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Analysis of the ripple effects of disruptions on multimodal container terminals operations: a System Dynamics approach ☆

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A R T I C L E I N F O

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A B S T R A C T

Current port risk analyses primarily examine disruptions at an overall port level and their impacts on the broader supply chain. However, they generally overlook how disruptions originating from a specific local-level component within a multimodal port (e.g., liner shipping, feeder shipping, rail transport, trucking, or yard operations) can propagate internally and affect other operational sectors within the port. To address this gap, this study develops a novel microscopic-level System Dynamics (SD) model to quantify these internal ripple effects 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 disruption scenarios derived from real-world accident records and field investigations are simulated to assess their effects on port performance comprehensively. 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 internal ripple effects clearly. Detailed scenario analysis enhances the understanding of these complex ripple effects, supporting robust and holistic strategies for improving port resilience.

1. Introduction

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 transhipment, emerge as crucial gateways connecting different transportation modes, including rail, road, and sea (Zhou et al., 2022, Liu et al., 2022b). 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 regarded as elements characterised by high levels of uncertainty among all parties involved in the CSCs, owing to

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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 disturbed port operations, spreading chaos in warehouses, container reallocation, disruptions in hinterland traffic, and damage to infrastructure, ultimately halting supply chain operability (Gu and Liu, 2023). Additionally, an analytical model has forecasted significant financial impacts due to 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, such as bottlenecking of vessels, accumulation of containers, delays in yard operations, and interruptions in 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 of CSCs (Liu et al., 2023b). As pivotal hubs that link multiple modes of transport for transhipment 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 evident by multiple studies detailed in Table 1. Therefore, modelling the ripple effect across multimodal container ports substantially benefits multiple stakeholders. Terminal operators can optimise the allocation of emergency resources, prioritise strategic initiatives, and enhance overall responsiveness. For instance, when facing seaside congestion, the model can help inform rational decisions on optimal resource allocation to different transport modes to realise the most cost-effective solution. Individual transportation service providers can develop more resilient schedules, reducing delays and costs. Additionally, policymakers can evaluate port infrastructure design and transportation networks from a broader perspective, supporting regional economic development.

After a detailed literature review on the resilience of container shipping, three primary challenges that require attention emerge. Firstly, unlike extensively researched topics such as marine accidents (Feng et al., 2024, Chen et al., 2025, Xian et al., 2025, 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., 2023a, Wang and Wang, 2023), resulting in vague and logically inconsistent connections. Therefore, port disruptions should be analysed based on micro-level variables defined through explicit cause-and-effect relationships. Although micro-level studies pose more significant challenges in terms of quantitative data requirements and tolerance for data uncertainty, they are essential for the clarity and reliability of research findings. Thirdly, disruptions in multimodal ports not only impact the efficiency of the affected area but also cause substantial indirect impacts on global container shipping (Xiao and Bai, 2022), regional distribution (Cao et al., 2025), port efficiency (Liu et al., 2023a), and supply chain costs (Jiang et al., 2021) through ripple effects, which significantly affect supply chain resilience. Despite its significance, to the best of the authors’ knowledge, these challenges remain under-researched. Bridging these gaps necessitates the development of a novel model to depict the causal relationships of disruptions utilising quantitative data within a multimodal framework, focusing on a port-centric perspective.

This study aims to pioneer a new methodology for modelling and analysing how port disruptions impact container terminal operations, specifically focusing on handling general containers using various loading and unloading equipment across multiple transportation modes. Given the dynamic and sensitive nature of port operations in response to disruptions, System Dynamics (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 caused by malfunctions, accidents, and congestion but also provides insights into emergency measures, such as identifying critical risks and the first response period. Moreover, leveraging historical data validates the model’s ability to predict the consequences of real-life disruption scenarios. Additionally, the model assists

Table 1
Indirect and direct costs of 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 price surged
Typhoon Maemi 2004 (Lam et al., 2017)	Natural Disaster	Northeast Asia ports	107 injured; $4.8 billion	91 days port close; $96 million
Tropical Cyclone Debbie 2017 (Lenzen et al., 2019)	Natural Disaster	Northeast Australian ports	14 fatalities; $2.67 billion	8,487 jobs; AUD 2,203 million
Labour strikes 2016–2017 (Gonzalez-Aregall and Bergqvist, 2019)	Man-made	Port of Gothenburg	10%-20% loss of container volume	$496 million

in identifying operational patterns by examining frequently occurring 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 promptly detect and respond to disruptions. For example, if a damaged quay crane is repaired within 72 h, it generally does not significantly impact the efficiency of port operations. 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 h 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 sets 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 study are outlined as follows:

(1) Supported by historical records and real data, this research effectively examines the ripple effects of port disruptions across various transportation modes, including liner shipping, feeder shipping, railway, and trucking.
(2) This research 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 disruption with detailed variables and feedback relationships is built to accurately reflect internal port dynamics under disruptions.

