

RISK-BASED RESILIENCE ANALYSIS AND OPTIMISATION FOR MULTIMODAL CONTAINER PORTS

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Abstract

Multimodal container ports are critical nodes in global supply chains. As disruptions caused by extreme weather, equipment failures, congestion, public health events, and other uncertainties become increasingly frequent, maintaining the operational resilience of ports has become a major challenge for both industry and academia. Due to the tightly coupled nature of port operations, disruptions occurring in one subsystem may propagate to the others and trigger ripple effects, thereby generating indirect losses that can exceed the direct consequences of the initial disruption. However, most existing studies conceptualise ports as single nodes within broader transport networks, and thus fail to capture the internal operational complexity of multimodal container ports, limiting the accuracy and practical value of their implications for resilience management.

This research aims to develop a holistic resilience-oriented framework for multimodal container ports that explicitly considers micro-level operational processes, subsystem interdependencies, and ripple effects in the event of disruption. The framework is designed to support resilience management across the preparedness, response, and recovery stages. To achieve this, the research first develops a System Dynamics (SD) simulation model to represent the operational processes of five interconnected subsystems, namely liner shipping, feeder shipping, railway, trucking, and container yards, and to analyse how disruptions of different types and magnitudes propagate through the port system. Based on the simulated time-dependent performance of the port, a resilience assessment framework is then established by combining an improved resilience quantification method with Evidential Reasoning (ER) to evaluate resilience across multiple transport modes and Key Performance Indicators (KPIs). Building on these results, a Sobol-based Global Sensitivity Analysis (GSA) framework is proposed to identify the critical disruptions and their interactions that most strongly influence overall port resilience. Finally, focusing on large equipment failures, an Opportunistic Maintenance (OM) optimisation model is developed to determine maintenance strategies that jointly balance cost and expected port resilience.

Using real-world operational, accident, and maintenance data from one of the top 30 container ports in the world, extensive numerical experiments were conducted to assess the performance of the proposed models. The findings confirm that the models can effectively and reliably capture ripple effects, quantify resilience across

different disruption scenarios, identify critical risk factors together with their combined effects, and provide decision support for resilience-oriented maintenance planning.

The techniques and models developed in this thesis provide useful insights and valuable implications for port resilience management from both theoretical and practical perspectives. From a theoretical perspective, this research advances port resilience studies from a predominantly network-level to a micro-level, operationally grounded perspective. It also establishes an integrated methodological framework that links dynamic simulation, resilience quantification, uncertainty analysis, and resilience enhancement coherently. From a practical perspective, the proposed methodology can be applied to any container port with a multimodal transport structure. It provides port operators, policymakers, and other multimodal transport stakeholders with a systematic, evidence-based tool to understand disruption mechanisms, assess resilience, prioritise critical risks, and design effective recovery strategies. Key findings demonstrate that quay crane and yard crane failures generate the strongest cross-subsystem impacts, with the yard being the most vulnerable area and congestion producing widespread ripple and lagging effects across port operations. Traffic congestion further disrupts liner, feeder, and railway operations through the linking role of internal trucking, while yard-side disruptions can propagate throughout the entire port system. GSA identifies liner quay crane disruptions as a dominant determinant of overall resilience and reveals that several individually moderate factors can generate substantial interaction effects under compound disruptions. Finally, opportunistic maintenance provides the greatest resilience benefits for deep water quay cranes, whereas additional maintenance of rail gantry and yard cranes often incurs higher costs without comparable resilience improvements. More broadly, this research contributes to enhancing the stability and sustainability of multimodal transport systems and the wider Container Supply Chains (CSCs).

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Abbreviations

Abbreviation	Full form
ABM	Agent-Based Modelling
AGV	Automated Guided Vehicle
AHP	Analytic Hierarchy Process
AIS	Automatic Identification System
ANOVA	Analysis of Variance
APC	Arbitrary Polynomial Chaos
BN	Bayesian Network
CBM	Condition-Based Maintenance
CM	Corrective Maintenance
CPPI	Container Port Performance Index
CPT	Conditional Probability Table
CSC	Container Supply Chain
CV	Coefficient of Variation
DAG	Directed Acyclic Graph
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DES	Discrete-Event Simulation
DoB	Degree of Belief
DS	Dempster-Shafer
ER	Evidential Reasoning
FAST	Fourier Amplitude Sensitivity Test
FAST-RBD	Fourier Amplitude Sensitivity Test with Random Balance Design
FMEA	Failure Mode and Effects Analysis
FRE	Functional Ripple Effect
FTA	Fault Tree Analysis

GCSN	Global Container Shipping Network
GSA	Global Sensitivity Analysis
ICC	Intraclass Correlation Coefficient
IT	Information Technology
KPI	Key Performance Indicator
LHS	Latin Hypercube Sampling
LSA	Local Sensitivity Analysis
MAPE	Mean Absolute Percentage Error
MCDM	Multi-Criteria Decision Making
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MLP	Multilayer Perceptron
NHPP	Non-Homogeneous Poisson Process
OAT	One-at-a-Time
OM	Opportunistic Maintenance
PAWN	Probabilistic Analysis for Non-linear propagation of WAVEforms under Non-parametric approach
PCE	Polynomial Chaos Expansion
PLE	Personal Learning Edition
PM	Preventive Maintenance
PN	Petri Net
RBF	Radial Basis Function
RSA	Regional Sensitivity Analysis
SA	Sensitivity Analysis
SCRM	Supply Chain Risk Management
SD	System Dynamics
SI	Sensitivity Index/Sensitivity Indices

SRE	Structural Ripple Effect
SVR	Support Vector Regression
TEU	Twenty-foot Equivalent Unit
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UQ	Uncertainty Quantification

CHAPTER 1 INTRODUCTION

This chapter provides an overview of the research background and practical motivations for developing a resilience framework for multimodal container ports. It then identifies the key research gaps, necessities, and methodological challenges that motivate this study. Based on these gaps and challenges, the research aims and objectives are formulated, followed by a summary of the main academic and practical contributions. Finally, the research scope and thesis structure are presented to clarify the organisation of the thesis and the logical relationships among the subsequent chapters.

1.1 Research background

In recent years, the enhanced accessibility of Container Supply Chains (CSCs) has increasingly opened up international business and trade opportunities in the logistics industry. Seaports, serving as pivotal nodes for container transshipment, emerge as crucial gateways connecting different transportation modes, including rail, road, and sea (Zhou et al., 2022b; Liu et al., 2022). Therefore, the resilience of port operations becomes paramount in maintaining the functionality of entire CSCs in the face of disruptions (Bai et al., 2023). However, ports are characterised by high levels of uncertainty among all parties involved in the CSCs, owing to their susceptibility to diverse risks, such as climate change (Lucio et al., 2024), disease outbreaks, and economic upheavals (Jiang et al., 2021). These events cause significant disruptions to the normal operations of multimodal ports. For instance, in November 2021, severe rainfall in Canada triggered floods and landslides, disrupting terminal functions and causing vessel delays (Wang et al., 2023c). Globally, the outbreak of the COVID-19 pandemic in December 2019 greatly disrupted port operations, causing chaos in warehouses, container reallocation, disruptions to hinterland traffic, and damage to infrastructure, ultimately halting supply chain operability (Gu and Liu, 2023). Additionally, an analytical model has forecast significant financial impacts from port disruptions (Jung et al., 2009). For example, a ten-day shutdown at the Ports of Los Angeles-Long Beach might lead to a daily loss between \$770 million and \$1.3 billion. Moreover, port shutdowns can lead to a cascade of logistical challenges, including vessel bottlenecks, container accumulation, delays in yard operations, and interruptions to hinterland transportation (Hossain et al., 2019).

Due to their unique geographical location and economic significance within the multimodal CSCs, the performance of ports under various disruptions represents a critical bottleneck affecting the overall efficiency (Liu et al., 2023d). As pivotal hubs that link multiple modes of transport for transshipment operations, ports are also susceptible to transferring risk from one transportation mode to another, also known as the “ripple effect” (Verschuur et al., 2022). For instance, port equipment failures could trigger the accumulation of vehicles or vessels, leading to internal congestion that reduces the operational efficiency of other transportation modes and results in overall underperformance (Lu et al., 2024). Previous research has indicated that indirect losses resulting from network effects may surpass direct losses, as evidenced by multiple studies detailed in Table 1.1.

Table 1.1. Indirect and direct costs of illustrative port disruptions.

Risk Type		Affected Port	Direct Damage	Network Damage
Hurricane Katrina 2005 (Trepte and Rice Jr, 2014)	Natural Disaster	Ports near New Orleans	1,833 fatalities; \$108 billion	45% cargo tonnage; \$882 million loss on agriculture; food prices surged
Typhoon Maemi 2004 (Lam et al., 2017)		Northeast Asia ports	107 injured; \$4.8 billion	91 days port close; \$96 million
Hurricane Sandy 2012 (Kunz et al., 2013)		Newark Bay and Upper New York Bay	\$4.2 billion in the Caribbean; \$78-97 billion in the US	Power outages caused \$16.3 billion in indirect losses; \$10.8-15.5 billion in business interruption losses
Tropical Cyclone Debbie 2017 (Lenzen et al., 2019)		Northeast Australian ports	14 fatalities; \$2.67 billion	8487 jobs; AUD 2203 million
Labour strikes 2016-2017 (Gonzalez-Aregall and Bergqvist, 2019)	Man-made	Port of Gothenburg	10%-20% loss of container volume	\$496 million
Cyclone Tauktae 2021 (Chowdhury et al., 2021)	Natural Disaster	APM Terminals Pipavav, India	\$95 million port damage; about 199 deaths	Total \$4.3 billion economic loss; 1.3 million households with power outage; 37 million people affected
The Suez Canal blockage in 2021 (Wan et al., 2023)	combined environmental, hydrodynamic, and operational factors	Suez Canal	The Suez Canal is blocked for 6 days	12% of global seaborne trade; delayed daily cargo flows valued at about 9.6 billion USD; short-term congestion, increased demand for major hub ports in Asia and Europe
Ransomware Attack, Japan in 2022 (Toulas, 2023; Venkat, 2023)	Man-made	Port of Nagoya, Japan	The Nagoya port unified terminal system is compromised; operation was disrupted for 2 days	12% of global seaborne trade; delayed daily cargo flows valued at about \$9.6 billion
US labour strikes 2024 (Sainato, 2024)	Man-made	East and Gulf Coast ports	36 ports along the US East and Gulf Coasts; \$3.7 billion	up to \$5 billion per day; \$2.1 billion trade per day at risk

Beyond these external vulnerabilities, the ports' core transshipment function further increases their internal instability. By linking multiple transport modes, including liner and feeder shipping, rail, and trucking, ports operate as tightly coupled systems in which disturbances in one mode can propagate to others (Zhang et al., 2025b). This high level of interconnectivity allows disruptions in a single subsystem to cascade throughout the entire network, amplifying operational instability and generating ripple effects across multiple transport modes, as evidenced by the previous studies in which the indirect damages caused by the ripple effects of such disruptions frequently exceed the direct losses (Bai et al., 2022). Due to the high connectivity of port systems, the rapid propagation of risks, and the extensive consequences they entail, incorporating the ripple effect into port resilience research is a crucial yet underexplored area in existing literature (Dolgui and Ivanov, 2021; Jiang et al., 2024b). Therefore, in this study, disruptions refer to an event that compromises the port operation functionality, potentially affecting other interconnected components within the port (Tsoulfas, 2025).

In contrast to other metrics employed to assess systems' responses to disruptions, the concept of resilience provides a holistic representation of the system's ability to remain reliable, robust, and recoverable (Gonçalves and Ribeiro, 2020). Consequently, resilience has become widely recognised, particularly in the maritime field, where it is often measured by performance over time (i.e., the resilience triangle as shown in Figure 4.2) (Wan et al., 2019b). Previous studies defined resilience through three fundamental criteria: (i) a gradual degradation process (i.e., a low rate of performance degradation), (ii) a swift restoration process (i.e., a high rate of performance restoration), and (iii) satisfactory performance throughout the observation timeframe (Cheng et al., 2022). However, existing research still lacks a clear, scientifically rigorous definition of an individual port's resilience under disruptions. A detailed comparative analysis of the relevant definitions and approaches is provided in Chapter 2.

Therefore, given the substantial indirect impacts caused by ripple effects, it is crucial to develop appropriate approaches that: (1) recognise the multimodal structure of ports and are capable of capturing how internal equipment and operational processes respond under disruptions; and (2) provide a methodological framework to evaluate both the overall resilience of a port and the resilience of its different subsystems under various disruptions. Building upon a clear definition of port resilience, the resulting analysis should support decision-

making both before and after disruptive events: (3) before disruptions, it should identify the significant resilience-influential factors facilitating the reduction of disruption likelihood and frequency; (4) after disruptions occur, it should provide guidance for implementing efficient and effective measures to restore port resilience. By integrating the above models into a coherent framework, it becomes possible to derive insights and practical recommendations for the operation and management of ports with multimodal transport systems. Such a framework supports efforts to mitigate risks, prevent disruptions, and restore port resilience following a wide range of disruptive events.

1.2 Research necessities and methodological challenges

Based on the research background discussed in Section 1.1, the primary research problem addressed in this study is that many existing studies on port risk and resilience treat ports as nodes within broader transport networks, while neglecting the complexity of internal port operations, which are the actual processes directly impacted by disruptions. This simplification limits the accuracy and practical usefulness of resilience management strategies for ports under disruptive scenarios. From this perspective, several research gaps and methodological challenges can be identified. Accordingly, to address these challenges, this thesis develops four technical models, each designed to address a specific methodological requirement within the overall framework. The necessity and challenges associated with each model are discussed below.

1) Technical model 1: An SD-based multimodal container port simulation model

Understanding port resilience requires capturing how disruptions originate and propagate within complex multimodal port systems. However, several challenges remain insufficiently addressed in the existing literature. Firstly, unlike extensively researched topics such as marine accidents (Shu et al., 2024) and transportation networks (Wang et al., 2023a; Xin et al., 2024), the critical role of ports as multimodal transshipment hubs has not received sufficient attention in the majority of maritime risk and resilience analyses (Almutairi et al., 2019; Verschuur et al., 2022; Nguyen et al., 2022). Secondly, existing literature on port resilience often adopts a macro-level perspective that fails to clarify the relationships among variables related to internal port disruptions (Liu et al., 2023c; Wang and Wang, 2023), resulting in vague and logically inconsistent connections. Therefore, port disruptions should be analysed using micro-level variables defined by explicit cause-and-effect relationships.

87 Although micro-level studies pose more significant challenges in terms of quantitative data requirements and
88 tolerance for data uncertainty, they are essential for the clarity and reliability of research findings. Thirdly,
89 disruptions in multimodal ports not only impact the efficiency of the affected area but also cause substantial
90 indirect impacts on global container shipping (Xiao and Bai, 2022), regional distribution (Cao et al., 2025), port
91 efficiency (Liu et al., 2023c), and supply chain costs (Jiang et al., 2021) through ripple effects, which
92 significantly affect supply chain resilience.

93 Despite their significance, these challenges remain insufficiently explored in the literature. Addressing
94 these issues requires developing a new SD-based simulation model that captures the causal relationships among
95 disruptions within a multimodal port system, using quantitative data from a port-centric perspective. The
96 proposed modelling framework must address the following challenges:

97 1.1) How to represent the operational processes of multimodal container ports and the interactions among
98 different transport modes.

99 1.2) How to use SD to represent the causal relationships among internal port disruptions and their
100 operational impacts using quantitative variables.

101 1.3) How to capture the ripple effects of disruptions propagating across interconnected transport modes
102 and logistics activities.

103 ***2) Technical model 2: A resilience quantification model***

104 The quantification of the resilience of port systems has attracted increasing attention from both academia
105 and industry (Gu et al., 2023; Nguyen et al., 2023; Xin and Yang, 2026; Chen et al., 2025). However, several
106 challenges remain insufficiently addressed in the existing literature. Firstly, as stated before, very few studies
107 on port resilience consider the diversified internal components and thus fail to acknowledge the ripple effects
108 across different transportation modes. Secondly, the state-of-the-art resilience triangle method, used to calculate
109 performance over time, is unsuitable for measuring port resilience because it overlooks crucial criteria. From a
110 port perspective, maintaining satisfactory performance throughout the observation period is critical and should
111 be a primary consideration. Thirdly, port resilience is often assessed using a singular metric, such as handling

capacity (Hossain et al., 2019) and demand fulfilment rate (Asadabadi and Miller-Hooks, 2020). However, given ports' intricate nature and diverse internal structures, a broader range of indicators should be used to evaluate port performance. Along with the challenges associated with measuring these indicators, existing studies provide limited methodological support for integrating heterogeneous performance indicators across different transport modes and hierarchical levels into a unified assessment of port resilience. To address these limitations, it is necessary to develop a resilience assessment method that captures multidimensional port performance across different transportation modes and operational levels. Such a method must address the following challenges:

2.1) How to quantify resilience values based on the operational performance of multimodal container ports across multiple transport modes and hierarchical levels?

2.2) How to develop appropriate indicators that accurately reflect port performance under disruptive conditions?

2.3) How to integrate multiple heterogeneous indicators into a unified framework for quantifying overall port resilience?

3) Technical model 3: An Uncertainty Quantification (UQ) model for critical risk factor identification

Recognising the unpredictable nature of port disruptions establishes a context where decisions to enhance resilience are inherently linked to uncertainty. Within this broad framework, it becomes necessary to evaluate how different uncertainties affect port disruptions and identify key determinants. Consequently, this necessitates the adoption of methodologies to accurately quantify uncertainty and to explain how changes in output (i.e., resilience) can be attributed to inputs (i.e., variability in disruptions). Global Sensitivity Analysis (GSA) is particularly suitable for this purpose, as it explores the entire feasible input space and quantifies each input factor's contribution to the variability of the output. More importantly, it can capture both the individual effects of disruptive factors and their interactions, which is especially important in multimodal container ports, where disruptions are rarely isolated and often propagate through ripple effects across interconnected subsystems.

Although GSA is highly effective for identifying highly influential disruptions, applying it to the context of port resilience introduces additional complexities. The first issue is the underrepresentation of real cases in current datasets, leading to a predominance of unknown disruptive scenarios over known ones. Moreover, due to the complex dynamics and highly nonlinear interactions among all influential factors, which are further compounded by the ripple effect, these interactions remain poorly understood. Furthermore, since different GSA methods originate from fundamentally different philosophies, they may yield varied and inconsistent outcomes when addressing the same issue (Razavi et al., 2021). Therefore, the challenge of addressing these inconsistencies in GSA and accurately measuring the actual impact of disruptions on port resilience remains unresolved. Accordingly, this model seeks to address the following challenges:

3.1) How to evaluate the potential impacts of unprecedented disruptions on port resilience in the absence of sufficient historical evidence?

3.2) How to identify the disruptions and their combined effect that pose the greatest influence on overall port resilience?

3.3) How to ensure the consistency and robustness of the GSA outcomes when assessing the influence of multiple risks?

4) Technical model 4: An opportunistic large equipment maintenance model

As one of the most critical infrastructures in container terminals, the maintenance of large equipment, such as cranes, presents additional complexity compared with conventional maintenance systems due to the strong operational dependencies between them (Garmouch et al., 2025). Take the berth and quay crane as an example. In practice, the berth–crane configuration can be regarded as a series–parallel system (Ebrahim et al., 2022). Multiple quay cranes serve each berth, and the failure of a single crane may interrupt berth operations and require vessels to be reassigned to other berths, a process commonly referred to as berth reallocation (Tian et al., 2024). At the port level, multiple berths operate in parallel, with each berth serving one vessel at a time, while operations across different berths remain operationally independent (Wang et al., 2025c). Existing studies typically incorporate quay crane maintenance into berth allocation and crane scheduling problems, and in some cases, consider disruption-related uncertainties during the planning stage (Vahdani et al., 2024). However, these

studies rarely address maintenance decisions after disruptions have actually occurred. In particular, limited attention has been paid to how maintenance strategies should be adjusted when this large equipment is subject to sudden external disruptions (Yimei et al., 2026). Moreover, in the relatively small body of literature that explicitly examines large equipment maintenance, they are often treated as independent assets (Garmouch et al., 2025). Such assumptions overlook the systemic implications of crane failures and neglect the role of ports as multimodal transshipment hubs. Both empirical evidence and existing studies (Zhang et al., 2025a; Zhang et al., 2025b) show that disruptions in one transportation mode can propagate to others, causing congestion and delays in vessel operations, rail transport, and truck movements. Consequently, large equipment maintenance plays a critical role in shaping the resilience of the entire port transport system. To address these limitations, it is necessary to develop a maintenance optimisation framework capable of capturing the operational dependencies of large equipment and the impacts of their maintenance decisions on port resilience. This modelling task involves the following challenges:

4.1) How to represent the operational dependencies between large equipment within a port terminal system?

4.2) How to incorporate OM decisions triggered by unexpected disruptions into the maintenance scheduling framework?

4.3) How to evaluate maintenance strategies by simultaneously considering operational costs and their impacts on overall port resilience?

Based on the above identified gaps and challenges, the research aims and objectives of this thesis are defined in the following section.

1.3 Research objectives

In response to the gaps and challenges identified in Section 1.2, this thesis aims to develop a holistic framework that explicitly considers interactions among transport modes in multimodal container ports and the resulting ripple effects during disruptions. The proposed holistic methodological framework is designed to support resilience management across all stages of disruption, including the preparedness, response, and recovery phases. Specifically, the framework has the potential to enable port operators to better understand

potential risk impacts on port resilience during the preparedness stage, to assess resilience during the early stages of disruptions, and to implement efficient restoration strategies during the recovery phase. In addition, it provides decision support for addressing indirect impacts of risks, the propagation of disruptions within port systems, and scenarios involving multiple concurrent risks. The developed techniques and models provide practical insights and management recommendations for port operators to manage disruptions directly. They also have broader implications for regional authorities, government bodies, logistics service providers, and other stakeholders, as they indirectly highlight the potential impacts of port disruptions on the wider transport and logistics system. To achieve these, the following subsidiary objectives are identified:

1. To reveal the gaps, limitations, and challenges in the research scope and methodologies of port risk and resilience studies through a systematic literature review.
2. To develop a simulation model that captures: (i) the operational processes of multimodal container ports; (ii) the interactions among different transport modes; (iii) and the propagation of disruptions within the port system under disruptions. (Technical model 1)
3. To establish a resilience assessment framework that quantifies resilience values based on port performance across multiple transport modes and hierarchical levels under different types and magnitudes of disruptions. (Technical model 2)
4. To construct a model for identifying the critical disruptions influencing port resilience, particularly capturing the combined effects of multiple concurrent disruptions arising from the ripple effect. (Technical model 3)
5. To formulate an opportunity maintenance (OM) optimisation model for port equipment under disruptions that identifies maintenance strategies capable of minimising costs while maximising resilience performance. (Technical model 4)

Accordingly, the overall objective of this research is to understand, quantify, prioritise, and improve the operational resilience of multimodal container ports under disruptions through an integrated modelling framework. The analysis focuses on disruption mechanisms and operational consequences within the port boundary, while wider macroeconomic impacts, strategic port competition, and optimisation of the external supply chain are not modelled directly.

1.4 Research contributions

Following the research aims and objectives defined in Section 1.3, this thesis makes several academic and practical contributions to a broad range of stakeholders concerned with port resilience, including port and terminal operators, government and regional authorities, transport service providers, logistics companies, cargo owners, and other supply chain actors. These contributions are organised in relation to the four technical models developed in this research, thereby demonstrating how the proposed framework addresses the identified gaps and challenges.

1) Academic contributions

1.1) Supported by historical records and real operational data, the proposed SD simulation model systematically captures the ripple effects of port disruptions across multiple interconnected transportation modes, including liner shipping, feeder shipping, railway, and trucking. This enables a more comprehensive analysis of how disruptions propagate within multimodal port systems and influence overall operational resilience, and offers a methodological foundation for analysing complex operational interactions under disruptive scenarios. (Technical model 1)

1.2) An innovative resilience calculation method is adopted to refine the conventional resilience measurement approaches commonly used in infrastructure and transportation systems. Unlike traditional methods that primarily focus on either performance degradation or recovery trajectories, the proposed method balances the importance of the rate of performance loss, the speed of system recovery, and the average performance level maintained during the disruption period, aligning with the criteria necessary for a resilient port. (Technical model 2)

1.3) Specific performance indicators are tailored for different transportation modes within the port, and their integration through the ER approach enables a systematic quantification of port resilience under disruption conditions. By incorporating operational performance across multiple interconnected transport modes into a unified assessment framework, this research advances the quantitative evaluation of port resilience and provides a more comprehensive representation of resilience in multimodal port systems. (Technical model 2)

239 1.4) Based on the SD simulation model and the resilience assessment model, GSA is integrated to
240 quantitatively evaluate both the individual and combined effects of disruptive factors on port operational
241 resilience. This integration extends the conventional descriptive simulation-based approach by enabling
242 sensitivity-based resilience analysis, thereby providing a more rigorous quantitative understanding of how
243 disruptions influence port system performance. (Technical model 3)

244 1.5) Empirical probability distributions for disruption factors are constructed based on historical disruption
245 records and observed operational data. To explore the uncertainty space efficiently, Sobol quasi-random
246 sampling is employed to generate disruptive scenarios. Compared with traditional sampling techniques such as
247 Latin Hypercube Sampling (LHS), the Sobol sequence provides a low-discrepancy sampling strategy that
248 distributes sample points more uniformly across the entire parameter space, enabling a more representative
249 exploration of uncertainty scenarios, ensuring that the full range of possible disruptive scenarios is
250 systematically captured. (Technical model 3)

251 1.6) Different sensitivity methods may produce inconsistent sensitivity results for the same model. To
252 enhance the methodological robustness and validation of the results, this study performs cross-validation using
253 three complementary GSA techniques: Sobol, the Fourier Amplitude Sensitivity Test with Random Balance
254 Design (FAST-RBD), and Probabilistic Analysis for Non-linear propagation of Waveforms under a Non-
255 parametric approach (PAWN). Moreover, an Intraclass Correlation Coefficient (ICC) test is conducted to assess
256 the consistency and reproducibility of the Sensitivity Index (SI). This combined verification process ensures
257 that the identified key disruptive factors are stable and method-independent, thereby strengthening the reliability
258 of the GSA results. (Technical model 3)

259 1.7) To enable rapid and efficient quantification of port resilience under different disruptive scenarios, an
260 ML-based approach is introduced to approximate port resilience values. By learning the relationship between
261 disruptive factors and the resilience values generated in technical model 2, the approach significantly reduces
262 the computational burden of repeatedly running complex simulation models. Multiple Machine Learning (ML)
263 algorithms are employed to ensure modelling robustness, and several validation techniques are applied to assess
264 the models' reliability and predictive performance. This approach provides an efficient surrogate modelling tool

265 for evaluating the impacts on system-wide resilience across a large number of disruptive scenarios. (Technical
266 model 4)

267 1.8) A multi-objective optimisation model for OM of quay cranes in container ports that explicitly balances
268 maintenance costs and port-level resilience is proposed. It extends existing studies on maintenance decision-
269 making by integrating port-level resilience into the maintenance decision framework. The proposed model
270 simultaneously considers economic and resilience objectives within a unified optimisation structure. By
271 incorporating real-world operational data, the framework characterises the trade-offs between maintenance cost
272 and resilience performance through Pareto optimisation, thereby advancing methodological resilience-oriented
273 maintenance modelling in complex multimodal port systems. (Technical model 4)

274 1.9) An original resilience evaluation and enhancement framework tailored for ports is proposed for broad
275 application across most multimodal container ports. The framework systematically integrates a sequence of
276 modelling techniques, including an SD simulation model, a reliable resilience measurement method, a multi-
277 indicator aggregation model based on ER, a Sobol-based GSA approach, and an OM optimisation model for
278 quay crane failures. Together, these components form a comprehensive framework that supports resilience
279 analysis and improvement throughout the disruption lifecycle, covering disruption prevention, response, and
280 recovery stages. (Technical model 1-4)

281 ***2) Industrial contributions***

282 2.1) The proposed resilience framework translates analytical outcomes into evidence-based decision-
283 support tools for port authorities and terminal operators. It provides operational guidance across different stages
284 of disruption management. During the preparedness stage, the framework helps port managers understand the
285 mechanisms of the ripple effect, quantify resilience levels across various disruptive scenarios, identify
286 vulnerable areas and critical disruptive factors, and their combinations. In the disruption response and recovery
287 stages, the framework assists port operators in implementing resilience-oriented operational strategies.

288 2.2) The proposed framework benefits other port-related stakeholders, including shipping lines, freight
289 forwarders, and third-party logistics providers, by enabling more accurate prediction and assessment of

290 disruption impacts. This improves risk awareness and coordination among supply chain actors, supporting better
291 operational planning and enhancing the resilience of the wider logistics network.

292 2.3) By capturing disruption propagation and ripple effects across multiple transportation modes, the
293 framework contributes to improving the stability of multimodal transport systems and global supply chains.
294 This is particularly important given the increasingly frequent disruptions caused by extreme weather,
295 infrastructure failures, and supply chain shocks.

296

1.5 Research scope and the thesis structure

This section defines the research scope and outlines the structure of the thesis. The scope of this research is limited to the operational resilience of multimodal container ports under disruptions, with particular attention paid to internal subsystem interdependencies and ripple effects. The thesis focuses on the modelling, assessment, uncertainty analysis, and resilience-oriented enhancement of port operations, rather than on broader macroeconomic, financial, or strategic port competition issues.

The development of the resilience framework in this research follows a coherent, progressive methodological structure in which each component builds on the results of the previous one. Following the general logic of risk modelling, understanding the potential impacts of disruptions is the first step in resilience analysis. In situations where historical disruption data are limited, simulation modelling provides an effective approach to analyse system responses under hypothetical disruptions. Therefore, a simulation model is first developed to capture the operational processes of multimodal container ports and to analyse how different types and magnitudes of disruptions affect port operations and generate ripple effects within the port system. Based on the simulation, port performance under various disruptions is then transformed into resilience values through a resilience assessment method. This enables port resilience to be measured from multiple perspectives and provides a basis for evaluating resilience during the early stages of disruptions. Subsequently, disruption-related features are used as model inputs and the calculated resilience values as outputs in a GSA to identify the disruptive factors and combinations of them that have the greatest influence on overall port resilience. Finally, the identified critical disruptions become the focus of resilience enhancement. When such disruptions occur, optimisation models are applied to determine appropriate maintenance decisions based on the operational features, structures, and mechanisms of the affected systems, to maximise resilience performance and minimise cost. Figure 1.1 presents a flowchart that illustrates the logical backbone of the developed methodology. The detailed explanations of their relationships and the research layout are depicted as follows.

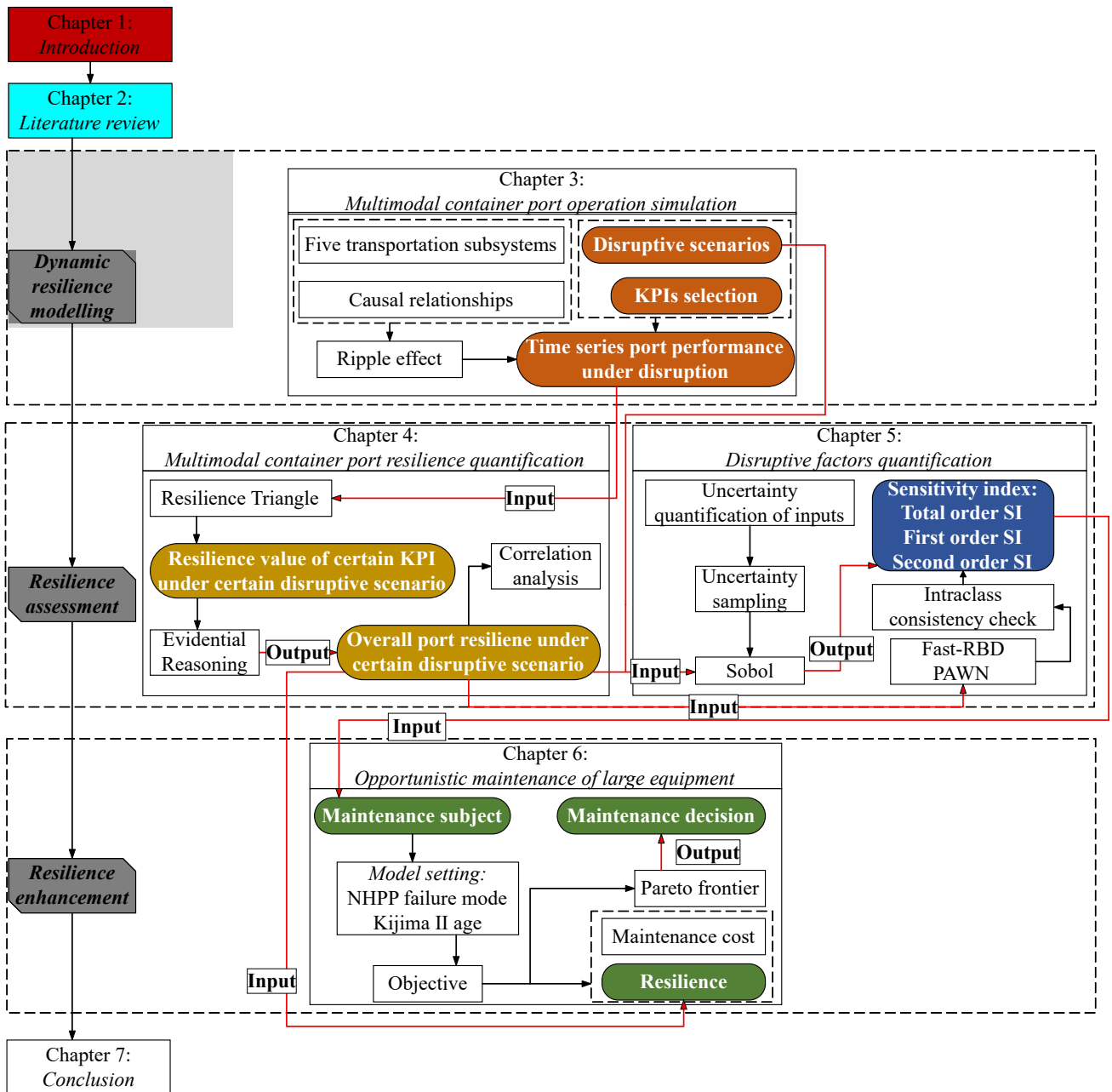


Figure 1.1. Methodology flowchart for the thesis framework. (Source: Author's own work).

This research consists of seven chapters. Chapter 1 introduces the fundamental research information, including the research background, objectives, research necessity, and the study's main contributions. Chapter 2 presents a comprehensive literature review that examines the research scope, concepts, and methodologies related to port risk and resilience, followed by a critical analysis of existing research gaps. The core content of the research is developed in Chapters 3 to 6, where the proposed models and frameworks are introduced,

327 validated and applied. A detailed overview of the connections between each research objective and the relevant
328 theories and methods is presented below.

329 As the foundation of the resilience analysis framework, **Chapter 3** develops a simulation model of
330 multimodal container port operations using the SD approach, encompassing five essential subsystems: liner
331 shipping, feeder shipping, railway transport, trucking, and container yards. Through causal relationships,
332 feedback loops, and interactions embedded in real-world operational processes, the model captures how
333 different types and magnitudes of disruptions affect port operational performance across multiple transportation
334 modes and performance indicators. It also demonstrates how these impacts propagate across interconnected
335 subsystems through ripple effects. The inputs of the simulation model consist of risk-related features, while the
336 outputs are time-varying port operational performance measured by multiple indicators. These outputs provide
337 the basis for the resilience assessment and risk analysis conducted in **Chapter 4**.

338 Building upon the simulation outputs from **Chapter 3**, **Chapter 4** converts the time-series port
339 performance data into resilience values using a scientifically grounded resilience triangle method that satisfies
340 the three fundamental characteristics of resilient systems. Subsequently, the Evidential Reasoning (ER)
341 approach is applied to aggregate multiple resilience indicators within a hierarchical structure. The hierarchy
342 consists of three levels: the overall port level, the subsystem level (covering the five subsystems, including four
343 transport modes and container yards), and the internal Key Performance Indicators (KPIs) within each
344 subsystem. As a result, **Chapter 4** provides resilience values for both the overall port system and its individual
345 subsystems under different disruptive scenarios. This mapping between disruptive scenarios and resilience
346 values is further used in **Chapters 5 and 6**.

347 **Chapter 5** focuses on identifying the disruptive factors that most significantly influence port resilience.
348 Different types and magnitudes of disruptions and their combinations are used as model inputs. Given the
349 potentially large number of possible combinations, Sobol sampling is employed to generate representative
350 random samples. These sampled disruptive scenarios are first input into the resilience assessment model in
351 **Chapter 4** to obtain overall port resilience values. These resilience values are then used as inputs to a Sobol-
352 based GSA, which calculates Sensitivity Indices (SIs) for individual disruptions and their combinations. This

353 process enables the identification and ranking of critical disruptions that have the greatest impact on port
354 resilience.

355 Finally, **Chapter 6** focuses on enhancing resilience by targeting the critical disruptions identified in
356 **Chapter 5**, specifically large equipment failures in the port. The chapter examines decision-making on
357 maintenance after a sudden disruption and before the next planned maintenance. Considering the series–parallel
358 operational relationship of port operation, together with disruption failure probabilities and Kijima II theory, an
359 OM optimisation model is developed. The model simultaneously minimises total costs and maximises expected
360 resilience values, where the resilience value is derived from ML algorithms trained on the relationship between
361 disruptive scenarios and resilience outcomes established in **Chapter 4**. The cost function incorporates both
362 maintenance costs and opportunity costs associated with disruptions and maintenance decisions. The model
363 generates a Pareto frontier of maintenance strategies, providing decision support for optimal quay crane
364 maintenance policies after disruption-induced failures.

365 **Chapter 7** provides a summary of the key aspects addressed by the proposed resilience framework and
366 emphasises the innovative modelling approach and its practical implications. It also discusses the limitations of
367 the current research and outlines potential directions for further development and future improvements of the
368 proposed methods.

369 **CHAPTER 2 LITERATURE REVIEW**

370 A substantial number of studies have investigated port resilience assessment. A recent literature review
371 shows that, in methodological terms, approximately 31% of the studies adopt simulation approaches, 23%
372 theoretical models, 16% optimisation modelling, 10% Bayesian methods, 8% semi-quantitative approaches, and
373 6% Multicriteria Decision Making (MCDM) methods (Mohsendokht et al., 2025a). While this review offers a
374 useful statistical classification and compares the advantages and disadvantages of these approaches, it pays less
375 attention to the fundamental purposes for which different methods are employed. For example, simulation
376 approaches are mainly used to analyse the propagation of ripple effect under disruptions, usually in port
377 networks where ports are represented as nodes (Zhang et al., 2026). Theoretical models are typically used to

define the resilience conceptually and to explain the fundamental relationship between system change and resilience (Bruneau et al., 2003; Balbi et al., 2025). Optimisation studies usually aim to improve or maximise resilience during the preparedness, response, and recovery stages (Zhen et al., 2022). Bayesian methods are more concerned with the causal relationships among risk factors affecting port resilience (Goerlandt and Islam, 2021), whereas MCDM studies commonly assess resilience through hierarchical indicators derived either conceptually or from port performance (Shakibaei et al., 2024). Therefore, this literature review is structured from two perspectives: research content and research method. Section 2.1 discusses port operational performance and the related concepts of risk and resilience from the perspective of research content, while Sections 2.2 to 2.5 review the literature from the perspective of research purpose, covering dynamic modelling based on simulation, resilience assessment, UQ and resilience enhancement, together with the relevant state-of-the-art methods.

2.1 Risk and resilience in multimodal container ports

Section 2.1 aims to establish the conceptual foundation of this study by clarifying the sources of operational risks in multimodal container ports, justifying the use of port operational performance as the basis for resilience assessment, distinguishing resilience from related concepts, and highlighting the importance of internal ripple effects in shaping port resilience.

2.1.1 Risk identification in multimodal container ports

To identify and understand the risks emerging within multimodal port terminals, it is first necessary to clarify the core functions of ports. On this basis, potential sources of disruption and corresponding risk categories that may interfere with port operations can be systematically identified and analysed. Generally, the fundamental functions of a port are the consolidation, distribution, and temporary storage of cargoes (Vis and de Koster, 2003). Therefore, the primary objective of port operations is to ensure the smooth and efficient flow of goods. To achieve these, ports operate as tightly coupled socio-technical systems integrating maritime access, terminal infrastructure, energy supply, digital platforms, labour, and hinterland transport networks. Disruptions affecting any of these components can rapidly propagate across the wider port system and beyond the port boundary. These risks can significantly disrupt port stability and operational continuity and may include port

404 congestion, traffic accidents, policy changes, terrorist attacks, natural disasters, and mechanical failures of
 405 equipment, among others (Li et al., 2024d). To develop targeted strategies for enhancing port resilience, it is
 406 essential to first accurately identify the risks that influence it and eliminate those that are insignificant. This
 407 section establishes a structured classification of port risk types. It outlines how such events typically unfold,
 408 providing a fundamental understanding of assessment and enhancement of port resilience in the following
 409 sections.

410 Disruptive factors affecting ports can be broadly categorised into external and internal causes (Li et al.,
 411 2024d). External factors include social threats (such as piracy and pandemics (Gu et al., 2023)), political
 412 instability, technological issues (e.g., cyber-attacks), and industrial fluctuations (such as supply chain
 413 disruptions (Jiang et al., 2021)), and natural disasters (Lucio et al., 2024). Internal factors, on the other hand,
 414 involve human error, equipment and infrastructure failures and organisational or managerial inefficiencies (Cai
 415 et al., 2024). Table 2.1 provides an illustrative classification of major risk factors in port systems.

416 Table 2.1. An illustrative classification of major risk factors in port systems.

Categories		References
Internal factors	Labour shortages	(Alyami et al., 2019)
	Operating errors	
	Lack of security awareness	
	Insufficient professional knowledge and skills	
	Poor supervision	
	Facility and equipment risks	(Loh et al., 2017)
	An imbalance between port capacity and demand	
	Over-ageing and defects of equipment	

External risks	Equipment breakdown		
	Port information technology (IT) system failure		
	Port infrastructure damage		
	Technical risks	Lack of advanced technology	(Wang and Wang, 2023)
	Organisation and management risks	Poor organisation of port production scheduling	(Wang and Wang, 2023)
		Imperfect management organization rules, and regulations	
		Lack of professional training or safety education	
	Economic and trade risks	Trade policies	(Chen and Rose, 2018)
		Customs rules	
		Global economic states	
Freight rates			
Labour costs of various countries			
Natural disaster	Earthquake	(Ivey Burden et al., 2015)	
	Hurricane		
	Heavy rain		
	High wind		
	Tsunami		
	Heatwave		

Public health event		(Liu et al., 2023c)
Security threats	Trafficking	
	Smuggling	
	Breaking in/theft	(Mohsendokht et al., 2025b)
	Terrorist attacks	
	Cyber attack	
Navigational risk of passing ships		
Risk caused by third-party operation	Delays caused by logistics or hinterland partners	(Zhang et al., 2025b; Zhang et al., 2025a)
	Untrained external personnel	
Risk from the surrounding area	Public infrastructure failure	
	Community factors	(Zhen et al., 2022)
	Industrial activities	

In this thesis, the distinction between macro- and micro-level analysis is defined according to the system boundary and modelling resolution. Macro-level approaches represent ports primarily as aggregated nodes within shipping, regional transport, or supply-chain networks and focus on network-wide consequences. In contrast, the micro-level perspective adopted here explicitly represents internal equipment, operational processes, resource constraints, performance indicators, and dependencies among transport subsystems within an individual port. The latter is required to identify how a local operational disruption develops into an internal ripple effect and to support targeted port-level management decisions. Due to their dynamic and less controllable nature, external factors, particularly climate-related and natural hazards, have been widely examined in port resilience studies (Verschuur et al., 2020). As these disruptions often occur and then are analysed at regional or system-wide scales, existing studies tend to focus on macro-level consequences, such as throughput reduction or trade delays (Li et al., 2025). In doing so, the system boundaries are often set at the supply chain level, rather

than the port itself. Moreover, this approach tends to generalise port functions and overlook the operational details of internal port systems. Therefore, ports are often treated as a single entity, and their internal functions and operational structure are generalised. In addition, these studies primarily focus on the risks or disaster events themselves, rather than on how ports internally operate and respond to such risks. As a result, they provide only a limited understanding of port operations. In particular, the role of ports as intermodal hubs, the interactions among different transportation subsystems, and the specific operating conditions within individual ports are rarely examined in depth. For example, by using vessel Automatic Identification System (AIS) data and simulating landside operation, a community of six ports in the southeastern United States was investigated to demonstrate the impact of 2016 Hurricane Matthew on port capacity and regional disruptions (Dhanak et al., 2021). At a broader level, empirical investigation uses AIS data to analyse 141 disruptive events across 74 ports and 27 disasters to analyse how ports are affected by and recover from natural disasters across different regions (Verschuur et al., 2020). Consequently, while these approaches are informative at the network or regional level, their practical value for individual port operators is relatively limited because ports are generally represented as aggregated nodes. Such abstraction overlooks equipment-level disruptions, internal operational processes, and cross-modal interactions, thereby limiting the ability to identify specific bottlenecks and develop targeted mitigation or recovery strategies.

Meanwhile, numerous studies have shown that internal factors, particularly human and equipment-related issues, pose more frequent disruptions to normal port operations (Wang and Wang, 2023). Although such disruptions may appear routine or less severe than large-scale external shocks, their high frequency and real-world occurrence make them particularly relevant for port management and operational decision-making. Currently, only a limited number of studies focus on internal port disruptions and their impacts. Most of these studies rely entirely on qualitative data sources, primarily derived from expert judgment or survey-based methods. For example, risk matrices were used to assess the impact of port disruptions on supply chains based on structured questionnaires and expert surveys (Goerlandt and Islam, 2021), expert ratings were used to assess the vulnerability of Tianjin port (Cao and Lam, 2019), and expert judgement and statistical analysis were used to assess port infrastructure resilience (Wang et al., 2023b). This limitation is largely attributed to the lack of detailed records of internal port accidents and the difficulty in accessing such data. Therefore, these methods often fall short of capturing the actual operation and disruption dynamics of ports.

To ensure that major studies in port and seaport risk identification and analysis are included, a supplementary targeted search was conducted in the Web of Science Core Collection. The search was based on the topic field using the terms “port”, “seaport”, “container terminal”, “risk identification”, “risk assessment”, “risk analysis”, “risk mitigation” and “risk management”. The search results were then screened according to title, abstract, keywords, citation ranking, and relevance to port, seaport, maritime transport, container shipping, and port-related operational risk. Studies focusing primarily on coastal pollution, public health, veterinary science, landslides, pipelines, or general environmental chemistry were excluded unless they directly addressed port or maritime operational risk.

The screened literature indicates that recent port and maritime risk studies can be broadly grouped into several streams. The first stream focuses on maritime accident and casualty risk analysis. For example, a data-driven BN model using accident data from GISIS and Lloyd’s Register Fairplay to identify key risk influential factors in global maritime accidents (Li et al., 2023a). This line of research is further extended by developing a data-driven BN model to analyse maritime casualty evolution across different timeframes (Zhou et al., 2024), as well as comparing the dynamic evolution of maritime accident patterns (Li et al., 2024a). These studies demonstrate the growing importance of probabilistic and data-driven methods in maritime risk analysis, but their focus remains mainly on ship-level accidents and casualty patterns.

The second stream concerns navigation and collision risks in port waters and restricted waterways. Fuzzy Fault Tree Analysis (FTA) is integrated with BN to estimate the occurrence likelihood of navigational accidents in Qinzhou Port (Zhao et al., 2022), while related studies have used AIS based methods, clustering, information entropy, and traffic complexity modelling to identify high-risk ship encounters and collision hotspots in complex port waters (Zohoori et al., 2023). These studies primarily focus on navigational risk rather than the operational processes inside container terminals.

The third stream addresses port-level resilience and disruption risks. A resilience assessment model is developed to evaluate ports as critical infrastructures under the COVID-19 pandemic (Panahi et al., 2022). A port congestion risk assessment model by combining Failure Mode and Effects Analysis (FMEA), fuzzy Bayesian reasoning, and Analytic Hierarchy Process (AHP) are employed to identify railway/barge service interruption, labour shortages, and truck-driver shortages as major congestion risk factors (Gui et al., 2022).

Moreover, multi-hazard risks to global port infrastructure and the resulting trade and logistics losses are quantified, showing that port resilience is influenced by engineering standards, operational thresholds, and recovery duration (Verschuur et al., 2023). These studies are closer to the port-risk focus of this thesis, but most of them assess risks at the infrastructure, congestion, pandemic, or general port-system level rather than explicitly modelling multimodal operational interactions within a single container port.

The fourth stream examines emerging risks arising from digitalisation, cybersecurity, and intelligent maritime systems. For instance, supervised ML applications in maritime risk analysis are reviewed (Rawson and Brito, 2023), while multi-event risk scenarios in blockchain-integrated maritime container shipping systems are analysed (Nguyen et al., 2022). These studies suggest that maritime risk research is increasingly moving towards data-driven, network-based, and probabilistic methods. Overall, the recent literature shows that port and maritime risk research has made substantial progress in accident risk modelling, navigation safety, cyber security, infrastructure risk, congestion assessment, and resilience evaluation. Methodologically, BN and its fuzzy extensions, FTA, FMEA, AHP, ML, AIS-based analysis, network analysis, and multi-hazard assessment are frequently used. Nevertheless, a clear gap remains. Nevertheless, a clear research gap remains in the micro-level modelling of operational disruption propagation within multimodal container ports. This gap motivates the development of a micro-level, simulation-based framework for analysing operational disruption propagation and resilience in multimodal container ports.

Moreover, given the inherently multimodal nature of ports, it is essential to account for all relevant transport modes to fully capture the complexity of port operations and their interdependencies. Compared to single transportation modes, risk assessment of multimodal transport has not been studied extensively (He et al., 2021). For example, in the framework for estimating typhoon-related losses in seaports, only shipping-related elements, such as berths and cranes, are considered (Cao and Lam, 2018). Moreover, while some studies recognise the risks faced by ports due to their functions in multimodal transport networks (Asadabadi and Miller-Hooks, 2020, Hosseini and Al Khaled, 2021), research into the mechanisms between these systems remains unexplored.

In summary, existing literature on port risk analysis tends to adopt a macro-level perspective, focusing on major losses. While valuable, this approach often oversimplifies the complexity of internal port operations and

overlooks critical aspects of container transfer and handling across different transport modes. For example, internal disruptions, such as quay crane failures, yard congestion and inventory accumulation, are underrepresented, despite their frequent occurrence and substantial impact on port performance. Second, the feedback mechanism within the port system is often excluded or oversimplified, reducing the ability to capture the cascading consequences of disruptions. To improve the accuracy and relevance of port risk assessments, it is essential to move beyond generalised macro-level models and incorporate the interdependencies among multimodal transport modes at the micro level.

2.1.2 Measurement of port performance under risks

In this subsection, various dimensions for assessing port performance are first outlined. Building upon the above analysis of port operational risks, the rationale for using operational efficiency as the measurement of port performance is also elaborated.

Port performance has been assessed using a wide range of well-established indicators proposed and identified from multiple perspectives, including financial performance, customer service, internal operational processes, logistics network, technological capability, and environmental sustainability, among others. These indicators, which have been proposed and applied in previous studies (Praharsi et al., 2025; Ha and Yang, 2017; Ha et al., 2019; Zhang et al., 2024), are summarised in

Table 2.2.

Table 2.2. An illustrative review of port performance indicators.

Type	Indicator
Operational performance (Vahdani et al., 2024)	Time efficiency of operational processes (ship loading and unloading rate, berth occupancy, crane efficiency, number of vessels, idling time at berth, vessel turnaround time, truck turnaround time, dwell time, and average pre-berthing waiting time); throughput-oriented productivity (traffic handled, the number of vessels handled, and throughput)

Financial and economic performance (Notteboom et al., 2023; Tsoufas, 2025)	Revenue-generating capability, financial robustness, cash-flow stability, capital mobilisation and investment attractiveness, value creation within the regional and national economy
Service and logistics performance (Verschuur et al., 2023)	Reliability of service, customer-perceived service quality, network connectivity, gate accessibility, and cost of hinterland distribution
Capability development (Wang et al., 2023b)	Workforce skills and expertise, organisational capital and corporate social performance
Technology (Zhou et al., 2022a)	Automation, intelligent infrastructure, integrated monitoring and optimisation system
Social, environmental and governance performance (Liu et al., 2025; Wang et al., 2025a; Yang et al., 2025)	Contribution to social welfare and local development, commitment of management to responsible governance, efficiency of energy use, greenhouse gas and pollutant emissions, wastewater and discharge management, adoption of renewable energy sources, stakeholder influence, regulatory and policy environment affecting port operations

As the aim of this study is to examine the resilience of port operations, only performance indicators that are associated with port operational efficiency are considered appropriate. Other dimensions, although important, fall outside the scope of this study and are therefore not explicitly analysed. Operational efficiency indicators can generally be classified into two categories: volume-based and time-based. Volume-based indicators, such as throughput and total container handling volume, are relatively insensitive to short-term disruptions and therefore have limited ability to capture variations in operational resilience under disruptions (Mustafa et al., 2021). Consequently, this study adopts time-based port efficiency indicators, which are more responsive to operational disruptions and better reflect the dynamic port resilience.

2.1.3 Concept for measuring port performance under risks

In this subsection, various concepts for assessing transportation systems under risk are reviewed, and the rationale for adopting resilience as the primary indicator of port performance is articulated.

Many concepts have been adopted to evaluate the performance of transportation systems under risk, among which the concept of resilience has gained growing scholarly attention recently (Wan et al., 2018). Traditionally, risk is characterised by the combination of severity and its likelihood or frequency (Aven, 2012). As a result, risk assessment primarily emphasises statistical fitting of probabilities and consequences (Choi, 2021). In contrast, resilience assessment takes a more holistic view by evaluating a system's capacity to anticipate, withstand unexpected hazards, preserve essential functions, and recover swiftly. This is particularly relevant for port operations, where the ability to continue functioning during and after disruptions is critical. A wide range of concepts and measures have been used to evaluate how port systems perform under disruptive conditions. Table 2.3, therefore, provides an illustrative summary of the concepts most relevant to this study.

Table 2.3. Illustrative concepts and measures related to port resilience.

Measures	Interpretation/description	References
Robustness	The capability to resist or absorb hazardous events or disruptions. It is the quality of strength, health, and endurance.	(He et al., 2021)
Vulnerability	The degree to which a transportation system is susceptible to that may limit its ability to endure, handle and survive hazardous events.	(Jiang et al., 2023)
Importance	Defined as the role that the presence and location of a specific element play with respect to the average global and local connection properties of the whole network.	(Cohen et al., 2024)
Recoverability	Defined as the capability of providing normal operational functions after hazardous events or disruptions.	(Huynh and Walton, 2011)
Resilience	Defined as the ability of an entity or system to return to a normal condition after its original state has been affected by hazardous events or disruptions.	(Zhang et al., 2025a)
Redundancy	The availability of substitutable resources, spare capacity, or alternative operational arrangements that allow a system to maintain functions when disrupted.	(Wang et al., 2026a)

Rapidity	The speed at which a system can contain disruption impacts and restore its performance to an acceptable or normal level.	(Bruneau et al., 2003)
Adaptability	The speed at which a system can contain disruption impacts and restore its performance to an acceptable or normal level.	(Notteboom et al., 2021)

549 Drawing on the definition of robustness and its application in transportation systems (Angeloudis et al.,
550 2013), robustness primarily captures a system’s resistance to disruption, typically by the minimum performance
551 level reached during a disturbance. As such, it emphasises the “absorptive” capacity but pays limited attention
552 to recovery. Similarly, vulnerability focuses mainly on the degradation phase, characterising how sensitive a
553 system is to disruptions and how rapidly or severely performance declines, rather than how it rebounds after. In
554 port studies, criticality or importance is often defined through network topology and interdependencies (e.g.,
555 node centrality, connectivity, and spillover effects), which is valuable for identifying system-wide bottlenecks
556 but does not reflect the internal operational functions and process-level performance within the port. Meanwhile,
557 recoverability concentrates on post-disruption outcomes, which are how well and how quickly performance
558 returns after the disruptions. Given that this study aims to evaluate how port performance evolves throughout
559 the entire disruption cycle, from initial impact, through degradation and adaptation, to recovery, resilience is
560 selected as the most appropriate concept.

561 Although resilience is broader than risk and can be understood as a system’s capacity to withstand, adapt
562 to, and recover from adverse conditions, its empirical assessment in this thesis is based on the performance
563 under disruptive scenarios. In this sense, port resilience assessment depends on how risks, disruptions, affected
564 components, and operational consequences are conceptualised. Therefore, the limitations identified in port risk
565 research in section 2.1.1, particularly the dominance of macro-level perspectives and the limited representation
566 of internal multimodal operational interactions, also have implications for port resilience studies.

567 **2.1.4 Ripple effects in multimodal container ports**

568 Within the context of port operations, studies have shown that major disruptions lead to prolonged waiting
569 times, underscoring the significance of understanding and mitigating these ripple effects to enhance port
570 operations (Guo et al., 2023). This terminology represents a conceptualisation of risks cascading through a

571 network, spreading from one segment to another, and inducing indirect secondary losses due to the
572 interconnectivity and dependency among network elements.

573 The concept of a ripple-effect framework, including redundancy, flexibility, and resilience analysis, was
574 first introduced in 2018 (Dolgui et al., 2018). In the field of interconnected networks, two classical models for
575 studying the ripple effect were proposed: the Functional Ripple Effect (FRE) model, characterised by overload
576 and underload failures (Liu et al., 2022a), and the Structural Ripple Effect (SRE) model, characterised by loss-
577 dependency and isolation failures (Shi et al., 2021). The ripple effect refers to the propagation of disruptions
578 from one node to other parts of the supply chain, potentially impacting the entire network due to the inherent
579 interconnectivity and interdependency among supply chain functions. It is also known by terms such as “risk
580 diffusion”, “snowball or domino effect”, “cascading effect”, and “disruption propagation” (Ghadge et al., 2022).
581 Complementary concepts include the bullwhip effect, where minor fluctuations at the end-consumer amplify
582 step by step through supply chains, causing significant disruptions among upstream suppliers, and the risk-
583 pooling effect, which reduces demand variation by centralising risks to achieve economies of scale (Schmitt et
584 al., 2015).

