leading to cargo accumulation; (2) skipping the port, which results in cargo loss; or (3) rerouting to an alternative port, ensuring cargo is still transported. The simulation results indicate that a higher proportion of vessels opt to wait, causing substantial congestion at the affected ports. Since skipping results in permanent cargo loss and rerouting requires complex logistical coordination, waiting is often the preferred choice in real-world scenarios, further exacerbating congestion at the disrupted port.

Third, throughput capacity and recovery strategies of both directly and indirectly affected ports determine the overall recovery trajectory. If all affected ports resume operations simultaneously, the port with the highest throughput becomes the dominant factor in resilience recovery. However, under sequential recovery, indirectly affected ports cannot restore operations until the directly affected ports regain functionality. If a directly affected port has a significantly lower throughput than the indirectly affected ports, the rapid recovery period will be prolonged until the accumulated cargo at indirectly affected ports is processed.

The sharp resilience recovery observed in Figure 5.10(b), when the recovery rate reaches 1.2 can be explained by these factors. In that simulation, the disruption period lasts six days, with recovery ratios set at 0.5, 0.8, and 1.0 on the first three recovery days, followed by 1.2 from the fourth day onward. The waiting and rerouting probabilities are both set at 0.3, while the skipping probability is 0.4. Additionally, as indicated in Figure 5.12, the directly affected port has the highest throughput, and a separate recovery strategy is applied. At the onset of the recovery phase, the affected port must first clear the backlog of waiting vessels before normal operations can resume. By the fourth recovery day, when the recovery rate reaches 1.2, the accumulated cargo backlog has been processed, leading to a sharp increase in resilience.

In conclusion, port network resilience is governed by multiple interrelated factors, including the duration of disruption, vessel behavioural responses, recovery strategies, and port throughput capacity. These factors collectively shape the recovery process regardless of the specific port community in which the disruption occurs.

5.4 Summary

5.4.1 Contributions

The GCSN plays a critical role in the world economy by enabling the efficient movement of cargo across international boundaries. Studying this network is essential for understanding its dynamics and vulnerabilities, optimizing logistics and transportation strategies, and developing robust responses to disruptions. Enhancing the resilience and efficiency of the GCSN contributes significantly to the stability and sustainability of global trade, benefiting economies and societies globally. A comprehensive literature review highlights notable gaps in existing research, particularly in the construction of shipping network models (e.g., network modelling and port community detection) and resilience evaluation (e.g., advanced disruption simulation techniques). To address these gaps, this study proposes a novel resilience assessment framework for the GCSN, incorporating an enhanced simulation model and analyzing resilience from the perspective of port communities. The key contributions of this research are outlined below.

First, an enhanced simulation model is designed to assess the resilience of the GCSN by integrating cascading failure and recovery mechanisms. The model incorporates detailed ship behaviors in response to disruptions, such as waiting, rerouting, and skipping, while introducing a temporal dimension to track the evolution of the GCSN over time.

Furthermore, to effectively partition the GCSN into groups of tightly connected nodes and model it as a directed and weighted network, the Infomap algorithm was employed for community detection. This method accounts for transportation direction, capacity, and distances between ports, enabling the identification of cohesive port communities within the GCSN. The algorithm optimizes the port community structure by leveraging port connections, transportation flows, and geographical proximity. Utilizing container ship movement data from 2017 to 2023, a novel port community structure was detected within the GCSN. This structure not only retains the network's scale-free and small-world properties but also achieves a more decentralized and balanced configuration, enhancing its resilience and analytical clarity.

Based on the enhanced simulation model and analysis from the perspective of port community, key academic insights are obtained, which have been concluded in Section 5.3.4. in addition, practical suggestions can be generated as follows.

5.4.2 Practical Suggestions

The practical recommendations presented in this section are intended for a range of key stakeholders involved in maritime and port operations. These include national and regional governments, port authorities, logistics and shipping companies, infrastructure planners, and emergency response agencies. Each recommendation is associated with specific stakeholder responsibilities and decision-making roles, aiming to provide actionable strategies to enhance the long-term resilience of the global shipping network.

(1) Infrastructure Investment and Contingency Planning

a. Critical Node Prioritization

Targeted investments in structurally important ports can reduce the risk of cascading disruptions throughout the network. Ports with high degree, betweenness, PageRank, and eigenvector centrality should be prioritized for resilience infrastructure investments and contingency planning due to their structural importance in the network. For example, ports like Singapore, Rotterdam, or Shanghai may serve as priorities due to their connectivity and cargo throughput.