The research is structured as follows. Section 2 reviews the relevant literature, covering topics such as port disruptions, the development of SD in port operation, and ripple effects. In Section 3, leveraging the actual operational logic of a container terminal, a causal loop diagram and stock and flow diagrams are established, identifying key variables and Key Performance Indicators (KPIs) based on both secondary data and expert opinions. Section 4 describes the data collection and model validation method, and performs scenario analysis by employing accidental data. Section 5 compares the consequences of these risks and highlights significant insights and implications. Finally, Section 6 summarises potential improvements and outlines a future research agenda.

2. Literature review

This section examines the state of the art in related research, analysing it to identify gaps and suggest possible enhancements to the proposed model. Specifically, the literature addresses three key areas: port risk analysis, the application of SD in port operations, and the ripple effects of port operational disruptions.

2.1. Port risk analysis

Disruptive factors affecting ports can be broadly categorised into external and internal causes (Li et al., 2024). External factors include social threats (such as piracy and pandemics (Gu and Liu, 2023)), political instability, technological issues (e.g., cyber-attacks), and industrial fluctuations (such as supply chain disruptions (Jiang et al., 2021)), and natural disasters (Lucio et al., 2024). Internal factors, on the other hand, involve human error, equipment and infrastructure failures and organisational or managerial inefficiencies (Cai et al., 2024). Due to their dynamic nature, external factors are often perceived as having a more severe impact on ports, making them the most critical source of uncertainty. Therefore, existing studies tend to focus on the macro-level consequences of these disruptions, such as throughput reduction, delays in global trade, or indices of resilience and vulnerability. 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.

However, 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). 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 rating were used to assess the vulnerability of Tianjin port (Cao and Lam, 2019), expert judgement and statistical analysis were used to assessment 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 operations and disruption dynamics of 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 losses caused by typhoons in seaports, only the shipping-related elements, such as berths and cranes, are considered (Cao and Lam, 2018). Moreover, while some studies recognise the consequences of 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 instead incorporate the interdependencies among multimodal transport modes from a micro-level perspective.

2.2. Application of SD in port operations analysis

In comparison with other methods previously employed in port operation analysis, such as the heuristic method (Zohoori et al., 2023b), focus group (Islam et al., 2021), mathematical modelling (Xiao and Bai, 2022, Zhen et al., 2022), case study (Rogerson et al., 2022, Kim et al., 2021), network theory (Rousset and Ducruet, 2020). Simulation is a powerful tool for understanding interactions in complex systems, monitoring system transitions, and aiding in strategic decision-making. SD, Agent-Based Modelling (ABM) (Ivanov, 2017), Discrete Event Simulation (DES), and Monte Carlo Simulation are among the standard simulation methods used to capture the dynamics of real systems (Ghadge et al., 2022). Their advantages and disadvantages in the context of modelling port disruptions are summarised in Table 2.

The objective of this study is to simulate the ripple effect within a port system under various disruption scenarios. This requires a comprehensive understanding of the interactions of internal operational flows between related variables. To effectively capture and assess such complexity, a system thinking approach based on SD is most appropriate (Sterman, 2010). Fundamentally, past research demonstrates that SD is a robust choice dealing with the complexity and multi-dimensional interactions of a real-world system (Ghadge et al., 2022, Ivanov, 2017). Additionally, SD is particularly effective in illustrating and quantifying complex systems as they evolve, by establishing the causal connections among various factors, risks, and their outcomes (Ghadge et al., 2022, Bell et al., 2023). Unlike many mathematical models, which could lead to unsolvable issues due to restrictive algorithms, SD is praised for its straightforward and realistic approach to demonstrating both linear and nonlinear behaviours (Er Kara et al., 2020). Moreover, SD facilitates scenario-based sensitivity analyses (Valaei sharif et al., 2023a), enabling the evaluation of potential scenarios by adjusting variables to reflect different risk conditions.