585 Studies of container transport networks show that connectivity patterns and capacity allocation strategies
586 play a dominant role in determining how disruptions propagate (Zhang et al., 2026). Network resilience is
587 sensitive to the degradation or removal of highly connected nodes or corridors, with multiple concurrent failure
588 points significantly amplifying vulnerability (Jiang et al., 2024a; Lu and Qiu, 2025). A substantial body of
589 literature has examined the ripple effects of port disruptions on shipping lanes, trade routes, and the global port
590 network. For example, a cost-based container assignment model has been applied to assess the impact of two
591 disruptive scenarios, specifically seismic and political conflicts, on liner routing along the Southeast Asia to
592 Europe trade lane (Achurra-Gonzalez et al., 2019). A D-vine copula-based quantile regression model has been
593 used as a stress test to investigate the cascading impact of Chinese ports on global container trade, identifying
594 the container trading routes most severely impacted during simulated disruptions (Xiao and Bai, 2022).
595 Moreover, a queuing model has been employed to investigate the mechanisms of network disruptions and the
596 resulting ripple effects on the global port transport system (Guo et al., 2023). An SD model has been used to
597 illustrate how port congestion propagates through all ports in the same rotation and to pinpoint its “tipping point”

during the pandemic (Bell et al., 2023). At the regional level, Dhanak et al., (2021) present a hybrid multimodal simulation (port waterside and landside operations) applied to six US ports to assess resilience. This tool helps planners estimate how quickly a port can recover under different disruptive scenarios, including not just quay or vessel traffic but also landside terminal operations, truck or rail access and hinterland connections. In addition, the Motter-Lai cascade model has been applied to simulate container-load redistribution, capturing the ripple effect between seaports and dry ports (Lu and Qiu, 2025). Furthermore, the interdependence between inland port infrastructure and its surrounding supply chain has been modelled and assessed using BN to show the ripple effects in terms of geography, service provision, and access for repairs (Hossain et al., 2020).

Based on the above definition and literature, ripple effects can emerge in any interconnected system under disruption. Despite ports functioning as complex and tightly integrated entities that provide multiple interrelated services, internal ripple effects within port systems remain largely understudied. Existing limited research has only focused on port routing schedules, port infrastructure, and the global shipping network and individual transport modes (Cai et al., 2024), without adequately addressing the multimodal nature of port operations or the cross-modal propagation of disruptions. This oversight limits a thorough understanding and effective mitigation of potential disruptions. To address this gap, this chapter investigates the roles of various transportation modes in propagating disruptions and examines their influence on the port system's efficiency explicitly.

Through the above review, traditional, static risk-management approaches for port operators are insufficient to address the dynamic nature of contemporary port disruptions. Strengthening resilience requires an integrated, system-level understanding and the ability to conduct dynamic modelling, resilience assessment, UQ, and recovery planning.

2.2 Dynamic modelling of operational risks in multimodal container port

In this chapter, Section 2.2.1 reviews the necessity and application of simulation-based dynamic modelling in port risk and resilience research from a methodological perspective. Building on this foundation, Section 2.2.2 further focuses on SD, highlighting its suitability, compared with other simulation approaches, for

capturing feedback structures, time-dependent disruption propagation, and internal ripple effects, thereby providing the rationale for the modelling choice adopted in Chapter 3.

2.2.1 Simulation-based dynamic modelling

As ports operate as complex socio-technical systems characterised by interdependencies across maritime operations, terminal processes, and hinterland connections, analysing disruption impacts requires dynamic modelling approaches. Static assessments are insufficient to capture how disturbances evolve, propagate through interconnected subsystems, and trigger adaptive operational responses. In port risk management, simulation methods have attracted considerable attention due to their ability to capture the complex and dynamic nature of transportation systems (Guo et al., 2023; Li et al., 2024b). For example, a resilience-assessment and network-recovery framework is developed that integrates cascading failures, recovery mechanisms, and temporal evolution to simulate how the Global Container Shipping Network (GCSN) responds to and recovers from disruptive shocks (Wang et al., 2025b). At a regional scale, the VISSIM simulation platform is used to develop a multimodal port resilience assessment tool. Their model simulates inter-port interactions and evaluates how the closure of one port influences traffic redistribution and operational conditions at neighbouring ports. Such simulation-based studies provide valuable insights into cascading effects and network adjustments under disruptive scenarios (Dhanak et al., 2021).

Simulation techniques such as SD, Agent-Based Modelling (ABM), Discrete-Event Simulation (DES), graph-theory-based simulation, Monte Carlo Simulation, and optimisation-based models are widely employed to analyse complex system behaviour, track system evolution, and support long-term decision-making (Ivanov, 2017). Their advantages and disadvantages in the context of modelling port disruptions are summarised in Table 2.4.

Table 2.4. Comparison between different simulation methods.

	ABM (Ivanov, 2017)	DES	Monte Carlo	SD (Ghadge et al., 2022)
System-wide feedback				✓

Chain reaction		✓		✓
System evolution	✓			✓
Dynamic interactions	✓			✓
Causal relationships	✓			✓
Scenario Analysis	✓	✓	✓	✓
Non-linear relation	✓			✓
Accumulation effects	✓	✓		✓

Among them, SD stands out for its capacity to model and visualise dynamic systems by mapping causal relationships among variables (Ghadge et al., 2022; Bell et al., 2023). Compared with mathematical approaches that often encounter computational limitations, SD offers a more intuitive and flexible means of capturing both linear and nonlinear dynamics (Er Kara et al., 2021). Furthermore, SD is particularly suitable for assessing resilience under varying disruptive scenarios through parameter adjustments and simulation experiments (Valaei Sharif et al., 2023). SD-based simulations effectively captured time-dependent factors, including escalation of disruption duration, capacity degradation, and recovery processes. For systems characterised by temporal changes in their behaviour, SD outperformed other previously utilised simulation methods, as supported by earlier works (Chen et al., 2021; Becerra-Fernandez et al., 2020). Moreover, the time-varying outputs derived from SD serve as a foundation for calculating resilience values. Based on previous literature analysis, the adaptability and strength of SD were recognised; therefore, SD is selected in this research to establish causal relationships within the port under risk and simulate the ripple effect. The detailed review of the features and development of SD is presented in Section 2.2.1.

2.2.2 System Dynamics application in port risk and resilience research

One of the objectives of this research is to simulate the ripple effect within a port system under various disruptive scenarios. This requires a comprehensive understanding of the interactions of internal operational

flows between related variables. Fundamentally, past research demonstrates that SD is a robust choice for dealing with the complexity and multi-dimensional interactions of a real-world system (Ghadge et al., 2022; Ivanov, 2017). Therefore, to effectively capture and assess such complexity, a systems thinking approach based on SD is most appropriate (Sterman, 2010).

However, it is important to recognise that most existing SD models primarily focus on ripple effects in large-scale systems characterised by complex, multi-variable interactions (Liu et al., 2023c) and are often used to address the complex interdependencies among port operations, energy, resources (Garbolino et al., 2016), technology, regional economics, and pandemics (Korzebor and Nahavandi, 2023; Anderson et al., 2023) from a macro-level perspective. For instance, SD was utilised to examine how policy influences disaster-preparedness behaviours among industry actors, revealing a bi-directional relationship between regulatory measures and industry responses (Kwesi-Buor et al., 2019). More recently, due to the disruptive influence of COVID-19, there has been heightened attention towards developing effective mitigation policies to maintain normal port operation. An SD model of dual-port operations has been developed to simulate the effects of two proposed alleviation strategies aimed at managing uncertainty and disruptions during COVID-19 (Lin et al., 2022). It was also applied to explore the impact of COVID-19 on shipping and port operations across five subsystems, assessing economic impacts under six scenarios regarding epidemic duration and capacity recovery (Zhou et al., 2022b). Incorporating the SEIR model, a novel SD-based container congestion evaluation model has been developed to simulate the impact of different port congestion governance measures under COVID-19, using Ningbo Zhoushan Port as a case study (Liu et al., 2023a). Moreover, augmented by mathematical programming, an SD model has been used to explore the relationships among container handling time, congestion time, sailing time, and container dwell time at ports in the trans-Pacific trade lane. This approach effectively demonstrates the ripple effects of port congestion across all ports within the same port rotation sequence (Bell et al., 2023). Furthermore, SD was adopted and implemented through a conceptual framework and data-driven simulation to evaluate the congestion at Shanghai Port (Xu et al., 2021a).

Existing studies often incorporate variables derived from broader network or macro-level contexts, which generally lack direct causal linkages compared to micro-level operational variables within a single intermodal port, such as the number of berths, cranes, internal trucks, handling speeds, and external truck turnaround times.

As a result, causal relationships in many existing models are inferred primarily from statistical correlations or empirical observation rather than from explicit operational logic and feedback mechanisms embedded within port subsystems. Meanwhile, the limited integration of micro-level variables and internal feedback structures reduces causal transparency and constrains the applicability of such models for operational decision-making. To address these limitations, this study develops an SD model from a micro-level perspective, explicitly incorporating real-world operational variables and endogenous causal feedback loops. By modelling port operations at an appropriate scale, the proposed framework enables a more accurate representation of internal system interactions and provides clearer insights into how ripple effects evolve across interconnected port elements during disruptions.

2.3 Resilience assessment of multimodal container terminal

This subsection is structured into two parts based on the research objectives and the methodology adopted in this study. The first part reviews the theoretical foundations related to the definition and conceptualisation of resilience. The second part reviews recent developments in MCDM methods and justifies the selection of the ER approach to construct a comprehensive assessment framework.

2.3.1 Resilience assessment method in transportation systems

Many concepts were adopted to evaluate the performance of transportation systems during exposure to risks, among which the concept of resilience has gained growing scholarly attention recently (Wan et al., 2018). Consequently, this has resulted in the development of many metrics and indicators (Eisenberg et al., 2019). Summarising previous studies, resilience metrics are categorised into three types: topological, attribute-based, and performance-based (Wang and Yuen, 2022), as shown in Table 2.5.

Table 2.5. Comparison of different resilience metrics.

Advantages	Disadvantages	References
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Topological metrics	1) Simple, suitable for a large-scale network; 2) focus on network structure.	1) Sacrifices accuracy; overlooks traffic flow and redistribution; 2) neglects dynamic features	(Bai et al., 2023; Asadabadi and Miller-Hooks, 2020; Dui et al., 2021; Liu et al., 2023d)
Attribute-based metrics	1) Reflects system dynamics; 2) facilitates comparison across different systems.	1) Definition varies among attributes and requires predefinition; 2) exclusively focus on specific periods.	(Gu et al., 2020; Xu et al., 2022; Cheng et al., 2022)
Performance-based metrics	1) Reflects system dynamics; 2) assess the performance throughout the entire duration; 3) standardise different dimensions.	1) Hard to evaluate the instantaneous rate of change	(Gu and Liu, 2023; Zhen et al., 2022; Zohoori et al., 2023)

Topological metrics originate from graph theory principles (Bai et al., 2023), attribute-based metrics focus on particular features like recovery speed or efficiency, which may vary based on the chosen attribute, and performance-based metrics assess resilience in terms of system degradation and restoration throughout the disruption and restoration phase (Cheng et al., 2022). Graphically, performance-based metrics often measure resilience as the area beneath the performance curve, also known as the “resilience triangle” (Wan et al., 2018). For instance, resilience is conceptualised using a time-dependent performance function, representing system functionality as a continuous performance curve rather than a binary operational state. This approach captures how performance evolves over time, providing a dynamic measure of both the impact of disruptions and their recovery. Although specific performance indicators vary widely across systems and studies, using performance-based methods simplifies selecting appropriate measurement dimensions. It enables the standardisation of

metrics across different dimensions, making it a recognised and popular choice in resilience measurement (Wan et al., 2018; Zhang et al., 2026). In this study, port disruptions adversely affect several KPIs. As a result, performance-based metrics are deemed the most suitable for assessing resilience in this context.

The resilience triangle remains a widely adopted method in performance-based assessments, which was first introduced as early as 2003 (Bruneau et al., 2003), where resilience is measured by comparing the system’s performance after an external shock with its initial level, along with the duration needed for recovery to the original performance level. The understanding of resilience has recently expanded and is now widely used. It no longer merely signifies a return to a stable equilibrium but now encompasses the capacity of socio-technical systems to sustain a specific mode of operation (Pan et al., 2022). Therefore, a highly resilient system should exhibit: (i) a gradual decline in performance (i.e., low degradation rate), (ii) a swift restoration of performance levels (i.e., high recovery rate), and (iii) consistently satisfactory performance throughout the evaluation period (Cheng et al., 2022). The three features are also used as three criteria to measure port resilience in this study. Table 2.6 provides a comparison of the formulas based on the resilience triangle and their consistency with three fundamental resilience criteria. Specifically, formulations that integrate over the complete disruption and recovery timeline but do not distinguish between degradation and recovery phases (Bruneau et al., 2003; Simonovic and Peck, 2013) fail to satisfy criteria (i) and (ii), as they mix the separate attributes of resilience. Given the complexity of the adopted method, full details are provided in Section 4.2. The formulation adopted in this study is also presented in Table 2.6 to enable direct comparison with existing resilience measures, while its detailed interpretation and implementation within the proposed port resilience framework are provided in Eq. (4-2) in Section 4.2.2. The relevant notation is provided in Table 2.7.

Table 2.6. Overview of the resilience triangle and its alignment with the resilience definition.

Reference	Formulation of the resilience triangle	Meet the resilience definition		
		(i)	(ii)	(iii)
(Bruneau et al., 2003)	$\int_{T_i}^{T_r} (100 - P(t)) dt$			✓

(Simonovic and Peck, 2013)	$\frac{\int_{T_i}^{T_r} P(t)dt}{\int_{T_i}^{T_r} P_0(t)dt}$	✓		
(Franchin and Cavalieri, 2015)	$\frac{\int_{T_i}^{T_r} P(t)dt}{P_0(t)(T_i - T_r)}$	✓		
(Habibi et al., 2025)	$\frac{\int_{T_i}^{T_r} P(t)dt}{T_i - T_r}$	✓		
(Mugume et al., 2015)	$\frac{\int_{T_i}^{T_r} (P_0(t) - P(t))dt}{P_0(t)}$	✓		
(Cimellaro et al., 2010)	$\alpha \frac{\int_{T_i}^{T_f} f(t)dt}{\Delta T_f} + (1 - \alpha) \frac{\int_{T_f}^{T_r} r(t)dt}{\Delta T_r}$	✓	✓	
(Chanda and Srivastava, 2016)	$\frac{\int_{T_i}^{T_r} [P_0(t) - \min\{P(t)\}]dt}{\int_{T_i}^{T_r} [T_r P_0(t) - \min\{P_0(t)\}]dt}$	✓		
(Kadri et al., 2015)	$\frac{\int_{T_i}^{T_r} P(t)dt}{(T_r - T_i) \int_{T_i}^{T_r} P_0(t)dt}$	✓		
	$R = \frac{T_i + F\Delta T_f + Rec\Delta T_r}{T_i + \Delta T_f + \Delta T_r}$			✓
(Ayyub, 2014)	$F = \frac{\int_{T_i}^{T_f} f(t)dt}{\int_{T_i}^{T_f} P_0(t)dt}$	✓	✓	
	$Rec = \frac{\int_{T_f}^{T_r} r(t)dt}{\int_{T_f}^{T_r} P_0(t)dt}$			

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Table 2.7. Notations employed in resilience quantification.

Notation	Description
T_0	Time when disruption occurs
T_i	Time when disruption impact onsets
T_f	Time when performance degrades to an unacceptable level, upon which the recovery action starts, if applicable
T_r	Time when system totally recovers
ΔT_f	Duration from T_i to the moment of lowest performance T_f
ΔT_r	Duration from T_f to the moment of total recovery T_r
$P_0(t)$	System performance level without disruption at time t
$P(t)$	System performance level under disruption at time t
$f(t)$	System performance level throughout the failure phase at time t
$r(t)$	System performance level throughout the recovery phase at time t

Most traditional resilience triangle methods do not satisfy the first two resilience criteria because they do not separate the degradation phase from the recovery phase. Under such practice, they might equate a robust system with slow recovery to one with poor robustness but high recovery capability. Therefore, this study introduces and validates an improved computational method from previous literature (Ayyub, 2014), refining the original resilience triangle. This method explicitly addresses the three distinct terms: (i) inherent reliability, (ii) average robustness, and (iii) average recovery capacity, aligning more closely with port stakeholders' expectations for a resilient port. A detailed comparison and interpretation are presented in Section 4.2.

2.3.2 Multiple indicator aggregation models

Multiple indicator aggregation models serve as crucial instruments for synthesising diverse structural data when assessing the resilience of systems with multiple indicators (Wen et al., 2024). When applied to port resilience, it enables evaluation of an extensive array of factors, surpassing the limitations of focusing solely on

754 a single aspect of the port, thereby significantly enhancing evaluation quality. In light of the requirements of the
 755 research subject, objectives, and data structure, several commonly used multi-criteria aggregation methods were
 756 reviewed, and the ER approach was selected as the most appropriate. The comparison is summarised in Table
 757 2.8.

758 Table 2.8. Comparison of other commonly used methods for aggregating multiple indicators.

Aggregation methods	Advantage	Disadvantage
Utility Values (weighted sum)	Simple and computationally efficient	Cannot evaluate resilience at the subsystem level.
AHP (Gui et al., 2022)	Clear hierarchical structure	The number of pairwise comparisons and consistency requirements increase rapidly with matrix order, increasing cognitive burden and potentially reducing judgement accuracy.
Fuzzy set (Gu and Liu, 2023)	Handle uncertainty	Assume monotonicity among criteria and do not expose middle-layer results.
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Wang et al., 2022a; Chen and He, 2024)	Data-driven evaluation	Ignore epistemic uncertainty and provide no mechanism for conflict resolution.
Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Liu et al., 2023b; Liang et al., 2025a)	Reveals causal relationships	Heavily reliant on expert judgment and results, highly dependent on subjective inputs.
Bayesian Network (BN) (Liang et al., 2025a)	Handle uncertainty	Demand conditional-independence assumptions and substantial prior data, both impractical in our context.

759 Based on Table 2.8, the reviewed aggregation methods differ substantially in their treatment of hierarchy,
760 uncertainty, subjectivity, data requirements, and intermediate assessment results. Weighted-sum approaches are
761 computationally efficient but tend to collapse multidimensional information directly into a single score,
762 providing limited insight into intermediate subsystem performance. AHP provides a clear hierarchical structure,
763 but the number of pairwise comparisons increases rapidly with the matrix order, making consistency more
764 difficult to maintain and potentially reducing judgement reliability as the number of criteria increases. Fuzzy
765 set approaches are effective in representing linguistic uncertainty, although their results depend strongly on the
766 specification of membership functions and may provide limited transparency regarding intermediate assessment
767 levels. TOPSIS is relatively straightforward and data-driven but does not explicitly represent epistemic
768 uncertainty or conflicting evidence. DEMATEL is useful for revealing causal relationships among criteria, but
769 its outcomes rely heavily on expert judgement. BN can represent probabilistic dependencies and uncertainty,
770 but requires substantial prior information and specification of conditional relationships, which may be difficult
771 to obtain for port disruption scenarios.

772 Proposed by Yang and Singh (1994), ER introduces an alternative aggregation mechanism grounded in a
773 distributed evaluation structure and the evidence synthesis principles derived from Dempster-Shafer (DS) theory
774 (Dempster, 2008). In contrast to conventional MCDM methods, it represents attribute performance through
775 belief distributions assigned across a predefined set of mutually exclusive evaluation grades. This belief-based
776 representation explicitly incorporates various forms of uncertainty into the assessment process. Furthermore,
777 ER provides a unified analytical framework that integrates quantitative observations and qualitative expert
778 judgments while systematically accounting for associated uncertainties. Most importantly, ER establishes a
779 multi-level framework comprising KPIs with a hierarchical structure, ranging from top-level port resilience to
780 bottom-level indicators that clearly illustrate the relationships and dependencies between levels. Information at
781 each level is assessed and processed independently before being aggregated upwards. This progressive handling
782 is well-suited for aggregating hierarchical criteria of large volumes of scenarios, as it preserves intermediate
783 belief distributions across all levels, ensuring transparency in the identification of resilience at any specific level
784 (Yang and Xu, 2013).

In this research, the focus extends beyond assessing the port's overall resilience. It also includes the resilience of various transportation modes due to 1) their significant managerial value and 2) the dynamic behaviours of these modes under disruptions, which reveal patterns of ripple effects. Additionally, the aggregated criteria originate from different areas of the port and hence are inherently independent. Advanced ER-based models were applied in various resilience-related studies, such as navigational risks in inland waterways (Zhang et al., 2016), port vulnerability (Jiang et al., 2021), and canal vulnerability (Jiang et al., 2023). In comparison, ER yields more objective conclusions than traditional aggregation models, such as AHP and DEMATEL. Consequently, ER is chosen to enable the practical assessment and integration of the resilience of individual transportation mode and their interdependence. Despite these advantages, ER also has several limitations. Its results can be sensitive to the construction of the assessment hierarchy, the definition of evaluation grades, and the assignment of criterion weights. In this study, these limitations are mitigated by constructing the hierarchy according to the operational structure of the port, determining resilience grades from the distribution of simulated KPI resilience values, and adopting entropy-based weights rather than subjective expert weighting. In addition, complete belief distributions are used to avoid unassigned belief mass.

2.4 Uncertainty quantification method

Section 2.4 provides a methodological review of UQ for identifying critical risk factors in multimodal container ports. Accordingly, this section first outlines the significance of UQ in port resilience research, then compares SA with other representative UQ methods, and subsequently reviews major SA approaches to justify the methodological choice adopted in Chapter 5.

2.4.1 The role of uncertainty quantification in port resilience research

A significant advancement in managing port disruptions involves refining uncertainty assessments and accurately tracing their origins within the affected components. In other words, this involves understanding how port resilience changes with varying types and degrees of disruption. More broadly, it aims to capture how fluctuations in input parameters influence model results. To achieve this, the selected modelling approach should fulfil three primary objectives: (a) scientific discovery, which explores causal relationships and examines how a system is affected by various parameters, scales, and their combinations and interactions; (b) factor reduction

and prioritisation, which identifies redundant uninfluential factors to be removed and influential essential factor to be prioritised; (c) decision support, which assesses the sensitivity of model outcomes to different scenarios, decisions, and uncertainties (Razavi et al., 2021).

2.4.2 Comparison between uncertainty quantification methods

Given the wide range of available UQ methods, a systematic comparison is required before identifying the most suitable approach for analysing port resilience under disruptions. From the perspective of this study, the selected method should meet the objectives mentioned above. Since existing UQ methods differ substantially in their analytical focus and practical applicability, Table 2.9 presents a comparative review of representative methods in terms of their main functions.

Table 2.9. Comparison of UQ methods.

Method	Main Function	Whether it meets the three objectives		
		(a)	(b)	(c)
Markov Chain (Sun et al., 2024)	Models risk evolution through state transition probability	✓		✓
MCDM (Liu et al., 2023b)	Evaluates disruptions by weighting and aggregating multiple conflicting criteria			✓
BN (Liang et al., 2025b)	Establishes causal relationships and conditional probability among disruptive factors through graphs	✓		✓
FTA (Qazi et al., 2018)	Identifies and quantifies failure logic by decomposing into contributing causes	✓		✓
FMEA (Wan et al., 2019a)	Evaluates potential failure modes, their causes, and effects to prioritise risk mitigation	✓		✓
Petri Nets (PN) (Sun et al., 2021)	Models dynamic, concurrent, and event-driven risk evolution processes using states and transitions.	✓		✓

Analysis of Variance (ANOVA) (Fisher, 1992)	Statistical tests whether variations in outputs are significantly affected by input factors.	✓		
Sensitivity analysis (SA) (Schmitz et al., 2023)	Quantifies how input variations influence output to identify key contributing disruptive factors	✓	✓	✓

As can be seen, SA is particularly well-suited to this task, as it enables a detailed breakdown of output uncertainties, attributing them to specific factors and their interactions. This approach is closely aligned with “factor prioritisation”, one of the four primary objectives of SA (Schmitz et al., 2023).

2.4.3 Sensitivity analysis methods for port resilience

SA is categorised into Local Sensitivity Analysis (LSA) and GSA (Schmitz et al., 2023). The LSA method, also known as “one at a time” (OAT), involves altering a single variable at a time while holding the other variables constant to observe changes in the output. A representative example for the application of LSA is shown in section 3.3 in modelling validation and result analysis. It is generally unsuitable for complex, high-dimensional models due to its limitation to single-parameter variations. In contrast, the GSA method evaluates the effects of input parameters across the entire feasible range of the input space, allowing the analysis of interactions among input parameters (Cheng et al., 2023, Saltelli et al., 2010). While LSA is straightforward and effective for analysing easy models, it falls short in handling complex models featuring high-dimensional, nonlinear, and interdependent variables, primarily because it does not fully explore the entire range of input parameters (Cohen et al., 2024).

GSA can be categorised into four types: derivative-based, distribution-based, variogram-based, and regression-based approaches (Razavi et al., 2021). Derivative-based methods evolve from LSA by calculating local sensitivities at various “local points” across the input space and then aggregating them to form a GSA. Within this group, the Morris method is often utilised (Morris, 1991). Distribution-based methods evaluate the distributional properties of outputs to understand how different input combinations influence these characteristics. Variance-based methods, favoured for their clear conceptual framework and simple implementation, break down the overall variation in the output into components reflecting individual effects and their combinations. Among these methods, Sobol (Sobol', 2001) and the Fourier Amplitude Sensitivity Test

(FAST) (Cukier et al., 1973) stand out as particularly prevalent. Notably, the Sobol method surpasses FAST by quantifying interaction effects, which illustrate the degree of interactions between variables (Sobol', 2001). Moreover, some distribution-based approaches go beyond traditional variance analysis to investigate the impact of inputs on the output's higher-order moments, often referred to as "moment-based" methods. These strategies excel in processing data with pronounced skewness and effectively handling kurtosis. Key techniques in this group are PAWN (Pianosi and Wagener, 2015) and Regional Sensitivity Analysis (RSA) (Spear et al., 1994). The variogram-based approach bridges derivative and distribution-based methods (Razavi et al., 2019), but since it is relatively new, its stability, applicability, and practicality have yet to be fully demonstrated. In the regression-based method, a set of response surface points is modelled using coefficients in a linear regression framework. This approach has been criticised for its substantial dependence on pre-existing assumptions, which can oversimplify the interactions between inputs and outputs, especially in cases involving non-linear and non-monotonic relationships (Song et al., 2015). Therefore, to effectively reveal the relationships between disruptive factors and their impact on port resilience, this research adopts Sobol as the primary method for SA. Subsequently, it utilises PAWN and the improved FAST-RBD to verify sensitivity and employs ICC to analyse the consistency of the results.

SA is widely applied across multiple domains, including climate change (Collins et al., 2012), hurricanes (Iman et al., 2005), earthquakes (Chen and Zhang, 2021), hydrology (Schmitz et al., 2023), and epidemics (Lu and Borgonovo, 2023). The expanding use of SA highlights its potential to emerge as an independent discipline, offering significant advantages to the broader scientific community (Razavi et al., 2021). However, there remains a notable limitation in the application of GSA models to enhance resilience in transportation operations research sectors (Taghizadeh et al., 2021). A few examples are as follows: In autonomous driving, PAWN density-based SA was used to pinpoint operational areas and conditions prone to dangerous human behaviours, thereby enhancing safety measures in autonomous vehicles (Coppola et al., 2023). Likewise, employing variance-based SA helped calibrate microscopic traffic flow models through "factor fixing" (Punzo et al., 2015), highlighting the importance of SA in transportation management. In the field of operations management, an innovative GSA is proposed to pinpoint suppliers at risk in multi-product supply chain networks, incorporating a risk aggregation model to mitigate variability (Mizgier, 2017). Additionally, variance-based SA was applied in deep-tier supply chains to equip decision-makers with strategic insights to improve network resilience by

871 identifying and prioritising critical suppliers that significantly influence performance variability (Taghizadeh et
872 al., 2021). To assess community vulnerability to natural hazards, a refined social fabric index was developed.
873 To validate the model's robustness, internal uncertainty and GSA were employed (He et al., 2023). Building on
874 this framework, the authors used OAT SA as the core method in subsequent research. This methodology,
875 integrated with DS theory and clustering, was specifically designed to evaluate regional resilience against the
876 preliminary impacts of earthquakes (He and Guan, 2024).

877 Overall, the application of SA can be broadly categorised into three main functions: (1) In model validation,
878 it is applied to ensure model robustness and reliability by varying parameter values (Liu et al., 2023a). (2) In
879 policy-oriented research, this approach is used to assess how changes in parameters influence policy outcomes,
880 offering insights into the potential effectiveness and implications of various policy options (Liu et al., 2020).
881 These two practices are especially prevalent in current research in engineering and operations management,
882 mostly through LSA. (3) It is also aimed at reducing uncertainties in model configurations and identifying key
883 parameters. For instance, GSA is widely used to screen and prioritise inputs in hydrology and water quality
884 research (Cohen et al., 2024; Schmitz et al., 2023; Cheng et al., 2023).

885 In summary, although SA is highly transferable across contexts and applicable in numerous fields, an
886 extensive literature review has identified three primary shortcomings in its application to port resilience: (1)
887 Most studies employ LSA for model validation, which fails to provide accurate, measurable SI for critical
888 disruptive factors. (2) There is a significant disconnection between sophisticated theoretical SA methodologies
889 and their practical implementations, as evidenced by one class featuring proposals for advanced and refined SA
890 methods with a simple demonstrative case developed by SA experts. The other comprises application papers in
891 which weak SA is performed by researchers outside the SA field (Razavi et al., 2021). (3) Fundamentally
892 different philosophical approaches to uncertainty tracing are adopted in different SA methods, leading to
893 inconsistencies in outcomes. Addressing this issue, a few studies utilise multiple SA techniques for cross-
894 validation and perform consistency checks on the results of SI, including variance-based Sobol and moment-
895 independent Delta methods (Taghizadeh et al., 2021); Polynomial Chaos Expansion (PCE), Stochastic
896 Collocation (SC), and Arbitrary Polynomial Chaos (APC) (Zhao et al., 2019); Sobol, PAWN, and Patient Rule

897 Induction (PRI) (Jaxa-Rozen et al., 2021). This study aims to address these issues by refining the application of
898 SA to enhance the practicality and reliability of port resilience assessments.

899 **2.5 Resilience enhancement of multimodal container port**

900 Effective response and recovery after disruptions are essential for improving system resilience. Most
901 resilience enhancement studies adopt optimisation-based models, while a smaller number apply game-theoretic
902 approaches to examine strategic interactions among port stakeholders, such as competition in one-stop logistics
903 services (Ye et al., 2024), trade activities between adjacent ports (Chen et al., 2024), and capacity sharing and
904 investment decisions (Li et al., 2022c). Game-theoretic approaches are particularly suitable for analysing
905 strategic interactions among multiple decision-makers, whereas engineering-oriented approaches commonly
906 focus on technical reliability and restoration of individual assets or infrastructure, and economically oriented
907 approaches often prioritise cost or operational efficiency. The present research instead adopts a resilience-
908 oriented operational perspective: equipment-level decisions are evaluated according to their implications for the
909 performance of the entire multimodal port, including cross-subsystem ripple effects. The contribution therefore
910 lies not merely in optimisation itself, but in linking operational disruption propagation, port-level resilience, and
911 maintenance cost within a unified decision framework.

912 **2.5.1 Optimisation-based resilience enhancement**

913 Mathematical modelling and optimisation approaches enable the comparison of alternative recovery
914 strategies and the identification of optimal resilience enhancement plans. Moreover, they are well-suited to
915 analysing complex and interdependent port systems under disruptive scenarios. Studies that aim to enhance port
916 resilience through optimisation can generally be classified into several categories according to their research
917 focus and modelling objectives, as shown in Table 2.10.

918 Table 2.10. Comparison between different port resilience enhancement studies.

Resilience indicators	Optimisation focus
-----------------------	--------------------

Port network	Shipping route optimisation (Yuan and He, 2025)
Port operation	Cargo flow optimisation within the port (Xing et al., 2026), maintenance personnel allocation (Wang et al., 2026b)
Port infrastructure	Port electric distribution network optimisation (Pan et al., 2025), port electric-hydrogen energy system network optimisation (Tang et al., 2026)
Port information system	Network optimisation between the port information layer and the physical layer (Wang et al., 2026a)

Based on the above review, existing studies have largely focused on resilience enhancement at the network, infrastructure, or system-integration levels. However, limited attention has been paid to improving resilience within a single port following operational disruptions. Past research indicates that port equipment damage is a critical factor affecting normal port operations. At the same time, it represents an area where port operators can actively enhance resilience through improved management practices and optimised maintenance strategies. Therefore, this study concentrates on improving resilience at the operational level by examining maintenance planning and recovery management following internal operational disruptions.

2.5.2 Opportunistic maintenance under port accidents

Maintenance activities for the general large-scale infrastructure equipment are commonly categorised into two types: Corrective Maintenance (CM) and Preventive Maintenance (PM) (Li et al., 2020). CM refers to interventions carried out after a failure has occurred, with the primary objective of restoring the equipment to operational status. PM, by contrast, is performed either at predefined time intervals or when certain criteria are met. While PM is intended to reduce the likelihood of failures, excessive implementation can result in unnecessary inspections and interventions, leading to a waste of labour, time, and financial resources (Xu and Zhang, 2025). Conversely, insufficient PM may cause deterioration in equipment condition to go unnoticed, increasing the risk of unexpected failures and the subsequent need for unplanned CM (Li et al., 2022a). Although CM and PM are widely adopted in practice, recent advances in digitalisation and intelligent monitoring have broadened the range of available maintenance strategies. In particular, Condition-Based Maintenance (CBM)

937 enables maintenance actions to be scheduled based on real-time assessments of equipment health and
938 degradation, thereby anticipating failures before they occur (Lin et al., 2020).

939 Research on optimal maintenance strategies for repairable systems dates back to the 1960s, where
940 maintenance optimisation is formalised within a mathematical framework (Barlow and Hunter, 1960; Al-Jabouri
941 et al., 2024). Then, a comprehensive review in 2020 shows that maintenance optimisation research can be
942 broadly organised according to single-unit and multi-unit systems, deterioration-state modelling, condition
943 monitoring, inspection planning, repair/replacement decisions, and different forms of dependence among
944 system components (Jonge and Scarf, 2020). This indicates that maintenance optimisation has developed into a
945 mature research area, particularly for industrial systems where equipment degradation, failure risk, repair cost,
946 and reliability are jointly considered.

947 Classical reliability theory models how maintenance actions affect the future condition of equipment by
948 distinguishing between perfect repair, minimal repair and imperfect repair. Perfect repair or replacement restores
949 equipment to an as-good-as-new condition, while minimal repair only restores it to an operating state without
950 materially changing its failure tendency. Imperfect repair lies between these two extremes (Moubray, 2001). As
951 early as 1996, it was emphasised that the maintenance of deteriorating systems is often imperfect: after
952 maintenance, the system is not as good as new, but becomes younger than before maintenance (Pham and Wang,
953 1996). Virtual-age models provide a widely used way to represent imperfect maintenance effects. General repair
954 models for repairable systems using the idea of virtual age are first developed (Kijima, 1989), and then it is
955 classified by imperfect repair models according to whether the repair effect is expressed through reduction of
956 failure intensity or reduction of virtual age (Doyen and Gaudoin, 2004). These models provide the theoretical
957 basis for representing different maintenance levels through different restoration effects. In this thesis, this logic
958 is used to connect failure replacement, moderate repair and minimal maintenance with different effective ages
959 after maintenance.

960 Maintenance decisions also usually involve multiple and conflicting objectives. Traditional maintenance
961 optimisation often aims to minimise long-running maintenance cost, maximise reliability or availability, reduce
962 maintenance time, or minimise system downtime. However, in complex operational systems, these objectives
963 may conflict. A maintenance action that improves reliability may increase immediate cost or downtime, while

964 a low-cost action may leave the system more exposed to future failure. A Pareto-frontier approach in multi-
965 objective maintenance optimisation is used to identify maintenance actions that satisfy reliability requirements
966 while minimising maintenance cost and maintenance time (Certa et al., 2011). This supports the use of Pareto-
967 based analysis when maintenance decisions cannot be reduced to a single objective without imposing subjective
968 weights.

969 On the other hand, for multi-component systems, OM has been widely studied as an effective maintenance
970 strategy (Boujarif et al., 2025). The main idea of OM is to take advantage of an existing maintenance opportunity,
971 such as a failure event, planned shutdown, production interruption, or access window, to conduct additional PM
972 on related components. By grouping maintenance actions, OM can reduce repeated setup costs, avoid duplicated
973 downtime, and improve the coordination between maintenance and operations (Tian et al., 2024). Previous
974 studies have developed OM models by considering component age, residual life, repair time, imperfect
975 maintenance effects, economic dependence, structural dependence, and resource constraints (Li et al., 2021).
976 For example, OM has been applied to multi-dependent manufacturing systems by explicitly modelling economic
977 and structural dependence and synchronising maintenance planning with production schedules (Boujarif et al.,
978 2025). Recent studies have further extended OM by considering imperfect repair, random repair time, soft and
979 hard failures, residual values, and stochastic deterioration (Wang et al., 2021).

980 The applicability of OM stems from the interdependence among system components and maintenance
981 activities. When such relationships exist, intervention on one component may create an opportunity to service
982 other related components concurrently. These interdependencies are commonly classified into three categories:
983 (i) economic dependence, where joint maintenance leads to lower overall costs than separate interventions; (ii)
984 structural dependence, where components are physically or operationally linked such that maintenance on one
985 requires access to others; and (iii) stochastic dependence, where the failure behaviour of one component affects
986 the reliability or degradation process of another (Wang et al., 2022c). From the perspective of large equipment
987 maintenance in container terminals, both (i) and (ii) are particularly relevant. These dependencies are important
988 for large port equipment because quay cranes, yard cranes, rail-mounted gantry cranes and other handling
989 equipment are not only individual assets but also parts of operationally connected subsystems, which could be

classified as a series-parallel system. The detailed description of large equipment maintenance operations and maintenance activities within the ports is further presented in Chapter 6.

Research on maintenance scheduling and optimisation for port equipment remains relatively limited in comparison with other extensively studied industries, such as railway (Sedghi et al., 2021; He et al., 2025; Cheng et al., 2020), wind turbines (Zhang and Zeng, 2015; Xu, 2025), aviation (Muecklich et al., 2023), and nuclear power plants. The existing literature can be broadly categorised into three main groups (Boland et al., 2013): studies that examine the cost implications of maintenance activities (Lin et al., 2020; Ebrahim et al., 2022), research that explores maintenance performed during opportunistic windows such as breakdowns or operational interruptions (Boujarif et al., 2025), and work that aligns maintenance planning with production schedules (Abyaneh et al., 2024). Among these three categories, most studies incorporate maintenance within the planning of berth scheduling or inventory management problems, and occasionally model disruption-related uncertainty beforehand (Tian et al., 2024; Abyaneh et al., 2024; Vahdani et al., 2024), rather than addressing maintenance decisions after disruptions have occurred. For example, an integrated optimisation problem involving berth allocation, quay crane assignment and truck deployment, with explicit consideration of quay crane maintenance, is considered to show that quay crane maintenance can directly affect the coordination among berths, quay cranes and horizontal transport resources (Wang et al., 2024a). This line of research has also been extended to low-carbon terminal operations, demonstrating that quay crane maintenance can be embedded within broader terminal operation optimisation under environmental and economic constraints (Wang et al., 2025c). Opportunity-maintenance-based scheduling has also been explored in bulk and specialised terminal contexts. An opportunity-maintenance-based scheduling optimisation model for ship-loading operation systems in coal export terminals (Tian et al., 2024). In automated container terminals, maintenance and fault recovery have been further linked with integrated equipment scheduling. The integrated scheduling of quay cranes, yard cranes and automated guided vehicles under quay crane faults is investigated to minimise loading and unloading time by determining the operational range of adjacent quay cranes and reallocating unfinished container-handling tasks after a quay crane fault occurs (Li et al., 2024c). Nevertheless, the decision objectives remain centred on operational efficiency or cost, while the influence of maintenance decisions on disruption propagation and port-level resilience is not explicitly modelled.

Other recent studies focus more directly on quay crane downtime and failure-related operational disruption. A genetic-algorithm-based optimisation model is developed to minimise quay crane downtime in container terminals. It considers planned maintenance, unplanned failures, equipment idle-time coordination and job scheduling within a single optimisation model to coordinate these elements to reduce crane idle time and operational disruptions (Garmouch et al., 2025). Particularly, limited attention has been paid to how maintenance decisions should be adapted when port equipment is subject to sudden external disruptions, with a focus on enhancing and restoring resilience. Moreover, within the relatively small body of literature that explicitly addresses maintenance, this equipment is often treated as an isolated asset, disconnected from other transportation modes (Yimei et al., 2026). Such an assumption overlooks the broader systemic implications of equipment failure and neglects the port's role as a transshipment hub connecting multiple transportation modes. For example, recent studies have explored the combined optimisation of crane cluster CBM and spare parts management using reinforcement learning, accounting for uncertainties related to procurement lead times, costs, equipment downtime, and spare parts shortages (Yao et al., 2024). Under extreme weather conditions, the joint scheduling of multiple types of port-handling equipment based on predefined resilience recovery priority rules has been studied by developing a mixed-integer programming model and solving it using heuristic algorithms (Yimei et al., 2026).

2.5.3 Surrogate-based resilience evaluation for optimisation

Unlike conventional optimisation problems, where the objective can be expressed explicitly as a closed-form function of decision variables (Bocchini and Frangopol, 2012), resilience evaluation usually requires repeated execution of complex numerical procedures. This makes direct optimisation computationally expensive, especially when a large number of candidate solutions must be explored (Zhang et al., 2025a). This difficulty becomes more pronounced when resilience is derived from simulation-based models, because each function evaluation may require a full system simulation under a given disruptive scenario, followed by post-processing and indicator aggregation. To address this challenge, surrogate models have been widely introduced as a computationally efficient alternative to direct model evaluation (Wang et al., 2022b). The basic idea is to train an approximation model that captures the mapping between the input variables and the resulting resilience values and then use this approximation in place of the original high-cost evaluation model during optimisation

(Tang et al., 2024; Li and Mostafavi, 2025). In this way, the optimisation process can be conducted more efficiently without requiring repeated execution of the full resilience assessment procedure. Recent advances in ML provide an opportunity to improve the efficiency of resilience estimation (Wang et al., 2022b). In this research, ML is used only as a surrogate tool to facilitate the evaluation of the optimisation objective, rather than as a central methodological contribution (Abyaneh et al., 2024). Given the breadth and maturity of the existing literature on ML models and applications (Li et al., 2023b), a detailed discussion of different model types and their comparative advantages and disadvantages is not provided here.

2.6 Research gaps and challenges

In summary, as critical hubs for cargo transshipment, multimodal container ports have long attracted significant research attention. However, amid rising risks and uncertainties, there is a growing need for researchers to develop more advanced resilience-oriented approaches. From a resilience perspective, considerable potential lies in understanding how port systems dynamically evolve under disruptions, accurately assessing their performance changes, and providing scientifically grounded management strategies accordingly.

The methodological choices in this thesis are determined by the different analytical requirements of the resilience-management process. SD is adopted because disruption propagation within multimodal ports is dynamic and feedback-driven, requiring explicit representation of causal relationships and time-dependent operational behaviour. The resilience measurement and ER approaches subsequently transform heterogeneous KPI responses into comparable subsystem-level and overall resilience measures while preserving the hierarchical port structure. GSA is then employed because it can quantify both individual and interaction effects of uncertain disruptive factors across the entire input space. Finally, multi-objective optimisation is adopted because post-disruption maintenance decisions involve an explicit trade-off between recovery cost and port-level resilience. These methods perform complementary functions rather than representing independent methodological choices. Therefore, the need to develop a holistic framework to achieve these objectives can be justified by the following limitations and challenges:

1) Limitations and challenges related to the research scope and focus

1.1) Most existing studies adopt a macro-level perspective, treating ports as single nodes within broader transportation networks. Such simplification overlooks the core transshipment function of ports, which operate as integrated hubs connecting multiple transport modes.

1.2) Moreover, the interactions among different transport modes within multimodal container ports are rarely explicitly modelled. In particular, the ripple effect by which disruptions propagate across these interconnected subsystems remains insufficiently examined.

1.3) In addition, many studies on port risk and resilience do not analyse resilience from the perspective of internal port operations. In particular, port performance in terms of transshipment efficiency and operational throughput is seldom used as a direct indicator for assessing resilience.

2) Limitations and challenges related to the methodological perspective

2.1) There is a lack of a holistic resilience framework targeted for multimodal container ports that systematically integrates risk modelling, resilience assessment, UQ, and the development of resilience enhancement strategies.

2.2) Existing approaches for resilience assessment do not fully capture the three key characteristics of a resilient system, limiting their ability to provide a comprehensive evaluation.

2.3) The multicriteria aggregation model adopted in previous studies often has limited capability to handle uncertainty, incorporate objective data, and explicitly represent indicator values across different hierarchical levels, which is necessary for analysing ripple effects.

2.4) Current studies that identify critical resilience influential factors generally examine risks individually and rarely consider the coupled effects of multiple concurrent risks.

2.5) Among the methods proposed to enhance resilience after disruptions, existing modelling approaches mainly focus on planned or condition-based maintenance policies. OM triggered by unexpected equipment failures is rarely incorporated into the maintenance scheduling framework.

Addressing these research gaps and challenges is essential for improving the understanding, assessment, and enhancement of resilience in multimodal container ports, thereby sustaining normal operations under risk and disruption conditions. Therefore, four technical models are developed in the subsequent chapters:

1. An operation simulation model for multimodal container ports under disruptions in Chapter 3 to address limitations 1.1 and 1.2.
2. A resilience assessment model based on port operational performance indicators in Chapter 4 to overcome limitations 1.3, 2.2, and 2.3.
3. A Sobol GSA model for critical risk factors identification in Chapter 5 to solve limitation 2.4.
4. An OM optimisation model for port equipment in Chapter 6 to handle limitation 2.5.
5. These models are interconnected through data inputs and outputs. Together, they form an integrated framework that collectively addresses limitation 2.1 by linking dynamic risk modelling, resilience assessment, critical factor identification, and resilience enhancement strategies.

The proposed methodological framework is expected to provide resilience-based practical decision support for port operators across different stages of disruption.

CHAPTER 3 A SYSTEM DYNAMICS BASED SIMULATION APPROACH ON THE RIPPLE EFFECTS OF DISRUPTIONS ON MULTIMODAL CONTAINER TERMINAL OPERATIONS¹

In this chapter, a novel microscopic-level SD model is proposed to quantify the internal ripple effects of a multimodal container port explicitly for the first time. Unlike existing macro-level SD studies in Supply Chain Risk Management (SCRM) that often oversimplify internal causal relationships, the proposed microscopic SD model accurately captures direct operational dependencies and interactions within a multimodal container terminal. Multiple disruptive scenarios derived from real-world accident records and field investigations are simulated to comprehensively assess their effects on port performance. The results demonstrate that disruptions such as quay crane failures and yard traffic congestion significantly impair operational efficiency. Notably, yard congestion triggers considerable delays in seaside operations and leads to substantial container accumulation, illustrating the ripple effects within the yard. Detailed scenario analysis enhances understanding of these complex ripple effects, supporting robust, holistic strategies to improve port resilience.

3.1 Introduction

As discussed and established in Chapters 1 and 2, understanding how ripple effects propagate within multimodal ports under disruptions is crucial for both academic research and industry practice. Against this background, this chapter aims to pioneer a new methodology for simulating how port disruptions impact container terminal operations, specifically focusing on handling general containers using various loading and unloading equipment across multiple transportation modes.

¹ The findings from this technical chapter have been published in the following journal paper. ZHANG, J., XIN, X., LIAO, Z., DUBEY, R., NGUYEN, T. T., LI, N. & YANG, Z. 2025. Analysis of the ripple effects of disruptions on multimodal container terminals operations: a System Dynamics approach. *Transportation Research Part E: Logistics and Transportation Review*, 202, 104264.

Given the dynamic and sensitive nature of port operations in response to disruptions, as well as the critical literature review in Chapter 2, SD is selected to simulate the complex dynamics of port operations, accounting for potential risk propagation and multiple causal relationships. This selection is rooted in SD's adeptness at representing complex causal relationships through feedback loops among different components, capturing the system's dynamic behaviours, and enabling the modelling of potential risks and uncertainties across various scenarios. Therefore, an SD model is developed to simulate the operations and inter-sectional interactions within a multimodal container port. Utilising quantitative data from real-world operations and accident records, scenarios that can best reflect the impact of port disruptions are designed to demonstrate the feasibility of the model, enhancing the practical significance of our research. This analysis not only illustrates the extent of the ripple effects of malfunctions, accidents, and congestion but also provides insights into emergency measures, including identifying critical risks and the first-response period. Moreover, leveraging historical data validates the model's ability to predict the consequences of real-life disruptive scenarios. Additionally, the model helps identify operational patterns by examining recurring phenomena, further grounding our study in real-world applicability. Furthermore, a comprehensive analysis of the dynamic evolution of risks aids various practical applications for different stakeholders. For example, it facilitates the development of real-time monitoring systems, risk identification systems, and decision-making frameworks for terminal operators to detect and respond to disruptions promptly. For example, the simulation results indicate that, under the investigated scenarios, restoring a disrupted quay crane within 72 hours can substantially limit its subsequent impact on port operational performance. When congestion occurs within the port, prioritising the efficiency of internal truck operations becomes crucial. External truck drivers' expected working time typically extends to about 1 to 1.5 hours without any intervention. It also supports individual transportation service providers with optimised berthing schedules, train schedules, truck routing and schedules to avoid known risk areas and maintain timely operations. Additionally, it aids policymakers in making informed decisions regarding resource allocation, prioritising investments in infrastructure, technology upgrades and personnel training programs. Implementing these measures promises to enhance sustainability and set the stage for profound, long-term transformations in supply chain management. These initiatives can fundamentally reshape industry standards and practices by fostering greater awareness and adoption of digitalisation and green strategies.

The key contributions of this chapter are outlined as follows:

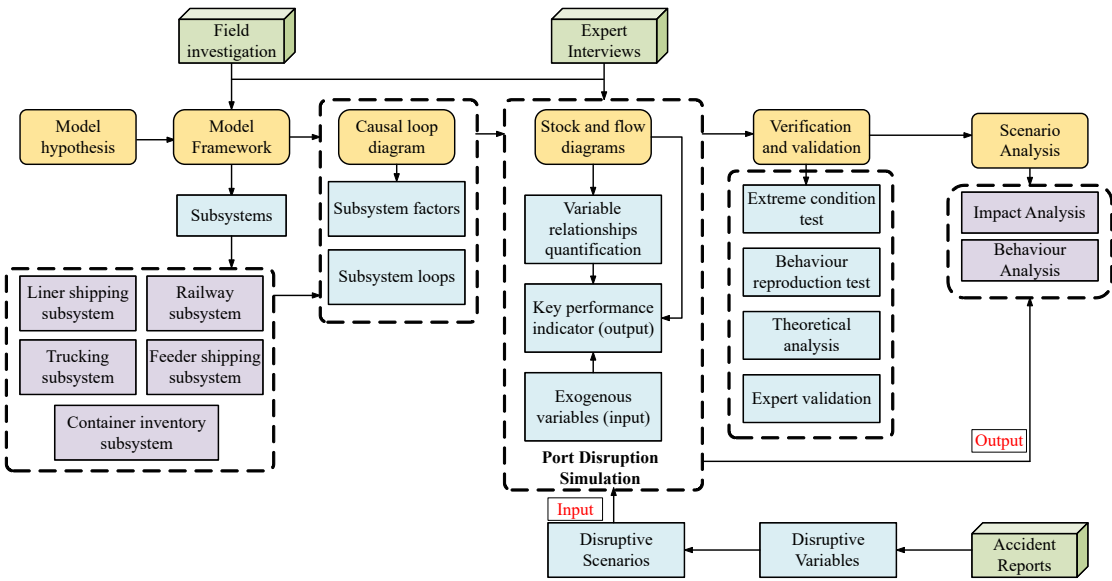
1. Supported by historical records and real data, this chapter effectively examines the ripple effects of port disruptions across various transportation modes, including liner shipping, feeder shipping, railway, and trucking.
2. This chapter introduces a novel SD model engineered explicitly for port disruptive operations, represented through a causal loop and stock and flow diagrams, aiming to simulate disruptions across diverse but connected transportation modes accurately.
3. A micro-level modelling framework on port disruptions with detailed variables and feedback relationships is built to reflect internal port dynamics under disruptions accurately.

The rest of the chapter is structured as follows. In Section 3.2, leveraging the actual operational logic of a container terminal, a causal loop diagram and stock-and-flow diagrams are established, identifying key variables and KPIs based on both secondary data and expert opinions. Section 3.3 describes the data collection and model validation methods and performs scenario analysis using accidental data. Section 3.4 compares the consequences of these risks and highlights significant insights and implications. Finally, Section 3.5 concludes this chapter.

3.2 Methodology: An System Dynamics-based simulation approach

This section outlines the methodology for developing a simulation of an SD model that focuses on the operations of a multimodal container terminal, specifically examining the impact of port disruptions across various transportation sectors within the terminal and their ripple effects. The construction of the SD model involves six generic steps, as shown in Figure 3.1. Firstly, the research hypothesis is formulated based on industry experience and current literature, establishing the system-wide boundary. Secondly, the model framework follows the proposed hypotheses. Thirdly, a causal loop diagram illustrates the feedback structure and visualises the interrelationships between relevant variables. This diagram is then transformed into a stock-and-flow diagram, which formulates equations describing the interactions among factors. Subsequently, model verification and validation are conducted to ensure the model's rigour. Additionally, scenario analysis is performed to identify influential parameters using actual data (Bell et al., 2023). The methodological novelties lie in how these steps are tailored and adapted to simulate the ripple effects of disruptions at a multimodal

1180 container terminal in the ensuing sub-sections. For this study, Vensim PLE software is used to draw causal loop
 1181 and stock-and-flow diagrams, conduct verification and validation tests, and run simulations.



1182
 1183 Figure 3.1. The flowchart of the SD simulation approach in Chapter 3. (Source: Author’s own work,
 1184 based on (Zhang et al., 2025b))

1185 3.2.1 Hypothesis of System Dynamics

1186 Before the model is fully introduced, the following hypotheses are set by both field investigation and past
 1187 literature (Jin et al., 2021; Li et al., 2022b; Liu et al., 2023c), and listed as follows:

- 1188 1. Liner shipping and feeder shipping are modelled separately due to their different requirements for
 1189 loading and unloading resources and their distinct functions in container collection and distribution.
 1190 Large liner vessels (long-haul services) visit transshipment ports, while small feeder vessels connect
 1191 the hub with neighbouring ports (feeder ports) in surrounding areas (Jin et al., 2021).
- 1192 2. As a transportation hub, inbound containers are imported by liner vessels and further distributed
 1193 through feeder vessels, trains, and trucks. Conversely, outbound containers are accumulated in storage
 1194 yards by feeder vessels, trains, and trucks before being dispatched by liner vessels (Jin et al., 2021).

3. Internal transportation within the container terminal is facilitated by internal trucks, which assist in the loading and unloading operations of liner vessels, feeder vessels, trains, and external trucks (Li et al., 2022b).
4. Internal and external trucks perform different operational roles within the terminal. External trucks arrive from outside the port, whereas internal trucks are considered as terminal resources. Therefore, internal trucks are not modelled as an independent arrival-and-queueing process. Instead, their availability is constrained by fleet size and allocation. Delays experienced by internal trucks due to yard congestion are captured through changes in their travel time and working efficiency. Accordingly, the time of internal trucks waiting for the yard crane is not considered. (Li et al., 2022b).
5. Port resources, such as the number of berths, cranes and internal trucks, restrict the efficiency of loading and unloading operations at the port (Liu et al., 2023c).
6. The general propagation mechanism within the port is assumed to operate as follows: yard congestion leads to increased truck density, which prolongs the travel time for internal trucks to reach other areas for loading and unloading. Since the loading and unloading operations in other areas require cooperation with internal trucks, inefficiencies in internal truck operations spill over to these areas, causing overall inefficiency throughout the port.

3.2.2 Framework of System Dynamics

Nowadays, container terminals' equipment, planning layouts, and operational procedures are highly standardised. Therefore, data collected from a real case study of a typical multimodal container terminal can be representative and used to create a conceptual generic multimodal container terminal model. From the perspective of multimodal transshipment operations, the port system is modelled using a modular approach encompassing five subsystems: liner shipping, feeder shipping, railway, trucking, and container yard. Liner shipping is responsible for large transoceanic shipments, while feeder shipping facilitates the regional distribution of these cargoes to coastal areas with smaller demand. Railways connect ports to inland destinations over long distances. Trucking is the most common component of the multimodal transportation network, owing to its flexibility and its crucial role in last-mile delivery. Additionally, many port areas are dedicated to container yards, which provide essential buffering and storage capabilities. Therefore, they are selected as subsystems.

Key risks integrated into this model include equipment failure, resource unavailability, and traffic congestion. Additionally, the model integrates the number of vehicles associated with each mode and the degree of port resource utilisation to assess the port performance. Container handling in the yard is a critical component of port operations across all subsystems, thereby interlinking them. As a result, inefficiencies in any subsystem can propagate to the others (Cai et al., 2024; Liu et al., 2023c).

All relevant concepts in the SD model are listed in Table 3.1. These factors were initially selected through a literature review and subsequently validated through field investigations and expert interviews.

Table 3.1. Classification of factors in the SD model.

Subsystem	Factors	Reference
Liner shipping	Arrival and departure rate of liner vessels, loading and unloading resources (berths, cranes), handling efficiency, capacity	(Zhou et al., 2022b; Liu et al., 2023c; Xu et al., 2021a)
Feeder shipping	Arrival and departure rate of feeder vessels, loading and unloading resources (berths, cranes), handling efficiency, capacity	(Lee and Jin, 2013; Emde and Boysen, 2016)
Railway	Arrival and departure rate of trains, loading and unloading resources (tracks, cranes), handling efficiency, and capacity.	(Xu et al., 2021a; Schulz et al., 2021; Liu et al., 2023c)
Truck	Arrival and departure rate of external trucks, internal trucks, yard cranes, handling efficiency, travelling speed, capacity, and travelling distance	(Liu et al., 2023c; Li et al., 2022b; Li et al., 2018)
Container Inventory	Container volume, export rate, import rate, cutoff time	(Li et al., 2023b; Jin et al., 2021; Lin et al., 2022)

3.2.3 Causal loop diagram of System Dynamics

The causal loop diagram illustrates the interactions among different transportation subsystems under disruptions. The cause-and-effect relationships are presented using arrows to specify the connections between

two variables. The origin of an arrow signifies the causative factor, while the arrowhead indicates the effect factor. Additionally, the symbols ‘+’ and ‘-’ define the effect of two factors, which can be positive or negative. A positive symbol is used when both factors exhibit the same tendency, while a negative symbol is used when they demonstrate opposite tendencies. Similarly, when a loop is composed of multiple factors, the symbols ‘+’ and ‘-’ are utilised to reflect the positive or negative nature of the loop.