It is crucial to establish a systematic and comprehensive framework for resource allocation to alternative or next-route ports. For instance, investments targeted at ports within a 300 km radius of high-centrality nodes can facilitate effective load balancing during disruptions, thereby enhancing network resilience.

The types of resources required for such investments differ according to the stakeholders involved. For example, governments and port authorities can allocate financial resources to support infrastructure enhancements, such as expanding terminal capacity, modernizing equipment, and constructing additional storage facilities to manage cargo overflow effectively. Additionally, they can establish regulatory frameworks to streamline resource deployment during disruptions. In contrast, logistics and shipping companies can contribute operational resources, including workforce allocation, logistical planning, and supply chain optimization, to mitigate the cascading impacts of port disruptions.

b. High-Throughput Community Strategies

Another key aspect is the management of throughput concentration across port communities. Port authorities should avoid overdependence on individual ports by ensuring that no single port's throughput exceeds the capacity of surrounding ports by more than an order of magnitude. For instance, if a port handles ten times the cargo volume of its nearby counterparts, its failure could overwhelm alternative ports, triggering cascading network disruptions. Allocating infrastructure investments to balance throughput among regional ports can mitigate this risk and reduce overdependence on a single hub.

Port authorities should also map high-throughput communities and implement decentralized routing systems. For example, within a community containing Ports A, B, and C, alternative routes can be optimized to maintain cargo flow in case one of the ports fails.

Additionally, logistics firms should establish pre-negotiated collaborative routing agreements with ports. These agreements would allow for seamless adjustments to alternative routes during disruptions, minimizing delays and maintaining supply chain continuity.

(2) Recovery Strategies

a. Simultaneous Recovery

For failed ports, port authorities should try to collaborate with interconnected regions to implement simultaneous recovery strategies where resources allow.

Recovery protocols for high-throughput regions should prioritize interconnected nodes within the network. For example, repairing key facilities simultaneously across ports within a regional cluster, such as Mediterranean ports, can help mitigate cascading effects.

To facilitate rapid recovery, authorities can designate rapid-response recovery teams equipped with shared resources, such as emergency cranes or barges, stationed near critical port clusters.

b. Sequential Recovery

When resources are constrained, and sequential recovery is the only viable option, priority should be given to restoring ports with high throughput and strong connectivity. This approach minimizes cascading effects and accelerates network stabilization.

Developing decision-making tools that evaluate recovery timelines, resource availability, and economic impacts can help optimize the sequencing of recovery efforts. Such tools can guide decisions on which ports to recover first under resource-limited conditions.

(3) Collaborative and Proactive Measures

a. Collaborative Frameworks

Ports that are geographically or operationally linked should establish mutual aid agreements to share resources and workforce during crises. For example, ports within the North Sea region could collaborate to provide support during disruptions.

Policy-makers should enforce collaboration through regional agreements, such as the European Union’s TEN-T network. These agreements can mandate proactive disruption planning and ensure better coordination among ports.

b. Holistic Resilience Assessment

Port authorities should combine centrality metrics with operational metrics, such as throughput and downtime costs, to develop composite indices for resilience prioritization. For example, a weighted scoring model could be used to rank ports and guide investment or recovery strategies effectively.

(4) Technology-Driven Approaches

a. Real-Time Monitoring and Prediction

Port authorities should deploy AI-driven early warning systems to identify risks such as extreme weather or geopolitical tensions. For instance, satellite data can be integrated to predict cyclone paths and assess their potential impact on ports in Southeast Asia.

Additionally, Internet of Things (IoT)-enabled sensors should be installed in ports for real-time monitoring of terminal congestion and ship delays, enabling timely interventions during disruptions.

b. Data-Driven Decision-Making

Simulation platforms should be used to model specific disruption scenarios and refine emergency response plans. For example, simulating the impact of port closures in East Asia on global shipping networks can provide insights into mitigating potential delays.

Predictive analytics can be employed to optimize resource allocation and determine appropriate stockpile levels at secondary ports, ensuring preparedness for unexpected disruptions.

5.4.3 Limitations and Improvement in the Future

There are certain limitations in this study, which can be improved in the future.

We integrated nearly seven years of vessel movement data into average daily operational data for simulation purposes, which did not account for certain dynamic factors such as seasonal fluctuations, trade volume variations, or technological advancements that alter port interactions. In the future, the dynamic conditions such as the detailed seasons can be included to make it more realistic.

All disruption simulations involved the configuration of multiple parameters. Beyond the distance and capacity tolerance parameters, many other parameters, such as the probabilities of vessel waiting, rerouting, and skipping, were not extensively analysed. Variations in these parameters would inevitably lead to differences in the simulation outcomes. In addition, the feasibility of simultaneous recovery strategies depends on resource availability, which was not explicitly modelled. Thus, adaptive recovery processes that account for evolving conditions during disruptions can be integrated in the future work.