While SD has been increasingly used to simulate disruptions in port and logistics systems, most existing studies adopt a macro-level perspective, focusing on strategic policy (Kwesi-Buor et al., 2019, Lin et al., 2022, Liu et al., 2023a, Bell et al., 2023, Xin et al., 2025). These models typically rely on statistically observed patterns and seldom reflect the underlying operational logic and actual feedback mechanisms within port subsystems. The lack of causal clarity and micro-level variables limits the practicality of such models for operational decision-making. This study addresses these gaps by developing an SD model from a micro-level perspective, incorporating real-world variables and causal feedback loops. In doing so, the study contributes a novel simulation framework for understanding disruption dynamics across multimodal port operations.

2.3. Ripple effects in port operations

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

Current literature on the ripple effect predominantly treats the port as a single node within the broader supply chain or shipping

Table 2
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-liner relation	√			√
Accumulation effects	√	√		√

route. Prior examples include optimising container assignment strategies through port skipping (Achurra-Gonzalez et al., 2019), assessing the geographic impact of port disruptions on surrounding supply chain operations (Hossain et al., 2020), evaluating the role of ports within international trade lanes (Xiao and Bai, 2022), analysing the downstream consequences of port failures along the same shipping route (Guo et al., 2023, Bell et al., 2023) and modelling the global reallocation of container cargo flows (Cao et al., 2025).

Based on the above definition, 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 only focused on individual transport modes (Cai et al., 2023, 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 paper investigates the roles of various transportation modes in propagating disruptions and examines explicitly their influence on the efficiency of the port system.

3. Methodology

This section outlines the methodology for developing a simulation of an SD model focusing 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 effect. The construction of the SD model involves six generic steps, as shown in Fig. 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 hypotheses in Section 3.1. 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 interaction between 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 such steps are tailored and adapted to simulate the ripple effect of disruptions on a multimodal container terminal in the ensuing sub-sections. For this study, Vensim PLE software is employed to draw causal loop diagrams and stock and flow diagrams, conduct verification and validation tests, and run simulations.

3.1. Model hypothesis

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

1. Liner shipping and feeder shipping are modelled separately due to their different requirements for loading and unloading resources and their distinct functions in container collection and distribution. Large liner vessels (long-haul services) visit transhipment ports, while small feeder vessels connect the hub with neighbouring ports (feeder ports) in surrounding areas (Jin et al., 2021).