The causal loops and the variables within different subsystems are identified and listed through field investigation and past literature, as shown in Table 3.2. Then, a causal loop diagram is drawn in detail, as seen in Figure 3.2. The causal dependencies are determined through a combination of operational logic, literature, field investigation, and expert validation. First, the main operational processes and variables are identified from previous studies and direct observations during the field investigation. Second, causal links are established only where a direct operational mechanism could be identified. For example, an increase in the number of vessels or trains reduces the availability of corresponding berths, tracks, or handling resources. Similarly, higher handling activity increases the demand for internal trucks, which raises truck density and may reduce truck travelling speed and handling efficiency through congestion. Finally, the structure and direction of these relationships were reviewed through expert interviews and field-based validation to ensure that they are consistent with actual operations. The explanations provided below detail the cause-and-effect logic within each loop, emphasising the role of these variables in port operations and their critical impact on port efficiency.

Table 3.2. Details of the causal loops in SD.

Notation	Subsystem	Detail
Loop1	Liner shipping	Liner vessels density ⁻ →Available resource for liner vessels ⁺ →Liner vessels loading and unloading efficiency ⁺ →Liner vessels departure ⁻ →Liner vessels density
Loop2	Liner shipping	Liner vessels loading and unloading efficiency ⁺ →Internal trucks for liner vessels ⁺ →Truck density ⁻ →Liner vessels loading and unloading efficiency

Loop3	Feeder shipping	Feeder vessels density $\rightarrow$ Available resource for feeder vessels $\rightarrow$ Feeder vessels loading and unloading efficiency $\rightarrow$ Feeder vessels departure $\rightarrow$ Feeder vessels density
Loop4	Feeder shipping	Feeder vessels loading and unloading efficiency $\rightarrow$ Internal trucks for feeder vessels $\rightarrow$ Truck density $\rightarrow$ Feeder vessels loading and unloading efficiency
Loop5	Railway	Trains density $\rightarrow$ Available resource for trains $\rightarrow$ Trains loading and unloading efficiency $\rightarrow$ Trains departure $\rightarrow$ Trains density
Loop6	Railway	Trains loading and unloading efficiency $\rightarrow$ Internal trucks for trains $\rightarrow$ Truck density $\rightarrow$ Trains loading and unloading efficiency
Loop7	Truck	Trucks density $\rightarrow$ Available resource for trucks $\rightarrow$ Trucks loading and unloading efficiency $\rightarrow$ External trucks departure $\rightarrow$ Trucks density
Loop8	Truck	Truck density $\rightarrow$ Traffic jam $\rightarrow$ Trucks loading and unloading efficiency $\rightarrow$ External trucks departure $\rightarrow$ Truck density

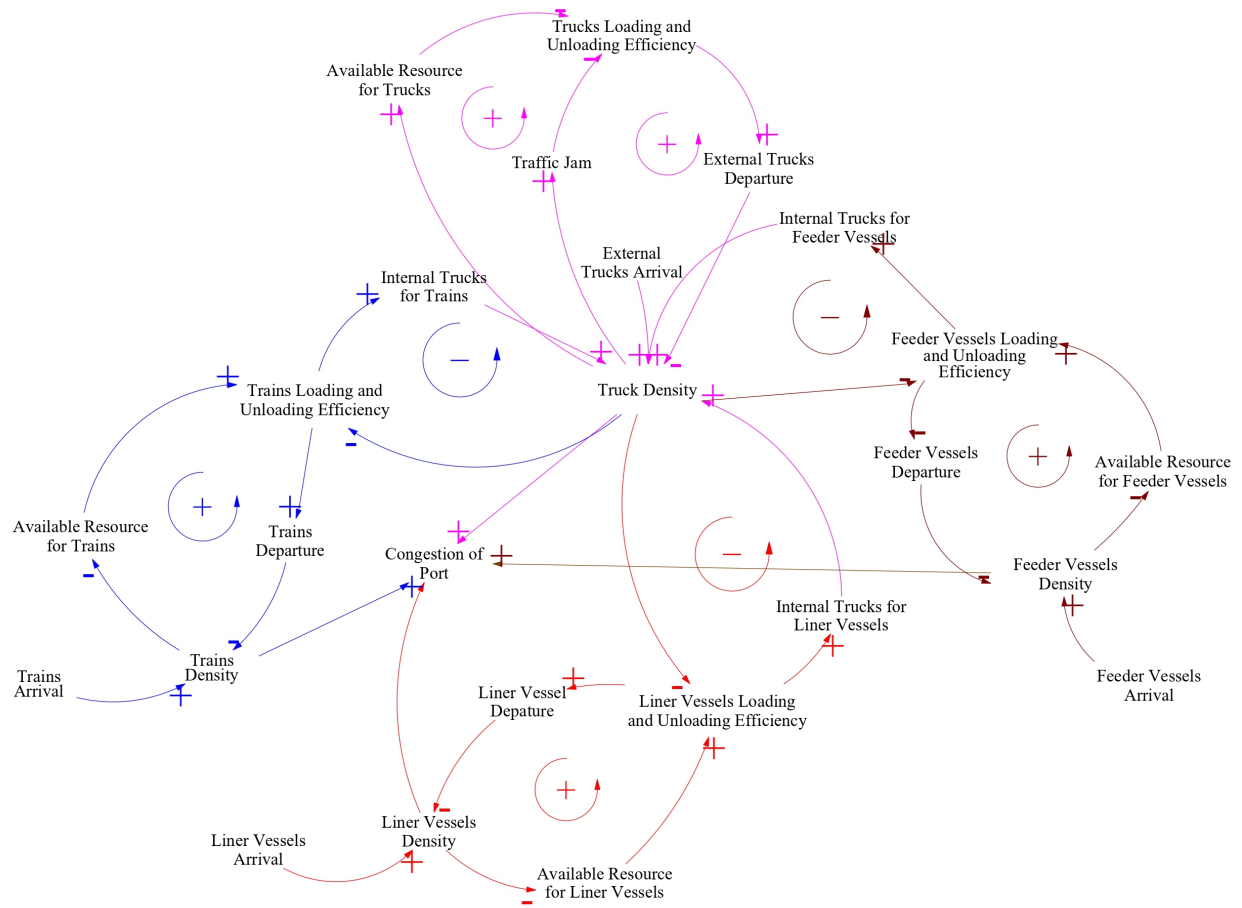


Figure 3.2. Causal loop diagram in SD.

In Table 3.2, Loop1 is a feedback loop focusing on the liner shipping subsystem, reflecting the causal relationships related to resource limitations. In liner shipping operations, the number of available resources limits service efficiency because loading and unloading vessels must be performed at designated berths with the relevant equipment. High efficiency expedites vessel departure rates, decreasing waiting vessels and releasing more available resources. Loop2 also includes variables in the liner shipping subsystem and represents a cyclic causal relationship involving internal trucks. Efficient loading and unloading operations also require coordination with internal trucks to move containers between the seaside and the container yard. Therefore, highly efficient operations demand adequate internal truck support. To maintain the pace, an increase in the number of internal trucks may induce higher internal truck density, subsequently leading to traffic jams. Moreover, traffic congestion leads to unnecessary delays, extending internal truck turnaround times and reducing operational efficiency. Without adequate support from internal trucks, the efficiency of liner vessels'

loading and unloading will diminish. Similarly, Loop3 (feeder shipping), Loop5 (railway), and Loop7 (trucking) share the same logic as Loop1. Loop4 (feeder shipping) and Loop6 (railway) share the same logic as Loop2.

Loop8 illustrates the cyclic relationship between truck density and the loading and unloading efficiency of external and internal trucks. Truck operations at a container terminal are divided into external trucks and internal trucks based on their operational scope. External trucks provide delivery or pickup services between the port and the hinterland and require pre-arranged appointments before entering the terminal. Internal trucks are mainly responsible for transporting containers between storage yards and other locations inside the terminal. The increased density of external and internal trucks can cause traffic jams, prolonging their turnaround time and reducing their operational efficiency. As a result, the departure rate of external trucks slows, causing a continuous accumulation in the container yard and further increasing the density of container trucks.

As a key variable, truck density influences not only the operations of external trucks through Loop7 and Loop8 but also the efficiency of other transportation modes through Loop2 (liner shipping), Loop3 (feeder shipping) and Loop6 (railway) via the operations of internal trucks.

3.2.4 Stock and flow diagram

Elaborating on the causal loop diagram, the stock and flow diagram quantifies the variables and organises them into five separate diagrams, which represent five subsystems, as depicted in Figure 3.3 to Figure 3.7. These specific, quantifiable variables are derived from past literature, field research and expert opinions, as depicted in Table 3.3 and Table 3.4.

The SD model categorises the variables into four types: level, rate, constants, and auxiliary variables. Level variables, or stock variables, are depicted as rectangular boxes. They calculate cumulative values over time, representing the difference between inflows and outflows. Rate variables, illustrated with arrows entering and exiting cloud-shaped symbols, indicate the rate of change for level variables. Constants are parameters with fixed values that serve as inputs for the model. Auxiliary variables play intermediate roles, linking level, rate, and constant variables and helping to articulate the underlying mechanisms. Additionally, based on the functions of variables within the model's logical structure, the KPIs are summarised in Table 3.3 serve as outputs. Constant

1289 variables, also known as input variables, are listed in Table 3.4 while the remaining variables are classified as
1290 intermediate.

1291 To assess how operational disruptions affect port efficiency across various transportation subsystems, KPIs
1292 are selected to capture delays (e.g., queue length), efficiency (e.g., turnaround time), and capacity stress (e.g.,
1293 container volume), as shown in Table 3.3. These KPIs are drawn from a comprehensive literature review and
1294 authoritative industrial sources. Specifically, they include reports, indices, and public data provided by
1295 international organisations e.g., The World Bank (The World Bank, 2023), consulting firms e.g., Drewry
1296 (Drewry Maritime Research, 2023), and port authorities e.g., Port of Long Beach (Port of Long Beach, 2025).
1297 Similarly, a set of exogenous variables is derived from field investigations and expert consultations from a major
1298 container terminal. To avoid redundancy, details about data collection, including their values and sources,
1299 typically covered in Section 3.3, are outlined in Table 3.4 instead. It should be clarified that the number of
1300 containers represents the container volume requiring loading and unloading during a vessel call, rather than the
1301 vessel's total carrying capacity. Vessel size is not explicitly modelled as an independent variable, as the present
1302 study focuses on terminal handling demand and its influence on operational performance. Different vessel calls
1303 may therefore involve different handling volumes within the specified ranges. Variables are included if they (1)
1304 directly influence operational bottlenecks or resource constraints; (2) participate in at least one feedback loop;
1305 or (3) represent quantifiable port efficiency. Different vehicles are denoted as $m = \{l, f, r, ex, in\}$ which stands
1306 for liner vessels, feeder vessels, railway trains, external trucks and internal trucks. It should be clarified that
1307 both internal trucks and external trucks are part of the trucking subsystem. They are treated separately here
1308 because they perform different operational roles and follow different operational logics within port operations,
1309 which makes it inappropriate to represent them using the same subscript notation. This distinction does not
1310 mean that internal trucks are regarded as a separate subsystem.

1311

Table 3.3. KPIs (Output variables) in SD.

Category	Notation	Corresponding index	Unit	Literature	Industry
Liner vessels	A_l	Number of Liner Ships at Anchorage	Vessels	(Liu et al., 2023c; Zhou et al., 2022b)	(The World Bank, 2023; Drewry Maritime Research, 2023)
Feeder vessels	A_f	Number of Feeder Ships at Anchorage	Vessels	(Emde and Boysen, 2016; Jin et al., 2021)	(The World Bank, 2023; Drewry Maritime Research, 2023)
Trains	A_r	Number of Waiting Trains	Trains	(Schulz et al., 2021)	(The World Bank, 2023; Drewry Maritime Research, 2023)
Trucks	A_{ex}	Number of External Trucks in Port	Trucks	(Liu et al., 2023c; Xu et al., 2021a; Li et al., 2018)	(The World Bank, 2023; Port of Long Beach, 2025)
	D_{exw}	External Truck Working Time	Hour	(Li et al., 2018; Sun et al., 2022)	(The World Bank, 2023; Port of Long Beach, 2025)

Containers

Vol

Volume of Containers in Port

Containers

(Liu et al., 2023c; Lin et al., 2022; Xu et al., 2021a)

(Port of Long Beach, 2025)

1313

1314

Table 3.4. Exogenous variables (Input variables) in SD.

	Notation	Variable	Unit	Estimation	Source	Reference
	λ'_l	Liner Ships Arrival Poisson Mean	vessels/Hour	1.5	Real data	(Bell et al., 2023)
Liner shipping system	B_l	Number of Liner Berths	Vessels	16	Real data	(Liu et al., 2023c; Zhou et al., 2022b; Lin et al., 2022; Xu et al., 2021a)
	E_l	Number of Quay Cranes for Liner Ships	Cranes	6	Real data	(Liu et al., 2023c; Xu et al., 2021a)

Feeder shipping system	C_l	Number of Containers per Liner Ship	Containers	RANDOM UNIFORM(1000, 3000)	Statistics representation derived from real data	(Zhou et al., 2022b; Emde and Boysen, 2016)
	η_l	Quay Crane Handling Efficiency for Liner Ships	Containers/Hour/cranes	30	Real data	(Liu et al., 2023c; Lin et al., 2022; Jin et al., 2021)
	D_{lb}	Liner Ships Berthing Time	Hour	1	Real data	(Zhou et al., 2022b)
	λ_f'	Feeder Ships Arrival Poisson Mean	vessels/Hour	0.3	Real data	(Bell et al., 2023; Lee and Jin, 2013)
	B_f	Number of Feeder Berths	Vessels	3	Real data	(Liu et al., 2023c; Zhou et al., 2022b; Lin et al., 2022; Xu et al., 2021a; Lee and Jin, 2013)
	E_f	Number of Quay Cranes for Feeder Ships	Crane	3	Real data	(Liu et al., 2023c; Xu et al., 2021a)

Train system	C_f	Number of Containers per Feeder Ship	Containers	RANDOM UNIFORM(500, 1000)	Statistics representation derived from real data	(Zhou et al., 2022b; Emde and Boysen, 2016; Jin et al., 2021)
	η_f	Quay Crane Handling Efficiency for Feeder Ships	Containers/Hour/cranes	30	Real data	(Liu et al., 2023c; Lin et al., 2022; Jin et al., 2021)
	D_{fb}	Feeder Ships Berthing Time	Hour	1	Real data	(Zhou et al., 2022b)
	λ_r'	Train Arrival Poisson Mean	Trains/hour	1.2	Statistics representation derived from real data	(Schulz et al., 2021)
	B_r	Number of Transshipment Tracks	Trains	4	Real data	(Schulz et al., 2021)
	E_r	Number of Cranes for Trains	Cranes	4	Real data	(Liu et al., 2023c)

Trucking system	C_r	Number of Containers per Train (actual containers carried by a train)	Containers	RANDOM UNIFORM(100, 150)	Statistics representation derived from real data	(Xu et al., 2021a; Schulz et al., 2021)
	η_r	Train Crane Handling Efficiency	Containers/Hour/cranes	30	Real data	(Liu et al., 2023c)
	λ_{ex}'	Truck Arrival Poisson Mean	TEU/hour	500	Real data	(Sun et al., 2022; Li et al., 2018)
	s_{ex}	Distance of External Truck Route	Km	5	Real data	(Li et al., 2022b)
	s_{in}	Distance of Internal Truck Route	Km	3	Real data	(Lee and Jin, 2013; Li et al., 2022b)
	ρ_j	Truck Density in Jam	Trucks/km	60	Average real data	(Greenshields, 1934){Pan, 2025 #672}
	ρ_c	Truck Density Critical	Trucks/km	20	Average real data	(Greenshields, 1934){Pan, 2025 #672}

v_{ex}	Truck Free Velocity	Km/Hour	30	Average real data	(Greenshields, 1934){Pan, 2025 #672}
D_{inl}	Internal Trucks Loading and Unloading Time	Hour	0.05	Averaged real data	(Sun et al., 2022; Li et al., 2022b)
E_y	Number of Yard Cranes	Cranes	48	Real data	(Liu et al., 2023c; Xu et al., 2021a; Li et al., 2018)
η_y	Yard Crane Working Efficiency	Containers/Hour/cranes	30	Real data	(Liu et al., 2023c; Li et al., 2018)
C_{ex}	External Trucks Capacity	Containers/trucks	2	Real data	(Li et al., 2022b)
C_{in}	Internal Trucks Capacity	Containers/trucks	2	Real data	(Li et al., 2022b)
E_{in}	Max Number of Internal Trucks	Trucks	60	Real data	(Li et al., 2022b)

Container import and export system	a_{ex}	Coefficient	Dimensionless	-1.5	Literature-derived empirical parameter	(Huynh et al., 2004)
	b_{ex}	Coefficient	Dimensionless	0.0045	Literature-derived empirical parameter	(Huynh et al., 2004)
	τ_{cut}	Exported Containers Cutoff Time	Hour	72	Averaged real data	(Li et al., 2023b)
	τ_{pick}	Imported Containers Pickup Time	Hour	RANDOM UNIFORM(72, 120)	Statistics representation derived from real data	(Jin et al., 2021)
	ψ_f	Feeder Ships Export Ratio	Dmnl	0.5	Averaged real data	(Lin et al., 2022)
	ψ_r	Train Export Ratio	Dmnl	0.5	Averaged real data	(Lin et al., 2022)
	ψ_{ex}	Trucks Export Ratio	Dmnl	0.5	Averaged real data	(Lin et al., 2022)
	ψ_l	Liner Ships Export Ratio	Dmnl	0.35	Averaged real data	(Lin et al., 2022)

CAP_f	Feeder ships capacity	Containers/vessels	RANDOM UNIFORM(500, 1000)	Statistics representation derived (Zhou et al., 2022b) from real data
CAP_r	Trains capacity	Containers/Trains	RANDOM UNIFORM(100, 150)	Statistics representation derived (Xu et al., 2021a; Schulz et al., 2021) from real data
CAP_l	Liner ships capacity	Containers/vessels	RANDOM UNIFORM(1000, 3000)	Statistics representation derived (Zhou et al., 2022b) from real data

3.2.4.1 *International liner shipping subsystem*

The international liner shipping subsystem concentrates on the operations of long-distance liner vessels arriving, unloading, loading, and departing on major trade routes, as shown in Figure 3.3. Such vessels play a crucial role in connecting major ports worldwide and collaborate with feeder vessels to facilitate the collection and distribution of containers.

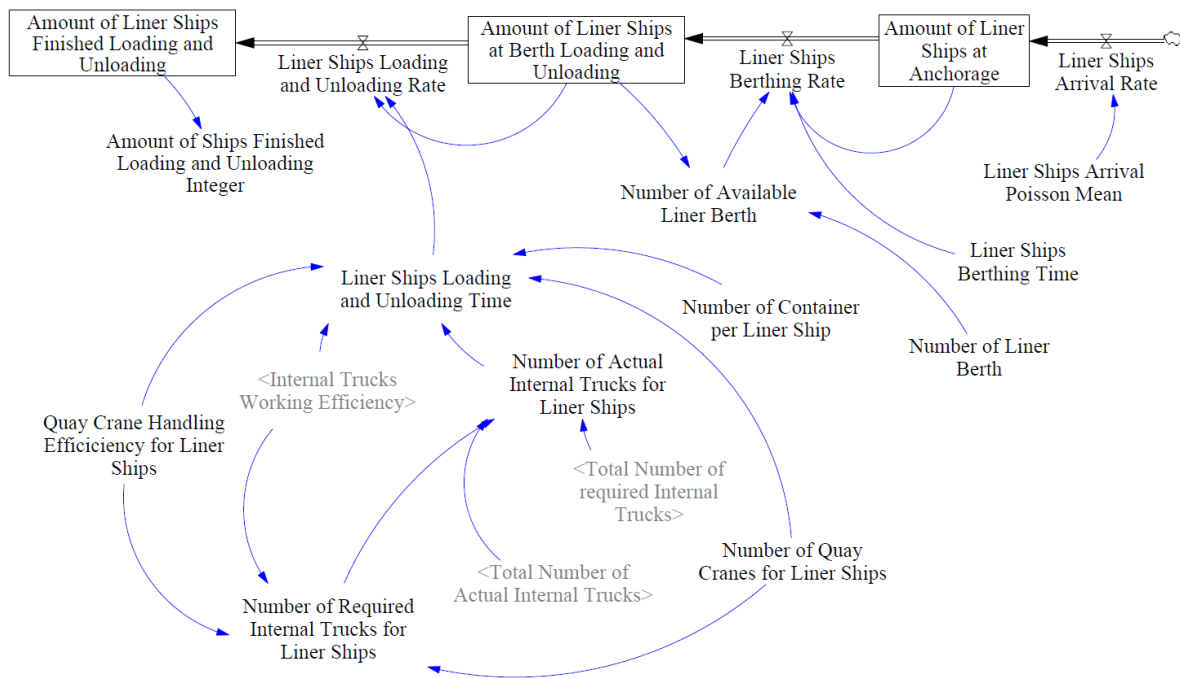


Figure 3.3. Liner shipping subsystem.

First, the stock variables represented by boxes are explained as follows. “Amount of Liner Ships at Anchorage” gradually accumulates with the arrival of new vessels and diminishes through berthing. “Amount of Liner Ships at Berth Loading and Unloading” is determined by the difference between vessels currently capable of berthing and those completing loading and unloading operations. “Amount of Liner Ships Finished Loading and Unloading” is accumulated with the rate of vessels finishing loading and unloading activities. These level variables are calculated by integrating the difference between the connected incoming and outgoing rate variables, indicated by arrows with double lines pointing to and from them.

1. Liner ships berthing rate (P_l)

Common industrial knowledge indicates that if all berths are unavailable, arriving vessels must wait at anchorage until they can undergo loading and unloading operations, therefore the number of available berths (B_{al}) is calculated by subtracting the number of berths currently occupied by vessels (L_l) from the total number of berths designed for liner vessels (B_l). Thus, the berthing rate is influenced by the lesser of two quantities: the number of available berths (B_{al}) or the number of waiting vessels (A_l) and berthing time for liner vessels (D_{lb}). If the number of available berths exceeds the number of waiting vessels, only the waiting vessels can berth; conversely, if the number of waiting vessels exceeds the available berths, the operation is limited by berth capacity. Therefore, the berthing rate can be calculated as follows:

$$P_l = \begin{cases} \frac{\min(B_{al}, A_l)}{D_{lb}}, & B_{al} > 0, A_l > 0 \\ 0, & else \end{cases} \quad (3-1)$$

$$B_{al} = B_l - L_l \quad (3-2)$$

2. Liner ships loading and unloading rate (μ_l)

Due to the parallel cooperation between internal trucks and quay cranes, the overall loading and unloading time for a liner vessel (D_{ll}) is determined by the maximum time required, causing the “bottleneck effect”. This time is calculated by dividing the number of containers to be loaded and unloaded by the number of loading equipment and the efficiency of this equipment. Then the loading and unloading rate is defined as the number of liner vessels processed per unit of time. It quantifies the efficiency of port operations concerning how quickly liner vessels can be processed. The condition $L_l > 0$ ensures that the rate is only calculated when vessels are being processed; otherwise, the rate is zero, indicating no operations. The loading and unloading time for a liner vessel (D_{ll}) is as follows:

$$D_{ll} = \max\left(\frac{C_l}{\eta_l E_l}, \frac{C_l}{A_l \eta_l}\right) \quad (3-3)$$

1348 where C_l is the volume of containers requiring loading and unloading, E_l is the number of quay cranes, η_l is the
 1349 efficiency of quay cranes operations, AI_l is the number of actual internal trucks, and η_i is the efficiency of
 1350 internal truck operations. The waiting time of internal trucks that is excluded from the model refers specifically
 1351 to queueing delays of internal trucks at quayside or yard handling points. In particular, congestion-related delays
 1352 are captured through the effect of truck density on travelling speed. Based on field observations and the
 1353 operational priority given to internal trucks, additional queueing delays at handling points are assumed to be
 1354 negligible and are therefore not modelled separately. The loading and unloading rate for liner vessels can be
 1355 modelled as:

$$\mu_l = \begin{cases} \frac{L_l}{D_{ll}}, & L_l > 0 \\ 0, & else \end{cases} \quad (3-4)$$

1356 3.2.4.2 Feeder shipping subsystem

1357 Feeder vessels transport containers between neighbouring ports, forming a hub-and-spoke structure, thus
 1358 facilitating collection and distribution services for liner vessels. Due to the different positions in the
 1359 transportation network structure, they are simulated in different sectors. However, the operational dynamics of
 1360 the feeder shipping system and its impact on other modes of transportation parallel those of the international
 1361 shipping subsystem. To avoid redundancy, the formulas related to feeder shipping are not reiterated, and only
 1362 the diagram is provided as shown in Figure 3.4.

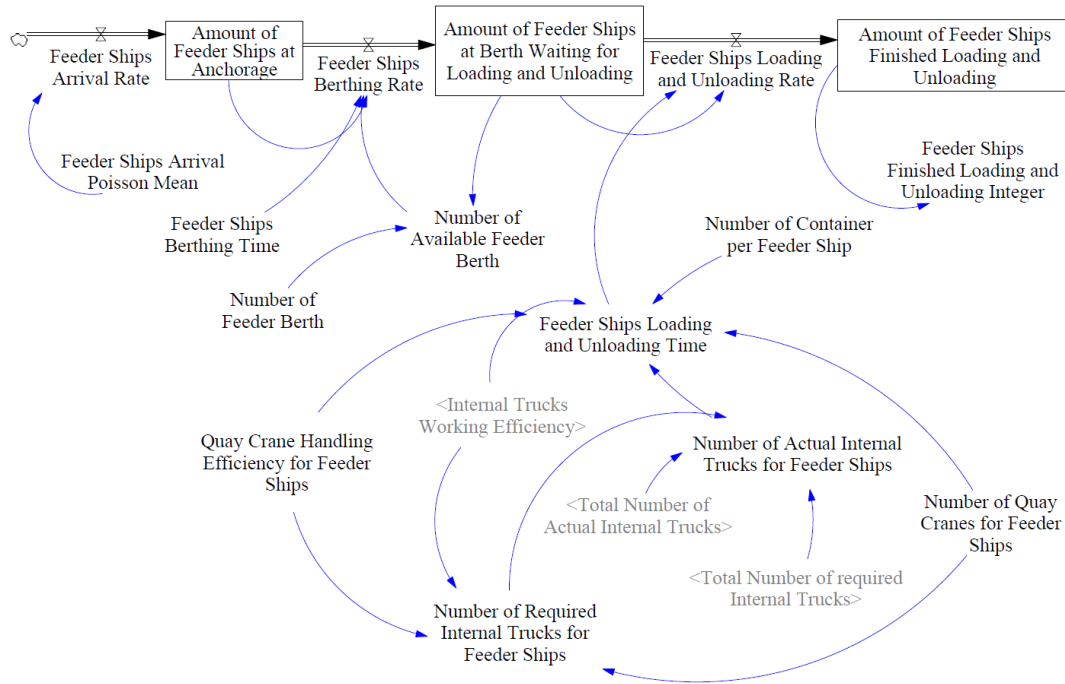


Figure 3.4. Feeder shipping subsystem.

3.2.4.3 Railway subsystem

A significant volume of containers is transported by railway via train tracks. Figure 3.5 shows the details of the railway subsystem. The railway subsystem operates under the disciplines of train arrivals, potential waiting periods if no transshipment tracks are available, transshipment processes, and departures.

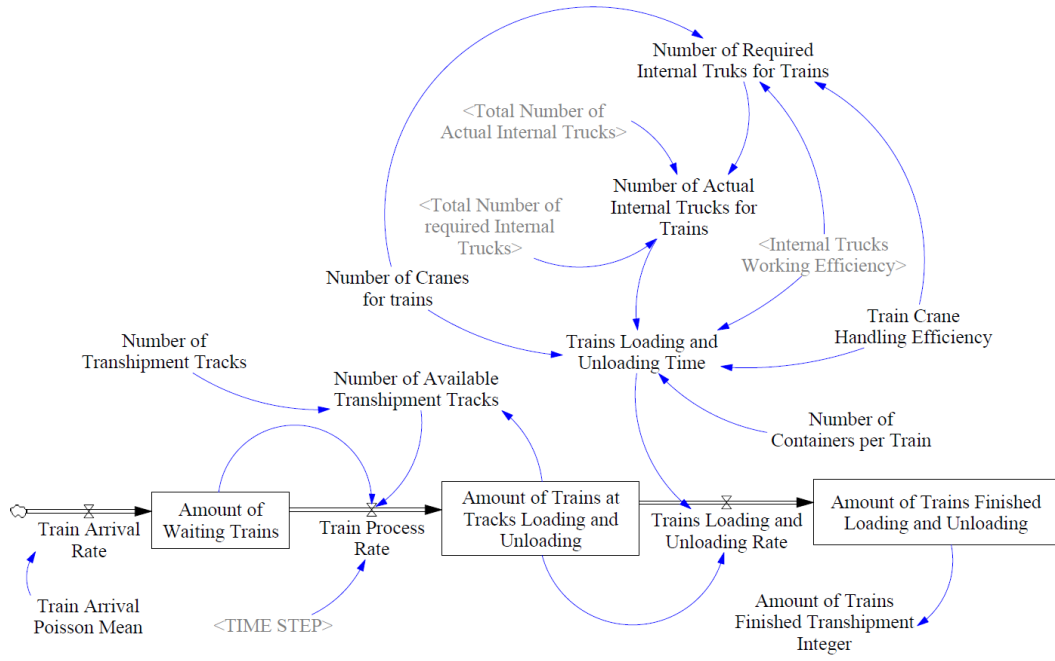


Figure 3.5. Railway subsystem.

1. Train process rate (P_r)

Field investigation and interviews with port staff indicated that, once a transshipment track becomes available, the time required for a waiting train to move to the assigned track is very short relative to the subsequent loading and unloading operation. This transit time is therefore neglected. Thus, the equation for calculating the process rate can be expressed as follows:

$$P_r = \begin{cases} \min(B_{ar}, A_r), & B_{ar} > 0, A_r > 0 \\ 0, & else \end{cases} \quad (3-5)$$

$$B_{ar} = B_r - L_r \quad (3-6)$$

where P_r is train process rate, B_{ar} is the number of available transshipment tracks, A_r is the number of waiting trains, B_r is the number of transshipment tracks, and L_r is the number of trains under loading and unloading operations.

2. Other variables

Besides the train process rate, the calculation of stock variables such as the number of waiting trains, the number of trains under loading and unloading operations (L_r), and the number of trains finished loading and unloading (F_r) is the same as explained in section 3.2.4.1. The loading and unloading rate for trains (μ_r) follows the same logic as Equation (3-4) in the liner shipping subsystem.

3.2.4.4 Truck subsystem

External truck operation can be generalised into four phases: arrival, transit within the port, container loading and unloading, and departure, as shown in Figure 3.6.

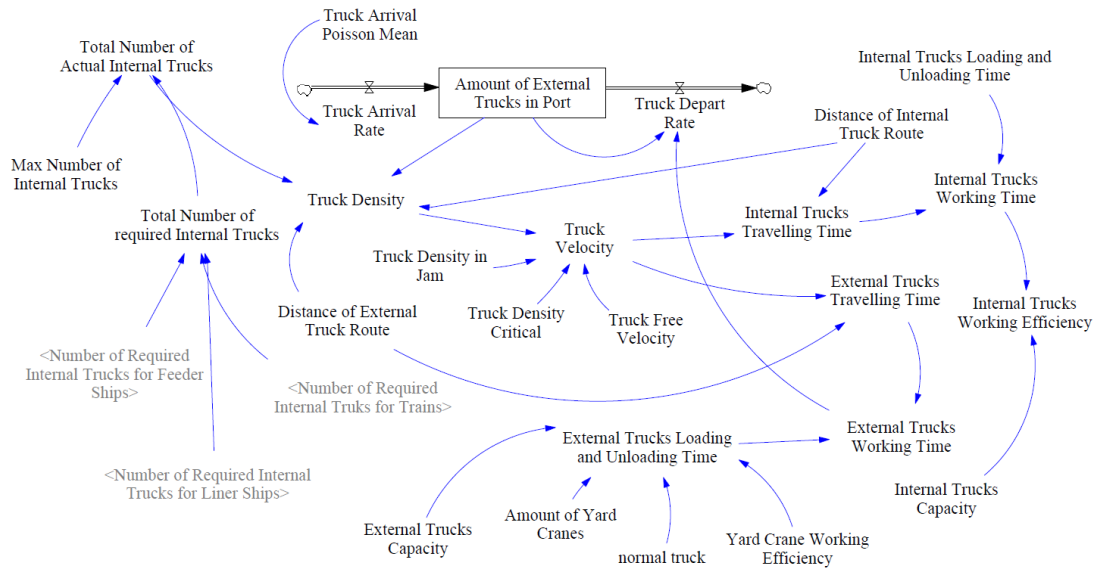


Figure 3.6. Trucking subsystem.

1. Truck velocity (v)

Traffic speed is depicted based on the fundamental road traffic theory, including traffic flow, traffic density, and vehicle speed (Greenshields, 1934), as shown below:

$$v = \begin{cases} \left(1 - e^{-\frac{\rho_j}{\rho_c}}\right), & \rho < \rho_c \\ v_{ex} \left(1 - \frac{\rho}{\rho_j}\right), & \rho < \rho_j \\ v_{ex} \ln\left(\frac{\rho}{\rho_j}\right), & \rho \geq \rho_j \end{cases} \quad (3-7)$$

In the equation, v represents the current truck velocity, v_{ex} denotes the free-flow velocity when there is no traffic jam, ρ is the current traffic density, and ρ_c is the level of traffic density at which traffic flow is maximised. It represents a tipping point: below this level, vehicles generally have the freedom to manoeuvre and accelerate, leading to optimal flow conditions. Above this density, interactions between vehicles become more frequent, leading to a decrease in overall traffic speed and flow. ρ_j is the jam density, which refers to the maximum traffic density beyond which traffic flow breaks down completely, leading to a traffic jam.

2. Truck departure rate (μ_{ex})

The departure rate of a truck is determined by the total working time spent inside the terminal, which consists of loading and unloading time as well as travel time.

The loading and unloading time for an external truck (D_{exl}) is calculated based on the number of cranes, their efficiency, and truck capacity. Previous studies (Huynh et al., 2004) provide empirical data and models that describe how changes in yard equipment availability or efficiency can affect D_{exl} , this relationship is characterised as follows:

$$D_{exl} = \frac{1}{a_{ex} + b_{ex}E_y\eta_y} CAP_{ex} \quad (3-8)$$

where CAP_{ex} is the capacity of external trucks, E_y is the number of yard cranes, η_y is the working efficiency of the yard cranes, a_{ex} and b_{ex} are empirical calibration coefficients adopted from the relationship proposed by Huynh et al. (2004). In this formulation, a_{ex} represents the baseline calibration term, while b_{ex} scales the effect of yard crane service capacity on external trucks loading and unloading time. Their values, -1.5 and 0.0045 , respectively, are adopted directly from the cited study. Subsequently, the total working time (D_{exw}) is calculated

1410 by adding together the loading and unloading time with the travel time (D_{ext}) within the terminal. The travel
 1411 time is determined by the distance travelled (s_{ex}) and the speed of the external trucks. Finally, the departure rate
 1412 of external trucks (μ_{ex}) is defined as the ratio of the number of trucks to their total working time, assuming that
 1413 trucks are present. The equations are as follows:

$$\mu_{ex} = \begin{cases} \frac{A_{ex}}{D_{exw}}, & A_{ex} > 0 \\ 0, & else \end{cases} \quad (3-9)$$

$$D_{exw} = D_{ext} + D_{exl} \quad (3-10)$$

$$D_{ext} = \frac{s_{ex}}{v} \quad (3-11)$$

1414 where A_{ex} represents the number of external trucks in the port.

1415 3. Number of actual internal trucks (AI_{in})

1416 During loading operations, internal trucks collect containers from storage yards and position them under
 1417 cranes for subsequent loading onto vessels or trains. Conversely, during unloading operations, internal trucks
 1418 retrieve containers from under the cranes and transport them to storage yards. Because internal trucks need to
 1419 coordinate with liner shipping, feeder shipping, and railway, their operational efficiency should theoretically
 1420 match that of each respective transportation mode. Therefore, the number of internal trucks required for each
 1421 transportation mode (RI_m) is calculated by dividing the product of quay crane efficiency (η_m) and the number
 1422 of available quay cranes (E_m) by the efficiency of the internal trucks (η_{in}). The rationale behind this directly
 1423 relates to the requirement for maintaining operational flow, which must be matched by adequate internal truck
 1424 availability. By adding the number of internal container trucks required to keep pace with each transportation
 1425 method, the total number of required internal container trucks can be determined, as shown below.

$$RI_m = \frac{\eta_m E_m}{\eta_{in}}, \forall m = \{l, f, r\} \quad (3-12)$$

$$RI_{in} = \sum_{m=l,f,r} RI_m \quad (3-13)$$

1426 where RI_{in} is the total number of required internal trucks. However, the resource of internal trucks is constrained
1427 by a maximum value E_{in} :

$$AI_{in} = \min(E_{in}, RI_{in}) \quad (3-14)$$

1428 where AI_{in} is the total number of internal trucks, and E_{in} is the maximum number of internal trucks available.
1429 Then, the actual number of available internal container trucks is allocated to various subsystems based on their
1430 demands. Therefore, the actual number of internal trucks in each subsystem can be modelled as follows:

$$AI_m = \frac{AI_{in} RI_m}{RI_{in}}, \forall m = \{l, f, r\} \quad (3-15)$$

1431 where AI_m is the number of actual internal trucks for transportation mode m .

1432 4. Internal truck working efficiency (η_{in})

1433 Internal trucks generally travel shorter distances, mainly for shuttling trips between the seaside and yards
1434 or between train tracks and yards. Similar to external trucks, the travel time of internal trucks (D_{int}) is
1435 determined by traffic density. The efficiency of internal trucks also depends on their working time (D_{inw}), which
1436 includes both travel time (D_{int}) and loading and unloading time (D_{inl}). This relationship can be modelled with
1437 the following equations:

$$\eta_{in} = \frac{C_{in}}{D_{inw}} \quad (3-16)$$

$$D_{inw} = D_{int} + D_{inl} \quad (3-17)$$

$$D_{int} = \frac{S_{in}}{v} \quad (3-18)$$

where s_{in} is the distance of the route of internal trucks. These equations quantify the internal trucks' efficiency by calculating the ratio of their capacity to their total operational time within the terminal.

5. Truck density (ρ)

The truck density in a container terminal is determined by dividing the total number of external and internal trucks by the distance they travel within the port, and can be modelled as follows:

$$\rho = \frac{A_{ex} + AI_{in}}{\max(s_{ex}, s_{in})} \quad (3-19)$$

The truck density will be further utilised to calculate truck velocities in Equation (3-7), thereby forming a cyclic feedback loop. The SIMULTANEOUS and ACTIVE INITIAL functions in Vensim PLE are used to indicate the dynamic changes in values.

3.2.4.5 Container inventory subsystem

A typical multimodal container port should bridge international liner shipping routes with domestic multimodal transportation networks. Therefore, this model examines container inventory from both import and export perspectives, as shown in Figure 3.7.

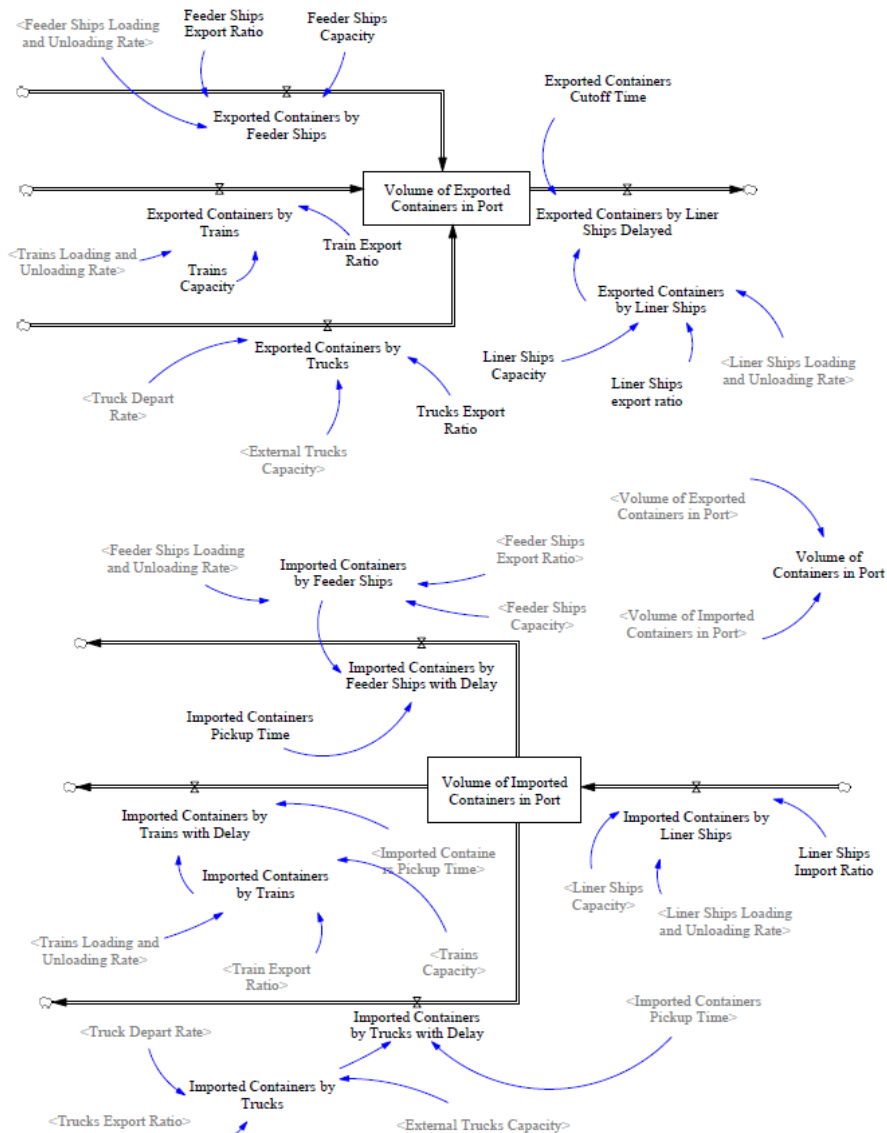


Figure 3.7. Containers inventory subsystem.

1. Volume of exported containers (Vol_{out})

During export, outbound containers are delivered from the hinterland via three subsystems (feeder shipping, railway and trucking) and stored in yards in preparation for long-haul liner voyages. In practice, all containers must be prepared and documented before a specified departure time, commonly referred to as the cutoff period. Therefore, the DELAY function in Vensim PLE is employed to represent the cutoff period, with the quantity of outbound containers calculated by:

$$Vol_{out} = \int (O_f + O_r + O_{ex} - O'_l) dt \quad (3-20)$$

$$O'_{l(t)} = O_l(t - \tau_{cut}) \quad (3-21)$$

$$O_m = \psi_m \mu_m CAP_m, \forall m = \{l, f, r, ex\} \quad (3-22)$$

1458 where Vol_{out} is the volume of export containers, O_m represents the volume of exported containers under
 1459 transportation mode m , O'_m is the volume of exported containers by transportation mode m considering the
 1460 cutoff period, τ_{cut} is the cutoff time for the exported container, and ψ_m and CAP_m represent the export ratio and
 1461 capacity of each transportation mode m .

1462 2. Volume of imported container (Vol_{in})

1463 Regarding imports, inbound containers are unloaded from liner shipping vessels and stored temporarily in
 1464 container yards, awaiting pickup by container trucks or distributed via domestic railway and feeder shipping.
 1465 Therefore, the quantity of inbound containers in the port is determined by the accumulation of inbound liner
 1466 vessels and the distribution of hinterland transport. Additionally, the DELAY function is utilised to characterise
 1467 the average storage duration of containers in the yard. The quantity of inbound containers in the port can be
 1468 determined by the following equation:

$$Vol_{in} = \int (Q_l - Q'_f - Q'_r - Q'_{ex}) dt \quad (3-23)$$

$$Q'_m = Q_m(t - \tau_{pick}), \forall m = \{f, r, ex\} \quad (3-24)$$

$$Q_m = (1 - \psi_m) \mu_m CAP_m, \forall m = \{l, f, r, ex\} \quad (3-25)$$

1469 where Vol_{in} is the volume of imported containers, Q'_m is the volume of picked up imported containers after
 1470 storage time τ_{pick} and Q_m is the volume of imported containers.

1471 3. Volume of containers in port (Vol)

The total volume of containers in the port can be modelled as follows:

$$Vol = Vol_{in} + Vol_{out} \quad (3-26)$$

3.3 Numerical experiments and results

3.3.1 Experiment preparation

3.3.1.1 *Data collection and processing*

To test the precision and reliability of the proposed SD model, a world-leading multimodal container port (i.e. top 30 in terms of container throughput) is selected to demonstrate the newly proposed methodology. This terminal plays a crucial role in consolidating and distributing containers across East and Northern Asia. Therefore, analysing the difference between normal circumstances and accidental scenarios yields valuable insights and lessons. Besides, this terminal features an advanced multimodal transshipment system, making it extremely essential to analyse and comprehend the ripple effects across various sectors.

The development of the SD model is grounded on three primary data sources: (1) A field investigation is conducted at the investigated port in September 2023, during which the real-time operational data are collected, and firsthand insights into daily port activities are gained. These findings help define the logical flow of container port operational processes. (2) Expert interviews are involved throughout the model development process, including the selection of KPIs (shown in Table 3.3) and variables (shown in Table 3.4), the quantification of relationships between variables and subsystems, model validation (shown in Table 3.5) and the choice of disruptive scenarios (shown in Table 3.8). (3) Internal accident reports of port accidents from 1998 to 2021 are used to identify representative disruptions and quantify disruptive scenarios (shown in Section 3.3.1.3).

The case study provides an empirical basis for developing and testing the framework rather than representing all multimodal container ports statistically. Although the core transshipment processes of modern container terminals are broadly comparable, individual ports remain heterogeneous in terms of scale, terminal layout, equipment configuration, modal composition, traffic demand, automation level, and operational policies.

Accordingly, the proposed model structure is intended to be transferable to ports with similar multimodal functions, while its parameter values and numerical findings are case-dependent. Application to another port would therefore require recalibration using local operational and disruption data and, where necessary, adaptation of the subsystem structure.

3.3.1.2 *Model verification and validation*

Previous literature (Sterman, 2000; Qudrat-Ullah, 2012) has systematically established validation methods for SD models, which are concisely listed in Table 3.5, which also describes their applicability and implementation results within this study. Tests involving integration error and modelling objectives are excluded due to their unsuitability for the SD model. All the conducted tests are successful, affirming the robustness of the applied validation methods. Regarding SA, it should be clarified that the SA applied in Chapter 3 for model validation and the scenario analysis in result illustration are essentially consistent with LSA defined in Chapter 2, since it examines the impact of changing one factor at a time within a limited range. This is fundamentally different from the GSA employed in Chapter 5. Therefore, to avoid confusion, the terms LSA and “scenario analysis” are used in Chapter 3.

Table 3.5. Various SD simulation model validation methods.

Validation	Suitability	Test results	Explanation of our procedure
Boundary adequacy	Yes	Pass	Interviews, direct inspection and participation of experts, see Appendix A.
Structure assessment	Yes	Pass	Interviews, direct inspection and participation of experts, see Appendix A.
Dimensional consistency	Yes	Pass	Tools provided by Vensim software.
Parameter assessment	Yes	Pass	Statistical method employed to evaluate the parameter.
Extreme conditions	Yes	Pass	Shown in Table 3.6 and Figure 3.8.

Integration error	No		Sensitive to the change of time step due to modelling objectives.
Behavioural robustness (via behaviour reproduction)	Yes	Pass	Shown in Table 3.7.
Behaviour anomaly	Yes	Pass	The model shows anomalous behaviour when the key causal loop is neglected.
Family member	No		No other related systems to compare.
Surprise behaviour	Yes	Pass	All model behaviours can be anticipated and recognised.
LSA	Yes	Pass	Shown in section 3.3.2.
System improvement	Yes	Pass	The modelling process is followed strictly.
Scenario robustness (across scenarios/contexts)	Yes	Pass	Shown in Appendix A.
Theoretical robustness (via analytical approach)	Yes	Pass	Shown in Appendix B.

1510

1511 (1) Extreme condition test

1512 Several extreme conditions are set in Table 3.6. Results demonstrate that the model's behaviours are
1513 predictable, as illustrated in Figure 3.8. It illustrates whether the SD model produces logically consistent
1514 behaviour under deliberately extreme input conditions. In Figure 3.8(a), a tenfold increase in liner vessel arrivals
1515 causes a rapid accumulation of vessels at anchorage because the arrival demand substantially exceeds the
1516 available berthing and handling capacity. In Figure 3.8(b), reducing the feeder quay crane handling efficiency
1517 to an extremely low level significantly decreases the number of feeder vessels completing their operations,
1518 reflecting the reduced service capacity of the subsystem. In Figure 3.8(c), reducing the number of available
1519 transshipment tracks to one leads to a substantial increase in waiting trains because the railway processing
1520 capacity becomes severely constrained. Similarly, Figure 3.8(d) shows that a tenfold increase in the external

1521 truck arrival rate results in a rapid accumulation of trucks within the terminal, as the inflow exceeds the available
1522 handling and departure capacity. These results are consistent with the expected operational behaviour of the
1523 corresponding subsystems and therefore provide evidence that the model responds reasonably under extreme
1524 conditions.

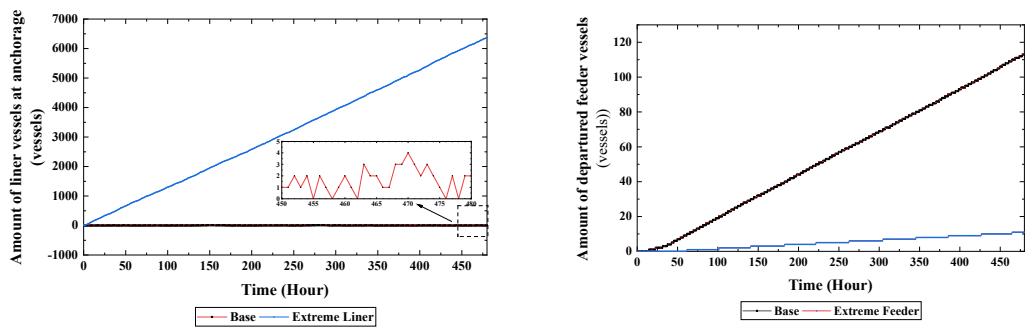
1525 Taken together, these validation procedures examine the model from complementary perspectives rather
1526 than relying on a single goodness-of-fit measure. Structural and expert validation assess whether the model
1527 represents realistic port operations, behaviour reproduction examines agreement with observed operational data,
1528 extreme-condition and sensitivity tests assess logical model responses, and theoretical validation checks the
1529 consistency of the underlying mathematical relationships.

1530

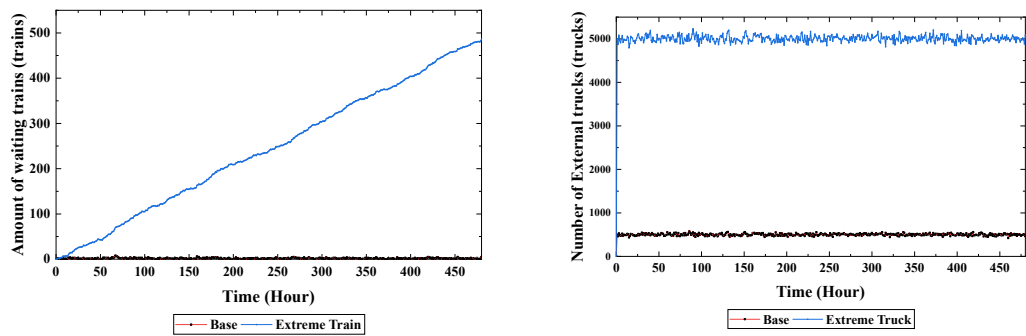
1531

Table 3.6. Input parameters for the extreme condition test.

	Liner shipping system	Feeder shipping system	Train system	Trucking system
Extreme condition name	Extreme Liner	Extreme Feeder	Extreme Train	Extreme Truck
Description	An extreme condition where an unusually high frequency of liner container vessel arrivals.	An extreme scenario in which the number of quay cranes available for feeder operations is reduced to the minimum operational level.	An extreme scenario in which the number of available rail tracks is reduced to the minimum operational level.	An extreme scenario with a high external truck arrival rate
Variable	Liner Ships Arrival Poisson Mean	Quay Crane Handling Efficiency for Feeder Ships	Number of Transshipment Tracks	Truck Arrival Poisson Mean
Base condition result	1.5	30	4	500
Extreme condition result	15	1	1	5000



(a) Number of liner vessels at anchorage when the arrival rate increases by 10 times (b) Number of departure feeder vessels when quay crane efficiency decreases to 1



(c) Number of waiting trains when the number of train tracks decreases to 1 (d) Number of external trucks when the arrival rate increases by 10 times

Figure 3.8. Extreme condition test results for the SD model.

(2) Behaviour reproduction

To validate the model's performance in practical applications, historical data are used to assess the accuracy of the prediction. Based on previous work (Liu et al., 2023c), an acceptable deviation range is set between -10% to 10%. In addition to the KPIs selected in this study, the model is further validated against an external and widely recognised industry benchmark, container throughput (Xiao and Bai, 2022; Wang et al., 2024b; Cao and Lam, 2018). It refers to the total number of containers handled at the port over a given time. As this study primarily focuses on the consequences across different transportation modes, container throughput is not

incorporated into the model as a KPI but is instead treated as an external benchmark for validation purposes. The actual hourly throughput is calculated using publicly available five-year average statistics of annual container volumes. The remaining average actual data were obtained through field investigation. The variation in simulated outcomes of both internal and external KPIs falls within the acceptable range, confirming the accuracy of the model configuration, as shown in Table 3.7.

Table 3.7. Results of behaviour reproduction test.

Variables	Average simulation outcome	Average actual data	Error range
Number of external trucks in the port	500.81	500	1.6%
Number of containers in the port	102107.5	110000	7%
Container throughput per hour	1251	1157	8.1%

(3) Scenario robustness

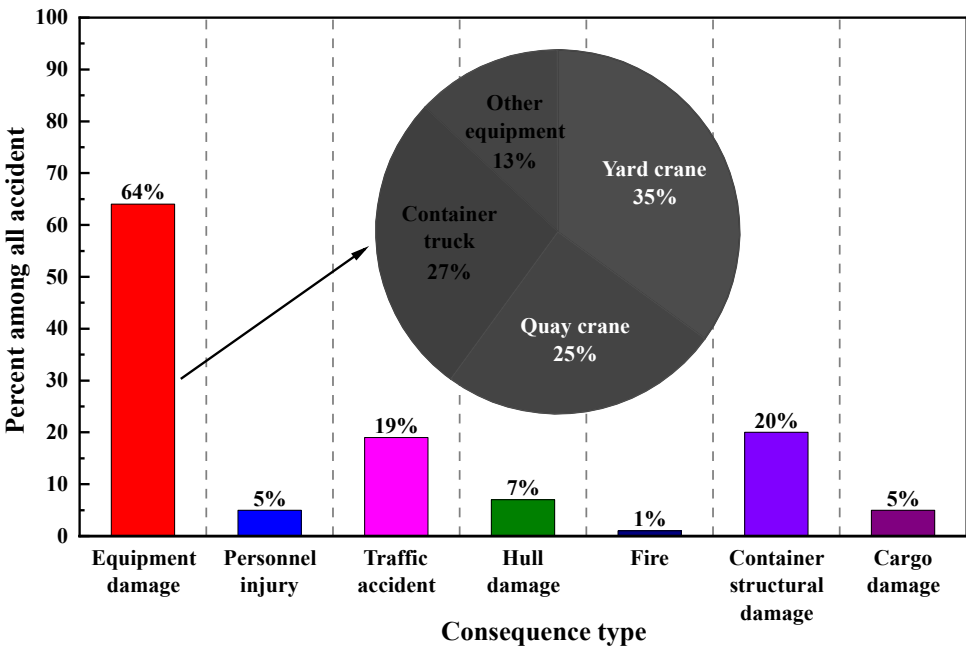
Firstly, expert validation, supported by the responses provided in Appendix A, confirms the applicability of the proposed model. The model is also theoretically grounded in the standardised physical layouts and operational processes of modern container terminals, including vessel arrival, berthing, and the collaboration of seaside and landside activities (Liu et al., 2023c). Furthermore, its modular structure allows for flexible data substitution without altering the overall architecture. By adjusting values, the model can be adapted to various port contexts, provided that their operational logic aligns with the model’s assumptions. These features collectively underscore the model’s robustness and its potential for broader applicability across diverse port settings.

3.3.1.3 Scenario setting

This section outlines the scenario setting for port disruptions. Given that ports are affected by a variety of disruptions, it is crucial to comprehensively evaluate the consequences of potential impacts by simulating a

1561 range of different scenarios. Furthermore, to demonstrate how ports are impacted by risks associated with
1562 different transportation modes and to illustrate their distinct ripple effects, risks are designed to originate from
1563 diverse subsystems.

1564 To design disruptive scenarios, a multi-criteria approach based on occurrence rate, severity and
1565 representativeness is developed, and real-world data and expert judgment are used for assessment. Real data are
1566 used to quantify the occurrence rate (see Figure 3.9) and severity (see Figure 3.10), while expert input is
1567 employed to assess the representativeness. As illustrated in Figure 3.9, equipment failure, traffic accidents, and
1568 container structure damage are among the most frequently occurring incidents in ports. Within the category of
1569 equipment failure, yard cranes, quay cranes, and container trucks are most affected. However, since the damage
1570 costs associated with container trucks and containers are relatively low, they are excluded. In terms of severity,
1571 equipment failure, traffic accidents, and personal injuries account for the majority of severe incidents.
1572 Specifically, personal injury incidents, although severe, are rare and fall outside the research boundary of this
1573 study and are therefore excluded. The detailed characteristics of each disruption are presented in Table 3.8.



1574

1575

Figure 3.9. Percentage distribution of port accident occurrences.

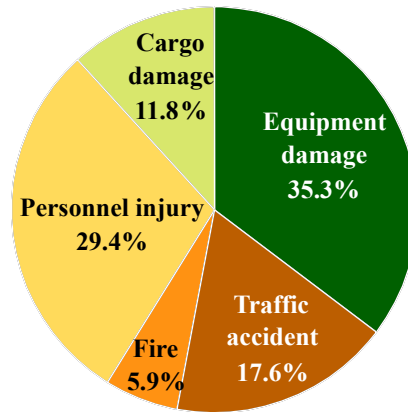


Figure 3.10. Percentage distribution of accidents involving major consequences.