While the simulation model was designed based on real-world cases, such as the disruption at Meishan Port Area in 2021 and the impact of Typhoon Bebinca in 2024, detailed recovery data such as specific waiting times, throughput changes, and operational adjustments during disruptions were not publicly available. As a result, the model could not be directly validated against real-world observations. In the future, collaborations with port authorities or shipping companies could provide access to such data, enabling a more comprehensive validation and refinement of the model.

In terms of the applicability, this analysis focuses on container shipping networks, and the findings may not generalize to other types of maritime or inland transportation systems. Therefore, in the future, the impact on special system such as the inland logistics and multi-modal transport systems, and dynamic conditions such as the detailed seasons can be included.

5.4.4 Chapter Conclusions

In summary, this study proposes an enhanced simulation model based on cascading effects and determines the optimized values of key parameters through experimental analysis, providing a valuable reference for future modelling research. Additionally, this study introduces a new research perspective by analyzing port failures and resilience enhancement strategies from the viewpoint of port communities. This approach broadens the scope of existing research while offering practical recommendations for improving the resilience of the GCSN. Consequently, this study holds both theoretical and practical significance. The model and methods provided and the academic insights could be generalized to other regions or applied to different types of shipping networks.

However, the resilience of ports and port communities remains a complex issue involving multiple factors, making it challenging and meaningful to explore. In the future, several areas warrant further exploration to advance the understanding of shipping network resilience, including 1) the integration of dynamic factors such as seasonal trade fluctuations, geopolitical events, and evolving port capacities; 2) the development of adaptive recovery strategies that account for real-time resource constraints and evolving disruption scenarios; 3) the collaborations with port authorities or shipping companies to obtain realistic data for more comprehensive model validation and refinement; and 4) the examination of interdependencies between maritime, rail, and road networks to create a holistic framework for global supply chain resilience.

Chapter 6 Conclusion and Future work

This chapter restates the main ideas of the thesis, discusses the methodology used, summarizes the goals and findings of each study, identifies the main contributions of the thesis, discusses its limits, and makes suggestions for future research.

6.1 Conclusion

This thesis is divided into six chapters. Chapter 1 has provided an introduction, including the background of resilience study in MTS, the major research gaps and motivation, the research scope and objectives, and the organization of this thesis. Chapter 2 has provided a thorough literature review of resilience research in MTS, including five main parts: infrastructure systems resilience, transportation systems resilience, WTC resilience, port resilience, and shipping network resilience. The definitions, research directions, and assessment methods of each part is presented, and research gaps are summarised in the end. Chapters 3, 4 and 5 are the core chapters of this report, which study the resilience modelling and assessment of WTC, port, and shipping network in MTS, respectively. This subsection will summarize the conclusion of this thesis, which are mainly divided into research contributions and research results.

Recognizing the importance of MTS in the global economy and the significance of resilience research in the current environment of various disruptions, this thesis has undertaken modelling and assessment studies on the resilience of MTS. In terms of research methodology, considering data availability, both data-driven methods and expert opinion extraction are employed. For data that is difficult to obtain, this thesis proposes a new method to extract experts' opinions based on Dempster-Shafer evidence theory and hesitant fuzzy linguistic terms. To establish causal relationships between variables, Bayesian network methods were also investigated. For available data, detailed data cleaning, analysis, and simulation model construction are conducted for different components. Specifically, for shipping networks, a method for detecting port communities based on the Infomap algorithm was proposed. In terms of research application, the three most critical components of MTS were selected for application analysis: WTCs, ports, and shipping networks. The main contributions of these application and analysis can be summarized as follows:

(1) For the WTC resilience study,

- We propose a discrete-event based simulation model to quantify WTC's resilience by collecting the AIS data of the Yangtze Estuary Deepwater Channel. The proposed model could simulate the operation of ships in the specific waterway, which is currently very limited in the literature.

- Based on the simulation model, we design different scenarios to test the system's performance such as ship delay and ship load. Based on the analysis of experiment results, several practical suggestions are provided for stakeholders, which could be useful for WTC's risk management.
- By taking ship load, ship delay and recovery cost into consideration, we propose a composite resilience indicator to help managers design rescue plan. Based on a real accident, we design different scenarios (rescue plans) for comparations, and the simulation results shows the effectiveness of the new indicator.