Table 3.8. Characteristics of disruptive scenarios.

Disrupted sectors	Disrupted component	Scenario name	Occurrence Rate	Severity	Typicality
Liner shipping	Quay crane	Scen1	Highest	High	Yes
Feeder shipping	Quay crane	Scen2	Highest	High	Yes
Railway	Train tracks	Scen3	Low	High	Yes
	Train crane	Scen4	Low	High	Yes
	Yard crane	Scen5	Highest	High	Yes
Yard	Traffic density (scale)	Scen6	High	High	Yes
	Traffic density (duration)	Scen7	High	High	Yes

Mathematically, Eq. (3-27) describes the relationship between the magnitude and duration of variation for a disruptive factor. It should be clarified that χ does not carry any specific real meaning. In this formulation, $\alpha(\chi)$ denotes the magnitude of variation and $\tau(\chi)$ denotes the duration of that variation. The specific variable names and corresponding values are given in Table 3.9.

1583 The entire simulation is set to last 480 hours to reflect the cyclical nature of container shipping; all
 1584 disruptions are scheduled to occur at the 200-hour mark when the variables are stable. The disruption's duration
 1585 spans multiple periods: 8 hours (one shift), 24 hours, 48 hours, 72 hours, 120 hours, 240 hours and 280 hours
 1586 (the end of the simulation).

$$\chi = \begin{cases} \chi_0, & t \leq 200 \\ \chi_0 + \alpha(\chi), & 200 < t \leq t + \tau(\chi) \\ \chi_0, & t + \tau(\chi) < t \leq 480 \end{cases} \quad (3-27)$$

1587 where $\chi \in \{E_l, E_f, E_r, B_r, E_y\}$, each combination of $\alpha(\chi)$ and $\tau(\chi)$ represents a different scenario.

1588 Table 3.9. Parameter settings of different scenarios.

Scenario name	Affected Variable χ	Affected level $\alpha(\chi)$	Affected time $\tau(\chi)$
Scen1	E_l	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
Scen2	E_f	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
Scen3	E_r	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
Scen4	B_r	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
Scen5	E_y	-4	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
Scen6	ρ	$\Delta x \in \{0.1\rho, 0.2\rho, 0.3\rho, 0.4\rho, 0.5\rho, 0.6\rho, 0.7\rho, 0.8\rho\}$	8
Scen7	ρ	0.5ρ	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$

1589 The simulation steps of the model are as follows:

1590 Step 1: Initialise the model using variables and values from Table 3.4.

1591 Step 2: If the current time is less than the simulation termination time, then update the system state based
 1592 on the equations in section 3.2.4. If the current time equals the start time of the disruption, then adjust the
 1593 parameter values according to Table 3.8 and continue updating the system state.

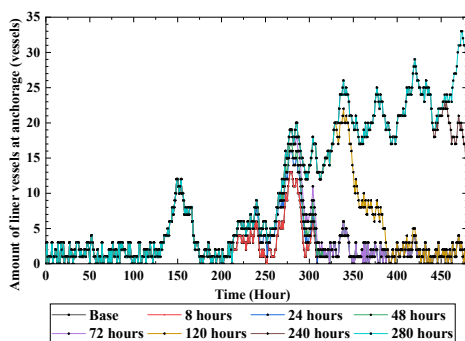
Step 3: Compile and save the results of the simulation using the variables summarised in Table 3.3.

Step 4: Repeat the process until simulations for all scenarios have been completed.

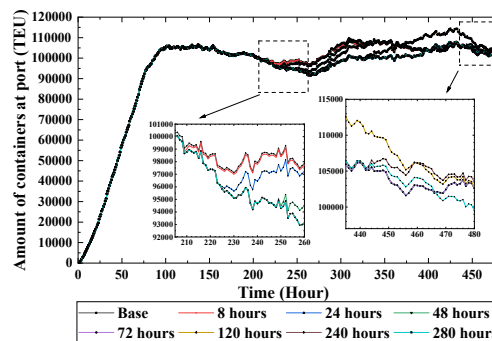
3.3.2 Experiment results

3.3.2.1 *Liner shipping disruption scenario*

The impact of the liner shipping disruptions on port efficiency is described from two perspectives: (1) directly, the reduction in quay cranes leads to an increase in the number of waiting ships at anchorage, as shown in Figure 3.11 (a); (2) indirectly, there are fluctuations in the number of containers stored in the yard due to the altered logistics dynamics, as seen in Figure 3.11 (b). Impacts on other areas are minimal and are therefore not demonstrated. In Figure 3.11, the legend indicates the duration of the disruption, while the x-axis represents the simulation time. The disruption is introduced after the system stabilises at 200 hours. The same applies to the subsequent similar figures.



(a) Number of liner vessels waiting in anchorage



(b) number of containers stored in the yard

Figure 3.11. The fluctuation of the KPI values when the liner quay crane is disrupted.

As the duration of the loss of a single quay crane extends, the number of ships at anchorage correspondingly increases. Figure 3.11 (a) shows that when the disruption lasts less than 72 hours, the increase in the number of ships is relatively small. However, after 120 hours, there is a significant spike in the number of ships affected, suggesting a tipping point. This disparity is evident when comparing the base model's maximum of 12 waiting

vessels to the 33 vessels stranded in the anchorage when quay crane downtime exceeds 280 hours. Besides, the result reveals that disruptions to quay cranes lasting more than 72 hours lead to a sharply nonlinear increase in liner containerships queue length. From a managerial standpoint, this finding indicates the need for a strict 72-hour repair threshold as a key intervention milestone. If a repair is projected to exceed this limit, terminal operators should swiftly implement contingency protocols, such as rerouting vessels to alternate berths, mobilising backup equipment, and temporarily adjusting berthing schedules, to contain the ripple effect and avoid further congestion.

Additionally, it affects not only seaside operations but also leads to the piling up of container volume within the yard, as depicted in Figure 3.11 (b), where an increase of up to 10,000 TEUs occupies limited port resources. Furthermore, the influence of quay crane failures persists beyond the dysfunction period, causing a delayed effect on container inventory. This also highlights the importance of robust landside contingency strategies. Terminal operators should establish additional storage capacity, refine container stacking strategies, and synchronise yard crane schedules to address fluctuating container volumes effectively. Furthermore, disruptions may persist beyond the completion of repairs, emphasising the need to maintain emergency measures and resource mobilisation plans for a while.

3.3.2.2 Feeder shipping disruption scenario

Compared to the loss of a liner quay crane, the malfunction of a quay crane used for feeder operations has a more minor impact on almost all KPIs, except for fluctuations in the number of containers in the yard. Figure 3.12 illustrates that the variation in container numbers increases as the duration of the disruption extends, with the most severe fluctuations reaching about 2,000 TEUs. The less intense or seemingly negligible impact may be due to the lower arrival rate of feeder vessels and the reduced container workload, thereby imposing less stringent demands on loading and unloading efficiency. This highlights that other services should be prioritised when facing disruptions.

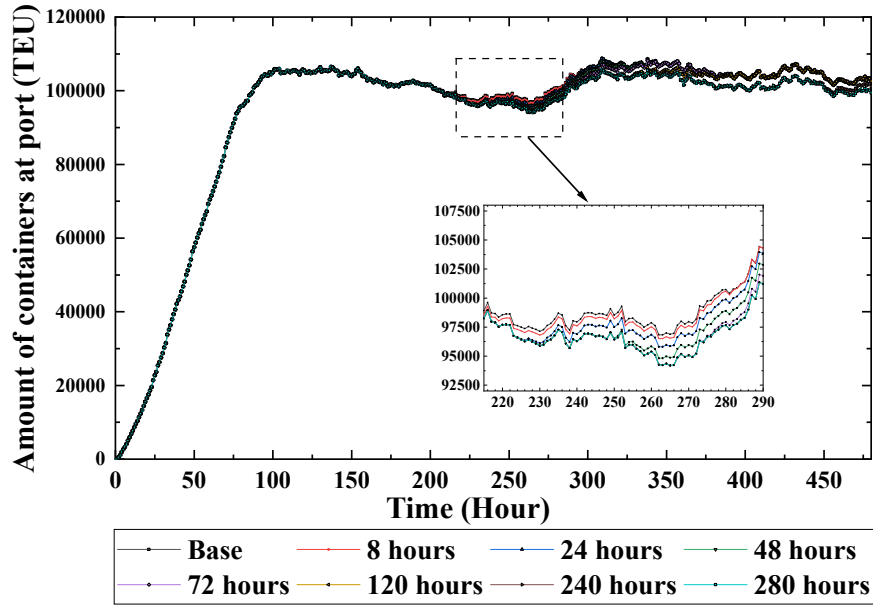
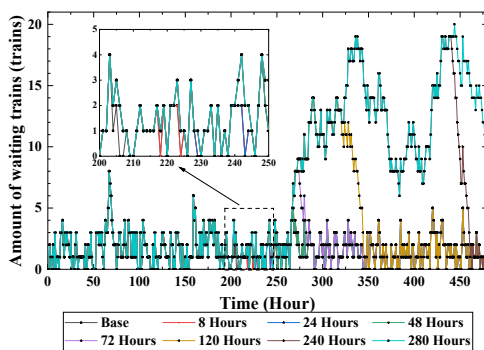


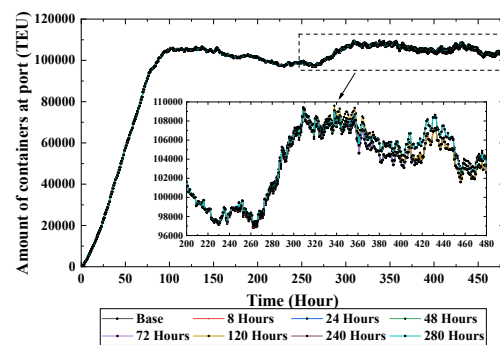
Figure 3.12. The number of containers stored in the yard when the feeder quay crane is disrupted.

3.3.2.3 *Railway area disruption scenario*

The disrupted components in the railway area can be summarised into two main types: the inaccessibility of railway tracks (Figure 3.13) and the malfunction of cranes conducting loading and unloading services (Figure 3.14). Only the metrics with significant changes are demonstrated and analysed; others with minor changes are neglected due to their lack of relative importance.



(a) Number of waiting trains



(b) Number of containers stored in the yard

Figure 3.13. The fluctuation of KPI values when the train tracks are disrupted.

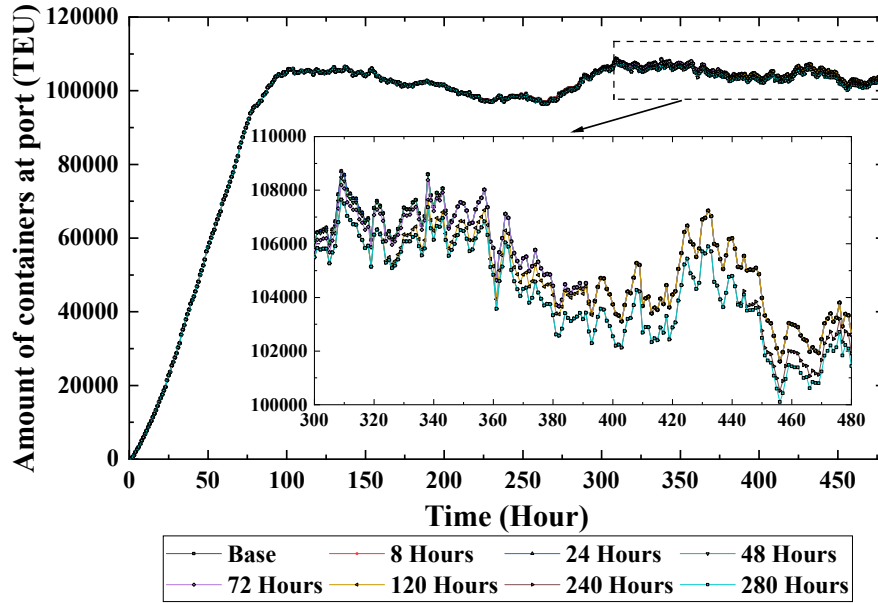


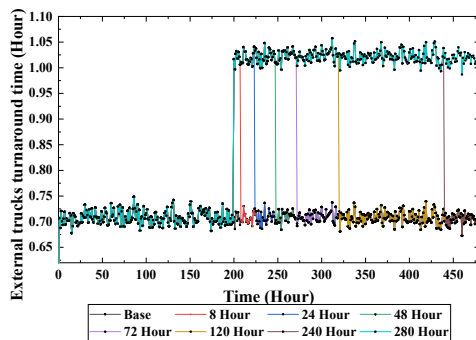
Figure 3.14. The number of containers stored in the yard when the train cranes are disrupted.

It can be observed from Figure 3.13 that the inaccessibility of train tracks leads to an increase in the number of waiting trains, from 5 to approximately 20 directly, and a rise in container volume of about 9,000 TEUs indirectly. In addition, there is a sharp increase in waiting trains after 120 hours, indicating a critical turning point between 72 and 120 hours. However, regarding the impact of train crane defects, the failure of a single crane only results in an increase of approximately 3,000 TEUs in container volume in the yard, as shown in Figure 3.14. Compared to failures in train tracks, the impact of inefficient handling is less significant. This may be attributed to the critical role of train tracks as essential infrastructure for railway operations. If damaged, an entire train could be delayed, unlike train cranes, for which alternative equipment might be more readily available. Therefore, in operational practice, railway infrastructure repairs should be completed within 120 hours to avoid major disruptions to normal port activities. If repairs are expected to extend beyond this threshold, port operators must implement contingency measures, such as deploying temporary tracks or utilising resources from nearby railway facilities to minimise downtime. In scenarios where both railway infrastructure and handling equipment are compromised, priority should be given to restoring the infrastructure first.

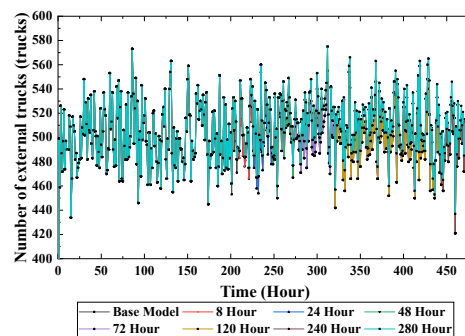
3.3.2.4 *Yard area disruption scenario*

Disruptions in the yard area are categorised into two components (yard cranes and traffic congestion) and three types (number of yard cranes, congestion scale, and duration). The loss of a single yard crane modestly affects both the number of container trucks and their turnaround time (Figure 3.15). However, as the scale of yard congestion escalates, the ripple effects extend to waiting liner vessels (Figure 3.16). Moreover, prolonged yard congestion severely deteriorates port operation efficiency across all transportation modes (Figure 3.17).

Figure 3.15 illustrates that the turnaround time for external trucks escalates from 0.7 hours to approximately 1 hour due to the failure of one yard crane. This metric is a critical KPI for port efficiency evaluation and decision-making by multiple stakeholders, including port operators, shipping companies, truck fleets, and shippers. Additionally, there was a minor disruption due to an accumulation of external trucks. However, this level of disturbance has not yet caused ripple effects. This may be because, typically, multiple yard cranes operate within a single block, allowing the loss of one crane to be compensated for by others.



(a) External truck turnaround time

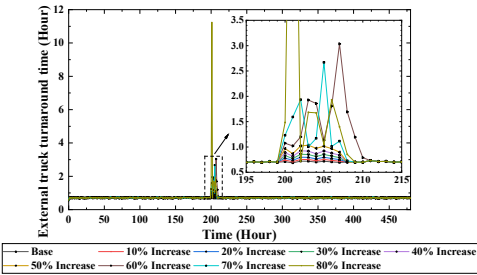


(b) Number of external trucks in port

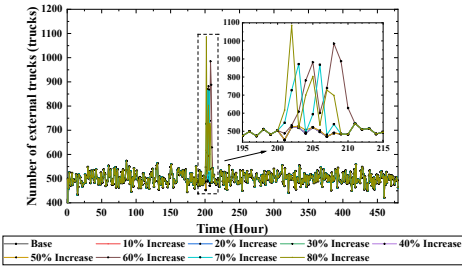
Figure 3.15. Fluctuation of KPI values when the yard crane is disrupted.

From Figure 3.16 (a) and (b), it is evident that the KPIs of container truck operations increase with the scale of port congestion. However, these fluctuations are transient, occurring within approximately 10 hours without extending further, which demonstrates the port's inherent resilience in offsetting the adverse effects of congestion.

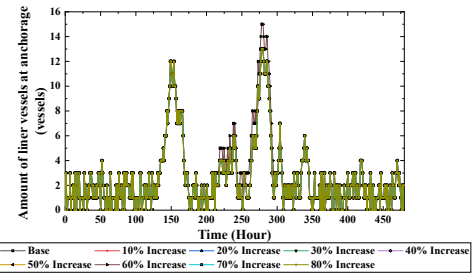
Moreover, the impact of yard congestion extends into other transportation modes through significant ripple effects. For example, as depicted in Figure 3.16 (c), there is a noticeable increase in the number of waiting liner vessels. This increase is accompanied by a substantial fluctuation in the container inventory, which reaches up to 4,000 TEUs as illustrated in Figure 3.16 (d). These changes are primarily due to the fact that port congestion restricts the mobility of internal trucks, which play a crucial role in facilitating coordinated transshipment operations across other transportation modes. In the event of accident-induced congestion, port operators should promptly clear affected sites, establish alternative routes, and regulate gate entry for external trucks. Simultaneously, maintaining the efficiency of internal truck fleets through dynamic routing and flexible resource allocation is crucial as well. Ongoing surveillance of yard container volumes and other key indicators will further support timely interventions to avert additional bottlenecks.



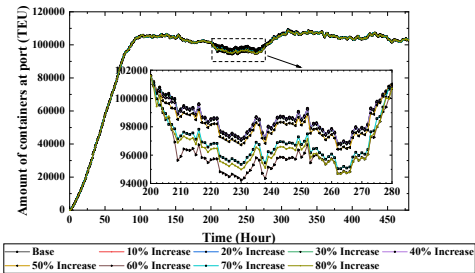
(a) External truck turnaround time



(b) Number of external trucks in port



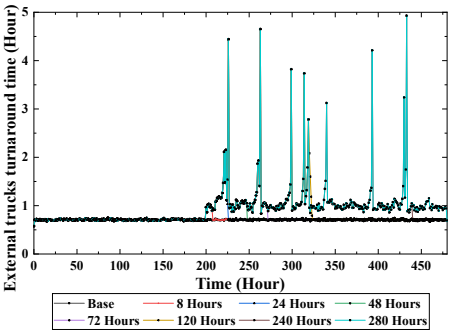
(c) Number of vessels at anchorage



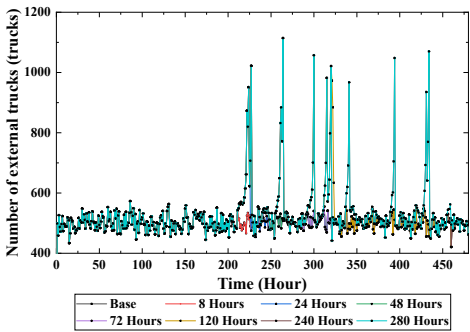
(d) Number of containers in port

Figure 3.16. Fluctuation of KPI values when truck density increases for 8 hours.

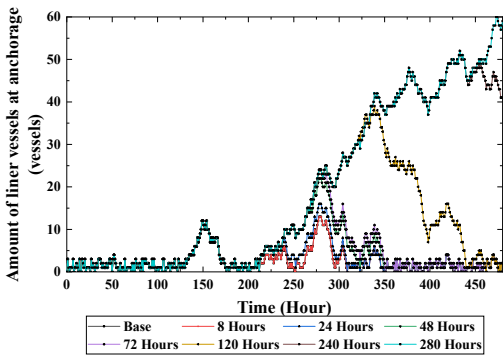
1684 The truck density is designed to increase by 50%, a rate commonly observed during congestion in historical
 1685 data. These disruptions not only directly impact truck operations but also spread their effects to nearly all other
 1686 transportation modes. As shown in Figure 3.17 (a), the turnaround time for external trucks reflects a consistent
 1687 pattern of rise and fall, with each cycle lasting between 20 and 50 hours. This indicates the system’s effort to
 1688 mitigate congestion, showcasing its capacity to maintain resilience. Consequently, the number of external trucks
 1689 in the port also follows this pattern, ranging between 500 and 1100 trucks, as seen in Figure 3.17 (b).



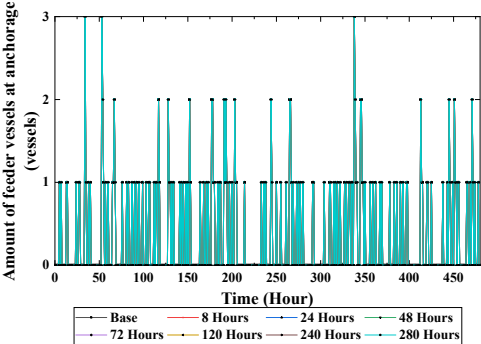
(a) External truck turnaround time



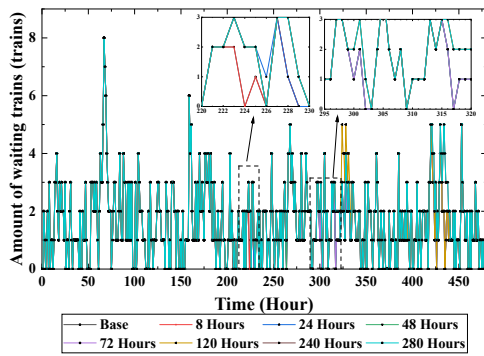
(b) Number of external trucks in port



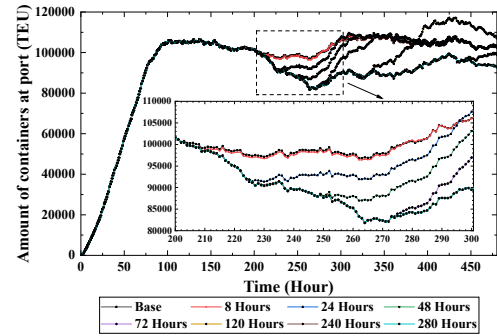
(c) Number of vessels at anchorage



(d) Number of feeder ships at anchorage



(e) Number of waiting trains



(f) Number of containers in port

Figure 3.17. Fluctuation of KPI values when truck density increases by 50%.

Beyond the immediate impacts on trucks, the ripple effects are most severe in the liner vessels and container inventory subsystems, as evidenced by Figure 3.15 (c) and (f). Trains also experience notable impacts, albeit to a lesser extent, as depicted in Figure 3.17 (e). In contrast, the feeder sector remains largely unaffected, as shown in Figure 3.17 (d). This pattern can be attributed to the fact that liner vessels, which arrive more frequently and handle larger containers than feeder vessels and trains, depend more critically on consistent and efficient port operations. Additionally, the result shows that prolonged yard congestion (>24 hours) leads to a systemic increase in container backlog and external truck turnaround time. This can be used to define operational thresholds for activating congestion mitigation protocols, such as opening additional gates, reassigning internal trucks, deploying additional Automated Guided Vehicles (AGVs) or notifying stakeholders in advance to reschedule deliveries. Simultaneously, dynamic yard storage strategies, such as real-time adjustments to container storage plans and flexible allocation of external storage locations, help optimise inventory usage.

In summary, the model's identification of ripple effects, especially from traffic congestion impacting rail and liner services, supports the establishment of a cross-modal early warning system. This would allow port operators to detect upstream bottlenecks and deploy targeted interventions before the ripple effect amplifies. The above analysis demonstrates the model's potential to guide real-time resource allocation, schedule adjustments, and risk communication. By integrating these thresholds and triggers into standard operating procedures, port stakeholders can significantly improve the resilience and responsiveness of terminal operations.

3.4 Discussion, insights, and implications of the System Dynamics model

Based on extensive simulations, this section summarises the impacts of various risks on ports and their behavioural patterns when facing these risks.

The representative port, chosen for its advanced multimodal transport system and complexity, reflects the characteristics of other ports, ensuring that the findings are broadly applicable across different port settings.

3.4.1 Impact analysis

To address the lack of standardisation in measuring risk impacts, consequences are classified into four levels based on established literature: minor, major, critical, and catastrophic. The assessment of disruption impacts is conducted by comparing KPIs between disruptive scenarios and the baseline. The KPI values of disruptive scenarios are treated as averages, derived from various magnitudes of the same type of disruption. Expert insights guide the establishment of numerical relationships for these levels, as detailed in Table 3.10.

Table 3.10. Impact measurement index.

Subsystems	KPIs	Minor impact	Major impact	Critical impact	Catastrophic impact
Liner shipping	A_l	$ A_l - A_{l0} \leq I$	$1 < A_l - A_{l0} \leq 5$	$5 < A_l - A_{l0} \leq 10$	$ A_l - A_{l0} > 10$
Feeder shipping	A_f	$ A_f - A_{f0} \leq I$	$1 < A_f - A_{f0} \leq 5$	$5 < A_l - A_{l0} \leq 15$	$ A_l - A_{l0} > 15$
Railway	A_r	$ A_r - A_{r0} \leq I$	$1 < A_r - A_{r0} \leq 5$	$5 < A_r - A_{r0} \leq 15$	$ A_r - A_{r0} > 15$
Trucking	A_t	$ A_t - A_{t0} \leq 600$	$600 < A_t - A_{t0} \leq 800$	$800 < A_t - A_{t0} \leq 1000$	$ A_t - A_{t0} > 1000$
	D_{exw}	$ D_{exw} - D_{exw0} \leq 0.8$	$0.8 < D_{exw} - D_{exw0} \leq 1$	$1 < D_{exw} - D_{exw0} \leq 10$	$ D_{exw} - D_{exw0} > 10$
Containers	Vol	$ Vol - Vol_0 \leq 100$	$100 < Vol - Vol_0 \leq 1000$	$1000 < Vol - Vol_0 \leq 10000$	$ Vol - Vol_0 > 10000$

1721 Based on Table 3.10, the influence of specific risks on the performance of each transportation sector is
1722 systematically outlined in Table 3.11. It provides an intuitive perspective on the consequences of each risk
1723 scenario, offering evidence to identify bottlenecks and strategically prioritise resource allocation. Additionally,
1724 it supports the development of targeted risk mitigation strategies tailored to specific transportation sectors.

Table 3.11. Consequences categorisation of port disruptions.

Cause \ Consequence	Cause	Liner shipping	Feeder shipping	Railway		Yard operations		
		Liner crane	Feeder crane	Railway crane	Railway tracks	Yard crane	Congestion Scale	Congestion Time
Liner shipping	Waiting liner vessels	Catastrophic	Minor	Minor	Minor	Minor	Minor	Minor
Feeder shipping	Waiting feeder vessels	Minor	Minor	Minor	Minor	Minor	Minor	Minor
Railway	Waiting trains	Minor	Minor	Major	Catastrophic	Minor	Major	Major
Truck	External truck number	Minor	Minor	Minor	Minor	Major	Catastrophic	Catastrophic
	Truck turnaround time	Minor	Minor	Minor	Minor	Major	Critical	Critical

Container	Container Volume	Critical	Critical	Critical	Critical	Minor	Critical	Catastrophic
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3.4.2 Behaviour analysis

In this section, common patterns and trends resulting from port disruptions are recognised by summarising the prevalent behaviours. The detailed findings are shown in Table 3.12. It shows that nearly all port disruptions have a ripple effect, emphasising the need to address the immediate aftermath and broader implications and implement comprehensive countermeasures. The prevalent lagging effect in most scenarios indicates that repercussions often persist beyond the initial disruption period. Additionally, cyclical fluctuations in trucks, notably in turnaround times and volumes, reveal a consistent pattern of disruption and recovery. Port operations demonstrate remarkable resilience, often returning to normal post-disruption.

Table 3.12. Behaviour identification of port disruptions.

Disruptions	Ripple effect	Lagging effect	Resilience
Quay crane number	yes	yes	yes
Feeder crane number	yes	yes	yes
Train track number	yes	yes	yes
Train crane number	yes	yes	yes
Yard crane number	no	no	yes
Congestion time	yes	yes	yes
Congestion scale	yes	yes	yes

The key findings of this study are summarised as follows:

- 1) Disruptions resulting in the loss of quay cranes and yard cranes exhibit the most significant impact on other transportation sectors, highlighting their critical roles in risk prevention strategies;

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- 2) The analysis of disruption aftermath reveals the high susceptibility of the yard area, where it experiences the most severe and frequent disruptions, particularly affecting container and truck volumes;
 - 3) In terms of risk propagation, yard congestion emerges as a significant concern, exhibiting the widest-reaching effects and impacting numerous other sectors significantly;
 - 4) The ripple and lagging effects are consistently identified across various disruptive scenarios, except for scenarios related to yard crane inefficiencies, showcasing their dominance in port disruptions;
 - 5) Prolonged yard congestion causes periodic fluctuations in the volume and turnover times of external trucks, indicating a cyclical pattern of disruption and recovery.
 - 6) The inherent resilience of port operations is validated in all scenarios, showing a consistent effort to overcome the negative effects and restore normalcy.

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Based on the above analysis, feasible action plans are proposed for different stakeholders, taking into account their respective roles and responsibilities within the port, as shown in Table 3.13.

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Table 3.13. Possible action plan for each stakeholder.

Stakeholders	Role in port management	Possible actions
Port authority and port operator	Port management	Real-time monitoring systems for early detection;
		Emergency protocols for disruptions;
		Maintain communication with internal/external partners;
		Regular inspections and timely repairs of key equipment;
		Clear recovery thresholds;
Government and public agencies	Long-term policy and port development	Maintain spare parts and backup resources.
		Allocate dedicated budgets for rapid repair;
		Policy frameworks and financial incentives for ports in resilient design;

		Facilitate coordinated projects among ports, rail operators, and road authorities;
		Streamline decision-making for fast-tracked regulatory approvals in disruptions;
		Invest in redundancy for critical infrastructure (e.g., additional quay cranes, external yards, railway tracks or stations).
		Collaborate with other stakeholders to minimise disruption impacts;
Logistics companies	Depending on the port service for import and export	Develop their own contingency plans under disruptive scenarios;
		Provide training for port-related staff.

1756 **3.5 Conclusions**

1757 This chapter introduces a novel SD model to analyse the impact of port disruptions on operations.
1758 The methodology incorporates several innovative features: 1) it presents a microscopic illustration of
1759 port operations across different transportation modes, enabling a more detailed and scientific
1760 characterisation of quantitative port activities; 2) this research pioneers the use of an SD model to
1761 examine the resilience of multimodal container terminals regarding the often under-discussed yet
1762 essential issue of port disruptions; 3) through scenario analysis, the model examines both the immediate
1763 damage and subsequent ripple effects across transportation sectors. The model's validity is confirmed
1764 through tests with real operational data, demonstrating its effectiveness and superiority in identifying
1765 bottlenecks and vulnerabilities through diverse risk scenario analyses. Additionally, the chapter reveals
1766 critical behaviour patterns such as lagging and ripple effects, cyclic fluctuations, and inherent resilience.
1767 It also deepens stakeholders' comprehension of port disruptions, leading to more precise and effective
1768 mitigation strategies against immediate and ripple effects. In addition, since the planning of most
1769 multimodal container terminals is standardised, the model developed in this research can be applied to
1770 most other terminals with similar structures. Consequently, the conclusions drawn in this study hold
1771 universal value for other terminals.

1772 Based on these conclusions, policy implications and recommendations are drawn:

(1) Risk prevention efforts should prioritise area(s) with the highest potential impact; therefore, protecting quay cranes and alleviating yard traffic congestion are essential, especially when resources are limited. Given that many quay crane failures result from the malpractice of truck drivers or operators, implementing regular assessments and training programs can improve risk awareness and operational safety.

(2) Response and recovery efforts should concentrate on the most vulnerable area(s), including managing container volume, coordinating external truck operations, and rescheduling vessel port calls. The solution includes automated stacking cranes, dynamic yard allocation, truck appointment systems, slot bookings for container handling, and enhanced port community collaboration (Lin et al., 2022).

(3) Promoting the understanding of the ripple effects of port disruptions deserves essential attention. When dealing with the aftermath of the disruptions, it is crucial to address the direct damage and anticipate and prepare for the potential spread of consequences to other sectors.

The SD model developed in Chapter 3 provides the dynamic operational foundation for the subsequent resilience assessment in Chapter 4. Although the simulation results reveal how KPIs fluctuate under different disruptive scenarios and how ripple effects propagate across port subsystems, they do not by themselves provide a unified measure of port resilience. Therefore, Chapter 4 builds on the time-dependent performance outputs generated by the SD model and converts them into resilience values and further quantifies the resilience of the overall port system and its individual subsystems under different disruptions.

CHAPTER 4 IMPACT OF THE RIPPLE EFFECT ON THE RESILIENCE OF MULTIMODAL CONTAINER PORT OPERATIONS²

The SD-based simulation model in Chapter 3 generates continuous-time series data that captures fluctuations in port operations. However, these data only reflects the state of the port system at specific moments and does not inherently demonstrate the port's ability to respond to disturbances. Therefore, it is crucial to transform the performance-time curve derived from the simulation model into a measure of system resilience while ensuring calculation accuracy. Moreover, in Chapter 3, the multimodal port system is modelled from a micro-level perspective, including liner shipping, feeder shipping, railway transport, trucking, and container yard. Explicitly representing the operational interdependencies among these subsystems, it demonstrates how risks triggered by disruptions generate ripple effects and propagate throughout the port system. This provides the analytical basis for the resilience assessment developed in the subsequent chapter. On this basis, Chapter 4 proposes a new integrated methodology that not only considers but also quantifies the ripple effects across different multimodal subsystems and their impact on overall port resilience. It employs real operational and accident data to assess the resilience of a multimodal container port under different disruptive scenarios, hence providing valuable insights into preventing systemic failures through targeted interventions at the subsystem level. The proposed integrated methodology comprises three principal components: the SD model developed in Chapter 3, a resilience analysis model that converts system performance into a resilience metric based on three fundamental criteria, and a comprehensive port system resilience assessment utilising ER. Each step, from the quantification of resilience values to aggregating information across subsystems, builds toward determining the port's overall resilience. Multiple disruptive scenarios are designed and derived to validate the effectiveness of the proposed methodology. The results demonstrate that the proposed approach effectively assesses port performance under disruptions, identifies critical subsystems, and supports timely recovery strategies. Applicable to other port systems, this approach offers essential insights for improving long-term resilience in container port operations.

² The findings from this technical chapter have been published in the following journal paper. ZHANG, J., XIN, X., DUBEY, R., NGUYEN, T. T., SHI, X., LI, N. & YANG, Z. 2025. Impact of the ripple effect on the resilience of multimodal container port operations: A system dynamics simulation approach. *Risk Analysis*, 45, 4903-4932.

4.1 Introduction

Foundational studies define port resilience as a combination of the inherent stability and the capacity to implement rapid mitigation strategies (Nair et al., 2010). Over time, this concept has evolved within the transportation field, now offering a comprehensive system-wide assessment of a system's reliability, vulnerability, and recovery capacity in the face of disruptions. Extensive studies have explored port resilience from qualitative (incl. conceptual), and quantitative perspectives, providing insights from various aspects, including the port-hinterland container transport network (Chen et al., 2018), capacity sharing, and cross-port investments during disruptions (Li et al., 2022c), economic and social impacts of port disruptions (Wei et al., 2022), the Ports Resilience Index against climate change in seaports (León-Mateos et al., 2021), and the prioritization of initiatives based on multi-scenarios and multi-stakeholders perspectives (Almutairi et al., 2019). Compared to other metrics that reflect a system's capability to respond to unexpected disruptions (Zhang et al., 2023), resilience captures a broader range of operational attributes and port characteristics. Enhancing resilience first requires advancing assessment capabilities through practical and efficient evaluation methods (Wang and Yuen, 2022; Nosrati Malekjahan et al., 2024). Accordingly, this research endeavours to propose a novel assessment methodology for port resilience, which, to the best of the authors' understanding, is the first to address how ripple effects propagate among multiple transportation modes within ports, thereby facilitating the development of response and recovery strategies.

This chapter aims to bridge identified gaps by developing a new simulation-based resilience measurement framework specifically tailored to assess the resilience of multimodal container ports, particularly in response to subsystem disruptions that involve the ripple effect. An SD model that simulates port operations is adopted from Chapter 3. This model leverages real port operational data and historical accident records to generate disruptive scenarios of varying scales and durations. Building on Table 3.3, nine widely recognised port efficiency metrics are selected as KPIs to quantify the influence of these disruptions. Building on this foundation, an innovative resilience calculation method is applied to assess port resilience based on selected KPIs, emphasising the highly recognised and demanded balance among the three essentials of a resilient system: reliability, robustness, and recovery. Building on this approach, a port resilience assessment method utilising ER is introduced, designed to synthesise and generate resilience profiles across different hierarchies. A three-level criterion framework is adopted to handle inputs from five transportation modes (middle-level criteria), within each transportation mode, except for the yard, which features two types of KPIs as bottom-level criteria. Additionally, resilience values obtained from simulation results are translated into a belief structure using the DS Theory. The criteria are assigned weights based on entropy-based methods, which consider data variability as an indicator of its significance. The approach is validated via extensive testing from

diverse perspectives, with its effectiveness substantiated by experimental, statistical, and correlation analyses. The model's applicability is demonstrated through an adaptable theoretical framework, broad application prospects, and significant practical value. Specific performance metrics are customised for different transport modes within the port, and their integration through ER enables a systematic quantification of port resilience in response to disruptions. This research is among the first to quantitatively incorporate performance across various transportation modes under disruptions into the systematic assessment of port resilience.

The structure of the rest of the chapter is as follows: Section 4.2 outlines the proposed framework for assessing port resilience, which includes the SD simulation, resilience calculation, and resilience evaluation model. Section 4.3 presents the experimental results, along with their corresponding analysis and interpretation. Finally, Section 4.4 summarises the findings.

4.2 Methodology: An integrated resilience assessment framework

A comprehensive description of the proposed methodology is given in this section to assess the resilience of multimodal container ports. External factors such as economic fluctuations, technological advancements, and regulatory changes are treated as upstream causes, and after their impact on internal disruptions is clearly identified, they can be integrated into the current model framework to evaluate the influence of external factors on port resilience. As shown in Figure 4.1, the methodology begins with simulating port operations under normal conditions using the SD introduced in Chapter 3. Subsequently, disruptive scenarios are introduced by adjusting specific variables, identified as disruption variables. The variation in value ranges of disruption variables simulates different levels of impact, with each scenario defined by disruption type, intensity, and duration. The selection of disruption variables and their corresponding value ranges is justified by historical accident reports from port operations and expert input, as detailed previously in Chapter 3. These disruptive scenarios are then used as simulation inputs to generate time-dependent outputs of port performance, measured through various KPIs. Given the multimodal structure of ports, each mode is evaluated using dedicated KPIs. For each disruptive scenario, the value of a given KPI under both normal and this disruptive scenario serves as input for calculating a resilience value based on the formula in Section 4.2.2. This process is repeated across all selected KPIs, generating a set of individual resilience values that reflect different aspects of port performance. The ER model receives these inputs and combines them to derive an overall resilience score, which serves as the final output and represents the port's integrated performance under the given

disruptive scenario. The subsequent sections will outline the procedures for applying the simulation model, calculating resilience for each KPI, and assessing port resilience.

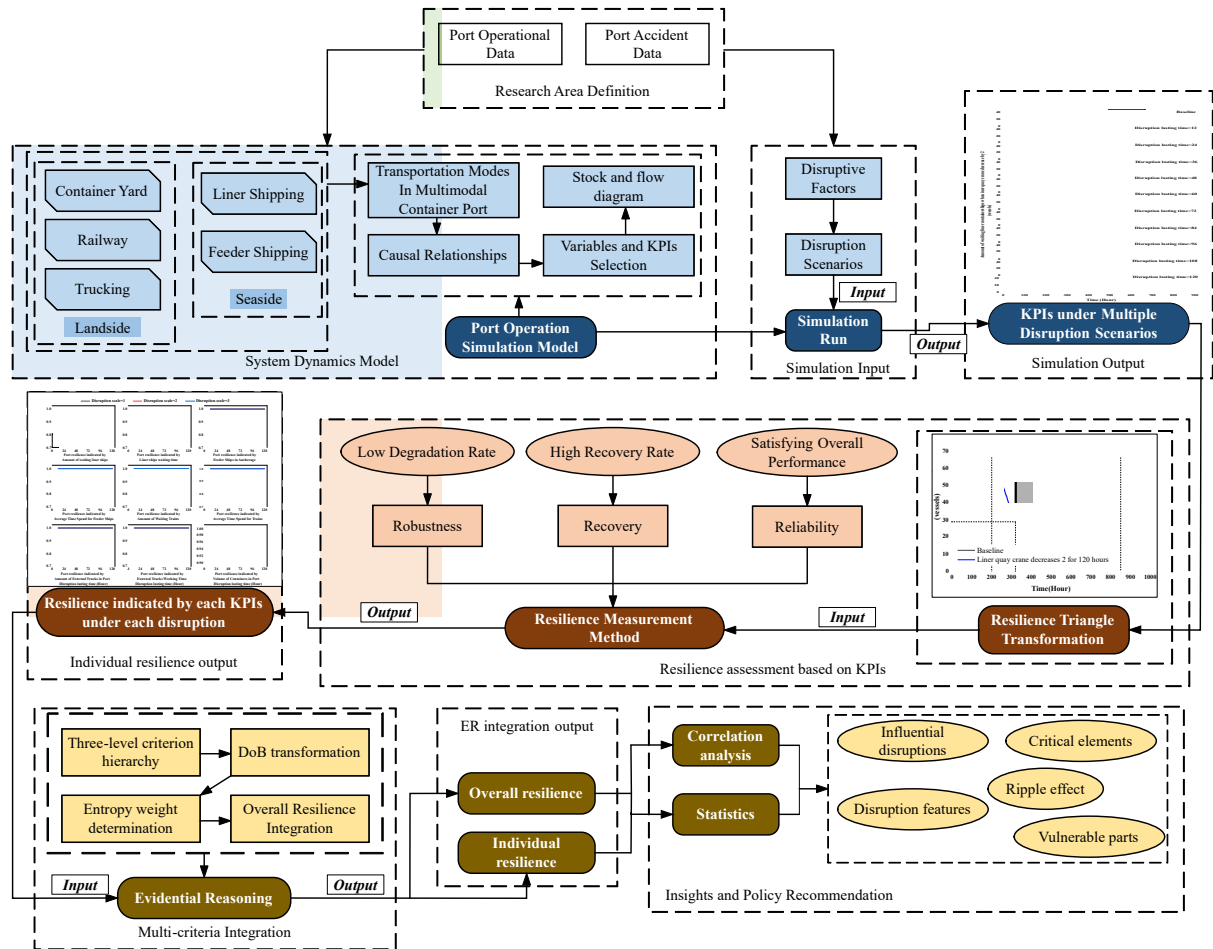


Figure 4.1. Methodology framework for Chapter 4.

4.2.1 Port operations simulation

As established in Chapter 3, the development process for a general simulation model comprises the following steps: (i) establishing modelling hypotheses (see section 3.2.1), (ii) identifying the simulation procedures (see section 3.2.3 and section 3.2.4), (iii) selecting input variables (see Table 3.4), and (iv) selecting output variables (KPIs). Although several KPIs associated with port performance have already been identified in Table 3.3, most of these indicators are defined from the perspective of cumulative quantities. To enable a more comprehensive evaluation of port performance, it is further extended by introducing several additional KPIs, as shown in Table 4.1. The newly identified KPIs can be obtained through the SD model developed in Chapter 3. The model details and validation results can also be found in Chapter 3.

Table 4.1. Identified KPIs in Chapter 4.

Category	KPIs	Reference
Liner shipping	Amount of waiting liner vessels	(Liu et al., 2023c; Zhou et al., 2022b)
	Liner vessels dwell time	
Feeder shipping	Amount of waiting for feeder containerships	(Emde and Boysen, 2016; Jin et al., 2021)
	Feeder vessels dwell time	
Railway	Amount of waiting trains	(Schulz et al., 2021)
	Trains dwell time	
Trucking	Amount of external trucks in the port	(Liu et al., 2023c; Xu et al., 2021a; Li et al., 2018)
	Turnaround time of external trucks	
Container yard	The inventory level of containers in the port	(Liu et al., 2023c; Lin et al., 2022; Xu et al., 2021a)

4.2.2 Resilience measurement method

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Based on the simulation in Chapter 3, port performance under normal conditions is presented as a time-dependent curve $P_0(t)$ in Figure 4.2. By adjusting the disruption variables, the disrupted performance curve $P(t)$ is also generated. Both curves are illustrated in Figure 4.2 at the same time. Although the performance curves represent the temporal dynamics of port operations, they do not provide a comprehensive measure of the port’s overall ability to resist and recover from disruptions. To overcome this limitation, the resilience triangle method is applied to convert the time-dependent performance curve into a single, integrated resilience value.

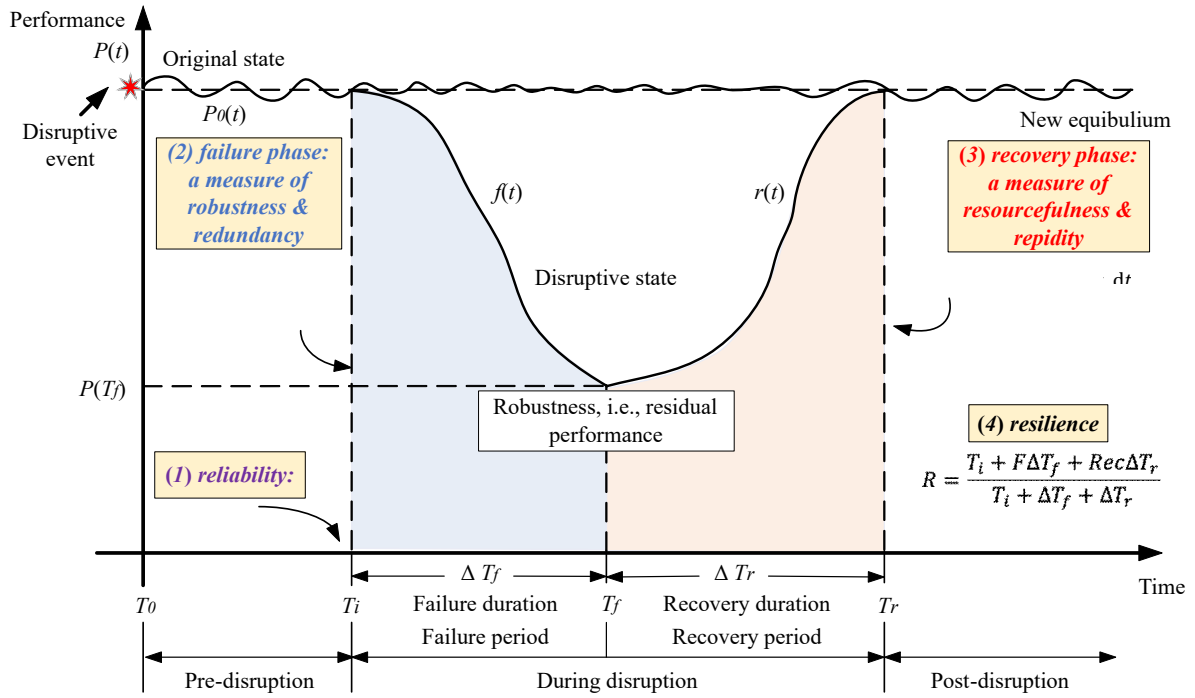


Figure 4.2. Resilience quantification using performance indicators. (Source: Author's own work, based on (Zhang et al., 2025a))

As explained in the previous section, the commonly used resilience triangle method, which no longer fully meets current needs, is depicted in Eq. (4-1). The notations involved are listed in Table 2.7 in Section 2.3.1.

$$\mathcal{R} = \frac{\int_{T_i}^{T_r} P(t) dt}{\int_{T_i}^{T_r} P_0(t) dt} \quad (4-1)$$

where $\mathcal{R}$ is the ratio of disruptive and normal performance during the disruptive and recovery periods. It is explained in detail that various configurations of $P(t)$ and T_r can yield identical resilience values $\mathcal{R}$, yet they may exhibit distinct resilience features (Sun et al., 2024). The misinterpretation stems from two inherent flaws. First, the traditional method does not formally define nor incorporate the performance turning point (i.e., the point when performance reaches the bottom and the recovery process begins) into the assessment, despite this point being visually identifiable and significant in shaping the performance curve. Consequently, the performance degradation and recovery phases are treated as a single continuous period. Second, this prevents the independent evaluation of robustness (before the lowest point) and recovery (after the lowest point).

To improve Eq. (4-1), this work adopts a novel resilience assessment that incorporates multiple perspectives, as shown in Eq. (4-2) and Figure 4.2 (Ayyub, 2014). As comparatively reviewed in Section 2.3.1, this method follows a structured and theoretically grounded approach, which has been recognised within the research community (Cheng et al., 2022; Sun et al., 2024). Yet, its application in port resilience evaluations remains unexplored.

$$R = \frac{T_i + F\Delta T_f + Rec\Delta T_r}{T_i + \Delta T_f + \Delta T_r}$$

$$F = \frac{\int_{T_i}^{T_f} f(t)dt}{\int_{T_i}^{T_f} P_0(t)dt} \quad (4-2)$$

$$Rec = \frac{\int_{T_f}^{T_r} r(t)dt}{\int_{T_f}^{T_r} P_0(t)dt}$$

where the failure profile F is considered as a measure of robustness and redundancy, and the recovery profile Rec is considered as a measure of resourcefulness and rapidity. Upon decomposing R , it is divided into three parts:

- (i) The normalised time required for a disturbance to take effect $\frac{T_i}{T_r}$. In theory, it indicates the proportion of the incident to the entire duration. However, in practice, the onset of effects from each disturbance varies. This factor quantifies the time required for the effects of a disturbance to take hold.
- (ii) The product of normalized failure performance F and normalized failure duration $\frac{\Delta T_f}{T_r}$.
- (iii) The product of normalized recovery performance Rec and normalized recovery duration $\frac{\Delta T_r}{T_r}$.

The notations involved in Figure 4.2 are listed in Table 2.7 in Section 2.3.1. Under each disruptive scenario, port performance is evaluated from the perspective of each KPI, resulting in a performance curve $P(t)$ as illustrated in Figure 4.2. In this method, $P(t)$ is further divided at time T_f , when performance reaches its minimum, into two parts: $f(t)$ representing performance degradation from the disruption onset to T_f and $r(t)$ for the recovery phase from T_f until the port performance returns to its original level. Under the port resilience framework, R is decomposed into three indicators: (i) inherent reliability, (ii) average robustness, and (iii) average recovery capacity. By extending previous models to incorporate all three core dimensions of resilience, this approach allows for an adequate

characterisation and summarisation of the resilience of a multimodal container port throughout the entire disruptive period.

4.2.3 Port resilience evaluation model based on Evidential Reasoning

According to Section 4.2.2, the time-independent assessment is converted into a set of resilience values corresponding to multiple KPIs (shown in Table 4.1). Therefore, a key methodological challenge is to integrate these KPI based resilience values to derive both overall port resilience and the resilience specific to each transportation mode. To address this, resilience values are calculated for each KPI under a given disruptive scenario. The ER approach then aggregates these into an overall value while retaining individual characteristics. The integration process is achieved through the following steps from Section 4.2.3.1 to Section 4.2.3.4, respectively:

- 1) **Formulation of hierarchy structure:** The hierarchy is formulated with three levels of criteria to account for multiple KPIs (bottom-level criteria) across transportation modes (middle-level criteria) and overall port resilience (top-level criteria).
- 2) **Resilience value and belief structure:** The steps introduced in section 4.2.2 determine the resilience value for each disruptive scenario. Subsequently, this score is mapped into a belief distribution.
- 3) **Weight determination:** The influence of low-level criteria on higher-level criteria is determined based on the information they encompass.
- 4) **Overall resilience integration:** Employing the established criteria hierarchy, the model calculates the port's overall resilience based on belief distributions and determined weights.

4.2.3.1 Part 1: Formulation of hierarchy structure

A hierarchical structure with three levels of criteria is constructed, as depicted in Figure 4.3. At the top level, the overall resilience of the port is denoted by R . At the second level, the port is segmented based on five distinct transportation modes: liner shipping R_1 , feeder shipping R_2 , railway R_3 , trucking R_4 , and container yard R_5 . Apart from R_5 , each mode comprises two types of KPIs labelled sequentially with the subscripts 1 and 2.

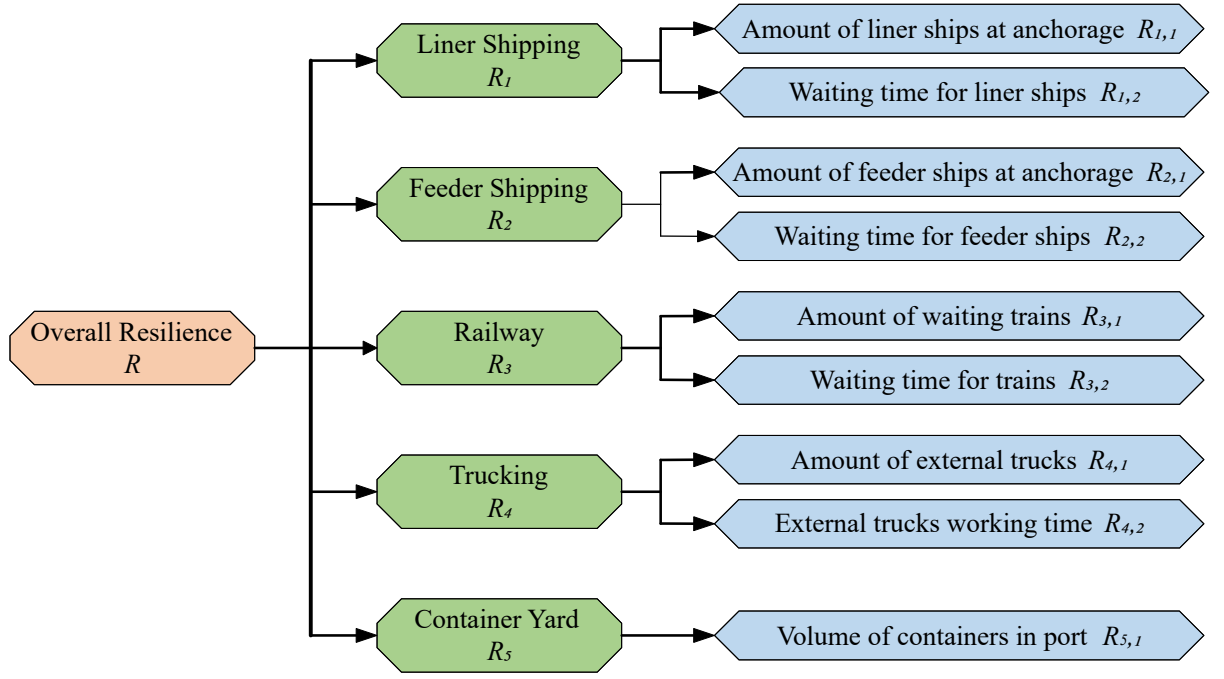


Figure 4.3. The three-level hierarchy for port resilience evaluation.

4.2.3.2 Part 2: Resilience value and belief structure

In this section, the hierarchical KPI notation is replaced by a one-dimensional representation of individual indicators. The KPIs previously denoted by $R_{w,v}$, where v and w merely indicate the hierarchical levels rather than having independent mathematical meaning, are now re-indexed as $EVI = \{e_1, e_2, \dots, e_i, \dots, e_l\}$, indexed by $i \in [1,9]$, where each e_i indicates one KPI in the original hierarchical structure. $S = s_1, s_2, \dots, s_l, \dots, s_L$ defines the alternative vector, containing a total of L disruptive scenarios. $H = \{H_1, H_2, \dots, H_n, \dots, H_N\}$ represents the set of resilience grades with N indicating the total number of grades. The resilience score for KPI e_i under a disruptive scenario l is given by $\alpha_i(s_l)$, and the procedure for obtaining it is outlined in Section 3.2. The range for each resilience grade is determined by the distribution of resilience values across all KPIs. For example, the four grades of R are defined as $\{'strong', 'moderate', 'weak', 'minimal'\}$ according to previous research (Xu et al., 2021b). When $\alpha_i(s_l)$ falls between two predefined grades, a linear distribution method is applied. The belief distribution $S(e_i(s_l))$, evaluated from the perspective of e_i under the specific disruptive scenario a_l , is presented below:

$$S(e_i(s_l)) = \{(H_n, \beta_{n,i}(s_l), \dots, (H_N, \beta_{N,i}(s_l)))\} \quad n = 1, 2, \dots, N \quad (4-3)$$

where $N = 4$, H_n represents the n th evaluation grade, and $\beta_{n,i}(s_l)$ indicates the Degree of Belief (DoB) from the perspective of e_i , the resilience of the port is evaluated as H_n under the disruptive scenario a_l . Significantly, $0 \leq \beta_{n,i}(s_l) \leq 1$ and $\sum_{n=1}^N \beta_{n,i}(s_l) \leq 1$. In this study, $\sum_{n=1}^N \beta_{n,i}(s_l) = 1$, which ensures that the assessment is complete and there is no residual mass unassigned to any grade, i.e., $\beta_{n,i}(s_l) \equiv 0$ for any e_i . This subjectivity is captured through the belief distribution framework, allowing for a thorough consideration of all available information.

4.2.3.3 Part 3: Weight determination

The resilience value of a specific KPI may demonstrate a biased influence on the overall evaluation outcomes of port resilience. Therefore, it is essential to effectively incorporate information from multiple KPIs to bridge this critical gap. This scenario exemplifies a classical multi-criteria assessment where it is critical to allocate weights to each information source (KPIs of the port) based on their significance. The entropy method is selected because the weighting objective in this study is to reflect the information contained in the observed resilience responses rather than decision-makers' subjective preferences. Compared with survey-based or AHP weighting, it derives weights directly from the KPI resilience values generated under the same disruptive scenarios, thereby reducing dependence on expert judgement and improving reproducibility. It also avoids the increasing number of pairwise comparisons and associated consistency requirements of AHP when multiple indicators are considered. This data-driven approach offers a practical alternative to expert-based judgement. Given that all KPIs are evaluated under the same set of disruptive scenarios, a KPI that exhibits greater sensitivity to these disruptions implies a stronger impact on the affected corresponding transportation mode. Such aspects should therefore be given higher priority in the resilience evaluation framework to ensure that their influence on overall port resilience is accurately represented. (Feng et al., 2023; Wang et al., 2022a; Shakibaei et al., 2024; Liu et al., 2017).