(2) For the port resilience study,

- A circular four-stage method is proposed to study port resilience, in which a port resilience assessment model using the Bayesian network is proposed. The novelty of this model is that we use six metrics (robustness, redundancy, visibility, flexibility, agility, recovery) to categorize resilience strategies and assess resilience capabilities (readiness and response), which can be employed to facilitate port managers to distinguish different strategies' specific functions and effectiveness and optimize strategy implementation.
- The major disturbances that are currently affecting ports are summarized.
- The Shanghai Yangshan Deepwater Port in China is used as the case study to exemplify the quantification of port resilience. Sensitivity analysis provides validation and detailed comparations of the effect of resilience strategies and metrics on resilience capacities. Forward and backward inferences identify different pathways to achieve a resilient port system. Three conclusions of the case study can be concluded as follows: 1) Natural disasters are major disruptors plaguing ports; 2) The overall resilience of automated terminals is higher than that of non-automated terminals; 3) All of these resilience strategies are important in enhancing port resilience. However, strategies to enhance visibility such as building real-time data management systems are the most important in terms of improving the readiness of ports; strategies to enhance recovery such as facility restoration are the most important to improve the response of ports.

(3) For the shipping network resilience study,

- Based on the Infomap algorithm, considering transportation direction, capacity, and distances between ports, a method for establishing port communities within the shipping network is proposed. This method aims to optimize the port community structure based on port connections, transportation flow between ports, and geographical proximity.
- An enhanced disruption simulation model is designed to assess the resilience of the shipping network by integrating cascading failure and recovery mechanisms. The model incorporates detailed ship behaviors in response to disruptions, such as waiting, rerouting, and skipping, while introducing a temporal dimension to track the evolution of the GCSN over time.
- Analysis of container ship movement data from 2017 to 2023 identified a novel port community structure within the shipping network through the Infomap algorithm. This structure retains the scale-free and small-world properties of the GCSN while becoming more decentralized and balanced, and offers a clearer and more holistic perspective for resilience analysis. Based on the resilience analysis of the GCSN from the perspective of port communities, key academic insights and practical management recommendations are proposed.

Overall, this thesis presents resilience modelling and assessment studies of key components within MTSs. The findings offer practical recommendations for strengthening the resilience of maritime operations, ensuring the system's capability to withstand and recover from disruptions. Moreover, the research methodology provided in this study demonstrates versatility and applicability across various contexts, offering a valuable framework for future investigations into the resilience of complex transportation networks.

6.2 Limitations and Recommendations

6.2.1 Limitations of Current Research and Recommendations for Future Research

In spite of the contributions, this thesis has several limitations that deserve future research.

(1) Limitations of the Waterway Resilience Study

The type of disturbance used in this waterway resilience study is a ship accident (such as ship grounding), which affects the operation of ships in the same lane behind the accident site. In addition to ship accidents (including grounding, collisions, explosions, etc.), there are many other disturbances that can cause similar delay impacts and can be simulated using the proposed model. However, this model currently does not account for the causal connections between various components in the waterway or losses in terms of personnel and economy. Therefore, the simulation model provided is not suitable for simulating all disturbances. Many disturbances, particularly accidents that require consideration of causality, may necessitate other models for comprehensive research.

When designing the rescue plan, we only considered the impact of the number of rescue vessels. We did not take into account the specific behaviours or responses of the stakeholders and the factors that influence their decisions, which may lead to other accidents or improvements. Future work should incorporate these elements to enhance the accuracy and applicability of the simulation model in various disturbance scenarios.

Another area for future work is the integration of real-time data and advanced analytics. By incorporating real-time monitoring and predictive analytics, the model could dynamically adjust to evolving conditions and provide more timely and accurate predictions of disruption impacts and recovery timelines. This could significantly enhance the model's usefulness in practical applications, such as emergency response planning and real-time decision-making.

Furthermore, exploring the effects of different types of rescue operations and their coordination could provide deeper insights into optimizing response strategies. This includes considering the deployment of rescue teams, the use of advanced technologies such as drones and autonomous vessels, and the coordination between different agencies and stakeholders.

Lastly, the model could benefit from a more comprehensive assessment of the long-term economic and environmental impacts of disturbances. This would involve evaluating not only the immediate effects of a disruption but also the downstream effects on supply chains, regional economies, and ecological systems. Such an assessment would provide a holistic view of the resilience of waterways and inform more sustainable and resilient planning and policy-making efforts.