Typically, the entropy weighting method begins with data standardisation to neutralise the influence of measurement units. However, this initial step is unnecessary when resilience values fall within the same range, as introduced in Section 4.2.2. The probability set P_i is computed based on the proportion of the l th disruptive scenario in the i th KPI, which is denoted by $p_i(s_l)$. Therefore, the probability used in the entropy calculation is obtained by:

$$P_i = \{p_i(s_1), p_i(s_2), \dots, p_i(s_L)\} = \left\{ \frac{\alpha_i(s_1)}{\sum_{l=1}^L \alpha_i(s_l)}, \dots, \frac{\alpha_i(s_L)}{\sum_{l=1}^L \alpha_i(s_l)} \right\} \quad (4-4)$$

The entropy of the i -th KPI, denoted as Q_i , is then determined based on the definition of information entropy:

$$Q_i = -\xi \sum_{l=1}^L p_i(s_l) \ln(p_i(s_l)) \quad (4-5)$$

$$\xi = \frac{1}{\ln L} \quad (4-6)$$

where ξ is a constant associated with sample size L . A larger Q_i means the i th KPI has more entropy, which suggests it offers less useful information. Therefore, the entropy weight w_i of KPI e_i is determined by:

$$w_i = \frac{\phi_i}{\sum_{i=1}^I \phi_i} \quad (4-7)$$

where $\phi_i = 1 - Q_i$ is the information utility value, and the entropy-based weight w_i for each KPI is derived by normalising its corresponding ϕ_i .

To capture cumulative effects and highlight extreme values, the weight assigned to each transportation mode is determined by summing all associated weights of KPIs.

4.2.3.4 Part 4: Overall resilience integration

Based on the belief distribution (Section 4.2.3.2) and weights (Section 4.2.3.3), the ER approach is applied to aggregate the values of KPIs from multiple transportation modes across the port, thus constructing a final belief distribution indicating the influence level of disruption. The basic probability mass $m_{n,i}$, representing the belief degree to which KPI e_i , supports the hypothesis that its upper-level transportation mode is assigned to grade H_n :

$$m_{n,i} = w_i \beta_{n,i} \quad n = 1, 2, \dots, N, i = 1, 2, \dots, I \quad (4-8)$$

$$m_{H,i} = 1 - \sum_{n=1}^N w_i \beta_{n,i} \quad i = 1, 2, \dots, I \quad (4-9)$$

where $m_{H,i}$ denotes the unallocated probability mass not attributable to any specific evaluation grade H_n by KPI e_i . This residual is separated into two components $\bar{m}_{H,i}$ and $\tilde{m}_{H,i}$, which are obtained by:

$$\bar{m}_{H,i} = 1 - w_i \quad i = 1, 2, \dots, I \quad (4-10)$$

$$\tilde{m}_{H,i} = w_i \left(1 - \sum_{n=1}^N \beta_{n,i} \right) \quad i = 1, 2, \dots, I \quad (4-11)$$

where $\bar{m}_{H,i}$ is bounded by the inherent weight of the criterion e_i , revealing how much other indicators influence the evaluation; $\tilde{m}_{H,i}$ results from incomplete assessment information.

According to the hierarchy structure in Figure 4.3, the basic probability mass from the bottom-level $R_{w,v}$ is first aggregated to the middle-level R_w using the recursive ER algorithm. This approach is then repeated until aggregation reaches the top-level R . The probability mass $m_{n,I(i)}$ quantifies the degree to which the i th KPI within the set $EVI(e_i)$ endorse the evaluation grade H_n , while $m_{H,i}$ unallocated probability mass not attributable to any specific evaluation grade by these KPIs. Initially, $m_{n,I(i)} = m_{n,1}$ and $m_{H,I(i)} = m_{H,1}$. The combined probability mass for $i = 1, 2, \dots, L$ are derived as follows:

$$m_{n,I(i+1)} = \Xi_{I(i+1)} (m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} + m_{H,I(i)} m_{n,i+1}) \quad (4-12)$$

$$\tilde{m}_{H,I(i+1)} = \Xi_{I(i+1)} (\tilde{m}_{H,I(i)} \tilde{m}_{H,i+1} + \bar{m}_{H,I(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)} \bar{m}_{H,i+1}) \quad (4-13)$$

$$\bar{m}_{H,I(i+1)} = \Xi_{I(i+1)} (\bar{m}_{H,I(i)} \bar{m}_{H,i+1}) \quad (4-14)$$

$$\Xi_{I(i+1)} = \left(1 - \sum_{t=1}^N \sum_{j=1, j \neq t}^N m_{t,I(i)} m_{j,i+1} \right)^{-1} \quad (4-15)$$

where $m_{n,I(i+1)}$ denotes the degree of support for H_n when recursively combining the DoB of the i -th KPI with $(i+1)$ -th KPI. $\Xi_{I(i+1)}$ serves as the normalization factor. After aggregating all the information, the combined DoB is obtained as follows:

$$\beta_n = \frac{m_{n,I(L)}}{1 - \bar{m}_{H,I(L)}} \quad n = 1, 2, \dots, N \quad (4-16)$$

$$\beta_H = \frac{\tilde{m}_{H,I(L)}}{1 - \bar{m}_{H,I(L)}} \quad (4-17)$$

where β_n represents the aggregated DoB that a resilience value is evaluated as H_n , and β_H is the aggregated DoB that remains unassigned to any specific evaluation grade, indicating the level of uncertainty in the assessment. Port resilience under the scenario a_l is characterized by the subsequent belief-based distribution:

$$\mathcal{S}(R(s_l)) = (H_n, \beta_n(s_l)), n = 1, 2, \dots, N; (H_N, \beta_N(a_l)) \quad (4-18)$$

where $\mathcal{S}(R(s_l))$ denotes the belief distribution of the overall port resilience under the disruptive scenario s_l . Through a linear transformation, a single overall resilience value $R(s_l)$ is derived. The same approach is used to evaluate the resilience of different transport modes.

$$R(s_l) = \sum_{n=1}^N \frac{n-1}{N-1} \beta_n(s_l) \quad (4-19)$$

4.3 Experimental results

4.3.1 Experiment setup and design

4.3.1.1 *Disruption settings*

To validate the performance and practicality of the methodology, the resilience assessment is applied to the same case-study port and empirical dataset used for the SD analysis in Chapter 3. The underlying operational, accident, and expert data are those described in Section 3.3. Moreover, given that most container ports adhere to a standardised layout and utilise consistent equipment, the nature of accidents tends to be uniform (Bogalecka and Dąbrowska, 2023; Lu and Borgonovo, 2023), which ensures that the insights gained from the study apply to other ports.

The data for this study are grounded on three primary data sources as detailed in section 3.3.1.3. The selection, the severity (Chen et al., 2022) and duration (Cao and Lam, 2018) of the representative disruptive scenarios are outlined previously in Table 3.8. The outputs of these scenarios serve as a basis for evaluating the consequences of disruption, providing the foundation for assessing port resilience.

Disruptions should be introduced after the system has stabilised to avoid initial biases. To ensure this, a warm-up period of 200 hours is applied. This duration is based on the observation that the values of all KPIs stabilise after approximately 200 hours under normal operating conditions. Additionally, to gather sufficient data and observe long-term behaviour patterns while ensuring representative results considering the liner shipping schedule, the simulation spans 920 hours. Each scenario is repeated 30 times to calculate average values and reduce noise. The disruptive scenarios and their parameter values are the same as Table 3.9 in Chapter 3. Subsequently, the resilience values are calculated using the methods detailed in Sections 4.2.2 and 4.2.3.

4.3.1.2 *Validation*

The proposed methodology should be validated from two aspects: the performance of the SD simulation model and the overall resilience assessment framework, respectively. The validation of the SD simulation can be found in section 3.3.1.2. The reliability and accuracy of the resilience measurement method have been verified and recognised through comparisons with traditional approaches (Cheng et al., 2022; Sun et al., 2024). Therefore, only the validation of the overall framework, which includes an SD model, a resilience calculation method, and the ER model, is included here.

In previous studies, most integrated frameworks only validated the simulation part, neglecting the validation of the entire framework (Feofilovs and Romagnoli, 2021; Blouin et al., 2024). Given the absence of systematic methods for validating such a framework, a limitation acknowledged by scholars (Chin et al., 2009), the extreme condition approach from SD validation is adopted. This approach examines whether the overall framework can effectively capture the dynamic behaviours of port resilience changes. Extreme scenarios, as detailed in Table 4.2, are designed for this verification. The results confirm that under extreme disruption conditions, resilience values decrease dramatically, as expected. Under these extreme conditions, the resilience of the associated KPIs often reaches a global minimum, sometimes nearing zero, as shown in Table 4.3.

Table 4.2. Scenario settings for the extreme condition test of the resilience quantification model.

Transportation mode	Base Value	Extreme scenario name	Extreme Value
Liner shipping	Liner quay crane = 6	ES 1	Liner quay crane = 1, liner quay crane disruption time = 200
Feeder shipping	Quay crane handling efficiency for feeder = 30	ES 2	Quay crane handling = 10, quay crane handling efficiency for feeder disruption time = 240
Railway	Number of transshipment tracks = 4	ES 3	Number of transshipment tracks disruption scale = 1, number of trans

hipment tracks disruption time = 200

Trucking Max number of internal trucks = 60 ES 4 Max number of internal trucks = 20

2090

Table 4.3. Extreme condition test results for the resilience quantification model.

Resilience value	ES1	ES 2	ES 3	ES 4
$R_{1,1}$	0.418	0.986	0.986	0.733
$R_{1,2}$	0.517	0.994	0.994	0.731
R_1	0.001	0.567	0.567	0.119
$R_{2,1}$	0.956	0.580	0.956	0.730
$R_{2,2}$	0.983	0.579	0.983	0.734
R_2	0.309	0.005	0.309	0.001
$R_{3,1}$	1.000	1.000	0.696	0.581
$R_{3,2}$	0.948	0.948	0.698	0.432
R_3	0.631	0.631	0.001	0.001
$R_{4,1}$	1.000	1.000	1.000	1.000
$R_{4,2}$	1.000	1.000	1.000	1.000
R_4	1.000	0.949	1.000	1.000

$R_{5,1}$	0.466	0.719	0.885	1.000
R_5	0.466	0.719	0.885	1.000
R	0.240	0.287	0.317	0.491

The validation in this chapter therefore focuses on the behaviour of the integrated assessment framework rather than repeating the validation of individual components. A valid framework is expected to preserve logical relationships between disruption severity, KPI deterioration, subsystem resilience, and overall resilience under extreme conditions.

4.3.2 Experimental results

In this section, the overall port resilience under different disruptive scenarios (see Table 3.9) is first analysed, identifying incident types significantly affecting overall resilience and their statistical characteristics. Secondly, the impact of these disruptions on various transportation modes is examined in detail. Lastly, through a correlation analysis, this section explores the characteristics of ripple effects within the port, thereby demonstrating the effectiveness of this study in understanding and managing port risks.

4.3.2.1 Results of System Dynamics simulation

The SD model generates time series data for 9 KPIs under various disruptive scenarios characterised by different types, magnitudes, and durations of disruptions. Given the extensive dataset, Figure 4.4 depicts the variance trend of liner container ships waiting at anchorage due to the damage of two liner quay cranes. The duration of the disruptions extends from 0 hours (baseline, no disruptions) up to 120 hours.

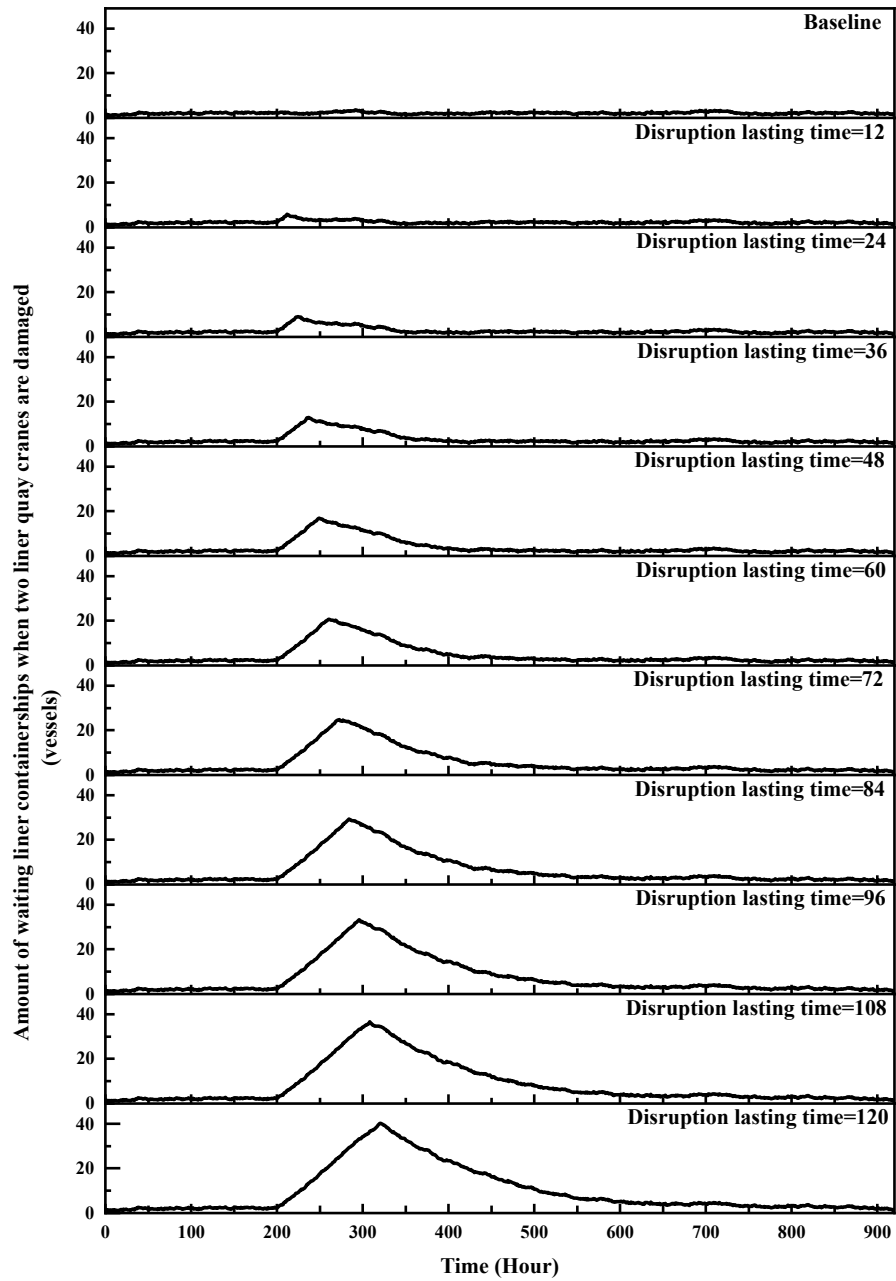
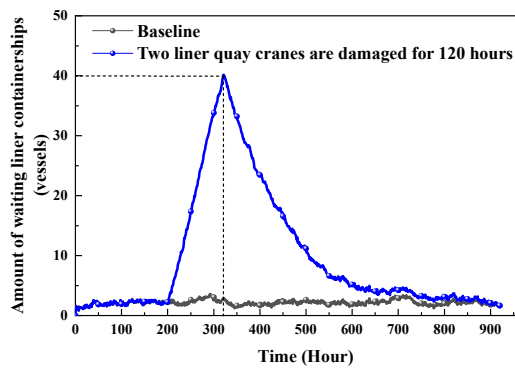


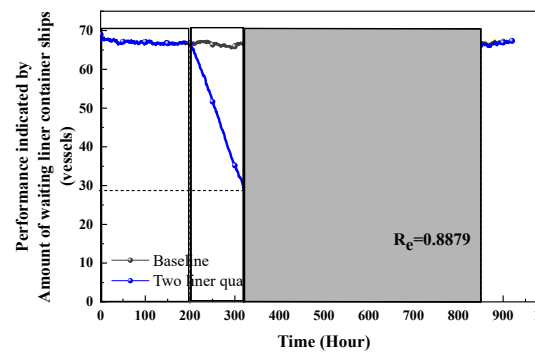
Figure 4.4. SD simulation results of the number of waiting liner containerships when two liner quay cranes are damaged under different disruption durations.

4.3.2.2 *Results of resilience indicated by Key Performance Indicators*

Considering the extensive dataset, which includes over 200 scenarios and 9 KPIs, an example involving a 120-hour failure of 2 liner quay crane is chosen to demonstrate the process of resilience calculation. A slice of Figure 4.4 is shown in Figure 4.5. The data are normalised based on the global maximum disruptive magnitude to construct resilience triangles, as shown in Figure 4.5. Subsequently, the resilience value is calculated using Eq. (4-2).



(a)



(b)

Figure 4.5. Illustration of resilience measurement based on performance indicator: The number of waiting liner containerships when two liner quay cranes are damaged for 120 hours.

Through the above steps, the resilience values indicated by all KPIs are calculated. Due to the vast amount of data, the results under the liner quay crane damage scenarios are selected as an example, as shown in Figure 4.6. In the case of quay crane disruptions, the scales correspond to the removal of 1, 2, or 3 cranes, indicating progressively severe operational impacts. The same scaling principle is applied to the remaining disruption types in Table 3.9.

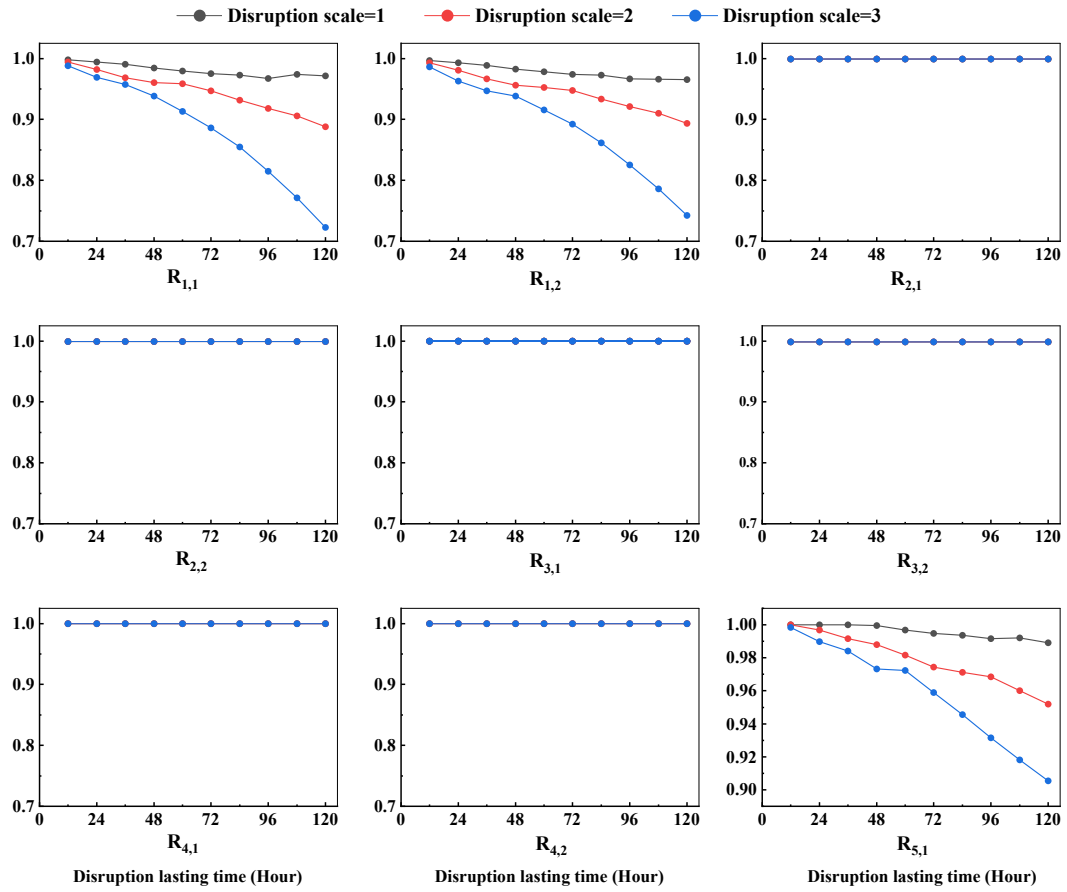


Figure 4.6. Resilience calculation results due to different scales of quay crane disruptions across different durations indicated by 9 KPIs.

4.3.2.3 Overall port resilience results

(1) Entropy weight results

Using the resilience values, the weights for each KPI and each transportation mode are determined based on the entropy weight method described in Eqs. (4-6)-(4-9), as shown in Table 4.4. From the perspective of transportation modes, container storage is of paramount significance, followed by liner and feeder shipping. Rail and road transport carry the lowest weight, aligning with typical industry patterns. At the bottom level, the weight of KPIs shows minimal variation, indicating that they are nearly equally important to their respective higher-level indicators.

Table 4.4. Entropy weight results (Three-decimal precision).

Resilience	Weight	Resilience	Weight	Resilience	Weight	Resilience	Weight	Resilience	Weight
R_1	0.198	R_2	0.219	R_3	0.127	R_4	0.138	R_5	0.319

$R_{1,1}$	0.485	$R_{2,1}$	0.508	$R_{3,1}$	0.475	$R_{4,1}$	0.582	$R_{5,1}$	1
$R_{1,2}$	0.515	$R_{2,2}$	0.492	$R_{3,2}$	0.525	$R_{4,2}$	0.418		

(2) Overall port resilience under different disruption events

Using resilience values and weights as inputs, the overall port resilience value across different disruptive scenarios is derived through ER. Since the primary objective of this research is to develop and validate a systematic framework for assessing port resilience, each disruptive scenario is predefined and treated deterministically, without incorporating uncertainty. This assumption applies to the results presented in Figure 4.7-Figure 4.11. Figure 4.7 illustrates the overall port resilience in response to different severities of liner quay crane disruptions. Generally, as disruption escalates (i.e., with longer durations and fewer operational quay cranes for liner shipping), the port resilience value decreases accordingly. The most pronounced decline in resilience occurs at 48 hours for L1, 24 hours for L2 and L3, indicating a potential breaking point. After 60 hours, the variation in resilience values among L1, L2, and L3 becomes minimal, and the decline rate due to prolonged disruptions also diminishes. This suggests that the disruption duration and magnitude have a limited influence on total resilience, likely because the port system's recovery capabilities reach a saturation point. However, before 60 hours, the resilience values drop markedly as the severity and duration of disruptions increase, demonstrating a heightened sensitivity. Therefore, more attention should be focused on managing the severity and duration of disruptions within the first 60 hours, where they tend to have a more pronounced effect.

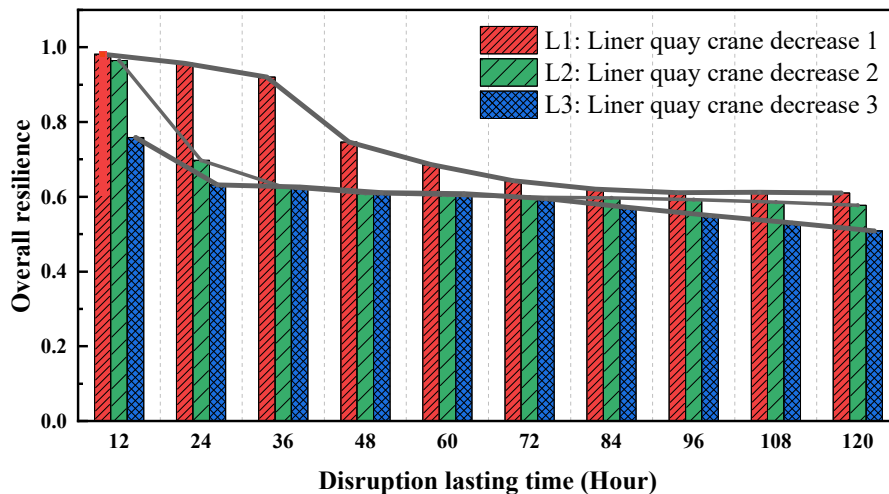


Figure 4.7. Impact of liner quay crane disruptions on overall resilience.

Figure 4.8 illustrates the overall port resilience in response to various feeder quay crane incidents. Like liner quay cranes, resilience values experience substantial decreases due to disruptions within the

first 60 hours, underscoring the importance of this period for effective mitigation and the restoration of normal operations. Additionally, the disparity between scenarios F1 and F2 is initially small (12-24 hours), widens during the 36-48 hour period, and then narrows, emphasising the criticality of the 36-48 hour period in managing and mitigating the disruption effects.

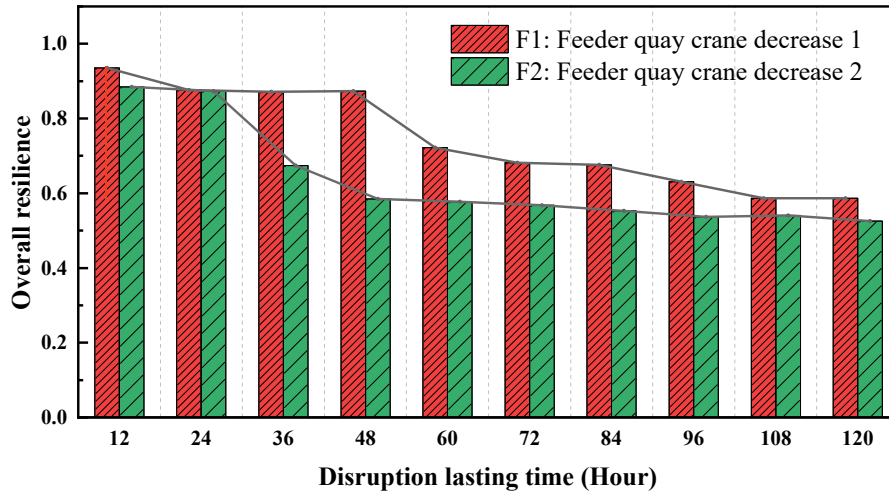


Figure 4.8. Impact of feeder quay crane disruptions on overall resilience.

Figure 4.9 shows overall port resilience under different severities of incidents involving train cranes. Throughout the study period, resilience levels for the T1 and T2 scenarios remain constant, with only the T3 scenario experiencing significant fluctuations when the disruption persists for 96 hours. This suggests that, compared to incidents involving liner and feeder quay cranes, accidents in rail operations have a lesser impact, possibly due to the higher self-recovery capacity or redundancy inherent in railway systems.

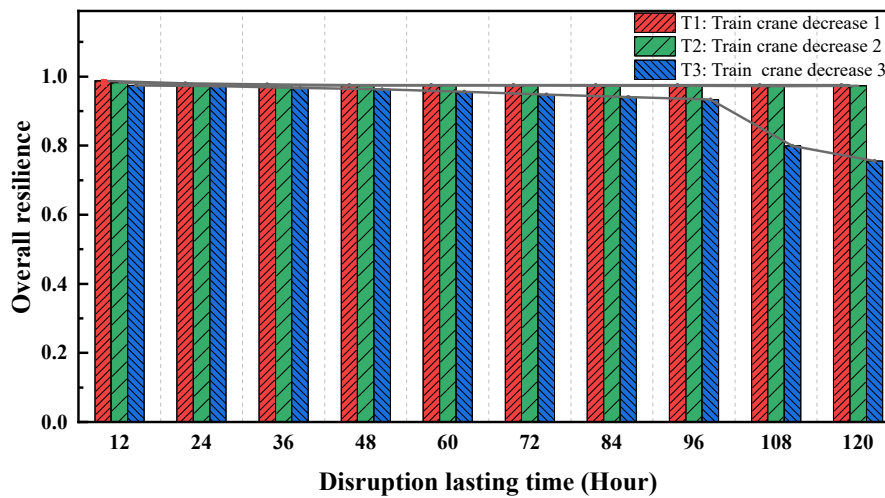


Figure 4.9. Impact of train crane disruptions on overall resilience.

Figure 4.10 depicts the overall port resilience under different traffic congestion scenarios. Under the D1 scenario, the port's resilience remains largely stable, indicating that this congestion level does not significantly impact normal port operations and remains within acceptable limits. In the D2 scenario, resilience exhibits a step-wise decline, with a significant drop occurring around the 60-hour mark, followed by stabilisation. This suggests that this duration represents a critical threshold for port resilience under D2-level congestion. Under scenario D2, resilience gradually diminishes over time. This declining trend disappears at D3, transitioning to consistently low resilience values that remain nearly constant over time, a pattern that also extends to D4 and D5. Moreover, the resilience levels at D5 are slightly higher than those at D3 and D4, possibly due to disruptions' complex and nonlinear effects on the overall port system.

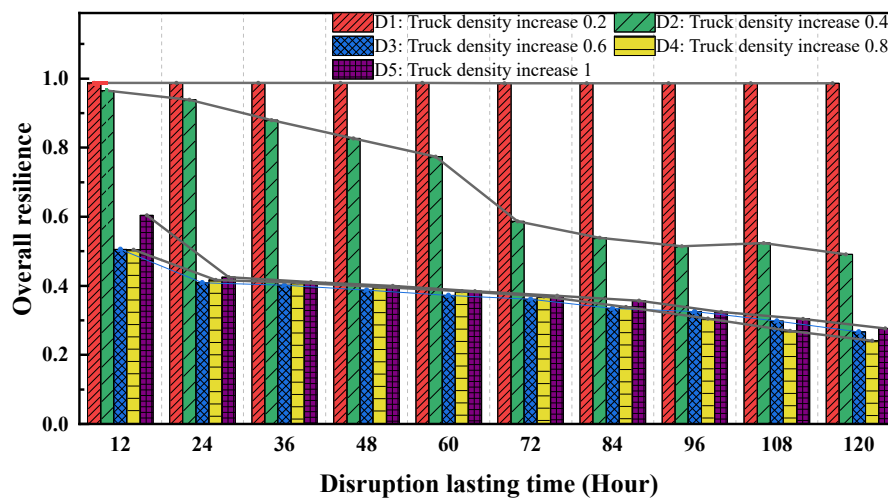


Figure 4.10. Impact of traffic jams on overall resilience.

Figure 4.11 illustrates the overall resilience values in the event of yard crane failures at the container yard. Since a container block is typically served by a group of yard cranes performing container handling tasks, the failure of a single crane is limited. Therefore, scenarios simulating the complete failure of all crane groups within a block are considered. Under scenarios Y1, Y2, Y3, Y4, and Y5, the number of yard crane failures and the durations have a minor impact on resilience. However, in scenario Y6, when the number of malfunctioning yard cranes exceeds 24, there is a substantial decline in port resilience, which further decreases as the disruption time increases. **The limited change under Y1–Y5 suggests that the remaining yard crane capacity can absorb moderate failures, whereas the sharp decline under Y6 indicates that this redundancy becomes insufficient once a larger number of cranes are simultaneously unavailable.** In practice, ensuring that the number of non-operational yard cranes remains below 20 is crucial to maintain normal operations at the port.

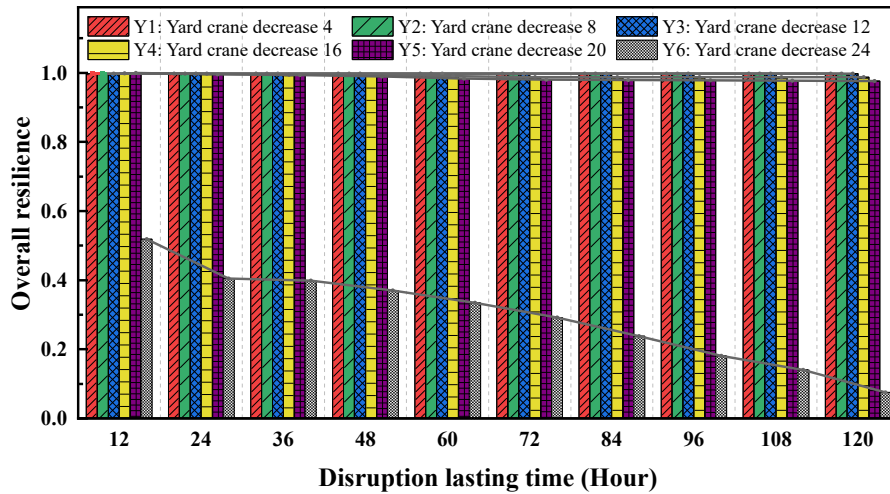


Figure 4.11. Impact of yard crane disruptions on overall resilience.

Figure 4.12 presents the statistical characteristics of overall port resilience, including mean, error bar, and median values across different types of disruptions. Traffic jams have the most significant impact on port resilience, followed by liner quay crane incidents, with train crane failures having the least impact. This analysis provides port managers with a clear ranking of the severity of different incidents, enabling them to develop tailored response strategies accordingly. The error bar results indicate significant fluctuations in resilience due to yard crane failures and traffic congestion, reflecting the high sensitivity of the system to the degree and duration of these disruptions. The difference between the mean and median values, coupled with the length of the error bars, suggests the presence of outliers. This indicates that the resilience scores in specific disruption categories, such as liner disruptions and traffic jam, include outliers significantly lower than most of the data, which may require special attention.

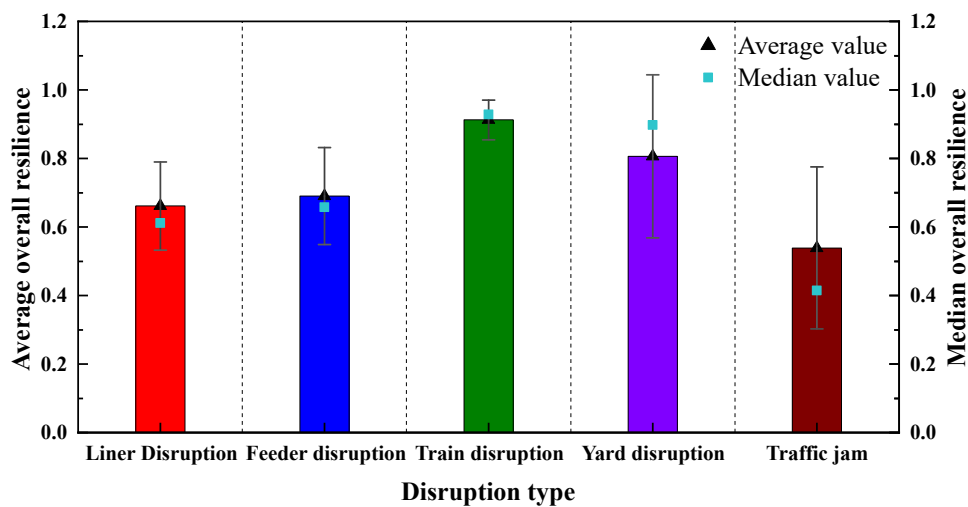


Figure 4.12. Average, error, and median value for overall port resilience under different types of disruptions.

4.3.2.4 Subsystem resilience under different disruptive scenarios

Figure 4.13 illustrates the average resilience values across five transportation modes (i.e., R_1, R_2, R_3, R_4, R_5) under different types of disruptions. Each axis represents a specific transportation mode, while each coloured line corresponds to a distinct type of disruption. The values along the axes indicate the resilience scores. The following analysis is conducted from two perspectives: (1) the comparative resilience of different transportation modes under the same disruptive scenario (i.e., along a single coloured line), and (2) the resilience of a given transportation mode under different types of disruptions (i.e., along a single axis). Based on these analyses, resource allocation can be strategically prioritised before, during, and after disruptions, and it also facilitates the identification of areas that are resilient and vulnerable.

Firstly, the impacts of a specific disruption type on different transportation modes are revealed. Liner quay crane disruptions have the most significant impact on the liner shipping, with resilience values around 0.3, followed by the railway, while others are less affected. This suggests a strong interdependence between liner and railway operations, with the railway particularly susceptible to such disruptions. Feeder quay crane disruptions predominantly affect feeder shipping operations, reducing resilience values to below 0.1, while having a minimal impact on others. Train crane failures primarily influence railway operations, where resilience values approximate 0.4, but their impact is less notable in other operations. Yard crane failures exhibit slight variation across transportation modes, maintaining resilience values above 0.7. Traffic jams significantly disrupt the liner, feeder, and railway operations, underscoring the essential role of container truck operations in linking seaside and railway activities. The impact on the truck operations is moderate, with the least influence on the container yard.

Secondly, the following analysis examines the resilience values of a specific transportation mode under various disruptions. The liner shipping records the lowest resilience when affected by liner quay crane disruptions, dropping below 0.4, with traffic jams also causing substantial reductions; however, it remains higher than against other disturbances. Similarly, the resilience of feeder shipping operations drops below 0.1 during its corresponding incidents, with traffic jams as the next most disruptive, highlighting operational similarities between liner and feeder shipping. The railway operations experience a resilience value of around 0.4 (train crane accidents), 0.6 (traffic jams), and 0.8 (other disruptions). The truck operations consistently exhibit resilience between 0.7 and 0.8 across all disruptions, with yard crane accidents posing the most significant risk. The container yard demonstrates

exceptional resilience across all disruptions, indicating a robust capacity to withstand risks. In summary, seaside shipping operations are the most vulnerable parts of the port.

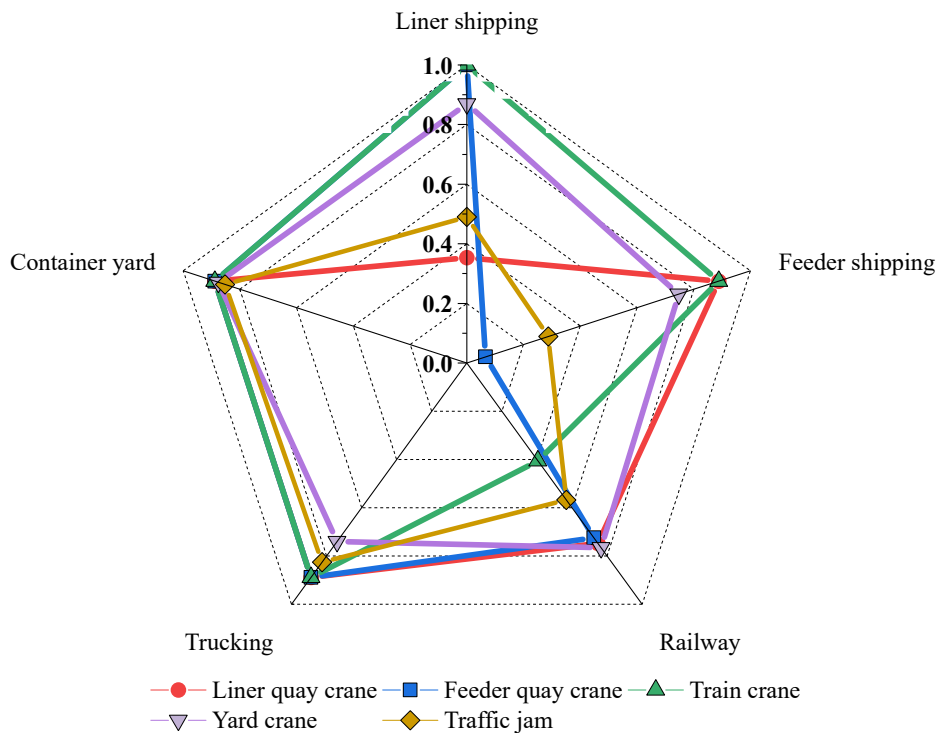
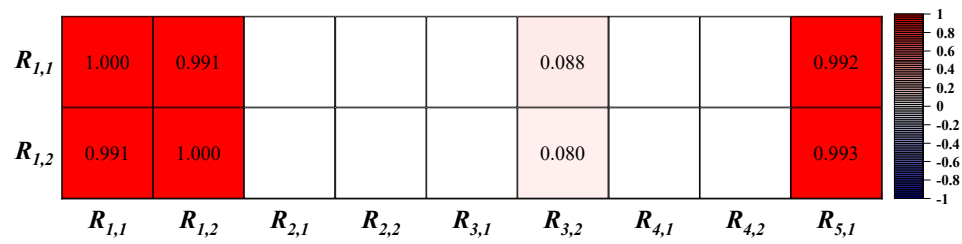


Figure 4.13. Subsystem resilience values under different disruptions.

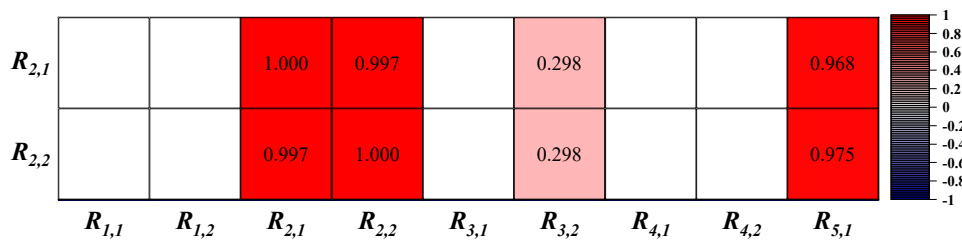
4.3.2.5 Correlation analysis

Figure 4.14 illustrates the correlation analysis results between different resilience values represented by different KPIs. Liner shipping disruptions in Figure 4.14 (a) and feeder shipping disruptions in Figure 4.14 (b) extend their impact to the container yard. However, disruptions in the railway operations only affect the container yard minimally, as shown in Figure 4.14 (c). Additionally, as shown in Figure 4.14 (d), the resilience values in the truck operations show strong correlations with those from all other transportation modes, indicating that disruptions originating from here in this subsystem propagate throughout the entire port, leading to widespread efficiency declines. Notably, in Figure 4.14 (e), the container yard is particularly correlated with the number of trains waiting at the port, highlighting that container backlogs significantly impair railway operational efficiency, but not the other way around. This effect extends to feeder shipping, underscoring the critical role of rail and waterborne feeder transport in the container port's logistics network. It is important to emphasise that the observed correlations between the resilience metrics of different transport subsystems reflect the dependencies among system ability, but they do not indicate the temporal sequence or lag in disruption

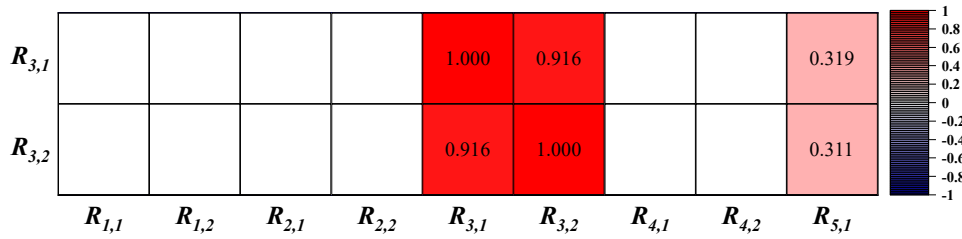
propagation. Thus, such analysis provides insight into association, rather than causation or timing of ripple effects.



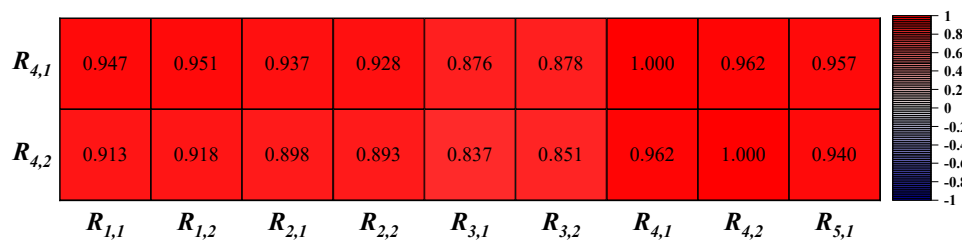
(a) Disruptions from liner shipping.



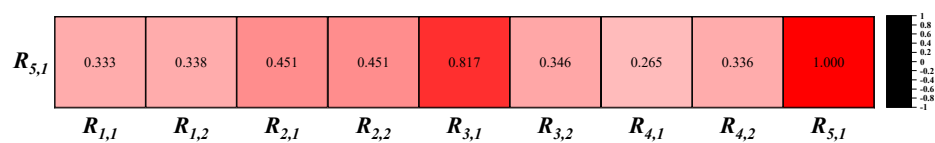
(b) Disruptions from feeder shipping.



(c) Disruptions from railway.



(d) Disruptions from truck operations.



(e) Disruptions from the container yard.

Figure 4.14. Interdependencies among resilience values from various KPIs of the port.

4.3.3 Implications

In this section, the implications of Chapter 4 will be discussed from three perspectives: implications on theory, practice, and policymaking.

From a theoretical standpoint, this work advances the current literature by addressing several critical gaps: 1) It challenges the conventional view in port risk management which obscures the understanding of ripple effects among interconnected transportation modes by enriching the literature based on a multimodal examination of port disruptions; 2) It refines resilience measurement by clearly distinguishing between robustness and recovery capabilities; 3) It innovatively proposes a framework for port resilience assessment by integrating SD, the resilience triangle, and ER.

From a practical standpoint, the theoretical framework, which accounts for the ripple effects that significantly impact real-world practices and adheres to a multimodal layout, aligns with actual operational needs. Consequently, this framework is adaptable to ports featuring similar multimodal transshipment systems, offering data-driven, practical, and reliable guidance for maritime decision-makers. Based on historical data, the framework objectively measures KPIs, the resilience of a specific transportation mode, and overall port resilience under various risk scenarios. Additionally, the correlation analysis enables a clear identification of accident propagation patterns and resulting ripple effects. In summary, this approach could provide relevant stakeholders with quantitative data on the resilience of their operations and equip safety managers and risk analysts with a tool to understand the ripple effects within ports transparently.

From a policy perspective, the proposed methodology has broad applicability and practical value. Its implementation can help port operators, government agencies, and regulators enhance risk prevention during the preparation stage, control risk propagation during disruptions, and accelerate recovery after incidents. In turn, this approach can mitigate the adverse impacts on shipping companies, cargo owners, port authorities, and especially on port workers and unions through the following:

1. This study demonstrates that traffic congestion and disruptions to quay cranes handling liner containerhips result in the most substantial decline in resilience. Accordingly, policymakers and port managers should prioritise these areas in their prevention and emergency response strategies, including routine maintenance, inventory of critical spare parts, redundancy in key resources, and investment in intelligent traffic control systems.

2. Resilience patterns under different disruption magnitudes and durations help identify intervention thresholds. In general, this study suggests that the first 60 hours after a disruption are the most critical period for resilience recovery. This calls for setting a tailored response time point for each disruption type. Besides, real-time monitoring and active alert systems can help mitigate ripple effects.
3. Analysing resilience across transportation modes helps identify vulnerable subsystems and develop targeted strategies based on their exposure profiles. For instance, feeder shipping is primarily affected by direct risks. It requires direct, mode-specific protection, whereas yard and liner operations are more susceptible to indirect ripple effects and thus require strategies against indirect disruptions.
4. By analysing the correlation of various KPIs under disruptions, this study identifies patterns of ripple effects within the port. Our findings indicate that disruptions originating on the seaside propagate to the yard side, and disruptions on the yard side affect the entire port. Therefore, policies should target these critical transmission points by enhancing coordination protocol mechanisms, such as regulating container flow between the seaside and yard side during peak hours, adjusting yard storage strategies, and managing internal port traffic conditions.

4.4 Conclusions

This chapter introduces a framework that incorporates SD simulation, resilience assessment method, and ER to examine the resilience of multimodal ports in the face of operational disturbances. It segments ports based on their transportation functions to examine the ripple effects across these modes. Its main contributions include 1) a micro perspective SD simulation tailored for multimodal container ports; 2) a novel resilience calculation method that distinctly captures the features of disruptive and recovery periods; 3) an ER approach capable of integrating interconnected and contradictory indicators; 4) an applicable framework that guides users in conducting their assessments to enhance global port resilience ultimately. Experimental results provide insights into how different transport subsystems and the entire port respond to operational disruptions, as well as the spreading patterns of ripple effects between these modes.

The resilience assessment framework developed in this chapter provide an essential basis for understanding how different disruptive scenarios affect port resilience. However, it mainly evaluates predefined disruption scenarios and does not fully reveal the relative importance of each disruptive factor or the interaction effects among multiple disruptions. To address this issue, Chapter 5 further uses

2331 the resilience values generated in this chapter as model outputs and applies GSA to identify the
2332 disruptive factors and combinations that most strongly influence overall port resilience.
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CHAPTER 5 RESILIENCE ASSESSMENT OF MULTIMODAL CONTAINER PORTS UNDER OPERATIONAL DISRUPTIONS: A GLOBAL SENSITIVITY ANALYSIS³

Chapter 4 quantifies port resilience under different disruptive scenarios. In order to expand the findings to directly reveal the relative importance of different disruptive factors or disentangle their interaction effects on overall port resilience, further analysis is required to identify and rank the factors that most significantly influence resilience loss. In response, this chapter introduces a novel UQ methodology for revealing the impact of various disruptions and identifying the interactions among them that could lead to a ripple effect. In this framework, port operations are first simulated through SD modelling in Chapter 3. The resulting performance is then transformed into resilience indicators, which are synthesised across subsystems using the ER method in Chapter 4. Finally, the Sobol GSA is employed to assess the influence of individual and joint disruptions. To assess the consistency of the results, the ICC is calculated for three different GSAs. Using historical failure data and field evidence, multiple disruptive scenarios are explored. The outcomes indicate that failures of yard and quay cranes have the greatest impact on port resilience. It is further observed that many disruptions arise from interdependent failures rather than individual malfunctions, leading to amplified ripple effects. The results provide a data-driven foundation for policymakers and port managers to shift from experience-based to evidence-based allocation of emergency resources, with evidence generated through large-scale simulations of plausible but previously unobserved disruptive scenarios. They also support cross-agency coordination for integrated resilience management against compound disruptions arising from ripple effects. In summary, this framework, for the first time, offers crucial insights for bolstering long-term resilience in multimodal container port operations from a systematic overall perspective.

5.1 Introduction

Container ports are exposed to a wide range of disruptions arising from natural hazards, operational failures, labour issues, geopolitical conflicts, public health crises, and other external shocks (Wang et

³ The findings of this technical chapter have been published in the following journal paper. ZHANG, J., XIN, X., DUBEY, R., NGUYEN, T. T., SHI, X., LI, N. & YANG, Z. 2026. Resilience assessment of multimodal container ports under operational disruptions: a global sensitivity analysis. *Transportation Research Part A: Policy and Practice*, 208, 104987.

al., 2024b). Given the inherently uncertain nature of such disruptions, decisions aimed at enhancing port resilience are inevitably made under uncertainty. Within this broad framework, it becomes necessary to evaluate how different uncertainties affect port disruptions and identify key determinants. Consequently, this necessitates adopting methodologies to accurately quantify uncertainty and explain how changes in output (i.e., resilience) can be attributed to inputs (i.e., variability in disruptions).

Within the context of UQ, SA methods are one of the most effective in screening out highly influential input parameters, which are categorised into LSA and GSA (Schmitz et al., 2023). The LSA method, also referred to as OAT, involves changing a single variable while holding the others constant to observe changes in the output. It is generally unsuitable for complex, high-dimensional models because it allows only single-parameter variations. In contrast, the GSA method evaluates the effects of input parameters across the entire feasible range of the input space, allowing the analysis of interactions among input parameters (Cheng et al., 2023, Saltelli et al., 2010).

To address the challenges regarding technical model 3 proposed in section 1.2, it is crucial to project potential disruptive scenarios through simulation, consider the ripple effect among these factors, and minimise model discrepancies. The Sobol quasi-random technique is used to sample disruptive variables extensively, exploring the full range of possible combinations to ensure that all disruptions that could affect port resilience are adequately examined. The SD model proposed in Chapter 3, chosen for its strength in modelling dynamic interactions (Liu et al., 2023c), is employed to simulate port disruptions and calculate resilience values for five transportation subsystems (i.e., liner shipping, feeder shipping, railway, truck, and yard) based on their operational performance under these disruptions. The ER model developed in Chapter 4, well-suited for integrating multiple indicators under uncertainty (Liang et al., 2025b), is employed to synthesise these values, forming an overall port resilience. Additionally, a GSA called Sobol's method (Sobol', 2001), chosen for its ability to examine both first- and second-order sensitivity influences, is employed to determine the comparative significance of disruptive factors affecting port resilience. To validate the reliability, the outcomes obtained from Sobol's method are compared with those from two other common GSA methods, namely FAST-RBD (Cukier et al., 1973) and PAWN (Coppola et al., 2023), using the ICC (Shrout and Fleiss, 1979) consistency checks. ICC is selected because it is effective for comparing differences between evaluation methods. The objective of this study is to scientifically identify disruptive variables that contribute most to the uncertainty in port resilience and support evidence-based risk management by translating sensitivity-based evidence into actionable implications. In addition, practically speaking, effective assessment requires appropriate SA to guide managerial efforts (Taghizadeh et al., 2021).

5.2 Methodology: Global Sensitivity Analysis-based disruptive factors identification

The proposed methodology is illustrated in Figure 5.1, which provides a flowchart of the integrated SA process for evaluating port resilience under disruptive scenarios. Initially, the preliminary work is set by SD, resilience quantification, and ER to incorporate operational and disruption data from the port, thereby calculating the overall port resilience value under various disruptions. Following this, GSA is employed to determine the significance of each type of disruptive variable. The experimental procedure of the framework includes: (1) establishing the range and probability distributions for disruptive variables; (2) sampling of these variables using Sobol sequences to represent each disruptive scenario, (3) inputting these samples into the preliminary work to derive overall port resilience values under different disruptive scenarios; (4) employing the characteristics of the sampled variables, sampling result and resilience values to compute different SI through GSA.

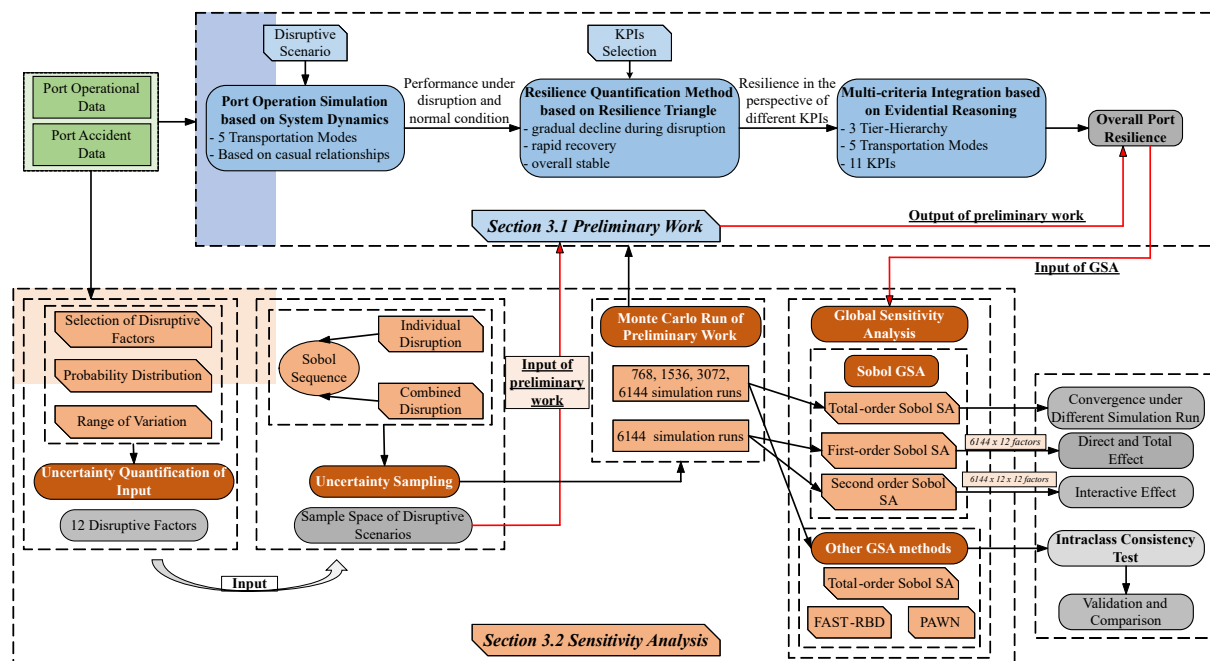


Figure 5.1. Flowchart of the framework for Chapter 5.

5.2.1 Preliminary work

Chapters 3 and 4 are the preliminary work underpinning Chapter 5. Their overall research process is briefly introduced here to maintain continuity. The detailed methodology and relevant procedures can be referred to in Chapters 3 and 4. In the preliminary work, the SD model simulates port operations

under a range of disruptive scenarios, evaluating port efficiency by monitoring changes in KPIs across various transportation modes. Subsequently, the resilience triangle method is applied to convert these time-varying KPIs into quantifiable resilience values. Ultimately, these resilience values for different port KPIs are aggregated into a global-level port resilience index, which is utilised as the output metric for the SA process described in Section 5.2.2. The model structure, parameter ranges, and variable definitions remain consistent with the empirically validated and justified previous work, which utilises evidence from over ten widely cited academic papers, three industrial organisations, and multiple domain experts.

5.2.2 Sensitivity analysis

5.2.2.1 Uncertainty quantification of input variables

Reliable GSA results depend on the appropriate selection of input variables and their probability distributions, underscoring the necessity to accurately characterise them to reflect real-world conditions (Schmitz et al., 2023). The objective of this chapter is to analyse how different disruptions affect port resilience. The inputs, therefore, should be distinctly categorised by disruption severity (Chen et al., 2022) and duration (Cao and Lam, 2018; Taghizadeh et al., 2021), and the resulting output is an assessment of the port's resilience in the face of these disruptions. Drawing on expert insights and historical records, this research identifies significant representative and prevalent disruptions in port operations. For more details, refer to section 3.3.1.3.

Following the selection of input variables, it is essential to specify their range of variation and associated probability distributions. Historical data introduced in section 3.3 are used to establish the maximum and minimum values for disruption severity and duration. Regarding probability distributions, multiple methods are available to quantify them depending on data availability: maximum likelihood estimation is generally used for extensive datasets, Bayesian inference is suitable for more limited data, and expert judgment can guide the definition of a plausible distribution when data are particularly sparse (Schmitz et al., 2023). Uniform distribution is adopted after careful consideration of the dataset's characteristics and past literature (Lu and Borgonovo, 2023). Although port accident records are available, the relative infrequency of such incidents over the observation period limits the reliability of traditional statistical models. Moreover, the highly unpredictable nature of these events further challenges efforts to derive precise parametric or probabilistic inferences about future disruptions. Under these circumstances, a uniform distribution offers a more robust and unbiased approach to capturing uncertainty, thereby avoiding overfitting of sparse data.

5.2.2.2 Sampling method

This process is typically realised using Monte Carlo simulations (Pohya et al., 2022), during which multiple iterations are performed with input variables created based on their designated probability distributions. Although increasing the number of simulations improves the convergence of statistical moment estimates, such as mean and variance, it also makes the traditional Monte Carlo method computationally costly due to the extensive combination of input variable combinations, rendering it practical only for models with rapid processing capabilities (Schmitz et al., 2023). Consequently, the adoption of an advanced sampling method that minimises the number of iterations yet comprehensively explores the sampling space and preserves statistical accuracy is essential.