(2) Limitations of the Port Resilience Study

Developing a resilient port system is a priority in planning and developing MTS. However, due to the multi-dimensional characteristics of the port system, it is still difficult to comprehensively measure the properties of this composite system. Although there has never been a consensus on how to measure the resilience of the infrastructure system, we believe that the BN is a promising tool for providing a comprehensive analysis and bringing systemic thinking. However, the use of BN brings limitations in this study. The construction of BN CPTs requires a large amount of data, and when statistical data is lacking, it needs to rely on expert opinions, which brings uncertainty and subjectivity to the model. Furthermore, since infrastructure resilience still lacks a universally accepted benchmark in terms of its measurement and definition, data-driven validation is difficult for the BN model. Nevertheless, the model is validated by sensitivity analysis. Therefore, in the future, ports should focus on the detection and data collection of various facilities, equipment, and resources in the system. In this thesis, we only conduct analysis on the Yangshan port in China. The resilience levels of automated and non-automated ports in other countries or other ports in China remain unknown, which may be closely related to geographic characteristics, social system, economic development, etc. This will be a meaningful topic of future work.

This thesis uses the implementation success of different resilience strategies to evaluate the resilience metrics, and then to measure the overall resilience capacity of the port, which sheds light on the resilience assessment of infrastructure and the sustainable development of MTS. In the future, if the collected data can be more reliable and objective, then resilience assessment can be performed across multiple dimensions and yield more precise information.

Furthermore, future work should explore the integration of real-time data and advanced analytics into the BN models. Incorporating real-time monitoring and predictive analytics could dynamically adjust to evolving conditions and provide more timely and accurate predictions of resilience levels and recovery timelines. This would significantly enhance the practical applicability of the BN models in emergency response planning and real-time decision-making.

(3) Limitations of the Shipping Network Study

We integrated nearly seven years of vessel movement data into average daily operational data for simulation purposes, which did not account for certain dynamic factors such as seasonal fluctuations, trade volume variations, or technological advancements that alter port interactions. In the future, the dynamic conditions such as the detailed seasons can be included to make it more realistic.

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In terms of the applicability, this analysis focuses on container shipping networks, and the findings may not generalize to other types of maritime or inland transportation systems. Therefore, in the future, the impact on special system such as the inland logistics and multi-modal transport systems, and dynamic conditions such as the detailed seasons can be included.

By addressing these limitations and pursuing these future research directions, the resilience and efficiency of the shipping network can be significantly enhanced, contributing to the stability and sustainability of global trade and benefiting economies and societies worldwide.

6.2.2 Recommendations for Industry Applications

To address the above limitations and improve the real-world application of MTS resilience research, the following recommendations are proposed for industry applications. These recommendations are categorized into policy, infrastructure, and operational strategies.

(1) Policy Recommendations

a. Develop Comprehensive Resilience Standards

Establishing international resilience standards for ports and shipping networks through collaboration with organizations such as the International Maritime Organization (IMO) would provide a uniform framework for assessing and enhancing resilience. These standards should include performance metrics for recovery times, response capabilities, and infrastructure robustness.

For instance, ports could be required to conduct periodic resilience audits that evaluate their infrastructure readiness, cybersecurity frameworks, and emergency response systems. Such audits would ensure compliance with globally recognized benchmarks and facilitate coordinated responses across the industry.

Such standards would primarily benefit international regulatory bodies and national maritime authorities by enabling performance benchmarking and facilitating harmonized response mechanisms across jurisdictions, thereby improving the global coordination of maritime resilience strategies.

b. Encourage Investments in Resilience-Enhancing Technologies

Governments and policymakers should incentivize investments in advanced technologies that enhance resilience, such as digital twins, predictive analytics, and real-time monitoring systems. Financial mechanisms, including tax credits, grants, and subsidies, can accelerate the adoption of these technologies.

For example, subsidies could be provided to ports that implement Artificial Intelligence (AI)-based traffic management systems capable of optimizing cargo flow during disruptions, thereby minimizing delays and operational inefficiencies.

By targeting public-sector agencies and port operators, such investment incentives can accelerate technology uptake, enhance operational adaptability, and reduce the economic impact of unforeseen events.

c. Mandate Regular Risk Assessments

Policymakers should require ports and shipping companies to perform regular, comprehensive risk assessments that consider vulnerabilities to various threats, including natural disasters, cyberattacks, and supply chain disruptions. These assessments should identify critical risks and outline mitigation strategies tailored to specific operational environments.

For instance, ports handling large cargo volumes could be mandated to conduct annual cybersecurity audits to protect against ransomware attacks and data breaches, which have become increasingly prevalent in recent years.

This recommendation supports both regulatory agencies and private sector operators by institutionalizing proactive risk management, ultimately strengthening system-wide resilience and minimizing downtime during adverse events.