Parameter exploration is conducted through the Sobol quasi-random cross-sampling scheme (Sobol sequence), which provides uniform sampling across the probability space, something not guaranteed by traditional random number generation. The distribution, while seemingly random, is methodically directed toward regions of the probability space that have not yet been sampled (Cohen et al., 2024). Another common sampling method is LHS, which partitions the range of each input variable into equal-probability intervals and generates samples accordingly. However, LHS may produce biased sampling results, leading to overrepresentation in some dimensions and omission in others (Pang et al., 2020). To address this challenge, the Sobol sequence employs sampling based on the (t, m, s) -net and has been validated for its uniform distribution characteristics (Niederreiter, 1988) {Pan, 2023 #673}.

5.2.2.3 Determination of output variables

Through sampling, various combinations of input variables are generated, each forming a distinct disruptive scenario. As described in Section 5.2.1, the SD simulator receives these scenario settings as inputs, which include the type or types of disruption χ , as well as their intensity $\alpha(\chi)$ and duration $\tau(\chi)$ as shown in Table 3.9. Subsequently, an overall port resilience value is generated as output.

5.2.2.4 Sobol sensitivity analysis

To connect the definitions in Chapter 3 with the SA, the previously distinct variables are recast into a unified notation. Specifically, variables that were originally denoted by different symbols are now represented by the same symbol with different subscripts. For example, for a certain disruption type χ_1 , its intensity $\alpha(\chi_1)$, and duration $\tau(\chi_1)$ are denoted as disruptive variable X_1, X_2 respectively.

The model $Y = f(X_1, X_2, \dots, X_k)$ is defined over Ω , which specifies the range of all possible values of the disruptive variable X . Y represent the port resilience under a given disruptive scenario

($X_1, X_2, \dots, X_K$). The first-order contribution of X_k can be formulated as $V_{X_k} \left(E_{X_{\sim k}}(Y|X_k) \right)$, in which $E_{X_{\sim k}}(Y|X_k)$ represents the expected port resilience Y obtained by averaging over all other disruptive variables other than X_k (denoted by $X_{\sim k}$) while X_k is fixed. Consequently, $V_{X_k} \left(E_{X_{\sim k}}(Y|X_k) \right)$ quantifies the variability of these expectations. A large variance suggests a more significant impact of a particular disruptive factor X_k on Y . The notation for SA is presented in Table 5.1.

Table 5.1. Notation for SA.

Notation	Description
L	The number of sampled disruptive scenarios, where each scenario is a combination of disruptive variables
K	Number of disruptive variables
$X_k, k \in \{1, 2, \dots, K\}$	The k -th disruptive variable
$X = \{X_1, X_2, \dots, X_K\}$	$L \times K$ matrix, representing all sampled combinations of disruptive variables (theoretical representation)
$\Omega = \{(X_k \mid 0 \leq X_k \leq 1)\}$	K dimensional hypercube representing all potential disruptive scenarios
$Y = f(X_1, X_2, \dots, X_K)$	Model output, representing the overall port resilience under a certain disruptive scenario
$X_{\sim k}$	$L \times (K - 1)$ matrix of all disruptive variables except for X_k
$E_{X_k}(\cdot)$	Expectation of $(\cdot)$ taken over X_k , representing the expected port resilience value under variation of X_k
$V_{X_k}(\cdot)$	Variance of argument $(\cdot)$ taken over X_k , representing the variability of port resilience under variation of X_k
S_k	First-order SI of X_k , representing the variance in the port resilience attributable solely to X_k
S_{T_k}	Total-order SI of X_k , representing the variance in the port resilience due to both X_k and its interactions with other variables
$S_{k,j}$	Second-order SI of X_k and X_j , representing the variance in the port resilience due to the interaction between X_k and X_j
A, B	$L \times K$ sample matrix of disruptive variables generated through simulation (realisations of X through simulation)

$\mathbf{A}_B^{(k)}$	$L \times K$ matrix where column i is from $\mathbf{B}$ and all other $K - 1$ columns are from $\mathbf{A}$
$\mathbf{B}_A^{(k)}$	$L \times K$ matrix where column i is from $\mathbf{A}$ and all other $K - 1$ columns are from $\mathbf{B}$

2476 The associated first-order SI, which measures the individual effect of a single disruptive variable
 2477 X_k on Y can be presented as:

$$S_k = \frac{V_{X_k}(E_{X_{\sim k}}(Y|X_k))}{V(Y)} \quad (5-1)$$

2478 where $V_{X_k}(E_{X_{\sim k}}(Y|X_k))$ denotes the first-order variance contribution of X_k . The $V(Y)$ is the overall
 2479 variance of port resilience Y . The inner expectation, $E_{X_{\sim k}}(Y|X_k)$ represents the port resilience Y under
 2480 fixed disruption X_k , averaged over all other disruptive factors. The outer variance then quantifies how
 2481 this conditional expected resilience varies as X_k changes across its range.

2482 The established variance decomposition formula indicates that the total variance $V(Y)$ can be split
 2483 into the first-order effect of the disruptive variable X_k and the interactive effects between X_k and all
 2484 remaining inputs $X_{\sim k}$:

$$V(Y) = V_{X_k}(E_{X_{\sim k}}(Y|X_k)) + E_{X_k}(V_{X_{\sim k}}(Y|X_k)) \quad (5-2)$$

2485 where $E_k(V_{X_{\sim k}}(Y|X_k))$ is also referred to as residual, representing the effect which could be traced to
 2486 $X_{\sim k}$ on $V(Y)$ under fixed X_k . The total-order SI is defined as:

$$S_{T_k} = \frac{E_{X_{\sim k}}(V_{X_k}(Y|X_{\sim k}))}{V(Y)} = 1 - \frac{V_{X_{\sim k}}(E_{X_k}(Y|X_{\sim k}))}{V(Y)} \quad (5-3)$$

2487 where S_{T_k} considers the overall influence of X_k on port resilience Y including its direct (first-order) and
 2488 interactive (higher-order) effects. $E_{X_{\sim k}}(V_{X_k}(Y|X_{\sim k}))$ represents the expected conditional variance of
 2489 port resilience Y if only X_k can be changed and $X_{\sim k}$ are fixed. Dividing it by the total variance $V(Y)$
 2490 obtains the fraction of the total variance $V(Y)$ that could be explained by the changes in X_k (including
 2491 both its individual and joint variance). From another perspective, it can be interpreted that
 2492 $V_{X_{\sim k}}(E_{X_k}(Y|X_{\sim k}))$ is the first-order contribution of $X_{\sim k}$, which means the contribution of other
 2493 disruptive variables to port resilience except X_k . Then subtracting this from the total variance $V(Y)$ will
 2494 give the contribution of all variances that is due to the changes of X_k .

According to Hoeffding decomposition (Sobol', 1990) where $f_k = f_k(X_k)$, $f_{kj} = f_{kj}(X_k, X_j)$ and so forth, yielding 2^K terms in total, the resilience function f can be decomposed in different dimensions, including individual impact and joint disruptions across all scenarios:

$$f = f_0 + \sum_k f_k + \sum_k \sum_{k < j} f_{kj} + \dots + f_{1,2,\dots,K} \quad (5-4)$$

where f_0 is a constant, which is the expected value of port resilience when all disruptive variables are certain. $f_k(X_k)$ is the isolated effect of the disruptive variable X_k to port resilience, $f_{ij}(X_k, X_j)$ is the interactive contribution of X_k, X_j to port resilience, and higher-order terms $f_{1,2,\dots,k}$ represent the joint contribution among three or more disruptive variables. Eq. (5-4) breaks down the function into a constant, the contributions of individual variables and their combinations. Based on the concept mentioned in Eq. (5-1), the specific calculation of each term is as follows:

$$f_0 = E(Y)$$

$$f_k = E_{X \sim i}(Y|X_k) - E(Y) \quad (5-5)$$

$$f_{ij} = E_{X \sim ij}(Y|X_k, X_j) - f_k - f_j - E(Y)$$

where f is the expected port resilience, f_k is the deviation in the expected port resilience resulting solely from variations in the disruptive factor X_k , aligning with the first-order effect. f_{kj} is the deviation in expected port resilience attributable to simultaneous variations in both X_k and $X_{k'}$, corresponding to the interaction effect. $E_{X \sim k}(Y|X_k) - E(Y)$ isolates the part of the resilience variation that can be uniquely attributed to the influence of X_i alone, excluding contributions from other variables or interactions. When disruptive variables X_k and X_j are varied at the same time, $E_{X \sim kj}(Y|X_k, X_j) - f_k - f_j - E(Y)$ represents the non-additive interaction between X_k and X_j , such as synergy or interference, where the joint effect is not simply the sum of individual effects. Based on Eq. (5-5), similarly, the partial variance formula can be determined by finding the variance:

$$V_k = V(E_{X \sim k}(Y|X_k)) \quad (5-6)$$

$$V_{kj} = V(E_{X \sim kj}(Y|X_i, X_j)) - V_k - V_j$$

2513 where V_k is the first-order contribution of the disruptive variable X_k and V_{kj} is the second-order
 2514 contribution of the interaction between X_k and X_j . By adding the effect across all orders, the overall
 2515 variance can be decomposed:

$$V(Y) = \sum_k V_k + \sum_{k < j} V_{kj} + \dots + V_{1,2,\dots,K} \quad (5-7)$$

2516 By dividing both sides by $V(Y)$, the decomposed form of the SI can be obtained:

$$\sum_k S_k + \sum_{k < j} S_{kj} + \dots + S_{1,2,\dots,K} = 1 \quad (5-8)$$

2517 Manual resolution of these decompositions is feasible for small-scale basic analytical models.
 2518 However, SI can be approximated through iterative sampling for large, complex models using
 2519 estimators. The Sobol method, which utilises Monte Carlo simulations, is detailed below. It computes
 2520 an individual resilience value Y based on a sampled dataset of k disruptive factors $X_1, X_2, \dots, X_K$.
 2521 Numerous studies across various fields have shown that Sobol's method provides higher accuracy
 2522 compared with other GSA methods (Pohya et al., 2022).

$$V_{X_k} \left(E_{X \sim k} (Y|X_k) \right) = \frac{1}{L} \sum_{j=1}^N f(\mathbf{A})_j f(\mathbf{B}_A^{(k)})_j - f_0^2 \quad (5-9)$$

2523 The variance in port resilience Y caused by a specific disruptive factor X_k is obtained by measuring
 2524 the changes of Y when X_k is fixed and can be further achieved by comparing the output from two
 2525 different matrices $\mathbf{A}$ and $\mathbf{B}_A^{(k)}$. $\mathbf{A} = [\mathbf{a}_{kj}]$ where $k \in (1, K)$ indicating the index of disruptive factors
 2526 and $j \in (1, N)$ indicating the index of simulation scenarios. $\mathbf{B}_A^{(k)}$ is constructed by substituting the i -th
 2527 column of $\mathbf{A}$ with that of matrix $\mathbf{B}$. Other matrices of similar structure are constructed accordingly.

2528 Eq. (5-9) was proposed by Sobol in 1993 and then improved to a more computationally efficient
 2529 form using a strategy called winding stairs in 2010 (Saltelli et al., 2010), as shown in Eq. (5-10):

$$V_{X_k} \left(E_{X \sim k} (Y|X_k) \right) = \frac{1}{L} \sum_{j=1}^L f(\mathbf{B})_j \left(f(\mathbf{A}_B^{(k)})_j - f(\mathbf{A})_j \right) \quad (5-10)$$

2530 For the total-order effect, Jansen's method (Jansen, 1999) is adopted. The efficiency and
 2531 superiority have been proven by numerous literature (Saltelli et al., 2009; Sobol', 2001):

$$E_{X \sim k} \left(V_{X_k}(Y|X \sim k) \right) = \frac{1}{2L} \sum_{j=1}^L \left(f(\mathbf{A})_j - f(\mathbf{A}_B^{(k)})_j \right)^2 \quad (5-11)$$

The approach used to calculate the total-order effect can be applied to compute the interactive effect between a pair of disruptive variables X_k and X_j , so Jensen's estimator can be generalised into:

$$E_{X \sim kj} \left(V_{X_k, X_j}(Y|X \sim kj) \right) = \frac{1}{2L} \sum_{w=1}^L \left(f(\mathbf{A}_B^{(k)})_w - f(\mathbf{A}_B^{(j)})_w \right)^2 \quad (5-12)$$

Eq. (5-12) calculates the squared difference of port resilience Y between two disruptive scenarios $\mathbf{A}_B^{(k)}$ and $\mathbf{A}_B^{(j)}$. It is used to estimate the variation in Y when X_k and X_j are varied while keeping other disruptive variables constant. Therefore, Eq. (5-10), Eq. (5-11) and Eq. (5-12) are selected to obtain the first-order, total-order and second-order SI accordingly.

From the estimation approach above, the calculation of S_k and S_{T_k} requires matrices $\mathbf{A}$ and $\mathbf{B}$, which involves $2L$ simulations. Besides, each disruptive variable requires K simulations for $\mathbf{A}_B^{(k)}$, resulting in a computational cost of $L(K + 2)$. For the second-order effect, an additional KL simulations are needed to obtain $\mathbf{A}_B^{(j)}$, thus the total computational efforts should be $L(2K + 2)$.

5.2.2.5 Consistency test between different sensitivity analysis

While Sobol SA has been proven to produce higher accuracy compared to other methods, this study enhances the validation of result accuracy by integrating two additional GSA methods and performing consistency checks using the ICC method. ICC is a statistical metric utilised to evaluate the consistency, reliability, or concordance of ratings among multiple assessors or across multiple evaluations (Shrout and Fleiss, 1979). It is frequently used in reliability research to measure the level of agreement in ratings assigned to the same subject by different assessors, or by the same assessor at different times.

The foundation of the ICC is based on ANOVA, and its formula is outlined as follows:

$$r = \frac{K}{K-1} \cdot \frac{P^{-1} \sum_{p=1}^P (\bar{s}_p - \bar{s})^2}{dev^2} - \frac{1}{k-1} \quad (5-13)$$

where K is the number of disruptive variables for which SI are calculated, P is the number of different SA approaches, and s_p is the SI obtained through the p -th approach, forming a dataset of $S =$

2553 $\{s_1, s_2, \dots, s_p\}$. $\bar{s}_p$ is the average value of s_p , $\bar{s}$ and dev^2 are the mean and deviation of the entire dataset.
 2554 The ICC introduced is the most common form. Additionally, five other classes of ICC can be derived
 2555 based on the randomness of evaluator selection and the number of measurements. These are summarised
 2556 in Table 5.2.

2557 Table 5.2. ICC types and their definitions.

ICC type	ICC name	Randomness	Number of measurements
ICC(1, 1)	Single raters absolute	Each disruptive variable is evaluated through a different random subset of P methods	Single measures
ICC(2, 1)	Single random raters	P methods are randomly selected, then each disruptive variable is measured by the same set of P methods	Single measures
ICC(3, 1)	Single fixed raters	P fixed methods are defined. Each disruptive variable is measured by the P methods	Single measures
ICC(1, P)	Average raters absolute	Each disruptive variable is measured by a different set of P randomly selected methods	Average measure
ICC(2, P)	Average random raters	P methods are randomly selected, then each disruptive variable is measured by the same set of P methods	Average measure
ICC(3, P)	Average fixed raters	P fixed methods are defined. Each disruptive variable is measured by the P methods	Average measure

2558 **5.3 Results and visualisation**

2559 This section should include the following contents: (1) data collection process, (2) identification
 2560 of disruptive factors, along with their value ranges and probability distributions, (3) generation of
 2561 simulation samples through Sobol sequences, (4) result verification and convergence test, (5) the

estimation of the total-order, first-order, and second-order SI of the disruptive factors, (6) consistency tests are applied to cross-validate the SI derived from multiple SA approaches, reinforcing the reliability of the results. As the data collection has already been described in Section 3.3, it is not repeated here.

5.3.1 Identification of disruptive factors

Statistical data and expert opinions are combined to select variables that affect port resilience and to determine their value ranges, as shown in Table 5.3. Expert input was obtained through structured interviews with port managers, selected for their extensive risk management expertise and over 10 years of experience in port operations, as shown in Appendix A.

Table 5.3. Input disruptive factors and their range of variability.

Accident type	Input variables	Notation	Lower bound	Upper bound	Unit
Liner quay crane	Number of equipment	X_1	1	3	Cranes
	Duration	X_2	12	120	Hours
Feeder quay crane	Number of equipment	X_3	1	2	Cranes
	Duration	X_4	12	120	Hours
Rail crane	Number of equipment	X_5	1	3	Cranes
	Duration	X_6	12	120	Hours
Yard crane	Number of equipment	X_7	4	24	Cranes
	Duration	X_8	12	120	Hours
Traffic congestion	Increase in truck density	X_9	0.2	1.0	-
	Duration	X_{10}	12	120	Hours

5.3.2 Model convergence using different samples

Employing a range of sample sizes and monitoring their convergence is essential for checking the stability of GSA methods (Cheng et al., 2023; Cohen et al., 2024). To this end, four sample sizes, 64, 128, 256, and 512, are chosen, corresponding to simulation runs of 768, 1536, 3072, and 6144, respectively. The selection of these sample sizes is justified by the optimal performance of the Sobol sequence when applied to powers of two (Schmitz et al., 2023), while the number of simulation runs is further specified according to the computational demand required for estimating S_i , S_{T_i} and $S_{i,j}$ as outlined in Section 5.2.2.4. Figure 5.2 indicates that variable rankings can be initially established with very few simulations and stabilise after 3072 runs, thus validating the sufficiency of the selected sample sizes.

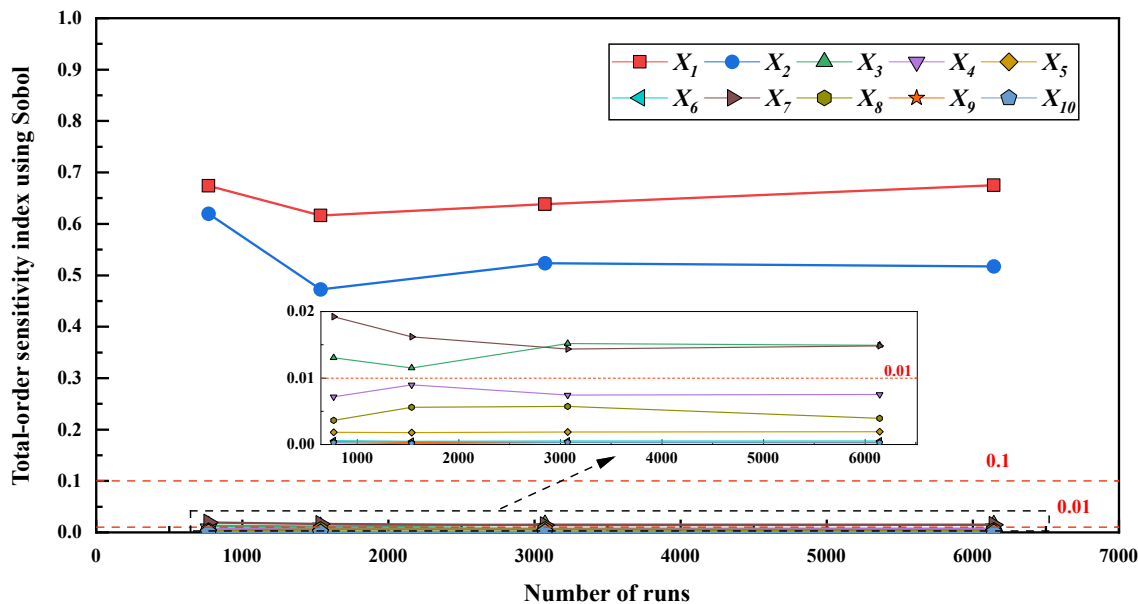


Figure 5.2. Total-order Sobol SI under various sample sizes.

To rigorously demonstrate the convergence of the results, a numerical experiment is conducted alongside the graphical analysis, showing that variability declines with increasing numbers of simulations. The Coefficient of Variation (CV) is widely adopted as an indicator of stability. Given the significant variation in the magnitude of the results, the relative percentage change is not appropriate as it overemphasises fluctuations in small-magnitude values. Therefore, a three-point sliding window CV is used to quantify and illustrate the stabilisation, as shown in Table 5.4.

Table 5.4. CV based on three-point sliding windows for each factor across different sampling sizes.

Factor	CV (sample 768-1536)	CV (sample 1536-3072)	CV (sample 3072-6144)
X_1	0.045255	0.049032	0.022456
X_2	0.139075	0.052926	0.011616
X_3	0.139006	0.138308	0.04005
X_4	0.12053	0.097191	0.023316
X_5	0.023408	0.03857	0.015731
X_6	0.076683	0.052403	0.056687
X_7	0.1482	0.070467	0.018589
X_8	0.234081	0.065434	0.230014
X_9	0.210875	0.086787	0.067073
X_{10}	0.362652	0.364194	0.057019

2591

2592 The CVs associated with nearly all disruptive factors decline steadily as the sample size increases,
2593 indicating convergence. While minor fluctuations are observed for X_1 and X_{10} during the second
2594 sampling window and for X_8 during the third, small variations of CV (X_1) and in low-SI factors (X_8)
2595 are generally acceptable in convergence assessment. In particular, the CV of X_{10} increases only
2596 marginally before decreasing substantially to 0.057019 in the final sampling window. This minor
2597 intermediate fluctuation is not considered practically significant, as the overall trend indicates clear
2598 stabilisation with increasing sample size. Based on this evidence, the model can be considered to reach
2599 a satisfactory level of convergence.

5.3.3 Visualisation of the results

This section examines the results obtained from Sobol SA, chosen for its ability to compute total-order, first-order, and second-order effects. Additional experiments are conducted to assess robustness across various sample sizes and methods, with further details provided in the subsequent section. The SALib package in Python, Vensim DSS for simulating port operations, and IDS software for implementing the ER algorithm are used.

Based on Section 5.2.2.2, a quasi-random sampling is performed to explore the multidimensional space involving 10 identified input variables, all of which are uniformly distributed. To present the sampling results visually, the ten-dimensional array is transformed into a two-dimensional array of sampling points, as shown in Figure 5.3. The total number of simulations is 6,144.

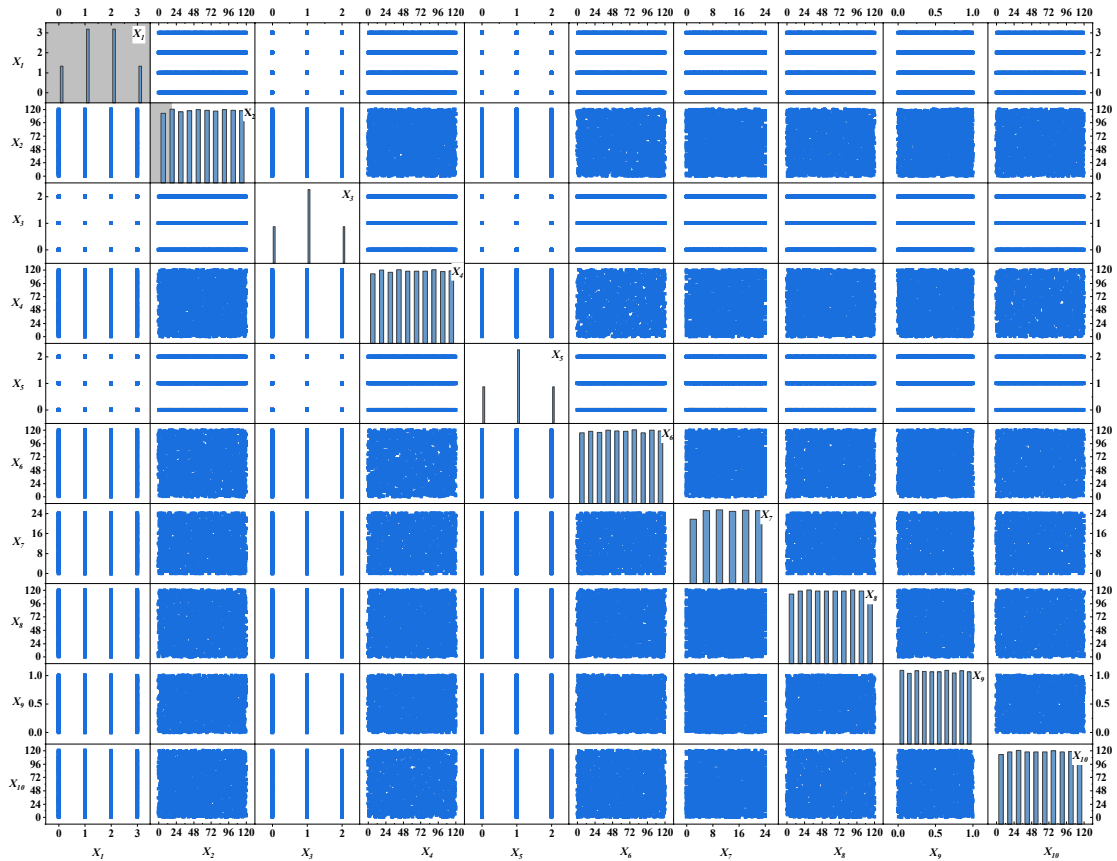


Figure 5.3. Sobol sampling results of 6,144 samples.

The generated samples are subsequently introduced into the SD model as disruptive scenarios for simulation. The resulting time-series KPIs are converted into resilience values and then integrated using ER to determine the overall port resilience.

In the Sobol SA process, the generated samples are used as input to quantify the variance of the output, which is the overall port resilience. The analysis identifies and categorises SI into total-order, first-order, and second-order, as demonstrated in Figure 5.4 and Figure 5.5. The aggregate height represents the total-order effect, encompassing first-order effects and interaction contributions. A Sobol SI value above 0.1 signals high sensitivity of influencing factors. Indices from 0.01 to 0.1 reflect moderate sensitivity, whereas values below 0.01 are classified as insensitive (Yan et al., 2023).

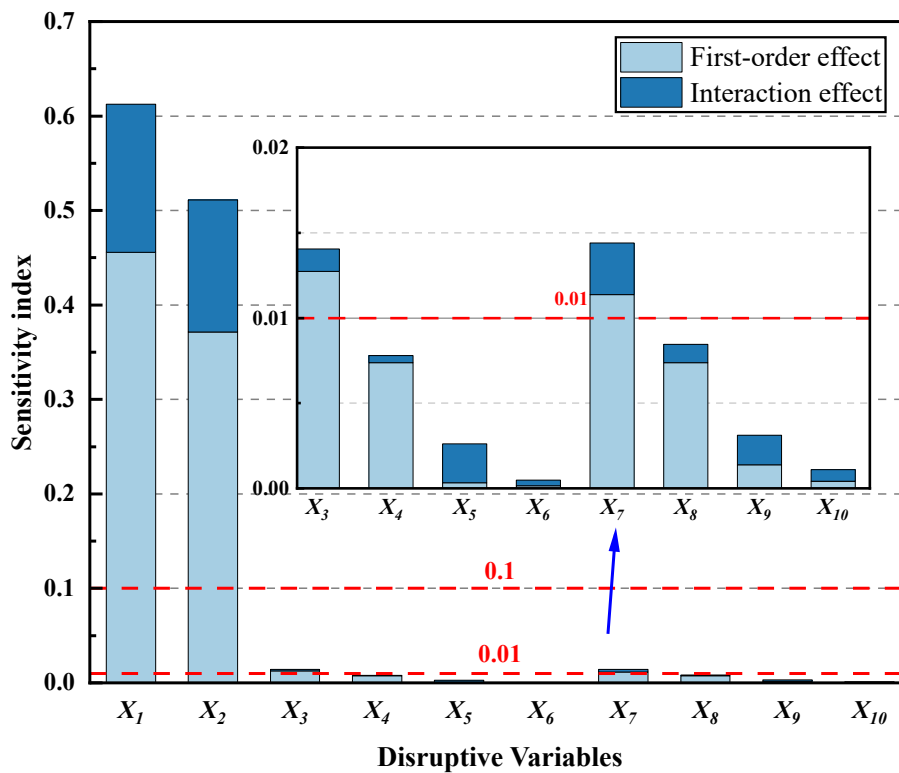


Figure 5.4. Sobol first-order and total-order SI under 6144 simulation runs.

Regarding the first-order SI, which illustrates the individual contribution of each disruptive variable on port resilience, the results indicate that the variation is predominantly driven by the number of liner quay cranes and the duration of their downtime, with S_k of 0.45 and 0.37, respectively (see Figure 5.4). These are followed by the number of feeder quay cranes and yard cranes, which also exhibit notable contributions, with S_k of 0.013 and 0.011, respectively. The occurrence of disruptions associated with these variables can lead to substantial fluctuations in port resilience. It is worth noticing that traffic congestion in the yard, which naturally receives the same amount of attention as crane failure in port management, does not appear to significantly influence port resilience uncertainty, at least not through a direct effect. Other variables in feeder shipping, railway, and yard area demonstrate relatively

low first-order effects, indicating that their individual impact on port resilience is limited and therefore may not require prioritisation in targeted adjustment strategies. From a broader perspective, approximately 80% of the overall variation in port resilience can be explained by disruptions occurring directly within the liner operation area, while the remaining portion stems from disruptions in other transport subsystems.

The total height of each bar in Figure 5.4 reflects the total-order S_{TK} , which includes both the individual contribution of a variable and its interactions with others. Eq. (5-1) indicates that the sum of first-order indices equals 1, while it does not apply to total- or second-order SIs. Overall, the trends in total-order SI are largely consistent with those of the first-order effects, suggesting that direct impacts rather than complex interactions primarily drive the port's resilience. Specifically, the total-order indices for the number of liner quay crane failures and their downtime duration are 0.67 and 0.51, respectively. Among all variables, the number of liner quay crane failures has the largest total effect, underscoring its pivotal role in sustaining port operational stability. The downtime duration follows closely, reinforcing the critical importance of maintaining high availability of liner quay cranes to enhance port resilience. Feeder quay cranes and yard cranes also contribute to port resilience through both direct and indirect effects, with total-order indices of 0.015 for both. These results underscore the importance of ongoing attention to their maintenance and rapid recovery capabilities. In contrast, the remaining variables show relatively minor influence on port resilience. Therefore, in resource-constrained scenarios, these factors may be deprioritised without significantly compromising overall system resilience.

Interaction effects are illustrated by the dark blue bar in Figure 5.4, and the specific variable pairs responsible for each interaction can be examined in greater detail in Figure 5.5. There is a substantial interaction between the number and the downtime duration of liner quay crane failures, contributing approximately 16% and 14% to the total-order effects, respectively. This indicates that a significant portion of their influence on port resilience arises from their interactions with other variables, rather than from their individual effects alone. Variables X_5 (number of train crane failures), X_7 (number of yard crane failures), and X_9 (yard congestion) are noteworthy for their disproportionately large interaction effects, which exceed their relatively small first- and total-order contributions. This suggests that while these variables may have limited standalone influence on port resilience, their combined impact with other variables could be considerable. These interaction effects indicate that port resilience is shaped by the combined effects of multiple disruptions, rather than by their individual contributions. Moreover, the combined impact of multiple disruptions may exceed the sum of their individual effects, forming a nonlinear $1 + 1 > 2$ effect. This highlights the need for more detailed analyses to understand these risk interactions and to develop flexible, adaptive mitigation strategies that go beyond linear,

single-variable interventions. Conversely, variables such as X_3 (number of feeder quay crane failures) and X_7 (number of yard crane failures) demonstrate high first-order and total-order indices (both exceeding 0.1), yet exhibit relatively low interaction effects. This implies that their impact on port resilience is primarily mediated by direct mechanisms. Another notable case is X_5 , representing the number of rail crane failures. Although its first-order effect is very small, its interaction contribution is considerably larger relative to its standalone effect. This suggests that rail crane failures have limited influence when occurring independently, but their impact on port resilience can be amplified when combined with disruptions in other subsystems. Nevertheless, the absolute sensitivity of X_5 remains relatively low compared with the dominant quay crane factors.

In summary, despite their limited standalone influence, variables with high interaction but low first-order effects can significantly affect port resilience through co-occurrence with other risks. This underscores the need for detailed data collection and additional interaction-focused analysis. In risk prevention and response planning, special consideration should be given to the joint effects of train crane failures, yard crane disruptions, and yard traffic congestion. The co-occurrence of these risks is likely a consequence of ripple effects, through which disturbances propagate across interconnected port subsystems and amplify their overall impact on resilience. While the thresholds of 0.1 and 0.01 help identify the sensitivity level, it should be emphasised that the actual impact of variables with limited first-order effects may change under dynamic conditions or in response to unexpected events. Such behaviours may arise from external factors or environmental changes that the current model does not fully capture.

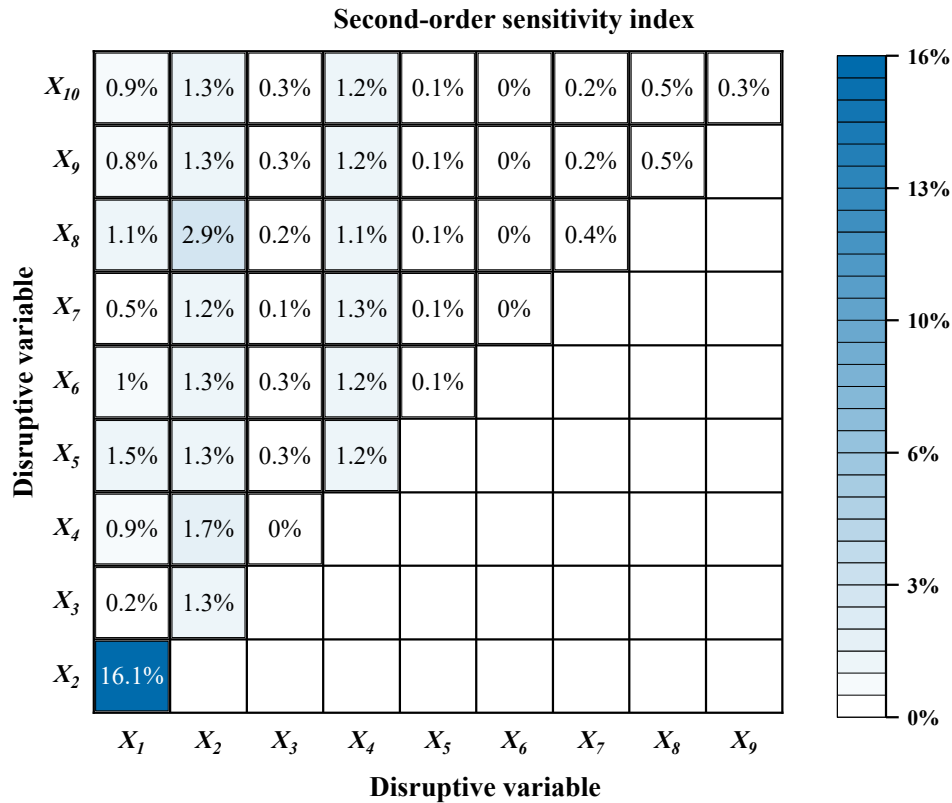


Figure 5.5. Sobol second-order SI under 6144 simulation runs.

While first- and total-order analyses highlight individual and overall influence, second-order analysis further uncovers key combinations between variable pairs. It is important to recognise that Sobol SI only quantifies the level of influence and does not distinguish between the positive or negative impacts of variable interactions. The percentages in the figure denote the extent of the interaction effect between two variables, relative to the sum of all possible effects across all variables.

Overall, interaction effects are generally weak, with a few notable exceptions. As shown in Figure 5.5, the interaction effects for most variable pairs fall below 1%, indicating that port resilience is predominantly driven by first-order (individual) effects. However, several combinations exhibit interaction effects exceeding 1%, and in some cases surpassing 10%, suggesting a substantial influence of interaction effects on resilience. The majority of low interaction effects among variable pairs implies that the port operates with a relatively modular structure, where localised disruptions can be effectively contained within individual subsystems due to their inherent recovery capacity. However, this low level of interconnectivity also implies that, if a local failure intensifies, the lack of strong cross-mode support may impose higher recovery burdens.

The most significant interaction effect is identified between the number and duration of liner quay crane failures. When these two factors co-occur, their combined impact on port resilience is

substantially amplified, far exceeding the additive effects of each variable in isolation. Under such conditions, higher severity is often accompanied by prolonged failure durations, resulting in a non-linear and disproportionately greater degradation of port resilience. The result implies a systemic bottleneck, possibly stemming from the functional interdependence of the two variables within the same operational subsystem. The exceptionally strong interaction between variables X_1 and X_2 may therefore reveal a latent vulnerability within the port's operation.

X_2 (duration of liner quay crane failure) shows notable interaction effects with X_8 (duration of yard crane failure) and X_4 (duration of feeder quay crane failure), indicating its strong potential to amplify the overall impact of disruptions on port resilience. Similarly, variable X_8 (duration of yard crane failure) also demonstrates strong interaction effects with several other factors, including X_2 (duration of feeder quay crane failure), X_1 (duration of liner quay crane failure) and X_4 (duration of feeder quay crane failure) respectively. This suggests that X_8 may serve as a key node that influences or is influenced by other variables. This observation aligns with the operational role of yard cranes, which are essential for supporting various modes of transport. Variables like X_2 and X_8 can be considered as key connectors within the network of interdependent disruptions. Their impact is not primarily exerted through direct effects, but through their interactions with other variables. The interaction effects of rail operations, container trucks, and container volume with other disruptive factors are minimal, indicating that these factors function largely as independent inputs within the port system.

The variables X_1 , X_2 , and X_8 collectively form a high-interaction cluster, with interaction indices consistently above 0.1, indicating a tightly coupled subsystem that plays a critical role in reinforcing disruptions. Such a structure significantly increases the likelihood and severity of compound disruptions.

5.3.4 Comparison with other Global Sensitivity Analysis methods

This section confirms the SI results through cross-method consistency checks. It is crucial to understand that variations in outcomes are a natural consequence of the fundamentally different logical reasoning of SA methods, which means these methods are complementary rather than competitive (Garcia et al., 2019; Ligmann-Zielinska et al., 2024). Additionally, acknowledging that results are heavily influenced by the sampling techniques, and some sensitivity techniques require particular sampling methods, only methods that are compatible with the Sobol sequence are selected, thereby removing external interferences. The FAST-RBD method, known for its broad recognition and usage (Cukier et al., 1973), is chosen for comparative analysis. Additionally, the PAWN method, which is better suited for handling asymmetric result distributions, is increasingly preferred to traditional Sobol methods (Coppola et al., 2023). Accordingly, this study employs PAWN as one of the comparative

methods. The results of all three methods, along with the rankings of each disruptive factor, can be seen in Figure 5.6.

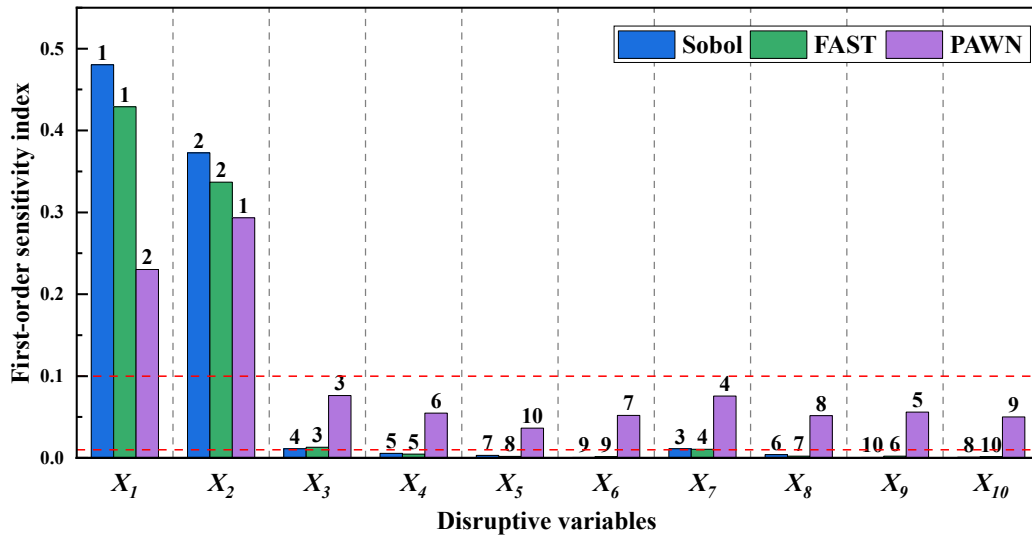


Figure 5.6. Comparison of SI computed with Sobol, FAST-RBD and PAWN.

The Figure 5.6 shows that the outputs from the Sobol and FAST-RBD methods align closely, following the same trends with slight variances. Evidence from other studies supports the consistency between these methods (Pohya et al., 2022). For future applications with limited computational resources, it is recommended to prefer the Sobol method for its ability to compute higher-order SI effectively. Additionally, the PAWN method is observed to compress larger values and amplify smaller ones, thereby narrowing the discrepancies among them. As previously discussed, the Sobol method was chosen as the primary approach due to its superior performance in low-sample environments and its capacity to quantify higher-order interaction effects. However, all methods reveal similar patterns, where liner quay crane disruptions are notably impactful, in contrast to the minimal influence of other variables. Despite minor methodological differences, all three approaches are consistent in recognising the liner quay crane to be the key component for port resilience. Such an analysis provides a basis for port operators to set priorities and optimise resource allocation toward key operational assets. Other critical elements, such as feeder quay crane and yard crane, possess an SI over 0.1, which confirms that those disruptions need to be considered essential as well.

For an in-depth validation of the SA's accuracy, the ICC consistency test is utilised, and the findings are shown in Table 5.5.

Table 5.5. Result of the ICC consistency test between three sensitivity methods.

ICC Type	ICC	CI 95%
ICC(1, 1)	0.779	[0.51, 0.93]
ICC(2, 1)	0.779	[0.5, 0.93]
ICC(3, 1)	0.773	[0.48, 0.93]
ICC(1, P)	0.914	[0.76, 0.98]
ICC(2, P)	0.914	[0.75, 0.98]
ICC(3, P)	0.911	[0.74, 0.98]

In the first and second columns, different types of ICC tests are detailed, with corresponding ICC values in the second column, where higher values signify greater consistency. The final column reveals the positioning of the consistency test outcomes within the 95% confidence interval. Analysis using 6 ICC tests indicates consistently high consistency. Such comparative analysis validates the results in identifying and quantifying influential factors for port resilience.

The reliability of the sensitivity results is therefore assessed from two complementary perspectives: convergence with increasing sample size and consistency across methods based on different sensitivity-analysis principles. The agreement in the identification of the dominant disruptive factors supports the robustness of the resulting prioritisation.

5.4 Discussion

The framework developed in this chapter is designed to directly address the complex and evolving risk management requirements faced by port stakeholders operating in increasingly multimodal environments. Specifically, the framework targets container ports characterised by the presence of two or more transportation modes, standardised cargo handling processes, and essential operational equipment. By focusing on these criteria, the framework seeks to offer stakeholders a decision-support tool that is not only practical and user-friendly but also robust in its analytical foundation and broadly accessible across diverse operational contexts. In developing this framework, particular attention is given to the internal operational disruptions that most acutely affect port

performance, such as equipment failures, process delays, and intra-terminal bottlenecks. While the primary emphasis is on internal dynamics, the framework acknowledges that external socio-economic factors and broader network-level interactions can play significant roles in shaping operational resilience. However, for analytical tractability and to ensure actionable insights for port managers, these externalities are deliberately held constant in the present model. This scoping decision enables greater specificity in modelling subsystem interdependencies and risk-propagation pathways within the port environment. A key strength of the proposed framework lies in its modular, parameterised structure, which enhances its adaptability across a wide range of container ports with similar multimodal characteristics. The framework can be recalibrated to suit ports with fewer transportation modes, different throughput capacities, or unique operational constraints by adjusting relevant parameters and subsystem couplings. This flexibility extends the model's practical applicability and supports its integration into existing risk management protocols at both established and emerging container ports. The preceding analysis has outlined the principal findings of this study and subjected them to rigorous robustness checks, including scenario-based sensitivity analyses and cross-validation against empirical data where available. These methodological steps underpin the credibility and generalisability of the results. The subsequent sections will further elaborate on the practical, policy, and stakeholder-specific implications of these findings, highlighting implementation pathways and areas for future research.

5.4.1 Implications for theory

This chapter advances the traditional resilience framework by integrating underexplored dimensions and providing a deeper theoretical interpretation, with particular focus on the structural and operational complexities of multimodal transport systems. Rather than confining resilience to conventional emphases on response speed and post-disturbance stability, this study broadens the conceptual landscape by explicitly introducing subsystem coupling relationships and mechanisms of risk propagation across interconnected modes, such as ripple effects. By foregrounding these elements, the research enriches the conceptual depth of resilience and aligns it more closely with the realities of modern transport systems, where tightly coupled subsystems and cross-modal dependencies are prevalent (Liu et al., 2023d; Wang et al., 2025a; Li et al., 2022b). Notably, this perspective challenges the prevailing tendency to treat resilience as a static or intrinsic attribute, instead framing it as an emergent and dynamic property shaped by evolving interdependencies among system components in multimodal environments. Furthermore, this study moves beyond conventional analyses that primarily address isolated or single-risk scenarios (Li et al., 2025) by investigating system behaviour under simultaneous and interacting disruptions. Through examining how key performance indicators and feedback structures respond to compound disturbances, the research extends the theoretical applicability of resilience to complex transportation networks characterised by nonlinearity and intermodal

interactions. This approach underscores the need to capture cascading effects and cross-modal feedback when assessing system robustness and recovery potential, thereby advancing the adaptation of resilience concepts to the multifaceted risk landscape of contemporary multimodal transport systems.

5.4.2 Implications for the managers and the policymakers

This chapter establishes a quantitative foundation for prioritising disruptions and optimising emergency resource allocation, advancing port operations from experience-driven to evidence-based decision-making in areas such as maintenance, inventory, and contingency planning. The following recommendations are derived directly from the analytical findings.

The distinction between first-order and total-order SI provides important insights into the structural nature of vulnerabilities and resilience within multimodal port systems. Disruptive factors with high first-order effects, such as liner quay crane failures, represent dominant single sources of uncertainty. This suggests that the resilience loss associated with these disruptions is primarily driven by their own features, rather than by complex propagation mechanisms. From a system perspective, such disruptions can be interpreted as locally critical components whose failure directly influences performance. Therefore, resilience improvements can be achieved through targeted, component-level interventions without necessarily requiring broader system intervention. Based on the previous results, liner quay crane malfunctions fall into this category of single-source dominant risks. Therefore, marginal improvements in their reliability can generate substantial system-wide benefits directly with highly effective and immediate rewards. Practical measures include the deployment of health monitoring sensors, optimised maintenance scheduling based on failure risk, ensuring the availability of critical spare parts, and establishing rapid replacement and repair protocols to minimise downtime. Compared with traditional experience-based approaches to emergency resource allocation and maintenance planning, such targeted, evidence-based allocation of emergency resources and maintenance scheduling enables resilience enhancement measures that not only improve operational resilience but also enhance cost-effectiveness.

Beyond liner operations, feeder quay crane failures emerge as a second-tier but structurally essential disruptive factor. Although their first-order effects are markedly lower than those of liner quay cranes, feeder crane disruptions still contribute non-negligibly to overall port resilience. This is because feeder operations constitute a critical link in multimodal transport, redistributing containers between international mainline services and regional networks. Moreover, despite differences in scale and capacity, feeder quay cranes share similar mechanical structures and operational workflows with liner quay cranes, implying comparable vulnerability mechanisms. Consequently, disruptions in feeder crane availability can propagate delays to yard operations and hinterland transport even when liner services

remain stable. In summary, feeder operations do not emerge as a bottleneck issue; instead, they define port resilience under non-extreme disruptive scenarios. Therefore, for ports that rely heavily on feeder-based transshipment, preventive and contingency plans should be in place.

In contrast, factors with relatively low first-order but high interaction effects represent systemic risks, whose influence on port resilience arises not from their standalone impact, but from their ability to amplify and propagate disruptions through interdependent subsystems. Such factors function as structural coupling points within the port system, and therefore require coordinated, cross-subsystem management strategies. For example, yard crane failures exemplify this interaction-dominant risk type. From an operational perspective, yard cranes serve as the interface between seaside and landside operations, linking vessel handling, trucking, and yard storage processes. Disruptions in yard crane operations can therefore magnify upstream and downstream delays, leading to disproportionate system-wide impacts. To mitigate these adverse interaction effects, yard management should not only focus on itself but also on its connection to other subsystems. Actionable measure includes dynamic storage allocation, coordinated and synchronised scheduling with seaside operations. In addition, it requires continuous situation monitoring and proactive preparation across other subsystems to mitigate the potential ripple effects.

Rail crane failures exhibit a similar but more latent risk profile. Individually, their influence on port resilience is modest. However, when rail crane disruptions coincide with failures in yard or quay crane operations, their combined effects become disproportionately large, often far exceeding their standalone contribution. This interaction-driven behaviour reveals a critical vulnerability of multimodal transshipment systems, in which simultaneous disruptions across multiple transport modes can rapidly overwhelm overall resilience. Such risks are particularly pronounced in ports with high rail modal shares, and hinterland connectivity plays a strategic role in sustaining throughput during disruptive periods.

Traffic congestion exhibits a similar amplification mechanism. Despite its low individual sensitivity, congestion shows notable second-order interactions with other equipment failures (e.g., yard cranes, liner quay cranes, and feeder quay cranes), indicating its role as a temporal and spatial risk amplifier. When a disruption leads to traffic congestion, reliability and robustness across multiple subsystems are reduced, and recovery processes are prolonged, which in turn generates negative feedback loops that further intensify these negative effects. This finding underscores the necessity of integrating congestion management into recovery planning, including the design of emergency access routes, priority lanes with time windows, and nearby transfer hubs. Importantly, such measures require coordination beyond the port boundary, involving hinterland transportation authorities and multimodal logistics providers.

High second-order SI between variables (e.g., X_1 and X_2 , X_2 and X_8) indicate that simultaneous disruptions can cause a sharp and substantial loss of port resilience, even when each disruption alone appears to be insubstantial and practically manageable. This reflects the non-additive and nonlinear nature of ripple effect in multimodal container ports and explains why ports may experience sudden operational breakdowns without clear early warning signs. Therefore, it poses a significant challenge for experience-based decision-making, as it often contradicts intuitive expectations from traditional single-risk scenarios. From a preparedness and governance perspective, these findings suggest that ports should move beyond single risk decision-making and instead be aware and prepare for simultaneous multiple disruptions. Actionable measures should start from systematically recording, examining, and prioritising combinations of risks that are likely to cause severe damage, but are difficult to foresee based on past experience alone.

Taken together, these findings indicate that port resilience is shaped by a small number of dominant, standalone risks, as well as by a much broader set of interaction-driven risks arising from the mutual reinforcement of multiple disruptions. While targeted interventions on critical assets such as liner quay cranes can deliver immediate resilience gains, managing interaction-dominant factors such as yard crane downtime, rail operations, and traffic congestion requires coordinated, cross-subsystem strategies.

Therefore, beyond management policies within the port, the establishment of a cross-agency collaborative response platform is essential for enhancing port resilience under compounded disruptions. In practice, operations such as railway dispatching, yard management, and berth scheduling are currently dealt with by separate departments and their holistic coordination and management are overseen. An integrated platform for cross-agency coordination, such as a joint monitoring centre or a collaborative emergency response hub, enables real-time data sharing, early detection of risk amplification, and coordinated decision-making. To further strengthen collaboration, incentive mechanisms can be introduced to reward operational adaptability during disruptions between stakeholders. Building on this work, the development of a digital twin architecture informed by the proposed SD-ER-GSA framework can enable an integrated approach that connects short-, medium-, and long-term resilience management within ports. Such a system would enable coherent support for risk identification, resilience assessment, consequence prediction, coordinated emergency scheduling, equipment maintenance planning, staff training, and strategic infrastructure investment, thereby ensuring that operational resilience is embedded throughout the port's life cycle.

While the proposed framework adopts a multimodal perspective, it is important to recognise that the scope of operational control of a container port operator is largely confined to internal terminal activities. Disruptions from external transportation, including rail and road connections, are typically managed by independent commercial groups or public agencies. Therefore, it is important to support a

multi-stakeholder approach to port resilience enhancement. For port authorities and terminal operators, the GSA provides evidence-based prioritisation of critical internal assets and recovery strategies. For external transport operators, such as railway and highway infrastructure management agencies, railway and trucking companies, the results highlight the conditions under which their disruptions may interact with terminal operations to amplify resilience losses, thereby informing coordinated response and information-sharing recovery. For shipping lines, the findings provide a clearer understanding of the underlying causes of port delays and support service recovery through informed rescheduling. Local and national government, maritime and coastal agency, urban and regional planning department, budget planning office and other public agencies can use these insights to support cross-sectoral planning, regulatory alignment, and targeted infrastructure investment, particularly in ports with high reliance on hinterland connectivity. To ensure effective implementation, the proposed measures should be adapted according to the distinct roles and influence of each stakeholder group. Therefore, applicable disruption strategies are mapped against key stakeholder responsibilities, as shown in Table 5.6.

Table 5.6. Disruption strategies based on stakeholder responsibilities of Chapter 5.

Stakeholders	Scope of control	Disruption impact	Disruption-based resilience strategy	Application of the proposed methodology	Contribution to port resilience
Port authority and terminal operator	Direct control (internal operations)	Degraded port operational performance and service reliability	Scheduling and design	Buffer zone design, coordinated scheduling, prioritising critical operations	Absorbs disruptions and reduces the influence of risk propagation
		Increased emergency costs and pressure	Disruption mitigation and response	Repair speed, emergency response plan, prioritised lane, emergency drill considering compounded disruptions	Improves response and recovery capability by enabling timely countermeasures that account for compound disruption effects.
		Equipment damage	Equipment maintenance	Predictive maintenance, health monitoring sensors, and spare parts inventory	Increases robustness and reliability by reducing the likelihood and severity of critical equipment failures

Government and public agencies	Policy-level and regulatory control	Loss of shipping lines and reduced port competitiveness	Risk accountability	Clear definition of risk ownership, responsibility allocation, and accountability tracking	Strengthens governance and coordination
		Reduced port throughput and hinterland connectivity	Port development direction	Strengthen policy guidance and funding in port infrastructure development and management, especially on resilience enhancement	Enhances long-term robustness by supporting resilience-oriented infrastructure investment
		Regional trade and supply chain continuity	Port functionality design against disruptions	Incorporate multi-disruptive scenarios into port design and planning, set appropriate thresholds and implement risk decoupling strategies	Reduces the influence of cascading failures
		Economic and social risks	Collaboration within government bodies	Collaborate with the highway, railway, and surrounding authorities for disruption	Enabling coordination and reducing disruption propagation between the port and the hinterland

		monitoring and coordinated response design			
Logistics companies	Indirect control (dependent on port functionality for international trade)	Schedule unreliability, reduced service level and long-term customer relationships.	Risk prevention and preparedness, and responses	Staff training, risk prediction, information sharing, and collaborative rescheduling	Enhances robustness and response by improving decision-making, information sharing, and flexible rescheduling.

5.5 Conclusions

A framework based on SD, resilience quantification, ER, and GSA is proposed to identify, prioritise, and quantify disruptive factors affecting port resilience and their interconnections, using real operational data and incident reports from port operations. The main contributions of this chapter are as follows: (1) GSA is employed to determine the extent of the disruptions' impact on port operational resilience. Consistency tests are conducted across three distinct GSA methods to ensure the accuracy of the findings and the robustness of the framework. (2) Drawing on real-world examples, this study employs Sobol's second-order SI to capture the compounded impact of concurrent disruptions on port resilience, which may be attributed to underlying ripple effects. (3) The SI obtained through the proposed framework, including total-order, first-order, and second-order, offers highly applicable guidance for risk-informed policymaking and operational planning aimed at enhancing resilience in multimodal port systems.

This study contributes to both theory and practice by providing a robust and transferable framework for analysing port operational resilience under complex and concurrent disruptions. Methodologically, the integration of SD, ER, and multiple GSA techniques advances resilience research and offers new insights into ripple effects that are often overlooked in existing studies. From a practical and policy perspective, the resulting first-order, total-order, and second-order SI offer an interpretable and evidence-based foundation for prioritising risks, allocating resources, and designing targeted operational and regulatory interventions. As such, the proposed framework supports academics in advancing resilience modelling, assists port managers in tackling operational risks, and informs policymakers in addressing pressing challenges.

The GSA results in this chapter identify that the critical disruptions, such as the failures of large-scale handling equipment are particularly important because they directly reduce operational capacity and may trigger further ripple effects across interconnected port subsystems. Therefore, Chapter 6 focuses on resilience enhancement after equipment-related disruptions by developing an opportunistic maintenance optimisation model that balances maintenance cost and expected port resilience.

2953 **CHAPTER 6 A RESILIENCE-BASED MULTI-OBJECTIVE** 2954 **DECISION-MAKING FRAMEWORK FOR OPPORTUNISTIC** 2955 **MAINTENANCE IN CONTAINER TERMINALS⁴**

2956 Towards the end of a resilience analysis is the solution to system recovery. Based on the results from
2957 Chapter 5, it is found that among various disruptive factors, frequent and unexpected equipment failures caused
2958 by the complexity of handling components and unstable working conditions severely affect port operations and
2959 resilience. In response, maintenance activities for such equipment account for approximately 11% of total port
2960 operating costs annually and this proportion is expected to increase with the growth of container throughput.
2961 Therefore, it is crucial to develop an optimal and balanced maintenance strategy that can simultaneously enhance
2962 equipment reliability, port resilience, and reduce maintenance costs. However, due to the strong operational and
2963 economic interdependencies among port equipment, their maintenance follows a complex series-parallel system
2964 structure. This configuration intensifies the difficulty of maintenance scheduling, yet at the same time creates
2965 opportunities for implementing OM. Despite this potential, traditional maintenance methods, largely based on
2966 periodic inspections or empirical judgment, are often ill-suited to the highly dynamic and disruption-prone port
2967 environments in which multiple interactive transport modes are involved. Therefore, this chapter develops a
2968 novel OM strategy triggered by unexpected equipment failures, integrating cost and resilience as multi-objective
2969 decision criteria. The proposed framework comprises three components: (1) a ML model for predicting port
2970 resilience, using disruptive scenarios as input features and the resilience values calculated by Chapter 4 as output
2971 targets; (2) an OM model that incorporates the realistic operational interdependencies of large port equipment,
2972 maintenance levels, failure distribution and maintenance costs; and (3) a multi-objective decision-making
2973 module that determines optimal maintenance strategies under sudden equipment failure based on Pareto-front
2974 analysis. Using real operational data from a case port, the proposed framework serves as a practical decision-
2975 support tool that guides improved maintenance strategies during the post-disruption recovery phase, assisting
2976 port managers in making informed decisions under highly uncertain operational environments.

⁴ The findings of this technical chapter are to be submitted as the following journal paper. ZHANG, J., XIN, X., DUBEY, R., NGUYEN, T. T., SHI, X., LI, N. & YANG, Z. Resilience-based multi-objective decision-making framework for opportunistic maintenance in container terminals. Transportation Research Part C: Emerging Technology.

6.1 Introduction

Ports are highly infrastructure-dependent physical systems whose operational continuity relies heavily on large-scale handling equipment, particularly quay cranes and yard cranes. Among port assets, cranes are especially critical because their reliability, availability, and maintainability directly determine port operating efficiency (Liu et al., 2018). These assets are capital-intensive, mechanically complex, and maintenance-intensive; accordingly, their failure and inadequate maintenance are widely regarded as one of the most significant risk factors undermining port performance (Berle et al., 2011). In practice, even the failure of a single quay crane during the service of a large vessel may delay operations by several hours. Because quay cranes are central to container loading and unloading, their failures can also trigger cascading effects on berth occupancy, container handling cycles, vessel turnaround time, and subsequent yard and hinterland operations (Garmouch et al., 2025). Moreover, as these machines operate under heavy loads and harsh conditions, both external disruptions and internal ageing contribute to a gradual increase in failure occurrence over time. In practice, advanced maintenance practices are widely recognised as an effective way to mitigate equipment-related risks and enhance port operational performance (Jalal et al., 2023).

However, maintenance activities have become a growing financial burden on port operations. On average, approximately 11% of annual operating expenses are allocated to maintenance activities, and this figure has grown at an annual rate of around 4% in recent years, largely driven by increasing container throughput (Lin et al., 2020). One practical way to reduce maintenance costs is through OM, which refers to a maintenance strategy where additional PM actions are carried out on other equipment when a maintenance opportunity arises, such as during a planned shutdown or when part of the system is already out of service. From the perspective of large equipment maintenance in container terminals, OM is particularly valuable and necessary because of the substantial economic dependency created by downtime and the structural dependency embedded in operational workflows. Detailed definitions and explanations of different maintenance strategies and dependencies are provided in Section 6.2.

Maintenance decision-making for large equipment in ports typically spans two levels. At the operational management level, the primary concerns are availability and the associated losses from downtime. At the engineering level, attention is directed towards the physical degradation mechanisms of critical components, such as the hoisting, trolley, travelling, wire ropes and control, as well as the effectiveness of maintenance interventions. Since this study aims to improve overall port operational performance, the decision object is defined at the equipment level. Accordingly, the internal physical degradation processes of individual component level are not explicitly modelled.

The application of OM to large equipment in port, however, involves additional complexity compared with other general systems. This complexity arises from the strong operational dependencies between these large pieces of equipment, which together form a series-parallel system. Take the berth and quay crane, for example; each berth is served by multiple quay cranes, and the failure of any single quay crane disrupts berth operations, often requiring the vessel to be reassigned to another berth, a problem commonly referred to as berth reallocation. At the port level, multiple berths operate in parallel, with each berth serving one vessel at a time. Operations across different berths are independent (Wang et al., 2025c). Similar dependencies can also be found in other large-scale lifting equipment systems, such as those between rail tracks and rail-mounted gantry cranes, and between yard blocks and yard cranes. For consistency, in this study, each large-scale asset is referred to as an equipment, a group of operationally interdependent equipment as a subsystem, and the port as a whole as the system.

To address the challenges identified in Section 1.2 4) this chapter proposes a large equipment OM framework for under unexpected disruption-induced shutdowns. The failure process of large equipment is modelled using a Non-Homogeneous Poisson Process (NHPP). The framework also captures the series-parallel operational dependencies among equipment under operational constraints. When an unexpected failure occurs, these dependencies create maintenance opportunities for other equipment that has not yet failed. Different maintenance strategies are then defined by two decisions: whether maintenance should be performed and which maintenance level should be adopted. The relationship between maintenance level and maintenance cost is represented through the Kijima type II virtual age framework (Kijima, 1989). In addition, a resilience-based multi-objective optimisation approach is developed to jointly evaluate maintenance cost and expected port resilience. The resilience term in the objective function is not a single deterministic resilience value under one predefined disruption scenario. Instead, it represents the expected resilience under possible future equipment states, which is calculated by combining the probability of each possible post-maintenance failure scenario with the corresponding resilience value. Directly calculating these resilience values through the full simulation-based resilience assessment framework would require repeated interactions among the SD simulation model, data-processing procedures and resilience aggregation model. Although each individual calculation is not computationally complex, the large number of repeated evaluations required in the optimisation process makes the direct use of full simulation outputs inefficient and time-consuming. Therefore, a machine-learning-based surrogate model is adopted after extensive comparison between 6 other similar models and selected for its best predictive performance. Different maintenance strategies change the port's susceptibility to failure, thereby leading to different probabilities of disruptive scenarios. The expected port resilience after maintenance is calculated by combining the probability mass function of all possible disruptive scenarios with their corresponding estimated resilience values. Finally, Pareto frontier analysis is employed to identify non-dominated maintenance strategies. By doing so, the proposed framework not only supports maintenance decision-making for large port equipment but also captures how maintenance decisions influence the overall

3043 resilience of port operations under the propagation of disruptions across multiple transport modes within the
3044 port system. The main contributions of this study are summarised as follows:

- 3045 1. Port resilience is innovatively incorporated as an optimisation objective, allowing the influence of
3046 maintenance decisions on the resilience of the overall port system to be explicitly captured. In addition,
3047 an ML model is introduced to predict resilience under different maintenance strategies and thus
3048 improve computational efficiency.
- 3049 2. An OM model is developed to generate maintenance decisions for large port equipment under a
3050 sudden failure based on operational and economic dependencies. It incorporates the NHPP as the
3051 failure distribution and Kijima II as the age function.
- 3052 3. A multi-objective optimisation model is developed for the OM of large equipment in container ports,
3053 jointly considering maintenance costs and expected port-level resilience, with Pareto frontier analysis
3054 used to identify non-dominated maintenance strategies.

3055 The remainder of this chapter is organised as follows. Section 6.2 presents the proposed OM model. Section
3056 6.3 applies the model to a real-world case study and discusses the results along with managerial implications.
3057 Section 6.4 concludes the chapter.

3058 **6.2 Methodology: Multi-objective opportunistic maintenance** 3059 **decision making**

3060 In this section, a mathematical model is developed to demonstrate the structure of the proposed OM model.
3061 The methodology is illustrated by a flowchart shown in Figure 6.1. Connections between the notation used here
3062 and that introduced earlier will be clarified at the relevant points throughout the chapter.

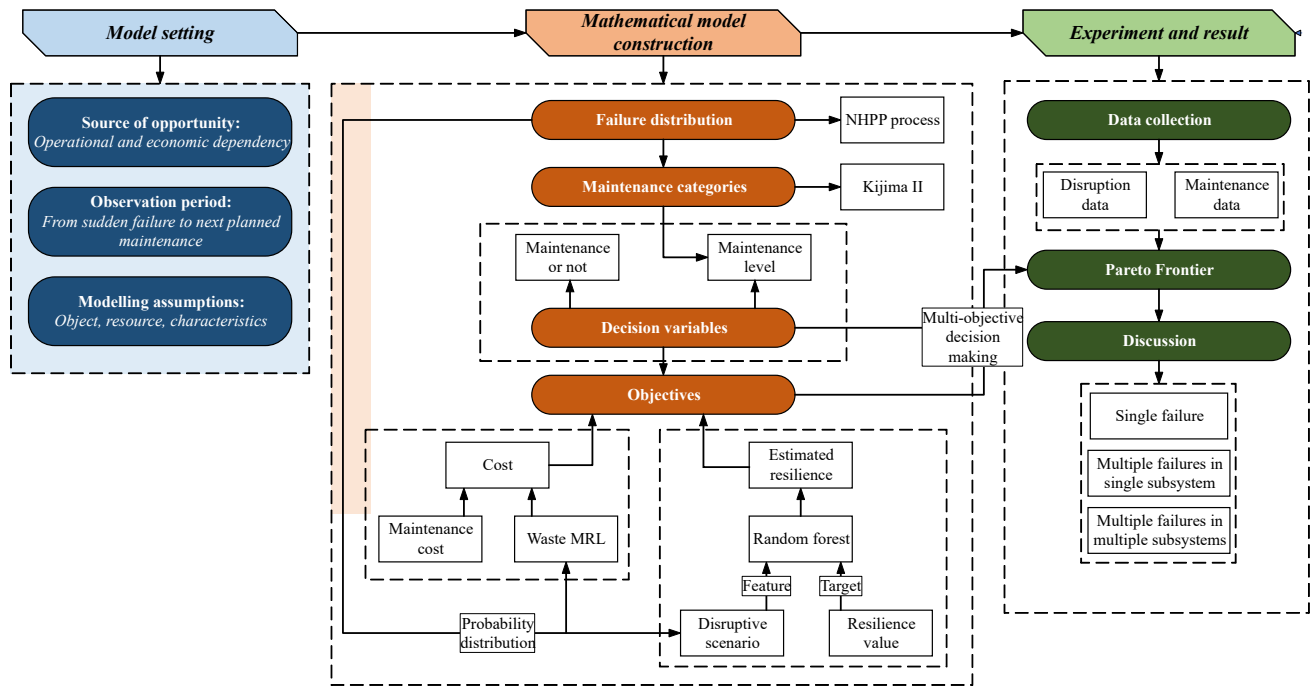


Figure 6.1. Flowchart of the methodology of Chapter 6.

An opportunity for maintenance is triggered by an external failure event occurring at time $t = 0$. Since port operations follow pre-established schedules, including planned maintenance and shutdown activities, maintenance decisions can only be made within the limited period between the occurrence of the unexpected failure and the next scheduled PM activity. This time interval is defined as the observation horizon, denoted by $\mathcal{H}$.

The research focuses on large equipment whose failures may affect not only the failed unit itself but also neighbouring equipment because of physical layout constraints and operational interdependence (Wang et al., 2025c). Quay cranes provide a representative example, as shown in Figure 6.2. When a quay crane fails, it must be moved to the edge of the berth or another safe position to avoid obstructing berth operations and to ensure operational safety. In the meantime, vessel operations must be halted and then reallocated. If the failed crane is not initially located at the edge of the rail, other cranes on the same rail may also need to be moved (Tian et al., 2024). This creates an opportunity to carry out OM on neighbouring cranes that have not failed. Similar operational logic applies to railway gantry cranes and yard cranes.

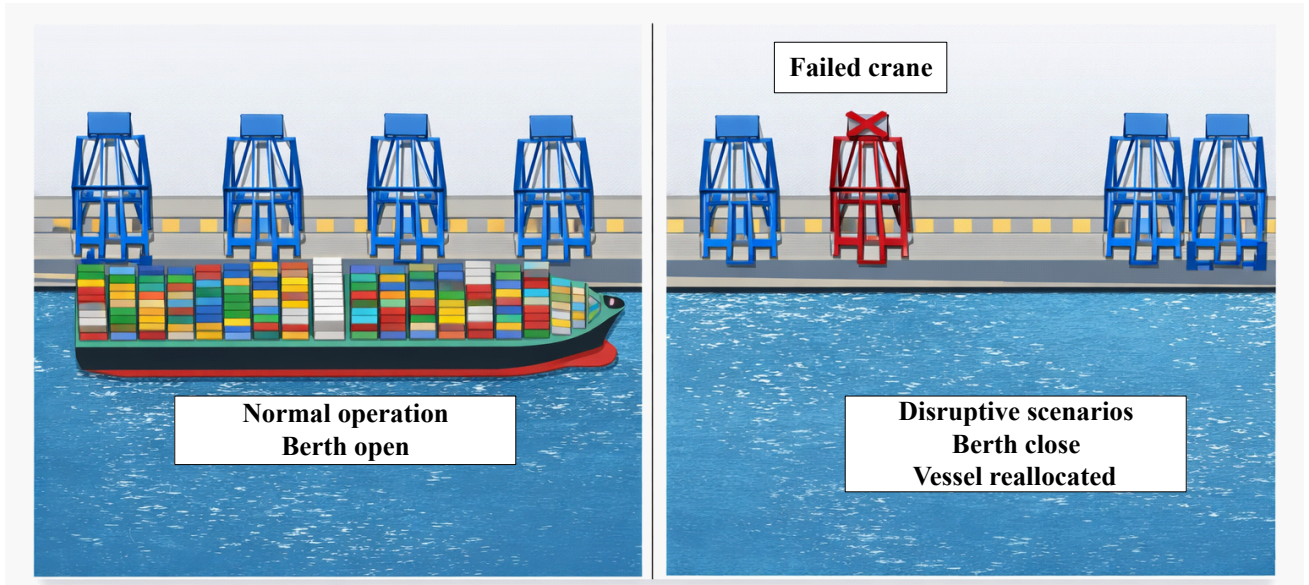


Figure 6.2. The operational dependency between quay cranes in the same subsystem.

Against this background, the model determines whether maintenance should be performed on non-failed but affected equipment after an unexpected failure event, and if so, which maintenance strategy should be adopted. The purpose is to evaluate the effects of alternative OM strategies on maintenance-related and operational outcomes. To support the modelling process, several assumptions are adopted.

1. Only equipment-level failures are considered in this study. Component-level failures are not modelled explicitly. That is, each large piece of equipment is treated as a single decision-making unit, and maintenance decisions are made at the equipment level rather than at the component level.
2. The large equipment considered in this study includes quay cranes, railway gantry cranes, and yard cranes. These equipment types share similar operational characteristics: failure of one unit will often affect neighbouring units due to their physical layout and constraints.
3. Quay cranes serving internal liner ships and feeder ships are modelled separately. This distinction is made because the two groups have different failure-process parameters due to their different operational conditions.
4. Equipment of the same type within the port is assumed to be homogeneous in nature. In particular, they are assumed to have identical physical characteristics and similar failure mechanisms associated with structural degradation. Accordingly, for the same type of equipment, the maintenance cost and maintenance duration associated with the same maintenance level are assumed to be identical across units (Wang et al., 2025c);.
5. Once a maintenance decision is made, the corresponding action is assumed to be implemented immediately within the planning horizon.

6. Although maintenance activities consume resources, the model assume that routine and critical components are available for the maintenance actions considered, whereas specialised components and major assemblies may involve substantial procurement lead times and are outside the scope of the current model.
7. For unexpected failures of critical equipment, replacement is assumed to be the preferred corrective action. Such decisions are influenced not only by repair efficiency but also by operational safety requirements and port compliance regulations.

6.2.1 NHPP process

A variety of statistical models, including the lognormal, Weibull, Gamma, and exponential distributions, are available for modelling failure processes (Jalal et al., 2023). However, these models are generally formulated for non-repairable populations or one-shot lifetime data, and are therefore more appropriate for describing the progressive degradation of a component from its initial condition to failure. In contrast, the large equipment examined in this study, such as quay cranes, are repairable systems with high asset values and long operational life. In practice, maintenance actions for such equipment are more often imperfect repairs or partial component replacements than complete renewal of the entire machine. As a result, their maintenance records typically consist of repeated failure-repair event histories accumulated over long-term operation, rather than precise observations of component-level degradation. Such data are better aligned with the assumptions and input structure of the NHPP model (BOLIA, 2015). Existing port-engineering studies have indeed used Weibull-based fitting to describe equipment failure behaviour (Li et al., 2021). The Weibull distribution occupies a central position in reliability analysis because its shape parameter provides a convenient way to characterise different failure-rate patterns over time. Empirical work on container-terminal equipment, such as rail-mounted gantry cranes and quay cranes, prioritises Weibull over normal and Rayleigh models (Lin et al., 2020). However, when the object of interest is the recurrent-failure process of a repairable system, the Weibull distribution is less adequate. In particular, it is not well-suited to calculate the expected cumulative number of future failures, the evolution of failure intensity over time, or statistical tests for failure trends. In return, the NHPP power-law process is specifically formulated for repairable systems and directly describes the expected cumulative number of failures and the time-varying rate of occurrence of failure (BOLIA, 2015). Therefore, the NHPP model is adopted in this study to represent the failure process of large port equipment at the whole-machine level

In this study, each equipment unit is indexed by u . Operationally dependent equipment units are grouped into subsystem g , with U_g denoting the set of equipment units belonging to subsystem g , and G denoting the set of all subsystems. Different equipment types are indexed by q , with each equipment unit u associated with one equipment type q . Let $\zeta_q(s)$ denote the intensity function of the NHPP and $Z_q(\varpi)$ its corresponding mean value function, where Age represents the effective age. The mean value function is defined as

$$Z_q(\varpi) = \int_0^{\varpi} \zeta_q(s) ds \quad (6-1)$$

In this study, the failure process of large equipment is assumed to follow a power-law NHPP, for which

$$Z_q(\varpi) = \gamma_q \varpi^{\delta_q}, \zeta_q(\varpi) = \gamma_q \delta_q \varpi^{\delta_q-1} \quad (6-2)$$

where $\gamma_q > 0$ and $\delta_q > 0$ are the scale and shape parameters for equipment type q , respectively. One of the fundamental properties of NHPP is that the probability of observing no failure in the interval $[0, \varpi]$ is given by

$$\Pr\{N_q(\varpi) = 0\} = \exp(-Z_q(\varpi)) \quad (6-3)$$

where $N_q(\varpi)$ denotes the number of failure events observed for equipment of type q over the interval $[0, \varpi]$. After a maintenance decision is implemented within the OM window, the effective age of the equipment unit u in equipment group g is denoted by $\widetilde{\varpi}_{ug}$. Based on the NHPP mean value function $Z_q(\cdot)$, the reliability of this equipment unit immediately after maintenance is expressed as

$$\mathbb{R}(\widetilde{\varpi}_{ug}) = \exp(-Z_q(\widetilde{\varpi}_{ug})), u \in U_g, g \in G \quad (6-4)$$

More importantly, maintenance planning is concerned with whether the equipment can survive during the future OM window. Given that equipment unit u in group g has survived up to the effective age $\widetilde{\varpi}_{ug}$, its conditional reliability over the future OM window $\mathcal{H}$ is given by

$$\mathbb{R}(\mathcal{H} \mid \widetilde{\varpi}_{ug}) = \exp\{-[Z_q(\widetilde{\varpi}_{ug} + \mathcal{H}) - Z_q(\widetilde{\varpi}_{ug})]\} \quad (6-5)$$

Accordingly, the failure probability of equipment u in group g over the future interval $[0, \mathcal{H}]$ is

$$P_{ug}^{\text{fail}}(\mathcal{H}) = 1 - \mathbb{R}(\mathcal{H} \mid \widetilde{\varpi}_{ug}), u \in U_g, g \in G \quad (6-6)$$

For an equipment group, the equipment units are treated as a series system. This means that the group remains operational only when all equipment units in the group survive during the OM window. Under the assumption that equipment failures are conditionally independent, the reliability of the equipment group g is therefore obtained as

$$\mathbb{R}_g(\mathcal{H}) = \prod_{u \in U_g} \mathbb{R}(\mathcal{H} \mid \widetilde{\omega}_{ug}) \quad (6-7)$$

This can be further simplified to

$$\mathbb{R}_g(\mathcal{H}) = \exp \left\{ - \sum_{u \in U_g} [Z_q(\widetilde{\omega}_{ug} + \mathcal{H}) - Z_q(\widetilde{\omega}_{ug})] \right\} \quad (6-8)$$

Hence, the corresponding failure probability of subsystem g is

$$P_g^{fail}(\mathcal{H}) = 1 - \exp \left(- \sum_{u \in U_g} [Z_q(\widetilde{\omega}_{ug} + \mathcal{H}) - Z_q(\widetilde{\omega}_{ug})] \right) \quad (6-9)$$

It can be seen that, for a series subsystem composed of independent equipment units whose failures are each described by NHPPs, the aggregated failure process of the subsystem also follows an NHPP. In particular, the cumulative intensity function of the subsystem is equal to the sum of the cumulative intensity increments of its constituent units, implying that the subsystem failure intensity can be obtained additively. This property makes the NHPP framework particularly convenient for modelling equipment groups with series dependence.

6.2.2 Maintenance opportunities

The following analysis examines how OM is triggered by failure events and how it is formally modelled. Suppose that an external risk event occurs in the port system at time $t = 0$ and causes the malfunction of one or several pieces of equipment. The subsystem to which the failed equipment services are immediately shut down, and the failed equipment is subject to immediate replacement. In accordance with port safety regulations, all other equipment serving in the same subsystem is required to cease operation, which creates maintenance opportunities on cranes that remain functional but are temporarily stopped. If OM is carried out for equipment u at subsystem g , the OM decision variable is set to $y_{ug} = 1$; otherwise, $y_{ug} = 0$. Accordingly, the relationship between the equipment state variable s_{ug} ($s_{ug}=1$ when equipment u fails, $s_{ug}=0$, otherwise) and y_{ug} is expressed in Eq. (6-10):

$$s_{ug} \leq y_{ug} \leq \sum_{u' \in U_g} s_{u'g}, \forall u \in U_g, g \in G \quad (6-10)$$

6.2.3 Maintenance categories

During maintenance activity, the equipment may undergo different levels of maintenance depending on its failure state, effective age, and practical repair requirements. The maintenance effects are commonly represented along a spectrum from perfect repair (restore the item to an as-good-as-new condition) or replacement, to minimal repair (restores the item to an operating state). Between these two extremes, imperfect repair represents a partial restoration effect, where the equipment after maintenance becomes younger than before maintenance but is not fully renewed (Dinh et al., 2022; Kijima, 1989). Accordingly, three maintenance levels are defined in Eq. (6-11) to represent these three maintenance effects. This classification is consistent with multi-level maintenance modelling in opportunistic maintenance, where different maintenance actions are associated with different restoration effects, costs, and maintenance durations (Boujarif et al., 2025).

Replacement refers to the corrective replacement of failed equipment or the replacement of its critical failed assembly. It is mandatory when equipment has already failed and is assumed to restore the equipment to as-good-as-new condition. Moderate repair refers to an imperfect maintenance action, such as partial component replacement, adjustment, refurbishment, or functional overhaul, which reduces the effective age of equipment but does not fully renew it. Minimal maintenance, also referred to as minimal repair, refers to the lowest maintenance level, such as inspection, lubrication, tightening, calibration, or minor adjustment. It restores or maintains operability during the OM window but has only a limited effect on accumulated ageing. These three levels are further distinguished by their restoration effect, maintenance duration, and cost.

$$x_{ug} = \begin{cases} 1, & \text{maintenance level 1, replacement} \\ 2, & \text{maintenance level 2, moderate repair} \\ 3, & \text{maintenance level 3, minimal maintenance} \end{cases} \quad \forall u \in U_g, g \in G \quad (6-11)$$

The variable x_{ug} denotes the maintenance level of equipment u . This variable is defined only when maintenance activity is carried out, i.e., when $y_{ug} = 1$ or $s_{ug} = 1$; otherwise, $x_{ug} = 0$. The relationship between x_{ug} and y_{ug} is given in Eq. (6-12).

$$x_{ug} \leq y_{ug} \leq 3x_{ug} \quad \forall u \in U_g, g \in G \quad (6-12)$$

Different maintenance levels consume different amounts of maintenance time which are defined by Eq. (6-13) where T_{ug}^m is the maintenance time of equipment u at subsystem g . T^r , T^{m1} , T^{m2} are the maintenance time of maintenance level 1, 2, 3 respectively. The value of these variables will be defined based on field investigation and interviews.

$$T_{ug}^m = \begin{cases} T^r, & x_{ug} = 1 \text{ or } s_{ug} = 1 \\ T^{m1}, & x_{ug} = 2 \\ T^{m2}, & x_{ug} = 3 \end{cases} \quad \forall u \in U_g, g \in G \quad (6-13)$$

The effects of maintenance actions are characterised using the Kijima type II virtual age framework (Kijima, 1989). This model assumes ageing as a cumulative process and allows maintenance actions to mitigate previously accumulated damage. This approach is appropriate for the present study due to the limited number and high value of each piece of equipment, resulting in important operational and economic consequences for maintenance decisions. In this context, it would be inappropriate to treat all completed maintenance actions as homogeneous repairs. Moreover, under the NHPP-based framework, a recorded repair completion may represent different types of intervention, such as replacement, adjustment, or partial refurbishment. The virtual age model, therefore, offers a practical way to distinguish heterogeneous maintenance effects through age reduction, while also reflecting differences in maintenance cost and resource input. Based on insights obtained from expert interviews and on-site investigations, the effect of different maintenance levels is shown in Eq. (6-14), where θ^m is the age reduction factor or maintenance quality factor.

$$\theta_{ug}^m = \begin{cases} 0, & x_{ug} = 1 \text{ or } s_{ug} = 1 \\ \theta^{m1}, & x_{ug} = 2 \\ \theta^{m2}, & x_{ug} = 3 \\ 1, & x_{ug} = 0 \end{cases} \quad \forall u \in U_g, g \in G \quad (6-14)$$

Following maintenance, the updated age of equipment u at subsystem g is determined by Eq. (6-15).

$$\widetilde{\omega}_{ug} = \theta_{ug}^m \omega_{ug} \quad \forall u \in U_g, g \in G \quad (6-15)$$

6.2.4 Maintenance cost

In this subsection, the economic impact of failures and maintenance actions is quantified by $\mathcal{C}$ including fixed cost and variable costs. Fixed costs are caused by one-time operational actions such as vessel reallocation and rescheduling, quay crane shutdown, berth area closures, and labour force mobilisation, while the variable costs depend on the level of maintenance actions. Variable maintenance cost c^r, c^{m1} and c^{m2} are defined for different maintenance levels, reflecting the use of varying repair materials, tools, and labour requirements. These are described in Eqs. (6-16)-(6-17), where c_g^f is the fixed cost for stopping the operation of subsystem g , and c_{ug} is the maintenance cost of equipment u of subsystem g .

$$\mathcal{C} = \sum_{g \in G} \left(1 - \prod_{u \in U_g} (1 - s_{ug}) \right) c_g^f + \sum_{u \in U_g} \sum_{g \in G} c_{ug} (s_{ug} + y_{ug}) \quad (6-16)$$

$$c_{ug} = \begin{cases} c^r, & x_{ug} = 1 \text{ or } s_{ug} = 1 \\ c^{m1}, & x_{ug} = 2 \\ c^{m2}, & x_{ug} = 3 \end{cases} \quad (6-17)$$

6.2.5 Expected resilience evaluation based on Machine Learning

Resilience is introduced as a complementary concept to reliability, with the aim of capturing system-wide performance beyond the equipment level, particularly the ripple effect across multiple transport modes within the port. In previous studies, a port-level resilience assessment framework incorporating ripple effects under different risk scenarios was developed (Zhang et al., 2025b; Zhang et al., 2025a). As the resulting resilience value is obtained from a system perspective, it provides insight into the influence of OM on overall port operational performance. Previous studies suggest that resilience depends on the type, severity, and duration of disruptions. Mathematically, it can be expressed as a function of the numbers and durations of failed subsystems across equipment types, as shown below:

$$R = R(F_1(\mathcal{H}), \bar{D}_1, \dots, F_q(\mathcal{H}), \bar{D}_q) \quad (6-18)$$

where $F_q(\mathcal{H})$ denotes the number of failed subsystems of equipment type q over the observation horizon (i.e., the OM window) $\mathcal{H}$, while $\bar{D}_q$ denotes the corresponding average failure duration. Each realisation of $\{(F_q(\mathcal{H}), \bar{D}_q)\}_{q=1}^Q$ therefore specifies a disruptive scenario and its corresponding resilience.

In this study, the surrogate model is required to support a large number of repeated evaluations within the OM optimisation process. Directly calculating all these resilience values through the full SD simulation and resilience assessment framework would require repeated model runs and data exchanges across several software procedures, which is inefficient for decision-making. This issue is further complicated when the failure duration is measured over a wide, discrete range across multiple equipment units, leading to a massive number of possible scenarios which cannot be exhaustively covered in the training dataset. Therefore, the surrogate model needs to provide reliable interpolation over a sparse and high-dimensional scenario space. For this reason, tree-based models such as Random Forest, LightGBM and XGBoost were not selected as the final surrogate modelling direction. Although these models are powerful for many prediction tasks, their prediction mechanism is based on recursive partitioning of the feature space, which may produce piecewise-constant or locally segmented predictions (Feng et al., 2024). In this study, the resilience response is expected to vary continuously with failure duration, equipment number and maintenance-related variables. Therefore, continuous regression models and

smooth nonlinear ML models are more suitable for approximating the resilience surface required by the optimisation model. Several candidate models were compared, including linear regression, ridge regression, polynomial ridge regression, spline ridge regression, Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel, and Multilayer Perceptron (MLP). Since the resilience value is bounded between 0 and 1, a logit transformation was applied to the target variable before model training, and the inverse transformation was used to convert predictions back to the original resilience scale. Among the tested models, MLP with logit transformation is selected due to its better predictive performance. Subsequently, the resilience values predicted by the MLP are used to estimate the expected resilience under potential future failure scenarios.

With d_q treated as constant, the evaluation of R reduces to the evaluation of $F_q(\mathcal{H})$. Let G_q be the set of subsystems of equipment type q . For each $g \in G_q$, define the binary variable $Y_q(\mathcal{H})$ by

$$Y_q(\mathcal{H}) = \begin{cases} 1, & \text{if subsystem } g \text{ fails within } [0, \mathcal{H}] \\ 0, & \text{otherwise} \end{cases} \quad (6-19)$$

Then, $F_q(\mathcal{H})$ is

$$F_q(\mathcal{H}) = \sum_{g \in G_q} Y_q(\mathcal{H}) \quad (6-20)$$

$$P(Y_q(\mathcal{H}) = 1) = p_g^{fail}(\mathcal{H}), P(Y_q(\mathcal{H}) = 0) = 1 - p_g^{fail}(\mathcal{H})$$

The expected resilience is

$$\max \mathbb{E}[R(F_1(\mathcal{H}), \bar{D}_1, \dots, N_q(F), \bar{D}_q)] \quad (6-21)$$

Because all subsystems are independent, it could be further written as

$$\max \sum_{q=1}^{|G_q|} R(\bar{n}, \bar{D}_q) P(F_q(\mathcal{H}) = \bar{n}) \quad (6-22)$$

Hence, it is further reduced to determining $P(F_q(\mathcal{H}) = \bar{n})$. If failures among subsystems of the same equipment type are mutually independent over $[0, \mathcal{H}]$, then $F_q(\mathcal{H})$ follows a Poisson-binomial distribution with exact probability mass function

$$P(F_q(\mathcal{H}) = \bar{n}) = \sum_{A \subseteq G_q, |A|=\bar{n}} \prod_{g_1 \in A} p_{g_1}^{fail}(\mathcal{H}) \prod_{g_2 \in G_q \setminus A} (1 - p_{g_2}^{fail}(\mathcal{H})), \quad (6-23)$$

$\forall \bar{n} = 0, 1, \dots, |G_q|$

3250 The above expression gives the exact probability of $\bar{n}$ failed subsystems of type q . However, when $|G_q|$
 3251 is large, direct computation is costly due to the combinatorial enumeration involved. A recursive method is
 3252 therefore introduced to improve computational efficiency. Re-indexing the subsystems in G_q by $\dot{g} = 1, 2, \dots, |G_q|$, let

$$\epsilon_{q,\bar{n}}^{(\bar{k})} = P\left(\sum_{q=1}^{\bar{k}} Y_q(\mathcal{H}) = \bar{n}\right), \bar{n} = 0, 1, \dots, \bar{k} \quad (6-24)$$

3254 where $\epsilon_{q,\bar{n}}^{(\bar{k})}$ represents the probability that exactly $\bar{n}$ out of the first $\bar{k}$ subsystems of type q fail within $[0, \mathcal{H}]$.
 3255 The initial conditions are

$$\epsilon_{q,0}^{(0)} = 1, \epsilon_{q,\bar{n}}^{(0)} = 0, \bar{n} \geq 1 \quad (6-25)$$

3256 The recursive relation is then given by

$$\epsilon_{q,\bar{n}}^{(\bar{k})} = \left(1 - p_k^{fail}(\mathcal{H})\right) \epsilon_{q,\bar{n}}^{(\bar{k}-1)} + p_k^{fail}(\mathcal{H}) \epsilon_{q,\bar{n}-1}^{(\bar{k}-1)} \quad (6-26)$$

3257 with the boundary condition

$$\epsilon_{q,\bar{n}}^{(\bar{k})} = 0, \bar{n} < 0 \text{ or } \bar{n} > \bar{k} \quad (6-27)$$

3258 After iterating over all $|G_q|$ subsystems of type q , the probability mass function of $F_q(\mathcal{H})$ is obtained as

$$P(F_q(\mathcal{H}) = \bar{n}) = \epsilon_{q,\bar{n}}^{(|G_q|)}, \bar{n} = 0, 1, \dots, |G_q| \quad (6-28)$$

3259 Based on the above recursive results, and given that $\bar{D}_q$ is treated as a constant, the expected resilience of
 3260 the port system can be expressed as

$$\mathbb{E}[R] = \sum_{n=0}^{|G_q|} R((n_1, \bar{D}_1), \dots, (n_Q, \bar{D}_Q)) \prod_{q=1}^Q \epsilon_{q, \bar{n}}^{(|G_q|)} \quad (6-29)$$

The above formulation maintains exact subsystem failure probabilities and avoids the excessive number of cases generated by exhaustive enumeration of failure combinations. It thus provides an efficient and accurate way to evaluate expected resilience and can be directly integrated with the resilience estimation approach developed above.

6.2.6 Multi-objective decision making

Based on the above, a multi-objective optimisation model for large port equipment under disruptions, incorporating port resilience under disruptive scenarios, is established as follows:

$$\begin{aligned} \min & \mathcal{C} \\ \max & \tilde{R} \\ x_{ug} &= \{1, 2, 3\} \\ y_{ug} &= \{0, 1\} \end{aligned} \quad (6-30)$$

Existing techniques for solving multi-objective optimisation problems can generally be divided into two main types: scalarization and Pareto-based methods (Burachik et al., 2014). Scalarization reduces the dimension of the objectives to a single objective by taking decision-maker preferences directly into the objective structure. Typical examples include the weighted-sum method, the ϵ -constraint method, and goal programming. These methods are computationally straightforward and can generate a single optimal solution. However, they require the decision-maker to specify weights, target values, or acceptable thresholds in advance. In the context of OM in container terminals, such prior preference information is difficult to define because the trade-off between maintenance cost and expected port resilience is highly context-dependent. For example, during severe disruptions, port operators may prioritise resilience recovery even at a higher cost, whereas under minor disruptions, cost control may become more important.

In this study, the two optimisation objectives are inherently conflicting. A higher maintenance level generally reduces the future failure probability and improves expected port resilience, but it also increases direct maintenance costs. Conversely, a low-cost maintenance strategy may preserve short-term economic efficiency, but it may leave the port more vulnerable to subsequent equipment failures and resilience loss. Therefore,

imposing a fixed weight or predefined preference structure on the two objectives may oversimplify the decision problem and obscure the practical trade-off faced by port operators.

Other multi-criteria decision-making methods, such as AHP, TOPSIS, VIKOR, and other ranking-based approaches, are useful when a finite set of alternatives needs to be evaluated according to predefined criteria. However, these methods are more suitable for ranking or selecting alternatives after candidate solutions have been generated, rather than for preserving the full trade-off structure of an optimisation problem. In this study, the purpose is not merely to select a single maintenance strategy, but to identify the cost-resilience trade-off among feasible maintenance decisions.

Therefore, a Pareto-based approach is adopted in this study. A maintenance strategy is regarded as Pareto optimal if no other feasible strategy can improve expected resilience without increasing cost, or reduce cost without decreasing expected resilience. The Pareto front thus provides a set of non-dominated maintenance strategies representing different compromises between economic efficiency and resilience improvement.

6.3 Results and discussion

This section first introduces the data collection process, and then presents the cases designed for the experiments, followed by model validation, experiment results and sensitivity analysis. Based on the extensive analytic results, the effectiveness of the proposed method is demonstrated, and corresponding managerial implications are further discussed.

6.3.1 Data collection

As this chapter requires data derived from previous chapters as model inputs, ensuring data consistency is of critical importance. Therefore, the same port case and the same core datasets as those used in the preceding chapters are retained in this chapter. In addition, maintenance-related data from the same port were collected. Given their essential roles in container handling operations, four types of large port equipment are considered, namely deep water quay cranes, feeder quay cranes, rail gantry cranes, and yard cranes. Their operational configuration reflects the series-parallel dependency structure discussed in the previous section. For each equipment type, five representative units were selected, covering equipment at different life-cycle stages, including newly commissioned units, middle-aged units, and ageing units. For these units, failure occurrence times requiring maintenance were recorded over a one-year observation period. The collected records include failures caused by both unexpected external events and age-related equipment deterioration, together with the corresponding maintenance actions or approximate repair types. The NHPP scale and shape parameters, γ_q and δ_q , respectively, were estimated using Maximum Likelihood Estimation (MLE) based on the recorded failure occurrence times of the selected equipment units during the one-year observation period (Jalal et al., 2023). The

3313 resulting parameter values were further checked against ranges reported in the relevant literature. In addition, a
 3314 questionnaire survey was conducted to collect supplementary maintenance information from port practitioners,
 3315 including maintenance costs, repair effectiveness, and other parameters required for the subsequent maintenance
 3316 optimisation analysis. The detailed technical parameters used in the model are shown in Table 6.1.

3317 Since the typical service life of quay cranes and yard cranes is approximately 15-20 years, equipment age
 3318 is divided into three representative groups: young, middle-aged, and old. Specifically, 3 years, 8 years, and 12.5
 3319 years are used to represent the three age groups, corresponding to 26,280, 70,080, and 109,500 operating hours,
 3320 respectively. In the baseline experiments, the age of all non-failed equipment units is fixed at 8 years,
 3321 representing the middle-aged condition. This fixed age setting is adopted instead of random age generation to
 3322 ensure that the effects of failure patterns, equipment types, and maintenance decisions can be isolated and
 3323 compared consistently.

3324 Table 6.1. Technical parameters in the equipment maintenance model.

Parameter	Value				Unit
	Deep water quay crane	Feeder quay crane	Railway gantry crane	Yard crane	
a_{ik}		$\begin{cases} 26280, & \text{young} \\ 70080, & \text{middle (baseline)} \\ 105120, & \text{old} \end{cases}$			hour
γ_q	2.21×10^{-5}	7.48×10^{-6}	1.82×10^{-6}	7.59×10^{-6}	-
δ_q	1.344328	1.344328	1.344328	1.344328	-
T^r	120	140	120	80	Hour
T^{m1}	2.5	3	4	1.5	Hour
T^{m2}	48	60	72	36	Hour
c^r	150,000	12,000	150,000	100,000	RMB

c^{m1}	3,500	2,800	2,200	1,500	RMB
c^{m2}	45,000	38,000	32,000	25,000	RMB
θ^{m1}	85%	80%	75%	90%	-
θ^{m2}	98%	95%	90%	99%	-
c_g^f	150,000	8,000	12,000	18,000	RMB
$\bar{D}_q$	4.5	6.0	2.5	8	Hour
$ G_q $	48	16	12	48	-
$\mathcal{H}$	720				Hour

6.3.2 Experiment setup

All computational experiments were conducted on a lightweight laptop equipped with an Intel i5-10210U processor, 1.60 GHz and 8 GB of RAM. To generate insightful operation suggestions and validate model robustness, 39 scenarios are included under 5 aims; an overview of all scenarios is provided in Table 6.2.

Table 6.2. An overview of all scenarios.

Experiment group	Total number of scenarios	Section number	Details
Single failure in a single subsystem	4	Section 6.3.4.2	One equipment unit is assumed to fail in each equipment type.

Multiple failures in a single subsystem	8	Section 6.3.4.3	For each equipment type, more than one unit fails within the same subsystem.
Cross-subsystem failure	7	Section 6.3.4.4	Simultaneous failures occur across two different equipment types. For three subsystems, a case involving deep water quay cranes, feeder quay cranes, and rail gantry cranes is included as an illustrative scenario.
High severity failure	2	Section 6.3.4.5	2 severe disruptive scenarios are considered: 1 involving simultaneous quay-side and yard-side failures, and another involving failures across all four equipment types.
Sensitivity analysis	18	Section 6.3.5	Sensitivity tests are conducted for 3 age groups, 4 realistic observation periods, 2 extreme observation periods, 3 repair level settings, 3 maintenance cost levels, and 3 fixed cost levels.

6.3.3 Model validation

The proposed model was validated at two levels. First, the ML-based resilience prediction model was assessed in terms of predictive accuracy and overfitting behaviour in section 6.3.4.1. Four commonly used error-based indicators, namely MSE, RMSE, MAE, and MAPE, were used to evaluate the prediction error. Overfitting was checked by comparing the model performance on the training and testing datasets.

Second, the multi-objective optimisation framework was validated through extensive scenario-based and parameter-based experiments. The model was tested under 3 different failure structures: (1) a single failure in a single subsystem; (2) multiple failures in a single subsystem, and (3) cross-subsystem failures. These scenarios examine whether the model can generate reasonable Pareto optimal strategies under different disruption patterns. In addition, two high-severity scenarios were designed to represent realistic high-risk and high-impact disruption conditions, allowing the model results to be judged against practical operational logic and managerial expectations.

From the perspective of input parameters, sensitivity analyses were conducted by varying equipment age, the observation period, repair effectiveness parameters, maintenance costs, and fixed costs. These tests examine whether the model responds consistently and logically to changes in key assumptions. In particular, extreme

parameter settings, such as the extended observation periods tested in Section 6.3.5.2, were included as robustness tests to assess whether the model remains stable under boundary conditions. Overall, the validation results demonstrate that the proposed framework is not dependent on a single baseline scenario. Instead, it produces interpretable, stable, and practically reasonable results across different failure patterns, parameter settings, and extreme operating conditions, supporting its reliability and robustness across potential scenarios.

Accordingly, validation of Chapter 6 considers both predictive validity of the resilience surrogate and behavioural robustness of the optimisation framework, ensuring that the final maintenance recommendations are not dependent on a single model, failure pattern, or baseline parameter setting.

6.3.4 Experiment results

6.3.4.1 *Machine Learning result*

Table 6.3 presents the predictive performance of different models used to estimate port resilience. The models were evaluated using MSE, RMSE, MAE, MAPE, and R^2 , together with the selected hyperparameter values. The linear regression and ridge regression models produced similar results, indicating that a purely linear specification has limited ability to capture the nonlinear relationship between failure conditions and resilience. The polynomial ridge regression model improved the prediction accuracy substantially, suggesting the presence of nonlinear effects in the data. However, the best overall performance was achieved by the MLP model with a logit transformation of the resilience target, which obtained the lowest MSE, RMSE, MAE, and MAPE, and the highest R^2 value among all tested models. Compared with the SVR-RBF model, the MLP further reduced the RMSE from 0.0251 to 0.0185 and increased R^2 from 0.9854 to 0.9921. Therefore, the MLP model was selected as the final predictive model for estimating resilience values under possible future failure scenarios. This choice is justified not only by its superior predictive accuracy but also by its ability to capture complex nonlinear input-output relationships while maintaining bounded resilience predictions through the logit transformation.

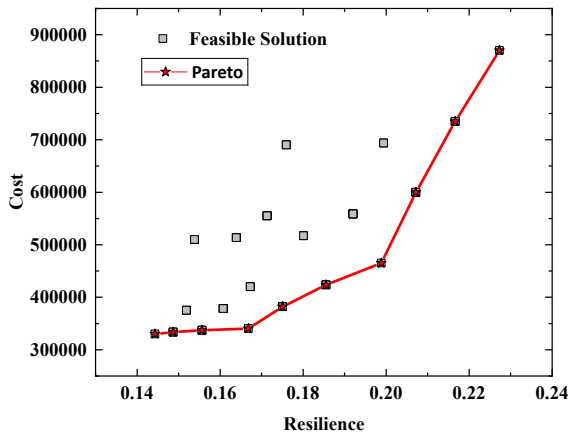
Table 6.3. Estimation results.

	MSE	RMSE	MAE	MAPE	R^2	Best hyperparameters
Linear regression	0.0043	0.0654	0.0488	9.02%	0.9013	-
Ridge regression	0.0043	0.0654	0.0488	9.03%	0.9013	$\alpha = 1.0$

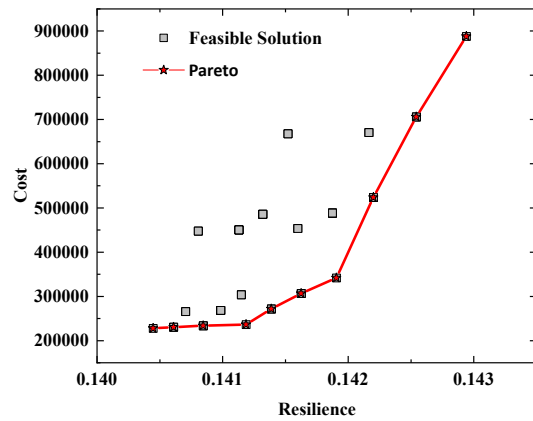
Polynomial ridge regression	0.0015	0.0382	0.0281	5.23%	0.9663	$\alpha = 0.1$
Spline ridge	0.0040	0.0631	0.0467	9.61%	0.9084	$n_{\text{knots}} = 4, \text{degree} = 2, \alpha = 1$
SVR RBF	0.0006	0.0251	0.0147	3.00%	0.9854	$C = 10, \epsilon = 0.01, \gamma = 0.1$
MLP with logit transformation	0.0003	0.0185	0.0126	2.29%	0.9921	$\alpha = 0.01, \text{hidden_layer_size} = (12, 8, 64), \text{learning rate} = 0.001$

6.3.4.2 *Single failure across each type of equipment*

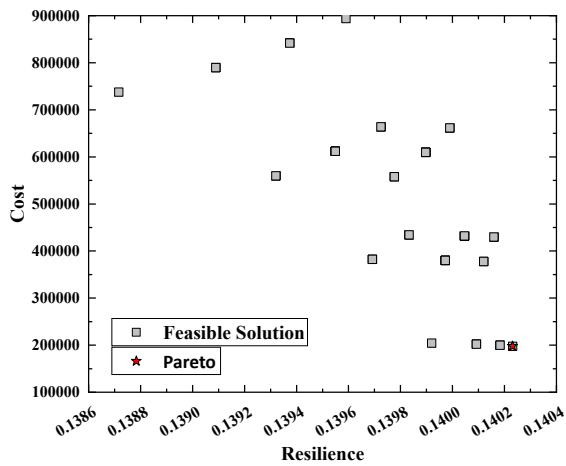
This subsection examines the optimisation results under single-failure scenarios for each type of equipment. In all scenarios, the age of the failed equipment and the remaining equipment units is fixed at eight years, corresponding to 70,080 operating hours. For each equipment type, one unit is assumed to have failed, while the optimisation model evaluates whether opportunistic maintenance should be conducted on the remaining units of the same equipment type. A total of 64 feasible maintenance strategies is generated for each scenario. The results are evaluated in terms of total maintenance cost and expected resilience. The expected resilience value should be interpreted as the expected port resilience after the maintenance decision is implemented over the prediction horizon, rather than the instantaneous resilience loss before repair. The Pareto front for 4 types of equipment is shown in Figure 6.3.



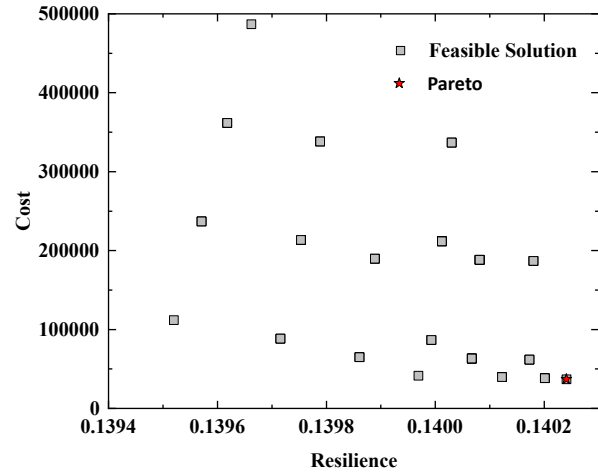
(a) A single deep water quay crane fails



(b) A single feeder quay crane fails



(c) A single railway gantry crane fails



(d) A single yard crane fails

Figure 6.3. Pareto front for a single failure across each type of equipment.

The Pareto results show clear differences across equipment types. For the deep water quay crane scenario, the Pareto frontier contains a relatively wide set of non-dominated solutions. The total cost increases from 330,000 to 870,000, while the expected resilience increases from 0.144 to 0.227. This indicates that, when a deep water quay crane fails, additional maintenance actions on the remaining units can lead to a noticeable improvement in expected system resilience. The upward-sloping Pareto frontier suggests a clear tradeoff between cost and resilience: low-cost strategies provide limited resilience improvement, whereas high-cost strategies achieve better resilience performance. However, the marginal improvement becomes less attractive after the medium-coloured region, indicating that port operators may not necessarily need to select the maximum-resilience solution if the available budget is limited.

A similar but much weaker tradeoff is observed in the feeder quay crane scenario. The Pareto frontier also moves upward as total cost increases, but the improvement in expected resilience is relatively small. The total cost rises from 228,000 to 888,000, while expected resilience only increases from 0.140 to 0.143. This means that OM for feeder quay cranes can improve expected resilience, but the magnitude of improvement is limited. Therefore, although several non-dominated strategies exist, the additional resilience benefit may not be sufficient to justify high-cost maintenance actions unless the port operator places a strong emphasis on resilience improvement or long-term risk reduction.

In contrast, the rail gantry crane and yard crane scenarios each produce only one non-dominated solution in the cost-resilience space. For the rail gantry crane scenario, the minimum cost strategy has a total cost of 198,000 and an expected resilience of 0.140. All other feasible strategies require higher costs but do not improve expected resilience. Similarly, for the yard crane scenario, the minimum cost solution has a total cost of 37,000 and an expected resilience of 0.140, while additional maintenance actions on the remaining yard cranes lead to higher

costs without producing a higher expected resilience value. However, the single point Pareto frontier in these two scenarios does not indicate a lack of feasible alternatives. Instead, it shows that all other feasible maintenance strategies are dominated when only cost and expected resilience are considered simultaneously.

Overall, the results demonstrate that the value of opportunistic maintenance depends strongly on the type of failed equipment. For deep water quay cranes, additional maintenance actions can substantially improve expected resilience, making the cost-resilience tradeoff meaningful. For feeder quay cranes, the same tradeoff exists, but the resilience gain is much smaller. For rail gantry cranes and yard cranes, the optimal decision under the cost resilience criterion is to repair the failed unit only, without conducting additional OM on the remaining units. This suggests that, under the 8-year equipment age assumption, OM is more justified for deep water quay crane, due to their stronger influence on system level resilience, whereas for other equipment types, additional maintenance may increase cost without improving the expected resilience.

Due to space limitations, detailed results, including total cost, maintenance cost, resilience values, and the corresponding maintenance actions, are provided for the 21 Pareto-optimal solutions under the single deep-water quay crane failure scenario, as presented in

Table 6.4. In each single-failure scenario, Unit 1 is assumed to have failed and is therefore subject to mandatory corrective replacement. Units 2, 3, 4 remain operational and represent neighbouring equipment for which opportunistic preventive maintenance may be performed. Each Strategy id corresponds to a particular combination of maintenance decisions for Units 2, 3, 4, where “–” indicates no maintenance, Level 2 represents minimal repair, Level 3 represents moderate repair, and Level 1 represents replacement. The Strategy detail columns therefore show the optimal maintenance action assigned to each non-failed unit.

Table 6.4. Detailed results for a single failure in a single subsystem.

Strategy id	Expected resilience	Total cost	Maintenance cost	Strategy detail		
				Unit 2	Unit 3	Unit 4
1	0.14436	330,000	180,000	-	-	-
3	0.14869	333,500	183,500	-	-	2
9	0.14869	333,500	183,500	-	2	-

33	0.14869	333,500	183,500	2	-	-
35	0.15566	337,000	187,000	2	2	-
41	0.15566	337,000	187,000	-	2	2
11	0.15566	337,000	187,000	-	2	2
43	0.16683	340,500	190,500	2	2	2
44	0.17503	382,000	232,000	2	3	2
47	0.17503	382,000	232,000	3	2	3
59	0.17503	382,000	232,000	3	2	2
60	0.1855	423,500	273,500	3	2	3
63	0.1855	423,500	273,500	3	3	2
64	0.19887	465,000	315,000	3	3	3
56	0.20719	600,000	450,000	3	1	3
32	0.20719	600,000	450,000	1	3	3
62	0.20719	600,000	450,000	3	3	1
54	0.21662	735,000	585,000	3	1	1
30	0.21662	735,000	585,000	1	3	1
24	0.21662	735,000	585,000	1	1	3

22	0.22733	870,000	720,000	1	1	1
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A cost-benefit margin analysis was further conducted on the Pareto-optimal solutions to examine whether additional maintenance expenditure can be justified by the corresponding improvement in expected resilience. The marginal cost was measured as the additional cost required to obtain a 0.001 increase in expected resilience. The results show that the combination of moderate repair provides the highest marginal benefit. When the total cost increases from 330,000 to 340,500, the expected resilience increases from 0.14436 to 0.16683 (strategy 1 and strategy 43). This represents a resilience improvement of 0.02247 with only 10,500 additional cost, indicating that low-cost OM actions are highly cost-effective. In particular, the minimum marginal cost per 0.001 is 313 within this low-cost region (strategy 41 and strategy 43), suggesting that applying minimum repair to more healthy equipment units produces substantial resilience improvement at a relatively low additional cost. However, the marginal cost increases sharply after this point. When the total cost increases from 340,500 to 465,000, the expected resilience further improves from 0.16683 to 0.19887 (strategy 43 and strategy 64), but the marginal cost per 0.001 resilience gain rises to approximately between 3,104 and 5,061. This indicates that although the corresponding maintenance actions continue to improve resilience, their cost-effectiveness is lower than that of the minimum repairs. The most expensive region appears when the total cost increases from 465,000 to 870,000 (strategy 64 and strategy 32). In this range, the expected resilience increases only from 0.19887 to 0.22733, while the marginal cost per 0.001 resilience gain reaches approximately between 12,605 and 16,226. Therefore, the maximum resilience solution is associated with a very high marginal cost and may not be the most economically efficient choice unless the port operators give priority to resilience maximisation.

Overall, the cost-benefit margin analysis suggests that the most balanced strategies are located in the low-to medium-cost region of the Pareto frontier. Strategies involving moderate repairs provide the greatest resilience improvement per unit cost, while strategies involving replacement achieve the highest resilience but at a substantially higher marginal cost.

6.3.4.3 *Multiple failures in a single subsystem*

Table 6.5 summarises the experimental settings and optimisation results for scenarios in which multiple units fail within the same type of equipment. For each equipment type, two failure levels are tested: two failed units and three failed units. The total number of feasible strategies, the number of Pareto-front strategies, the minimum total cost, and the maximum resilience value obtained in each scenario are also provided.

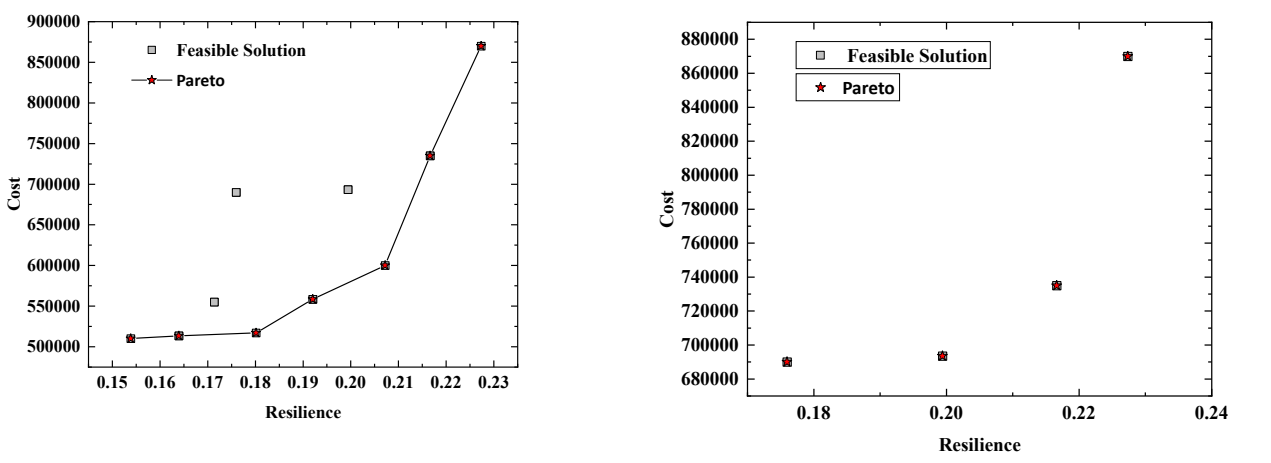
Table 6.5. Setting and results for multiple failures in a single subsystem.

Scenario id	Equipment type	Failed count	Number of all strategies	Number of Pareto front strategies	Min total cost	Max resilience
MS01	Deep water quay crane	2	16	9	510,000	0.2273
MS02	Deep water quay crane	3	4	4	690,000	0.2273
MS04	Feeder quay crane	2	16	10	448,000	0.1429
MS05	Feeder quay crane	3	4	4	668,000	0.1429
MS07	Rail gantry crane	2	16	1	378,000	0.1401
MS08	Rail gantry crane	3	4	1	558,000	0.1397
MS10	Yard crane	2	16	1	62,000	0.1401
MS11	Yard crane	3	4	1	87,000	0.1399

The deep-water quay crane scenarios produce the highest resilience value among all equipment types, with a maximum resilience of 0.2273 in both the two-failure and three-failure cases. However, the minimum total cost increases from 510,000 in MS01 to 690,000 in MS02, indicating that a larger number of failed deep-water quay cranes requires a higher basic repair cost while maintaining the same maximum resilience level. A similar pattern is observed for feeder quay cranes. The maximum resilience remains 0.1429 in both MS04 and MS05, while the minimum total cost increases from 448,000 to 668,000 when the number of failed units increases from two to three. This indicates that feeder quay crane maintenance can improve resilience, but the port level benefit is much smaller than that of deep water quay cranes. Therefore, opportunistic maintenance for feeder quay cranes should be considered only when the decision-maker has sufficient budget or when long-term reliability

improvement is prioritised over short-term cost efficiency. In contrast, rail gantry crane and yard crane scenarios generate only one Pareto-front strategy in each case, which indicates that the minimum cost strategy also provides the best resilience outcome, and all other feasible strategies are dominated when cost and resilience are considered simultaneously. This result suggests that, under the 720-hour prediction horizon and the eight-year age assumption, the short-term disruptions or cost burden introduced by additional maintenance is not compensated by a sufficiently large system-level resilience improvement.