(2) Infrastructure Recommendations

a. Modernize Port Infrastructure with Smart Technologies

Investment in smart port technologies, including Internet of Things (IoT)-enabled sensors, automated cranes, and AI-driven predictive maintenance systems, can significantly enhance resilience. These technologies enable real-time monitoring of critical systems, early detection of potential failures, and efficient allocation of resources during disruptions.

For example, the Port of Rotterdam has successfully put IoT platform into operation, allowing for predictive maintenance that reduces the risk of structural failures.

These technologies are particularly valuable for port authorities and infrastructure planners, as they enable data-driven asset management and more agile operational responses, ultimately enhancing overall port resilience.

b. Strengthen Physical Infrastructure to Withstand Disasters

Disaster-resilient infrastructure, such as elevated port facilities, reinforced seawalls, and robust drainage systems, should be prioritized to mitigate the impacts of extreme weather events.

As demonstrated by the Port of New York and New Jersey, which invested in flood defenses and elevated infrastructure following Hurricane Sandy, such measures can significantly reduce recovery time and operational disruptions caused by severe weather.

Such measures are crucial for government infrastructure agencies, port engineering teams, and long-term urban planners, as they reduce recovery time, limit economic losses, and safeguard critical logistics hubs in increasingly volatile climatic conditions.

c. Establish Redundant Systems for Critical Operations

Ports should develop redundancy in critical systems, including backup power supplies, communication networks, and cargo-handling equipment, to ensure continuity during failures or disruptions.

For example, installing redundant communication networks and backup power generators can help ports maintain functionality during power outages or cyber incidents.

This recommendation primarily benefits port operators and facility managers by enhancing operational continuity, minimizing vulnerability to disruptions, and supporting faster recovery under adverse conditions.

(3) Operational Recommendations

a. Implement AI-Powered Decision Support Systems (DSS)

AI-driven DSSs should be adopted to optimize decision-making during disruptions. These systems can provide real-time recommendations for rerouting vessels, adjusting cargo schedules, and managing recovery operations.

For example, Maersk has deployed AI tools to optimize container rerouting during port congestion and extreme weather, which has minimized delays and operational costs.

This approach is particularly relevant for shipping companies, terminal operators, and logistics coordinators, as it enhances decision-making efficiency, reduces operational delays, and lowers overall disruption costs.

b. Enhance Workforce Training on Resilience Practices

Regular training programs should be implemented to ensure that port operators, logistics managers, and emergency responders are well-equipped to handle disruptions. Training content should include risk assessment, disaster response protocols, and the use of advanced technologies, such as blockchain and AI tools.

Certification programs in resilience management can further professionalize the workforce and enhance their ability to implement effective recovery strategies.

This recommendation addresses the needs of human resource departments, maritime training institutions, and operations managers by enhancing human capital, fostering resilience-oriented mindsets, and ensuring consistent and competent responses across the workforce.

c. Leverage Blockchain for Supply Chain Transparency

Blockchain technology can be utilized to create secure, tamper-proof records of cargo movements, contracts, and operational data. This improves transparency and coordination across the supply chain, reducing recovery times and operational inefficiencies.

The Port of Antwerp, for example, has implemented blockchain-based systems to streamline customs processes and improve cargo tracking, which has enhanced both resilience and efficiency.

This measure is especially beneficial for supply chain stakeholders—including port operators, customs authorities, and shipping firms—as it improves data integrity, reduces processing delays, and strengthens supply chain visibility in crisis situations.

Addressing the limitations identified in this thesis and implementing the proposed recommendations will significantly enhance the resilience of MTSs. By advancing global policy frameworks, investing in smarter and more sustainable infrastructure, and optimizing operational practices, the industry can build a robust and adaptive system capable of withstanding diverse disruptions. These measures will not only safeguard global trade but also contribute to the long-term sustainability and stability of the maritime industry.

6.3 Future Work

MTSs are exceedingly complex, and this thesis primarily studies them from the perspective of key infrastructure. However, beyond being a foundational operational infrastructure, MTSs also involve various companies, enterprises, and regulatory bodies. Additionally, MTS operations are intricately linked with inland connections. Therefore, the following points outline the future research directions I intend to pursue:

(1) Integration of Organizational Dynamics: Investigate the roles and interactions of companies, enterprises, and regulatory bodies within and beyond MTSs. This includes studying their influence on operational resilience and efficiency.

(2) Multimodal Transport: Explore the interdependencies between MTSs and inland logistics. This research will focus on how disruptions in one part of the network affect the overall system, and develop models that integrate maritime, rail, and road transport systems to create a seamless multimodal transport network. This will involve studying the interactions and dependencies between different transport modes and optimizing the flow of goods across these modes.

(3) Regulatory and Policy Impact: Assess the impact of regulations and policies on the resilience and efficiency of MTSs. This includes evaluating current policies and proposing new frameworks to enhance system resilience.

(4) Technological Advancements: Examine the role of emerging technologies, such as digitalization, automation, and artificial intelligence, in improving the resilience and efficiency of MTSs.

(5) Human Factors and Workforce Dynamics: Study the impact of human factors and workforce dynamics on the resilience and efficiency of MTSs. This research will consider training, labour conditions, and the role of human decision-making in system operations.

Based on the above, two detailed topics are introduced as follows.

(1) A System Dynamic Model Analysis of Port Resilience and Urban Sustainable Development

As the heart of the MTS, linking the MTS to the urban transportation system, ports are tied to cities' development. As Hoyle and Hilling (1984) conclude, "the port is, therefore, both a cause and a result of development". As technology, trade, and cultural imports come through the port, all can and do serve as mechanisms for urban and regional growth; either as the result of the ever-increasing spatial requirements directly related to the port activities, or through accumulated growth whose urban germination begins with the central port function. Today, the heterogeneous elements brought together at the port include: core and propulsive industries (port infrastructure, services, operations); dependent industries (maritime industry, freight traffic); functionally-linked industry (freight-forward agents, ship building and repairs); and, marketing industries related to the export sector (warehousing, distribution, banks, insurance companies, light manufacturing), along with the associate spatial agglomeration regional impacts and ancillary activities that grow up around these core industries.

Therefore, I want to develop a system dynamic model to simulate the dynamic relationship between the port and various industries in the city. Based on the proposed model, the effectiveness of resilience strategy/policies/investment of port and city can be evaluated.

(2) Resilience Analysis and Modelling of Maritime Supply Chain Network

With the fast development of maritime transportation, maritime supply chains become one of the largest complex networks in the world. Random failures and deliberate attacks on a single element (node or edge) in the network may cause a cascading breakdown of the whole system. Thus, the maritime supply chain network analysis is important as it can identify the key nodes in the network and evaluate and explore the property of the entire network and structure. However, the current research on the network analysis focus on the topology features and network structure, while the infrastructure attributes (shipping line and types) and functional attributes (economic, political value of port attachments) have been little explored. In addition, resilience analysis and modelling for maritime supply chains networks is lacking.

Therefore, I want to combine complex network theories and methods, including social network analysis and system simulation, to explore the resilience performance of maritime supply chain network, and develop methods to quantify, detect, and mitigate cascading consequences of attacks.

By addressing these areas, future research will provide a more comprehensive understanding of MTSs, considering not only their infrastructure but also the organizational, regulatory, technological, economic, environmental, and human dimensions that contribute to their overall resilience and efficiency.

6.4 Interdisciplinary Collaborations for Advancing Resilience Modelling

The complexity of disruptions in MTS, along with their cascading effects, necessitates resilience models that draw on expertise from multiple disciplines. Interdisciplinary collaborations provide the opportunity to integrate specialized knowledge, tools, and methodologies into resilience research, thereby improving the accuracy and effectiveness of modelling efforts. This section outlines key areas for interdisciplinary collaboration and their potential contributions to advancing MTS resilience modelling.

(1) Collaboration with Data Science Experts

Data science is critical for resilience modelling, as it provides the tools and methodologies necessary for processing and analysing large volumes of data. Collaborating with data scientists can improve the analytical depth and predictive capabilities of resilience models in the following ways.

a. Enhanced Data Analysis and Insights

Real-Time Monitoring: The integration of IoT devices and real-time monitoring systems can enable the collection of live data on disruptions, vessel movements, and recovery timelines. This allows for dynamic updates to resilience models.

Predictive Analytics: Machine learning algorithms can improve the accuracy of disruption forecasts, enabling pre-emptive strategies to mitigate potential impacts.

Anomaly Detection: Automated systems can identify irregularities in port and shipping operations, such as delays, equipment malfunctions, or weather disruptions, thereby reducing response times.

b. Optimization of Simulation Models

Large-scale datasets can be used to refine model parameters and calibrate resilience simulations to reflect real-world scenarios more accurately, such as cascading failures in shipping networks.

Techniques such as Natural Language Processing (NLP) can extract valuable insights from unstructured textual data, including incident reports and expert opinions, to enhance decision-making frameworks.

c. Development of AI-Driven Decision Tools

AI tools can assist stakeholders in real-time decision-making by generating optimal strategies for responding to disruptions, balancing economic, environmental, and operational trade-offs.