Similar to single failure, the results indicate a clear difference in the value of OM across equipment types, where deep water quay crane failures show the strongest potential for resilience improvement, followed by feeder quay crane failures. By contrast, rail gantry crane and yard crane failures show limited resilience improvement from additional maintenance actions. The Pareto frontier for the deep water quay crane under 2 failures and 3 failures is provided in Figure 6.4. Figures 6.4(a) and 6.4(b) correspond to scenarios MS01 and MS02 in Table 6.5, respectively. Each point in the figures represents one feasible maintenance strategy, so the total number of plotted points corresponds to the “Number of all strategies” reported in Table 6.5. The highlighted Pareto points represent the non-dominated strategies and correspond to the “Number of Pareto strategies”. The minimum cost reported in Table 6.5 is the lowest value on the cost axis among all feasible strategies, while the maximum resilience is the largest value on the resilience axis.



(a) 2 failures in a single deep water quay crane subsystem (b) 3 failures in a single deep water quay crane subsystem

Figure 6.4. Pareto front for multiple failures in a single deep water quay crane subsystem.

6.3.4.4 Cross-subsystem failures

Table 6.6 presents the scenario settings and optimisation results for cross-subsystem failure scenarios where simultaneous failures across different equipment types are considered. The purpose is to examine whether the benefit of OM changes when disruptions occur across multiple functional subsystems of the port. This setting

is more representative of compound operational disruptions, where failures may not be confined to one equipment category but may affect several parts at the same time. In each two subsystem scenario, one unit is assumed to fail in each of the two selected equipment types, and 6 cross-subsystem combinations are tested, namely CS01-CS06. In addition, a three-subsystem scenario is tested. The number of feasible strategies increases substantially in the cross-subsystem setting. For each two-subsystem scenario, 4,096 feasible strategies are generated with 6 healthy units. For the three-subsystem scenario, the number of feasible strategies increases to 262,144, with 9 healthy units.

Table 6.6. Scenario setting and results for cross-subsystem failures.

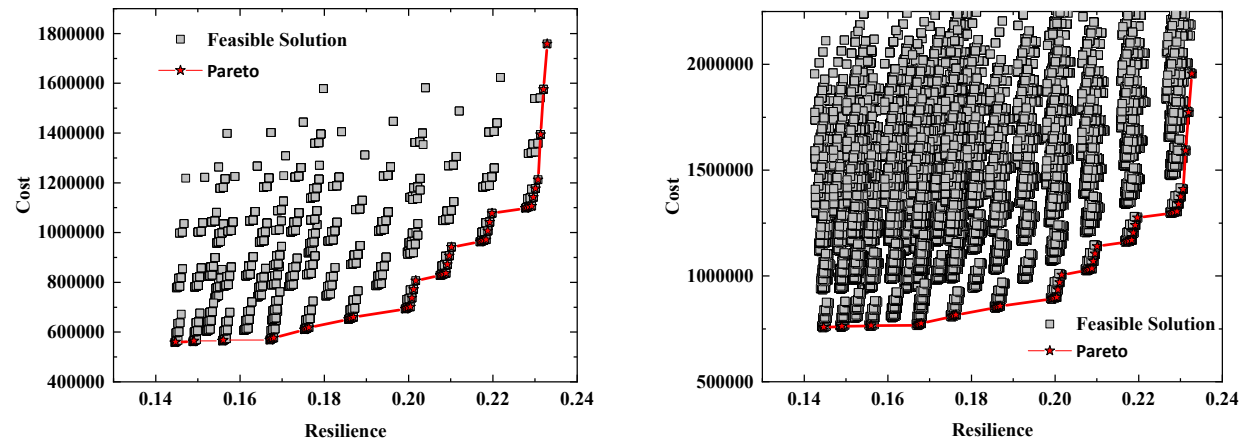
Scenario id	Equipment type				Number of all strategies	Number of Pareto front strategies	Min total cost	Max resilience
	Deep water quay crane	Feeder quay crane	Railway gantry crane	Yard crane				
CS01	1	1			4,096	191	558,000	0.23286
CS02	1		1		4,096	21	528,000	0.22731
CS03	1			1	4,096	21	367,000	0.22730
CS04		1	1		4,096	20	426,000	0.14283
CS05		1		1	4,096	22	265,000	0.14294
CS06			1	1	4,096	1	235,000	0.14021
CS07	1	1	1		262,144	196	756,000	0.23273

The results reveal that the deep water quay crane failure is the main factor determining whether a high level of expected resilience can be achieved. In CS01, where 1 deep water quay crane and one feeder quay crane fail, the maximum expected resilience reaches 0.23286, which is the highest value among all cross-subsystem

scenarios. This pattern reinforces the previous indication that deep water quay cranes act as the most resilient critical equipment type in the port. When a deep water quay crane is involved in the failure scenario, OM can meaningfully improve expected system resilience. However, when failures occur only in rail gantry cranes and yard cranes, additional OM does not improve the resilience outcome sufficiently to justify the extra cost.

The comparison between CS01 and CS07 provides another important insight. CS07 includes three simultaneous failures, involving 1 deep water quay crane, 1 feeder quay crane, and 1 rail gantry crane. This increases the number of feasible strategies from 4,096 in CS01 to 262,144 in CS07. However, the maximum resilience remains almost unchanged, decreasing slightly from 0.23286 in CS01 to 0.23273 in CS07. At the same time, the minimum total cost increases from 558,000 to 756,000. This suggests that adding rail gantry crane failure significantly increases the repair cost and the size of the optimisation problem, but it does not substantially increase the maximum achievable resilience. In other words, the Pareto frontier is mainly shaped by the quay-crane-related maintenance decisions, while rail gantry crane maintenance contributes little to additional port-level resilience improvement under the current setting.

The Pareto frontier in Figure 6.5 further supports this insight. In the low- to medium-cost region of Figure 6.5(a), minimum and moderate repair can improve resilience relatively efficiently. However, in the high-cost region, the curve becomes much steeper, indicating diminishing marginal returns. A large increase in maintenance costs is required to achieve only a small additional improvement in expected resilience. Therefore, the maximum resilience solution may not necessarily be the most economically efficient choice. This conclusion becomes clearer in CS07. Although CS07 contains a much larger number of feasible solutions, the Pareto frontier has a similar shape to CS01. The dense cloud of feasible solutions in Figure 6.5(b) shows that most strategies are dominated, especially those with high cost but limited resilience improvement. The result suggests that increasing the number of maintained equipment units does not automatically lead to better port resilience. Instead, the effectiveness of OM depends on whether the maintained equipment belongs to a subsystem that is critical to port-level performance.



- (a) 1 failed deep water quay crane and 1 failed feeder quay crane (b) 1 failed deep water quay crane, 1 failed feeder quay crane and 1 failed railway quay crane

Figure 6.5. Cross-subsystem failures.

Compared with the previous single equipment failure scenarios, the cross-subsystem results confirm that deep water quay cranes are the dominant driver of resilience improvement. Compared with the multiple failures in the single subsystem scenarios, the cross-subsystem results further show that the number of failed units is not the only determinant of resilience improvement. For example, the maximum resilience in CS01 is slightly higher than that in the scenarios where two or three deep water quay cranes fail within the same subsystem. This suggests that there may be a complementary effect between deep water quay cranes and feeder quay cranes, since both are quayside handling resources and jointly influence vessel-related capacity. However, this complementary effect is not observed when deep water quay crane failure is combined with rail gantry crane or yard crane failure, where the maximum resilience remains close to that of the deep water quay crane scenarios alone. Therefore, cross-subsystem OM is most valuable when the affected subsystems are functionally connected and jointly influence port performance.

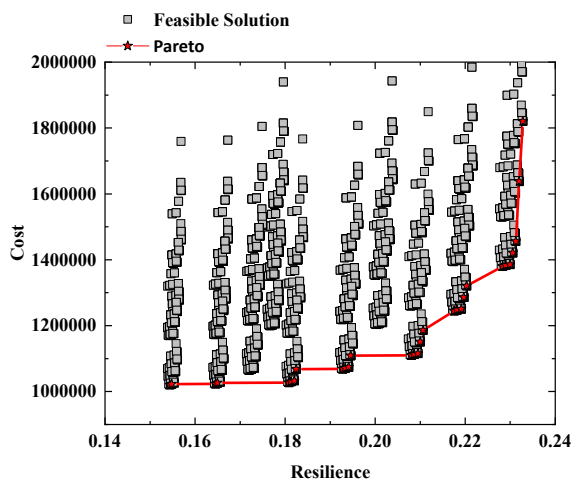
6.3.4.5 *High severity failures*

To further evaluate the robustness of the proposed optimisation framework, two high severity stress scenarios were designed to represent more extreme and port-wide disruption conditions, as shown in Table 6.7. The purpose is to test whether the model can still generate meaningful and interpretable maintenance strategies when the disruption becomes more severe and the decision space becomes substantially larger. The first scenario, HS01, represents a quay and yard mixed storm impact. This scenario is intended to approximate the impact of severe wind, storm surge, or intense weather conditions that damage both quay side and yard side handling equipment. The second scenario, HS02, represents a port-wide flood or landside disruptions. This scenario is designed to capture more spatially extensive disruptions, such as extreme rainfall or flooding.

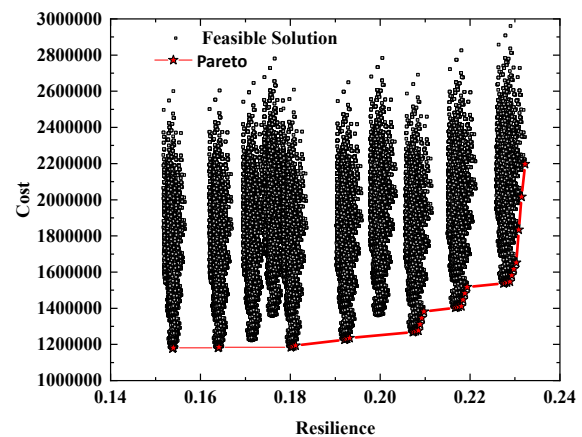
Table 6.7. Scenario setting and results for high severity failures.

Scenario id	Equipment type				Number of all strategies	Number of Pareto front strategies	Min total cost	Max resilience
	Deep water quay crane	Feeder quay crane	Railway gantry crane	Yard crane				
HS01	2	2	-	2	4,096	55	1,020,000	0.23281
HS02	2	1	2	2	262,144	98	1,178,000	0.23226

The results show that both high-severity scenarios are associated with much higher minimum total costs than the previous single failure and cross-subsystem scenarios. This is expected because more failed units require necessary corrective maintenance before any additional OM is considered. The minimum total cost increases from 1,020,000 in HS01 to 1,178,000 in HS02, however, the maximum resilience values are very close, with HS01 reaching 0.23281 and HS02 reaching 0.23226. This indicates that the higher severity scenario does not necessarily produce a higher post maintenance resilience level. It further suggests that the port level expected resilience reaches a saturation region. Additional failures in rail gantry cranes or yard cranes increase the repair burden and expand the decision space, but they do not substantially raise the maximum achievable resilience after maintenance. The Pareto front Figure 6.6 initially rises relatively efficiently but becomes much steeper in the high cost region. This indicates diminishing marginal returns: after a certain point, substantial additional maintenance expenditure is required to obtain only a small increase in expected resilience.



(a) Quay and yard mixed disruption



(b) Port-wide disruption

Figure 6.6. Pareto front for high severity failures.

For HS01, the expected resilience increases from approximately 0.1544 at the minimum cost solution to 0.2328 at the maximum resilience solution, while the total cost increases by 800,000. For HS02, the resilience improvement is very similar, increasing from approximately 0.1538 to 0.2323, but the cost increase is larger, reaching 1,020,000. This implies that HS02 is less cost-effective than HS01 in terms of resilience gain per unit cost. Compared with the previous single equipment failure analysis, the high severity scenarios confirm that OM is not equally valuable for all equipment types. The high severity scenarios show the same structural pattern. Even when yard cranes and rail gantry cranes are included in a severe disruption scenario, the major resilience improvement still comes from quay-crane-related maintenance decisions.

6.3.5 Sensitivity analysis

In the previous experiments, equipment age was fixed to isolate the effects of different failure patterns and maintenance strategies. However, equipment age is an important factor influencing failure intensity, maintenance necessity, and the expected benefit of OM. Therefore, an age-based sensitivity analysis is conducted in this section to examine whether the proposed optimisation framework remains stable under different age assumptions. In addition, the model is further validated by testing its behaviour under 2 more high failure severity conditions, i.e., a mixed storm impact and a port-wide flood disruption.

6.3.5.1 *Age group*

An age sensitivity analysis was conducted to examine how the optimal maintenance decisions and the associated cost resilience tradeoff change when the failed equipment belongs to different age groups, as shown in Table 6.7. Setting and results for age sensitivity analysis. Three age groups were considered: young equipment with 26,280 operating hours, middle-aged equipment with 70,080 operating hours, and old equipment with 109,500 operating hours. For each equipment type and age group, one unit was assumed to fail, while the remaining units of the same equipment type were considered for possible opportunistic maintenance.

Table 6.8. Setting and results across different age groups.

Equipment type	Age group	Number of all strategies	Number of Pareto strategies	Unique Pareto levels	Min cost	Max cost	Min resilience	Max resilience	Resilience gain
	Young	64	20	10	330,000	870,000	0.2466	0.3545	0.1080

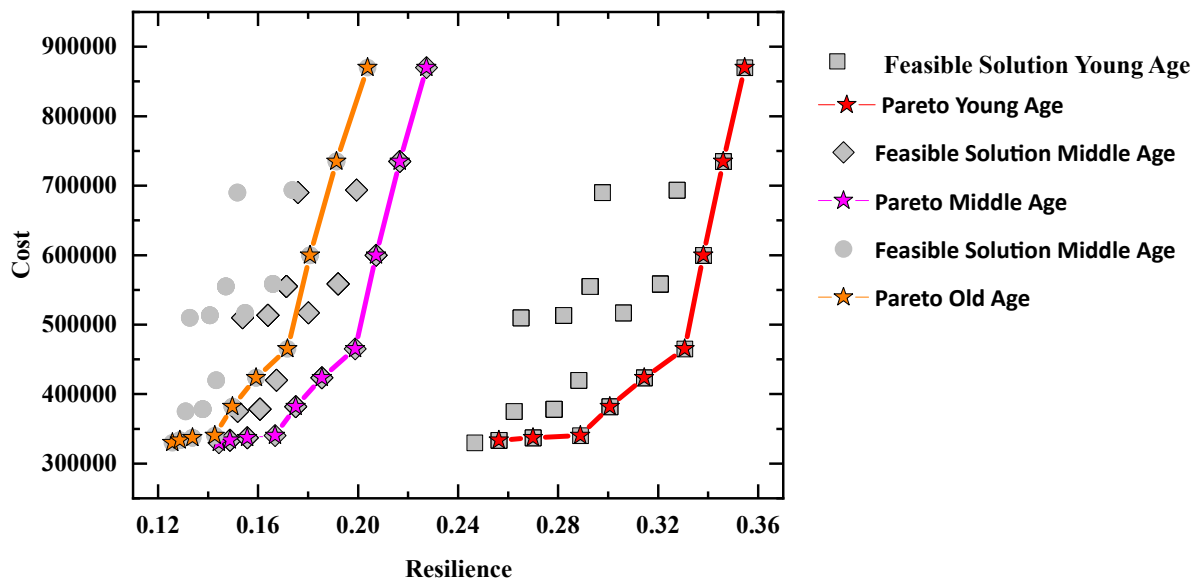
Deep water	Middle	64	21	10	330,000	870,000	0.1444	0.2273	0.0830
quay crane	Old	64	22	10	330,000	870,000	0.1257	0.2038	0.0780
	Young	64	20	10	228,000	888,000	0.1423	0.1455	0.0032
Feeder	Middle	64	22	10	228,000	888,000	0.1404	0.1429	0.00025
quay crane	Old	64	22	10	228,000	888,000	0.1401	0.1424	0.0023
	Young	64	1	1	198,000	198,000	0.1400	0.1400	0
Rail	Middle	64	1	1	198,000	198,000	0.1402	0.1402	0
gantry crane	Old	64	1	1	198,000	198,000	0.1403	0.1403	0
	Young	64	1	1	37,000	37,000	0.1396	0.1396	0
Yard crane	Middle	64	1	1	37,000	37,000	0.1402	0.1402	0
	Old	64	1	1	37,000	37,000	0.1404	0.1404	0

3571 The results show that equipment age has a clear influence on the resilience improvement potential of deep
 3572 water quay cranes. For this equipment type, the maximum expected resilience decreases from 0.3545 in the
 3573 young group to 0.2273 in the middle-aged group and further to 0.2038 in the old group. Similarly, the resilience
 3574 gain obtained by moving from the minimum cost solution to the maximum resilience solution decreases from
 3575 0.1080 to 0.0830 and 0.0780, respectively. Since the total cost range remains the same across the three age
 3576 groups, this indicates that ageing reduces the resilience benefit that can be obtained from the same maintenance
 3577 expenditure. The cost required to obtain a 0.01 increase in expected resilience also rises from approximately
 3578 50,014 in the young group to 65,079 in the middle-aged group and 69,202 in the old group. Therefore, although
 3579 OM remains meaningful for deep water quay cranes, its marginal cost effectiveness becomes weaker as
 3580 equipment age increases.

3581 The feeder quay crane results show a different pattern. Although the Pareto frontier exists for all three age
 3582 groups, the absolute resilience improvement is very limited. The maximum expected resilience decreases only

slightly from 0.1455 in the young group to 0.1429 in the middle-aged group and 0.1424 in the old group. The corresponding resilience gain is only 0.0032, 0.0025, and 0.0023, respectively. However, achieving these small improvements requires an additional cost of 660,000 when moving from the minimum-cost solution to the maximum resilience solution. As a result, the cost per 0.01 resilience gain is much higher than that of deep-water quay cranes, suggesting that opportunistic maintenance for feeder quay cranes is much less cost-effective, especially when the equipment becomes older. In contrast, rail gantry cranes and yard cranes produce only one Pareto optimal solution across all age groups. This indicates that the repair-only strategy dominates all other feasible strategies in the cost-resilience space. Additional OM increases the total cost but does not lead to a higher expected resilience value. Therefore, for these two equipment types, equipment age does not change the optimal decision structure under the current model setting.

Overall, the age sensitivity analysis confirms that the effect of age is equipment-dependent. Deep water quay cranes are the most sensitive to age, and their Pareto front shifts noticeably as age increases, as shown in Figure 6.7. Feeder quay cranes show only a weak age effect and very limited resilience improvement from additional maintenance. Rail gantry cranes and yard cranes remain dominated by the repair-only strategy regardless of age. These findings are consistent with the previous single failure and same equipment type failure analyses. Therefore, age-based maintenance planning should not apply the same maintenance rule to all equipment types. Instead, age information is most useful when the failed equipment belongs to a critical type.



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Figure 6.7. Pareto front for deep water quay crane across different age groups.

6.3.5.2 *Observation period*

A further sensitivity analysis was conducted with respect to the observation period $\mathcal{H}$, which represents the time interval from the current failure event to the next planned shutdown maintenance. In the previous experiments, it was fixed at the baseline value of 720 hours. However, in practice, it may vary depending on port operational plans, berth schedules, labour availability, and emergency maintenance arrangements. Therefore, testing different values is necessary to examine whether the proposed model remains stable under different planning horizons. In this analysis, one middle-aged deep water quay crane is assumed to fail, while the remaining deep water quay cranes are considered for possible OM. Four values of $\mathcal{H}$ are considered: 168 hours, 360 hours, 720 hours, and 1440 hours, representing short, medium, baseline, and long observation periods, respectively. The detailed settings are included in Table 6.9. Two additional values: 2,160 hours and 4,320 hours, are included as robustness tests. These two long horizons are not plotted in Figure 6.8 because they are not realistic in normal port maintenance planning; a port would normally not wait such a long time before the next planned maintenance window. Instead, they are used to test the numerical and behavioural stability of the model under extreme conditions.

Table 6.9. Scenario setting and results of different observation periods.

Base scenario	Observation period	$\mathcal{H}$	Number of all strategies	Number of Pareto strategies	Min cost	Max resilience
Single failure in the deep water quay crane	Short	168	64	19	330,000	0.9714
	Medium	360	64	19	330,000	0.4928
	Base	720	64	21	330,000	0.2273
	Long	1440	64	20	330,000	0.1358
	Robustness test	2160	64	20	330,000	0.1157
	Robustness test	4320	64	22	330,000	0.1065

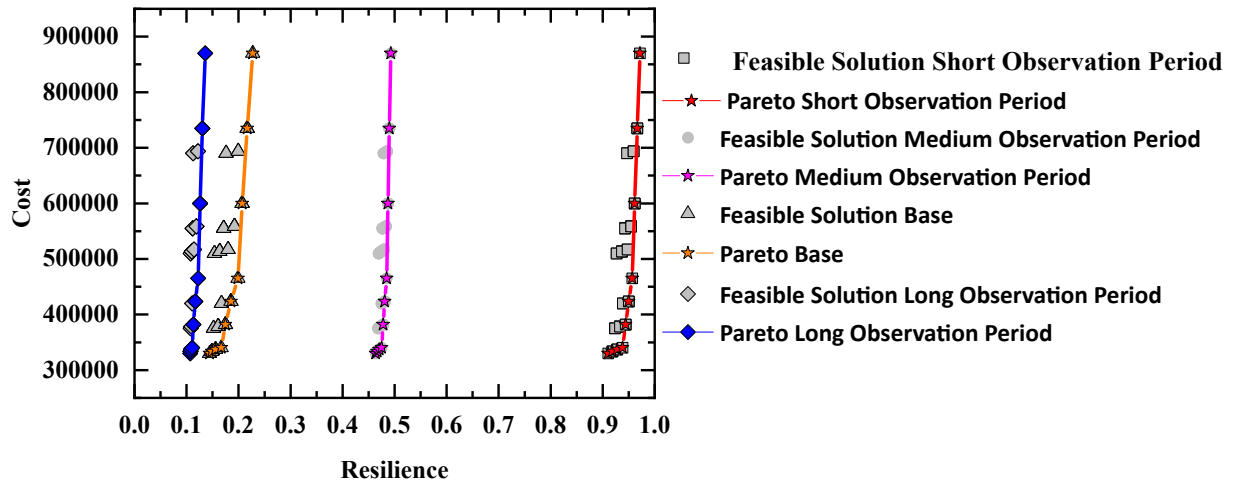


Figure 6.8. Pareto front for different observation periods.

The results show that the maximum expected resilience decreases as $\mathcal{H}$ increases. Under the short observation period, the port has relatively high expected resilience because it is exposed to future failure risks for a shorter time before the next planned shutdown maintenance. As the observation period becomes longer, the port must operate for a longer time under uncertainty, and the cumulative effect of future failure risks becomes stronger. Consequently, even the best maintenance strategy leads to a lower expected resilience. This indicates that the expected resilience is sensitive to the length of the planning horizon, which is consistent with the interpretation of $\mathcal{H}$ as a risk exposure period.

The Pareto fronts also show a clear compression pattern when $\mathcal{H}$ increases. For shorter horizons, the Pareto front spreads over a wider resilience range, meaning that different maintenance strategies lead to more distinguishable resilience outcomes. In this case, OM has a stronger decision value because the choice of maintenance action can significantly change the expected system performance. By contrast, when $\mathcal{H}$ becomes longer, the Pareto front shifts leftwards and becomes more compressed. This means that the difference between low-cost and high-cost strategies becomes smaller in terms of expected resilience improvement. Therefore, the marginal benefit of additional maintenance expenditure decreases under very long observation periods. From a maintenance decision-making perspective, this result suggests that OM is most useful when the next planned maintenance window is within a realistic short- to medium-term horizon. In such cases, targeted additional maintenance can improve the port's expected resilience before the next scheduled shutdown. Therefore, for critical equipment such as deep water quay cranes, a shorter or more flexible maintenance window may be necessary for port managers.

The robustness test scenarios further support the stability of the model. Although $\mathcal{H}=2,160$ and $\mathcal{H}=4,320$ are not realistic operational settings, the model still produces valid Pareto fronts and does not generate unstable

or contradictory optimisation results. More importantly, the structure of the recommended strategies remains consistent: the minimum cost solution corresponds to repairing the failed unit without additional OM, while the maximum resilience solution corresponds to applying the strongest maintenance action to all remaining candidate units. This consistency indicates that the optimisation framework is structurally stable under changes in $\mathcal{H}$.

6.3.5.3 *Maintenance quality*

A sensitivity analysis was further conducted for the repair effectiveness parameters θ^r, θ^{m1} and θ^{m2} representing the extent to which a maintenance action restores the effective age of the equipment. As shown in Table 6.10, 3 settings were considered: weak repair, baseline repair, and strong repair. For experimental simplicity, the same values were applied to all equipment types. This is a simplifying assumption, since in practice the maintenance quality may differ across equipment types and operating conditions. Nevertheless, using common values provides a controlled way to examine how the model responds to changes in repair effectiveness.

Table 6.10. Scenario setting and results for different repair levels.

Equipment type	Repair level	θ^r	θ^{m1}	θ^{m2}	Number of all strategies	Number of Pareto strategies	Min cost	Max resilience
All types of equipment	Weak	0.05	0.95	0.7	64	64	330,000	0.1753
	Base	As shown in Table 6.1.			64	21	330,000	0.2273
	Strong	0	0.75	0.4	64	61	330,000	0.2273

The results show that the maximum achievable resilience is highly sensitive to the assumed repair effectiveness level. Under the weak repair setting, the maximum resilience reaches only 0.1753, whereas both the baseline and strong repair settings achieve a maximum resilience of 0.2273. Since the minimum total cost remains unchanged at 330,000 in all three cases, this confirms the difference is caused by the change in the post maintenance equipment condition.

The weak repair scenario produces 64 Pareto strategies, meaning that almost all feasible strategies become non-dominated. It indicates that weak maintenance actions generate only small resilience improvements, so many strategies differ only marginally in terms of cost and resilience. As shown in Figure 6.9, the Pareto frontier

is therefore relatively flat, and the model has weaker discriminating power among alternative maintenance strategies. From a practical perspective, this suggests that if maintenance actions cannot substantially restore equipment condition, extensive OM may not be economically justified. By contrast, the baseline setting produces only 21 Pareto strategies, indicating that many strategies are dominated once the repair effects are sufficiently distinguishable. In this case, the model is better able to identify cost-effective strategies and eliminate those that increase cost without providing sufficient resilience benefit. The strong repair setting produces 61 Pareto strategies and reaches the same maximum resilience as the baseline case. This is mainly because the maximum resilience strategy in both cases corresponds to applying the strongest maintenance action to all remaining candidate equipment units. Once the equipment has already been restored close to a new or highly reliable condition, further strengthening the repair effectiveness parameter does not increase the maximum resilience substantially.

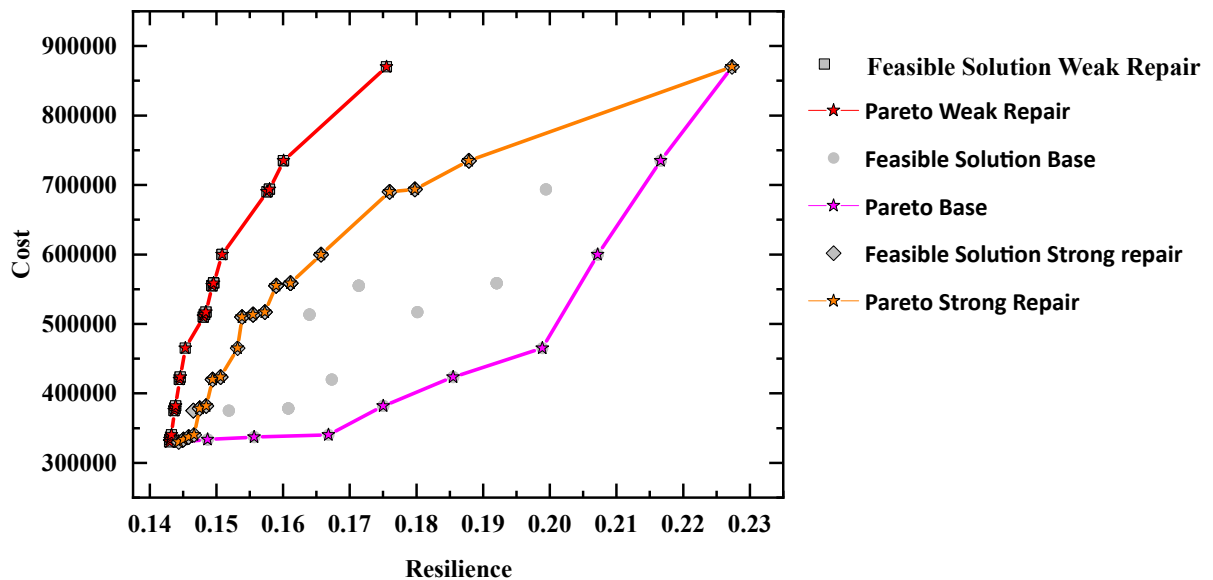


Figure 6.9. Pareto front for different repair levels.

6.3.5.4 Maintenance cost

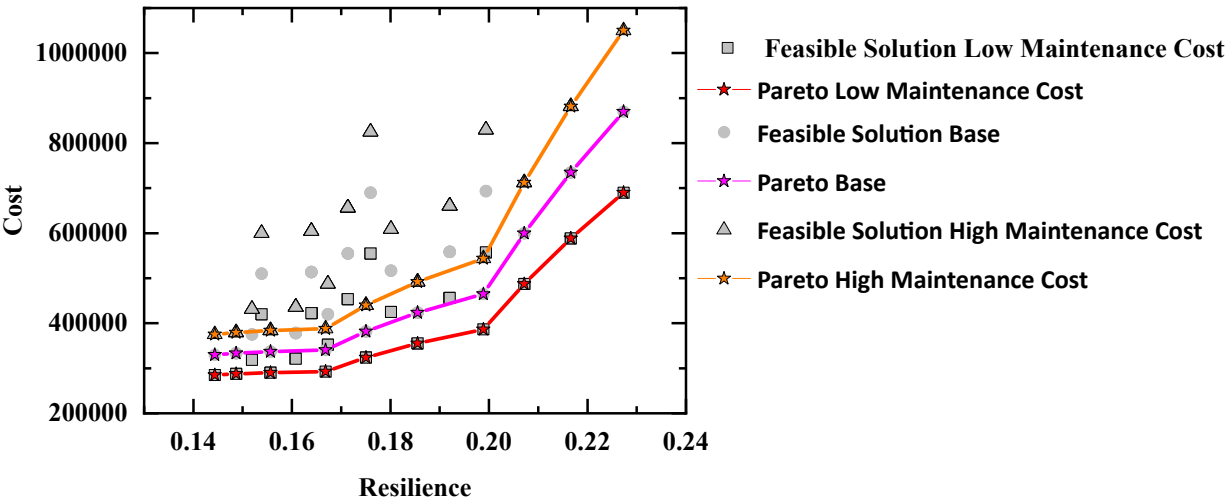
A sensitivity analysis was conducted to examine the effect of maintenance cost on the optimisation results. Three cost levels were considered: low cost, baseline cost, and high cost, corresponding to multiplying the baseline maintenance costs by 0.75, 1.00, and 1.25, respectively.

The results in Table 6.11 and Figure 6.10 show that changing the maintenance cost level affects the economic scale of the Pareto frontier, but does not change the achievable resilience values. Across the three cost settings, the maximum expected resilience remains 0.2273, while the minimum total cost increases from

3683 285,000 under the low cost setting to 330,000 under the baseline setting and 375,000 under the high cost setting,
 3684 which is consistent with the model structure. The number of Pareto optimal strategies also remains unchanged
 3685 across the three settings, with 21 Pareto strategies identified out of 64 feasible strategies.

3686 Table 6.11. Scenario setting and result for different maintenance costs.

Equipment type	Maintenance cost level	c^r	c^{m1}	c^{m2}	Number of all strategies	Number of Pareto strategies	Min cost	Max resilience	Knee cost	Knee resilience
All types of equipment	Low	Multiply by 0.75 for each type of equipment, respectively			64	21	285,000	0.1753	386,250	0.1989
	Base	As shown in Table 6.1.			64	21	330,000	0.2273	465,000	0.1989
	High	Multiply by 1.25 for each type of equipment, respectively			64	21	375,000	0.2273	543,750	0.1989



3687
 3688 Figure 6.10. Pareto front for different maintenance costs.

The knee point results provide further decision-making insight. In all three cost settings, the knee strategy remains the same and achieves an expected resilience of 0.1989. This strategy captures a large proportion of the available resilience improvement at a much lower cost than the maximum resilience strategy. By contrast, moving from the knee strategy to the maximum resilience solution requires a high additional cost while providing only a small further resilience improvement. Therefore, the maximum resilience solution may not be the most economically efficient choice, especially when maintenance costs are high. From a port management perspective, these results suggest that maintenance cost uncertainty should be incorporated into resilience-based maintenance planning. When maintenance costs are relatively low, more aggressive OM may be justified because the marginal cost of resilience improvement is lower. When maintenance costs are high, decision makers should be more cautious and may prefer intermediate Pareto solutions, particularly the knee strategy, rather than pursuing the maximum resilience solution. The results also indicate that port managers should not evaluate maintenance actions only by their absolute cost or maximum resilience contribution. Instead, they should consider the marginal cost of resilience improvement and select strategies that provide a balanced tradeoff between budget use and port resilience.

6.3.5.5 *Fixed cost*

A further sensitivity analysis was conducted by changing the fixed maintenance cost c^f . Three fixed-cost levels were tested: a low fixed-cost setting, where c^f is multiplied by 0.5; the baseline setting; and a high fixed-cost setting, where c^f is multiplied by 2.

The results in Table 6.12 and Figure 6.11 show that changing the fixed cost affects the total cost level but does not change the achievable resilience outcome. The maximum expected resilience remains unchanged at 0.2273 across all three settings. The number of Pareto optimal strategies remains 21 in all cases. This indicates that the fixed cost does not affect the physical recovery effect of maintenance actions, nor does it change the dominance relationship among maintenance strategies. Instead, it shifts the Pareto frontier upward or downward in the cost dimension.

Table 6.12. Setting and result for different fixed costs.

Equipment type	Fixed cost level	c^f	Number of all strategies	Number of Pareto strategies	Min cost	Max resilience
All types of equipment	Low	Multiply by 0.5 for each type of equipment, respectively	64	21	255000	0.2273

Base	As shown in Table 6.1.	64	21	330000	0.2273
High	Multiply by 2 for each type of equipment, respectively	64	21	480000	0.2273

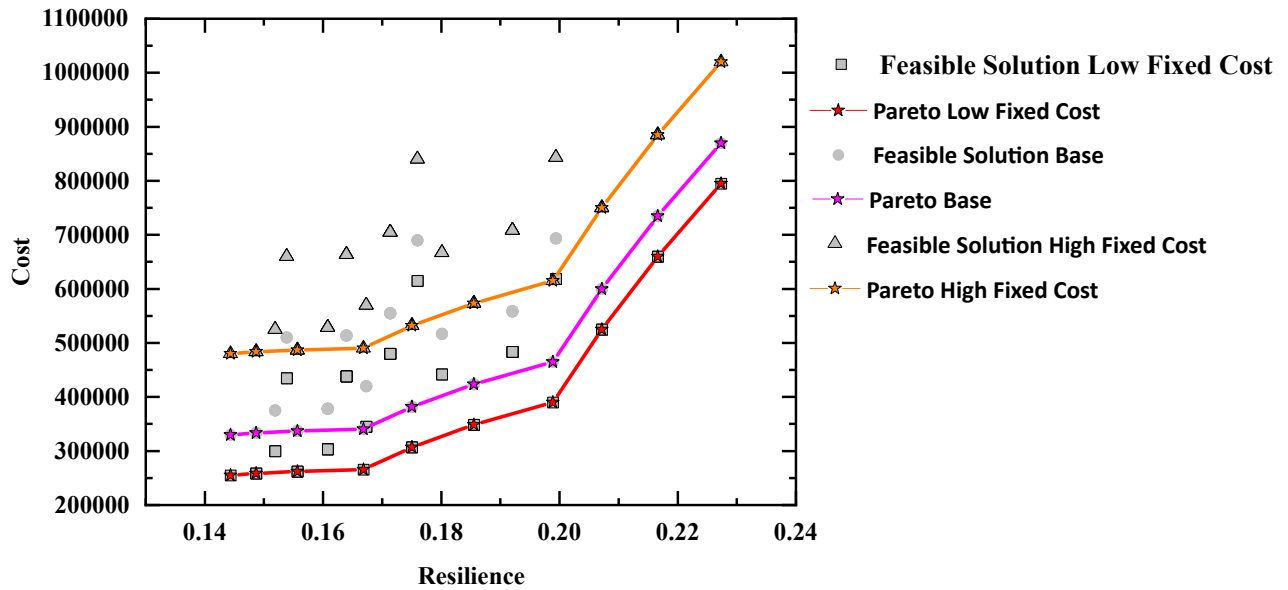


Figure 6.11. Pareto front for different fixed costs.

The fixed cost sensitivity results differ from the maintenance cost sensitivity results. When the maintenance action costs were changed, the marginal cost of resilience improvement changed accordingly. By contrast, changing the fixed cost does not affect the incremental cost between two maintenance strategies. From a model validation perspective, this result is reasonable and supports the internal consistency of the optimisation framework.

6.3.6 Discussion and implications

The experimental results provide several implications for resilience-based port maintenance management:

1. The results consistently show that the value of OM is highly dependent on equipment. Deep water quay cranes contribute most strongly to port-level resilience improvement, whereas rail gantry cranes and yard cranes show limited additional resilience benefit from OM in many scenarios. This suggests that maintenance resources should not be allocated uniformly across all failed or risky equipment.

Instead, port operators should prioritise equipment that plays a critical bottleneck role in terminal operations.

2. The results indicate that conducting more maintenance actions does not necessarily lead to higher port resilience. In several scenarios, especially those involving rail gantry cranes and yard cranes, additional OM increases cost without improving expected resilience. This finding is important for port management as it challenges the intuitive assumption that more extensive maintenance is always beneficial after a disruption. The effectiveness of OM depends on whether the maintained equipment belongs to a subsystem that has a substantial influence on port-level performance.
3. The Pareto front results highlight the importance of marginal cost effectiveness. The maximum resilience solution often requires a large increase in maintenance cost but provides only a small additional resilience gain beyond the knee region of the Pareto frontier. Therefore, decision makers should not rely solely on the maximum resilience strategy. Instead, intermediate Pareto solutions, especially knee point strategies, may provide a more practical balance between resilience improvement and budget constraints.
4. The sensitivity analyses show that maintenance decisions should consider not only failure occurrence but also the planning horizon, equipment age, repair effectiveness, and cost conditions. The observation period $\mathcal{H}$ represents the risk exposure window before the next planned maintenance opportunity. A longer $\mathcal{H}$ increases cumulative future failure risk and reduces the achievable expected resilience. Equipment age also affects the benefit of OM, but this effect is equipment-specific. Age has a strong influence on deep water quay cranes, while rail gantry cranes and yard cranes remain dominated by repair-only strategies across different age groups. This indicates that age-based maintenance planning should be combined with equipment criticality rather than applied mechanically.
5. The repair effectiveness sensitivity analysis suggests that ports should improve the quality of maintenance records. In practice, maintenance data should not only include cost and repair duration, but also the post maintenance condition improvement of equipment. Without reliable information on repair effectiveness, the resilience benefit of OM may be overestimated or underestimated. Therefore, port operators should develop equipment-specific maintenance databases that record failure histories, repair actions, effective age reduction, and post-repair performance.
6. The high-severity scenarios provide implications for emergency planning under extreme weather and port-wide disruptions. The results suggest that severe disruptions mainly increase the minimum recovery cost and the size of the decision space, but do not automatically increase the maximum achievable resilience. In such cases, rapid recovery of quayside handling capacity should be prioritised. Port-wide maintenance actions should be selective rather than uniform, because maintaining all affected equipment may substantially increase cost without producing proportional resilience improvement.

Overall, the findings support a shift from cost-based or equipment-level maintenance planning to resilience-based, port-level maintenance decision-making. For port managers, the key question is not simply which equipment has failed, but which maintenance actions can most effectively improve port-level resilience under the current disruption, budget, and planning horizon conditions.

6.4 Conclusions

This study develops a modelling framework for determining OM strategies for large port equipment under sudden failure events induced by external risks. A multi-objective optimisation approach is employed to explicitly capture the trade-off between maintenance cost and port-wide resilience. The assessment of port resilience is conducted using ML techniques, building upon datasets and methodologies established in previous studies. Real-world port data are used to estimate uncertain factors, including the failure probabilities and expected numbers of failures for different types of equipment. In addition, the Kijima type II virtual age model is adopted to represent the differences among maintenance actions in terms of maintenance effectiveness, required time, and associated cost. More specifically, this study examines a maintenance opportunity scenario in which the sudden failure of one piece of equipment forces neighbouring equipment to be shut down temporarily. Given such an opportunity window, the framework helps port operators determine whether OM should be carried out on the non-failed but suspended equipment and, if so, which maintenance action should be selected. By considering different failure events as well as combinations of simultaneous failures, the proposed model provides a set of feasible maintenance strategies for port operators under disruption conditions. To the best of the authors' knowledge, this is among the first studies to determine OM strategies accounting for ripple effects across multiple transport modes within the port.

CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH

This chapter provides comprehensive reflections and discussion of the existing research gaps and practical needs, together with the models and techniques proposed in Chapters 3 to 6. Particular emphasis is placed on explaining how each technical chapter contributes to the overall research aim and how the chapters are connected within an integrated resilience-based framework. This reflection is structured around the five research objectives, followed by a discussion of theoretical contributions, practical implications, limitations, and future research directions.

7.1 Implications of the research

The increasingly complex political situation, together with the growing frequency of extreme weather events, has posed significant challenges to port operations. To evaluate the impacts of these adverse events on ports, the concept of resilience has been introduced to describe a port's ability to withstand disruptions, adapt to adverse conditions, and recover throughout the disruption. Although resilience has gained increasing attention in supporting port operational management, existing practices and studies still face limitations due to the complexity of port operations. Therefore, there is a strong demand among stakeholders for advanced risk and resilience methodologies that can capture complex dynamic processes and improve understanding of the propagation mechanisms of ripple effects within ports.

7.1.1 Conclusions

The research objectives defined in Section 1.3 have been addressed through an integrated methodological chain across chapter 3 to chapter 6, where the output of one chapter provides the analytical foundation for the next. The thesis achieves its overall aim by moving from understanding port disruption mechanisms (chapter 3) to assessing resilience (chapter 4), identifying critical risks (chapter 5), and finally supporting resilience enhancement (chapter 6).

Objective 1 was achieved through the literature review and research gap analysis in Chapter 2. The review shows that existing port risk and resilience studies have often treated ports as single nodes within wider transport networks, with insufficient attention paid to the internal operational structure of multimodal container ports and the ripple effects among their subsystems. It also identifies methodological gaps in dynamic risk modelling, resilience quantification, uncertainty analysis, and resilience enhancement.

Objective 2 was achieved through the technical model 1 (SD simulation model) developed in Chapter 3. The model represents a multimodal container port as a system composed of five interconnected operational

subsystems, namely liner shipping, feeder shipping, railway, trucking, and container yard. By incorporating causal loop relationships, stock and flow diagrams, real operational logic, and disruption data, the model captures how disruptions of different types and magnitudes influence port operational performance. The results demonstrate that disruptions do not remain confined to the initially affected subsystem but propagate through interconnected subsystems and generate ripple effects. This addresses the objective of explaining the dynamic mechanisms through which disruptions evolve inside the port.

Objective 3 was achieved through the technical model 2 (resilience assessment framework) developed in Chapter 4. Building on the simulation outputs generated in Chapter 3, this chapter converts time-dependent KPI performance curves into resilience values. The ER-based hierarchical aggregation model further enables resilience to be evaluated at both subsystem and overall port levels. Therefore, Chapter 4 transforms dynamic simulation outputs into interpretable and comparable resilience measures, allowing port resilience to be assessed across multiple transport modes, operational indicators, and disruptive scenarios.

Objective 4 was achieved through the technical model 3 (Sobol-based GSA framework) developed in Chapter 5. While Chapter 4 evaluates resilience under predefined disruptive scenarios, Chapter 5 further identifies which disruptive factors and combinations of factors contribute most significantly to variations in overall port resilience. By using Sobol sampling and Sobol GSA, the model quantifies first-order, total-order, and second-order effects. This is important due to the combined impacts of simultaneous disruptions and the resulting ripple effects. The consistency of the findings is further examined by comparing the results with other GSA methods. Thus, Chapter 5 achieves the objective of identifying critical disruptions under uncertainty and provides a prioritised basis for resilience management.

Objective 5 was achieved through the technical model 4 (resilience-based OM optimisation model) developed in Chapter 6. The GSA results in Chapter 5 show that large equipment failures are critical disruptions affecting port resilience. Chapter 6, therefore, focuses on maintenance decision-making after unexpected equipment-related disruptions. By combining NHPP-based failure modelling, Kijima II virtual-age modelling, ML-based resilience estimation, and Pareto-frontier analysis, the OM model evaluates candidate maintenance strategies in terms of both maintenance cost and expected port resilience. This moves the thesis beyond resilience assessment and risk prioritisation towards resilience enhancement. The resulting Pareto front provides port operators with a set of non-dominated maintenance strategies, allowing them to balance cost efficiency and resilience improvement according to their operational priorities.

Across the four technical chapters, several specific findings emerge. First, quay-crane and yard-related disruptions generate the strongest cross-subsystem operational impacts, while congestion within the yard can propagate simultaneously to liner, feeder, and railway operations through the shared dependence on internal trucking. Second, the resilience analysis shows an asymmetric propagation pattern: disruptions originating on

the seaside tend to spread towards the yard, whereas yard-side disruptions can influence the wider port system. Third, the GSA consistently identifies liner quay-crane failures as a dominant determinant of overall port resilience and demonstrates that several factors with relatively modest standalone effects can generate substantially larger impacts through interactions with other disruptions. Finally, the maintenance analysis shows that the resilience benefit of OM is strongly equipment-dependent. Maintenance of deep-water quay cranes provides the largest improvement in port-level resilience, whereas additional maintenance of some rail and yard equipment may increase cost without providing proportional resilience gains. These findings indicate that resilience management should prioritise critical transmission points and selective recovery actions rather than treating all disruptions and equipment uniformly.

In summary, the objectives outlined in Section 1.3 have been achieved satisfactorily. In addition, the proposed methods and models show considerable potential as valuable tools for advancing understanding of port resilience under disruptions, supporting port operators in managing multimodal container ports, strengthening awareness among relevant government authorities, and helping multimodal transport stakeholders manage and avoid disruptions more effectively. The methods are also readily transferable to other multimodal container ports because of their strong applicability and generalisability to disruptions of different types and magnitudes. In addition, such transferability is fundamentally supported by the highly standardised nature of container terminal operations, layouts, and equipment. Therefore, the methods developed in this research provide significant contributions and implications in both theory and practice, which are discussed in the following section.

7.1.2 Theoretical contributions

This research makes three main theoretical contributions to the realm of port risk and resilience from three aspects.

1. It advances the resilience literature by shifting the focus from ports as simplified nodes in wider transport networks to ports as internally interconnected multimodal operational systems. In doing so, it develops a port-centric perspective that explicitly captures subsystem interdependence and the internal propagation of ripple effects, thereby offering a more realistic conceptualisation of how disruptions evolve within multimodal container ports.

2. It extends the theory of resilience assessment by linking dynamic operational behaviour with resilience quantification in a more rigorous way. Rather than relying on conventional performance-based measures that insufficiently distinguish between disruption and recovery, it combines simulation, an improved resilience calculation method, and ER to assess resilience across multiple transport modes and operational levels. This

3876 contributes to a more systematic and operationally meaningful way of measuring resilience in complex port
3877 systems.

3878 3. It broadens resilience research from assessment to decision-oriented resilience management. By
3879 integrating GSA, ML-based resilience prediction, and OM optimisation into a single coherent framework, it
3880 connects resilience modelling with uncertainty quantification and post-disruption decision-making. In this sense,
3881 the research contributes not only to understanding resilience but also to theorising how resilience can be
3882 analysed and improved across the preparedness, response, and recovery stages of disruption management.

3883 **7.1.3 Practical implications**

3884 The practical implications offer a broader rethinking of how multimodal ports should be managed under
3885 disruption. First, the findings imply that port resilience should be managed as an operational and cross-modal
3886 issue, rather than as a purely infrastructural or network-level concern. Because disruptions propagate across
3887 liner shipping, feeder shipping, rail, trucking, and yard operations, resilience cannot be effectively enhanced by
3888 treating each subsystem in isolation. In practice, this means that port operators need to move from fragmented
3889 management towards integrated operational control, with particular attention to critical connection points
3890 through which disruptions spread across the port.

3891 Second, resilience management should become more evidence-based, anticipatory, and time-sensitive. The
3892 results show that some operational disruptions, particularly those associated with quay cranes and yard
3893 congestion, can trigger disproportionate system-wide consequences, and that the early period following a
3894 disruption is especially critical for limiting resilience loss. This suggests that ports should not rely primarily on
3895 experience-based judgment after disruptions occur, but should develop pre-defined intervention thresholds,
3896 scenario-based contingency plans, and real-time monitoring mechanisms that enable earlier and more targeted
3897 action. In practical terms, resilience enhancement depends not only on response capability but also on the ability
3898 to identify where, when, and why intervention is most needed.

3899 Third, improving port resilience requires a shift from isolated asset management towards system-oriented
3900 recovery planning and coordinated governance. The results indicate that maintenance and recovery decisions
3901 should be evaluated in terms of their contribution to port-wide resilience rather than solely by local cost or
3902 equipment condition. At the same time, because many disruption effects extend beyond the port boundary,
3903 resilience enhancement also depends on stronger coordination among terminal operators, port authorities,
3904 shipping lines, hinterland transport operators, and public agencies. Therefore, resilient ports will increasingly
3905 depend on integrated decision support, differentiated investment in critical assets, and multi-stakeholder
3906 coordination mechanisms that align operational recovery with longer-term infrastructure and policy planning.

7.2 Limitations and further research directions

Building on the methodological framework and insights developed in this thesis, several future research directions are identified to further extend the operational detail, computational efficiency and practical applicability of multimodal port resilience analysis.

1. Building on the SD simulation framework developed in Chapter 3, future research can further incorporate fine-grained task-level operational decisions, such as truck assignment, crane sequencing and dynamic task dispatching.

2. Building on the resilience assessment framework developed in Chapter 4, future research can further improve the temporal representation of delayed ripple effects and dynamic subsystem responses.

3. Building on the GSA framework developed in Chapter 5, future research can further refine the probability distributions of disruptive factors when more historical disruption data become available.

4. Building on the OM optimisation model developed in Chapter 6, future research can further incorporate component-level degradation, condition monitoring and predictive maintenance information to support more detailed maintenance decisions.

Additionally, future research can also be conducted in the following directions:

1. In chapter 4, the resilience triangle method evaluates port performance mainly through operational-efficiency-oriented and time-based indicators, while other important dimensions of resilience, such as financial losses, environmental consequences, labour impacts, service reliability, governance capacity, and broader supply-chain effects, should be explored in the future.

2. In chapter 5, disruption variables are assigned uniform probability distributions because of sparse accident records and the difficulty of estimating robust parametric distributions. This is a reasonable modelling choice, but it also means that the probability structure of disruption occurrence may not fully reflect the true tail behaviour, asymmetry, or empirical dependence structure of real-world port disruptions. In the future, with more data, a more realistic distribution should be examined.

3. In chapter 6, the maintenance decision is defined mainly at the equipment level, whereas the internal physical degradation mechanisms of critical components are not explicitly modelled. Although it aligns with port-level operational management, future research should study the component-level diagnosis and maintenance optimisation that aligns with real engineering needs.

4. Future research could extend the proposed framework to smart and fully automated ports by incorporating automated equipment, intelligent control systems, and their associated operational dependencies. This would enable the simulation of automation-specific disruptions, such as control-system, communication, and cyber failures, and allow the resilience framework to be evaluated under increasingly automated port operations.

3941 **APPENDICES**

3942 **Appendix A. Expert interview involved in this research**

3943 To evaluate the robustness and applicability of the proposed model, expert interviews were conducted with
3944 three senior professionals in the maritime and port sectors from China, the UK, and Iran. Each expert has 10–
3945 30 years of experience and is recognised for their contributions to port management through publications and
3946 practice.

3947 The interviews address two core questions:

- 3948 1. Whether the model adequately reflects the operations of a multimodal port.
3949 2. Whether the model can be generalised to other ports with similar facilities.

3950 Key insights from the experts are summarised as follows:

3951 Table A1. Expert background and response for SD model validation.

Expert Number	Role	Country	Years of experience	Expertise	Verification	Applicability
1	Policymaker (Director)	China	Over 20 years	Port governance and risk management	The variables and subsystems included reflect the real challenges we see in port operations.	This model is highly applicable across different port settings.
2	Researcher (Professor)	UK	Over 20 years	Maritime transportation	The structure and the connection between subsystems are sound.	It can be adapted to various port environments.
3	Researcher	Iran	5 years	Risk analysis of complex systems	The model considers interactions between trucks, trains, and vessels. It is very close to real conditions.	The model’s structure allows it to be applied beyond just one specific case.

3952

Appendix B. Theoretical robustness validation for the System

Dynamics model

In this analysis, we assume that vessels are queuing in the port, i.e., the number of available berths is smaller than the number of waiting liner vessels, which is $B_{al} < A_l$. Under this condition, Eq. (1) can be reformulated as $P_l = \frac{B_{al}}{D_{lb}}$, and by substituting it into Eq. (3-2), we obtain the following equation regarding liner ships berthing rate P_l :

$$P_l = \frac{B_l - L_l}{D_{lb}} \quad (\text{B.1})$$

According to the inherent relationship between stock and flow variables in the stock and flow diagram, the stock variable, represented by a box, is defined as the integral of the net flow (i.e., the difference between the inflow and outflow variables, represented by arrows). Based on this formulation, the number of liner ships waiting at the anchorage can be derived as follows:

$$A_l = \sum_{t=0}^T \left(\lambda_l - \frac{B_l - L_l}{D_{lb}} \right) \quad (\text{B.2})$$

We assume that the efficiency of quay cranes is lower than that of internal trucks, which is $\eta_l E_l < A_{ll} \gamma_l$, resulting in internal trucks waiting under the quay cranes. Under this condition, Eq. (3) can be reformulated as $D_{ll} = \frac{C_l}{\eta_l E_l}$ and by substituting it into Eq. (4), we can obtain the following equation regarding the liner ship loading and unloading rate μ_l :

$$\mu_l = \frac{L_l}{D_{ll}} = \frac{L_l \eta_l E_l}{C_l} \quad (\text{B.3})$$

Once again, according to the relationship between stock and flow variables, the number of berths currently occupied by liner ships, which is the number of liner ships conducting loading and unloading work at the berth can be calculated by $L_l = \sum_0^t (P_l - \mu_l)$. By substituting it into Eq. (B.1) and Eq. (B.3), we can obtain the following equation of L_l :

$$L_l = \sum_{t=0}^T \left(\frac{B_l - L_l}{D_{lb}} - \frac{L_l \eta_l E_l}{C_l} \right) \quad (\text{B.4})$$

3971 Since our analysis primarily focuses on the stable condition of the number of vessels operating at berth,
 3972 the integral can be reasonably approximated by a product form during a stable period of Δt :

$$L_l \approx \left(\frac{B_l - L_l}{D_{lb}} - \frac{L_l \eta_l E_l}{C_l} \right) \Delta t \quad (\text{B.5})$$

3973 L_l can be expressed as:

$$L_l \approx \frac{B_l C_l \Delta t}{D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t} \quad (\text{B.6})$$

3974 By substituting Eq. (B.6) into Eq. (B.2), we can obtain:

$$A_l \approx \sum_{t=0}^T \left(\lambda_l - \frac{B_l}{D_{lb}} + \frac{B_l C_l \Delta t}{D_{lb}^2 C_l + D_{lb} C_l \Delta t + D_{lb}^2 \eta_l E_l \Delta t} \right) \quad (\text{B.7})$$

3975 As shown in Eq. (B.7), a reduction in the number of quay cranes E_l leads to an increase in the number of
 3976 vessels waiting in the port. Similarly, an increase in the vessel arrival rate λ_l also results in a higher number of
 3977 waiting vessels. In the following, we further examine how changes in another key variable, the number of berths
 3978 B_l , affect the number of vessels waiting in the port.

3979 Eq. (B.7) can be reorganised as:

$$A_l \approx \sum_{t=0}^T \left[\lambda_l + \frac{B_l}{D_{lb}} \left(-1 + \frac{C_l \Delta t}{D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t} \right) \right] \quad (\text{B.8})$$

3980 To determine the relationship between the number of berths B_l and the number of vessels waiting in the
 3981 port A_l , it is necessary to examine the sign of the coefficient of $\frac{B_l}{D_{lb}}$. Given that $D_{lb} C_l + D_{lb} \eta_l E_l \Delta t > 0$, therefore
 3982 $C_l \Delta t < D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t$, thereby indicating that the coefficient is negative. This implies a negative
 3983 correlation between the number of berths and the number of waiting vessels in the port.

3984 Since the model in this study is constructed in a modular fashion and the formulation for the liner shipping
 3985 area has been validated, the equations governing other subsystems can be considered valid as well.

3986

Appendix C. Publications arising from this thesis

- [1] ZHANG, J. L., XIN, X. R., LIAO, Z. G. & YANG, Z. L. 2024. System Dynamics based analysis of multimodal port accidents. 34th European Safety and Reliability Conference, Jun 23-27 2024.
- [2] ZHANG, J. L., XIN, X. & YANG, Z. L. Operational resilience assessment of Multimodal Container Ports: A Systematic Sensitivity Analysis. Proceedings of the 35th European Safety and Reliability Conference and the 33rd Society for Risk Analysis Europe Conference, 2025.
- [3] ZHANG, J., XIN, X., LIAO, Z., DUBEY, R., NGUYEN, T. T., LI, N. & YANG, Z. 2025. Analysis of the ripple effects of disruptions on multimodal container terminals operations: a System Dynamics approach. *Transportation Research Part E: Logistics and Transportation Review*, 202, 104264.
- [4] ZHANG, J., XIN, X., DUBEY, R., NGUYEN, T. T., SHI, X., LI, N. & YANG, Z. 2025. Impact of the ripple effect on the resilience of multimodal container port operations: A system dynamics simulation approach. *Risk Analysis*, 45, 4903-4932.
- [5] ZHANG, J., XIN, X., DUBEY, R., NGUYEN, T. T., SHI, X., LI, N. & YANG, Z. 2026. Resilience assessment of multimodal container ports under operational disruptions: a global sensitivity analysis. *Transportation Research Part A: Policy and Practice*, 208, 104987.

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