(2) Collaboration with Environmental Scientists

The resilience of MTS is closely tied to environmental factors, as ports and waterways are highly vulnerable to climate-related events and ecological challenges. Environmental scientists can contribute to resilience modelling in the following ways:

a. Risk Assessment for Natural Disruptions

Environmental models can simulate the impacts of extreme weather events, such as hurricanes, tsunamis, and rising sea levels, on port operations and infrastructure.

Long-term forecasting of climate-related disruptions can inform the planning and design of more resilient port systems and shipping networks.

b. Sustainable Recovery Planning

Environmental scientists can help develop recovery plans that prioritize ecological sustainability, such as restoring biodiversity and mitigating the environmental impacts of oil spills and other maritime accidents.

They can also assess the long-term ecological consequences of disruptions, providing insights for balancing economic recovery with environmental preservation.

(3) Collaboration with Social Scientists and Economists

Resilience is not solely a technical challenge; it also involves human and economic factors that influence system recovery. Social scientists and economists can provide critical insights in the following areas.

a. Stakeholder Behaviour Analysis

Social scientists can study the decision-making processes and recovery behaviours of key stakeholders, such as port operators, government agencies, and shipping companies, during disruptions.

Incorporating human behaviour models into simulations can improve the accuracy of resilience assessments by accounting for factors such as compliance, communication delays, and logistical constraints.

b. Assessment of Socio-Economic Impacts

Economists can evaluate the broader economic consequences of disruptions, including their effects on global trade, regional economies, and supply chains.

They can also help design cost-effective recovery strategies that optimize the trade-offs between operational efficiency and economic sustainability.

c. Community Resilience Planning

Collaborative efforts can focus on mitigating the social and economic impacts of disruptions on communities adjacent to ports, especially those heavily dependent on maritime trade. This involves developing strategies to ensure the equitable distribution of recovery resources.

(4) Partnerships with Engineers and Technology Innovators

Engineering expertise and technological innovation are crucial for enhancing the physical and operational resilience of MTS. Collaborations with engineers and technology developers can provide the following contributions.

a. Infrastructure Engineering

Structural engineers can evaluate and improve the robustness of port and waterway infrastructure to withstand natural disasters, accidents, and other disruptions.

Advanced simulation models can be developed to understand how infrastructure failures cascade across interconnected systems within MTS networks.

b. Automation and Robotics

The deployment of autonomous vessels, drones, and robotic systems can accelerate damage assessment and recovery operations.

These technologies can also be integrated into resilience models to evaluate their effectiveness in various disruption scenarios.

c. Digital Twin Development

Collaborations with technology developers can lead to the creation of digital twins of MTS infrastructure, enabling real-time testing and prediction of disruption scenarios in a virtual environment. Digital twins can serve as powerful tools for decision-making and resilience planning.

(5) Collaboration with Policymakers and Legal Experts

Policy and legal frameworks are essential for institutionalizing resilience measures and ensuring regulatory compliance. Policymakers and legal experts can contribute in the following ways.

a. Regulatory Compliance

Legal experts can help ensure that resilience models align with international maritime laws and conventions, facilitating regulatory compliance.

This alignment can also promote global standards for MTS resilience, ensuring consistency in how disruptions are managed across different jurisdictions.

b. Policy Impact Analysis

Collaborations can assess the effects of existing policies, such as environmental regulations or trade agreements, on the resilience of MTS. These insights can inform the development of more effective policies.

c. Development of Incentive Mechanisms

Policymakers can design incentives, such as subsidies or tax breaks, to encourage investments in resilient infrastructure and advanced technologies by MTS stakeholders.

(6) Academic Collaboration on Multidisciplinary Research

Academic institutions are uniquely positioned to drive interdisciplinary research and foster collaboration among diverse fields. Universities and research institutions can contribute through the following initiatives.

a. Interdisciplinary Research Centres

Establishing research centres that integrate expertise in maritime studies, data science, engineering, environmental science, and social science can facilitate the development of innovative resilience frameworks.

b. Collaborative Ph.D. Programs and Funding

Universities can create doctoral programs that train researchers to work across disciplines, equipping them with the skills needed to address complex challenges in MTS resilience.

Securing funding for multidisciplinary research projects can further accelerate advancements in resilience modelling.

(7) Conclusion

Interdisciplinary collaborations are indispensable for addressing the multifaceted challenges of resilience in Maritime Transportation Systems. Partnerships with data scientists, environmental scientists, social scientists, engineers, and policymakers can enhance the precision, applicability, and impact of resilience models. By leveraging diverse expertise, it is possible to develop robust, data-driven, and human-centered solutions that ensure MTS can adapt to disruptions, recover efficiently, and continue supporting global trade sustainably.

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