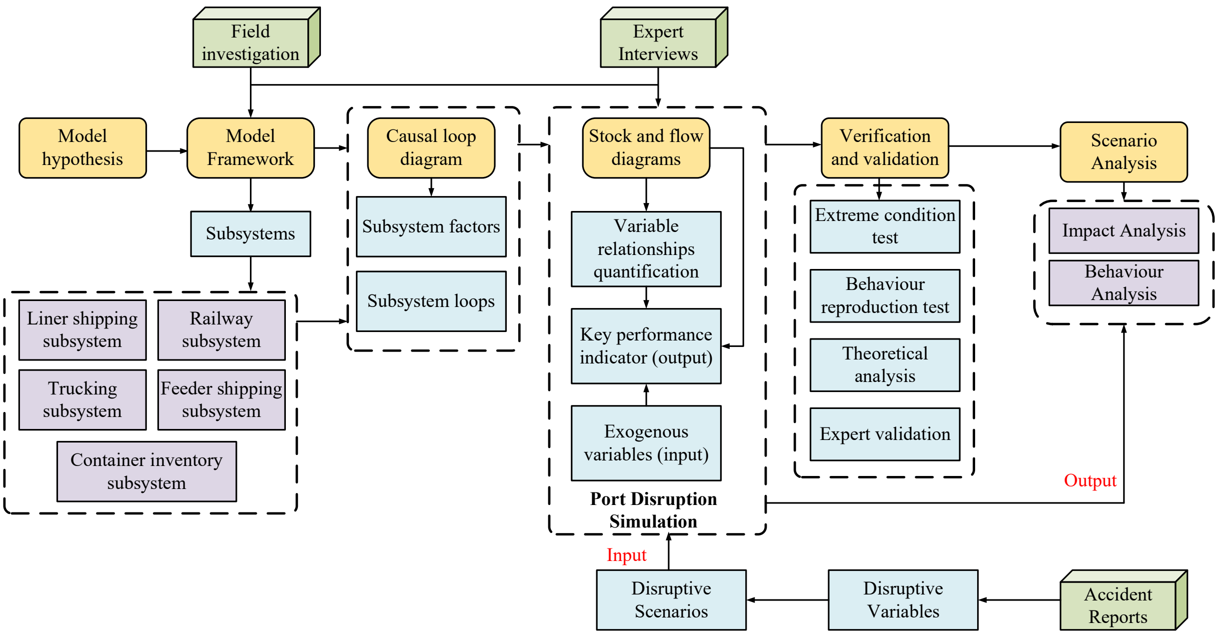


Fig. 1. Flowchart of the work.

2. As a transportation hub, inbound containers are imported by liner vessels and further distributed through feeder vessels, trains, and trucks. Conversely, outbound containers are accumulated in storage 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., 2022).
4. The yard area's operational vehicles consist of internal and external trucks. Internal trucks are prioritised over external trucks, maintaining a more stable operational efficiency and remaining unaffected by the number of external trucks. Therefore, the waiting time of internal trucks is not considered (Li et al., 2022).
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., 2023a).
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. Because the loading and unloading operations in other areas require the cooperation of internal trucks, inefficiencies in internal truck operations lead to inefficiencies in these areas, causing overall inefficiency throughout the port.

3.2. Model framework

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 transhipment 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 due to its flexibility and 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., 2023a).

All relevant concepts in the SD model are listed in Table 3. These factors were initially selected through a literature review and subsequently validated through field investigations and expert interviews.

3.3. Causal loop diagram

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 4. Then, a causal loop diagram is drawn in detail, as seen in Fig. 2. 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.

In Table 4, R1 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 the loading and unloading of vessels must be operated at designated berths with relevant equipment. High efficiency expedites vessel departure rates, decreasing

Table 3
Classification of factors.

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

Table 4
Details of loops.

Notation	Subsystem	Detail
R1	Liner shipping	Liner vessels density $\overset{-}{\rightarrow}$ Available resource for liner vessels $\overset{+}{\rightarrow}$ Liner vessels loading and unloading efficiency $\overset{+}{\rightarrow}$ Liner vessels departure $\overset{-}{\rightarrow}$ Liner vessels density
R2	Liner shipping	Liner vessels loading and unloading efficiency $\overset{+}{\rightarrow}$ Internal trucks for liner vessels $\overset{+}{\rightarrow}$ Truck density $\overset{-}{\rightarrow}$ Liner vessels loading and unloading efficiency
R3	Feeder shipping	Feeder vessels density $\overset{-}{\rightarrow}$ Available resource for feeder vessels $\overset{+}{\rightarrow}$ Feeder vessels loading and unloading efficiency $\overset{+}{\rightarrow}$ Feeder vessels departure $\overset{-}{\rightarrow}$ Feeder vessels density
R4	Feeder shipping	Feeder vessels loading and unloading efficiency $\overset{+}{\rightarrow}$ Internal trucks for feeder vessels $\overset{+}{\rightarrow}$ Truck density $\overset{-}{\rightarrow}$ Feeder vessels loading and unloading efficiency
R5	Railway	Trains density $\overset{-}{\rightarrow}$ Available resource for trains $\overset{+}{\rightarrow}$ Trains loading and unloading efficiency $\overset{+}{\rightarrow}$ Trains departure $\overset{-}{\rightarrow}$ Trains density
R6	Railway	Trains loading and unloading efficiency $\overset{+}{\rightarrow}$ Internal trucks for trains $\overset{+}{\rightarrow}$ Truck density $\overset{-}{\rightarrow}$ Trains loading and unloading efficiency
R7	Truck	Trucks density $\overset{-}{\rightarrow}$ Available resource for trucks $\overset{+}{\rightarrow}$ Trucks loading and unloading efficiency $\overset{+}{\rightarrow}$ External trucks departure $\overset{-}{\rightarrow}$ Trucks density
R8	Truck	Truck density $\overset{+}{\rightarrow}$ Traffic jam $\overset{-}{\rightarrow}$ Trucks loading and unloading efficiency $\overset{+}{\rightarrow}$ External trucks departure $\overset{-}{\rightarrow}$ Truck density

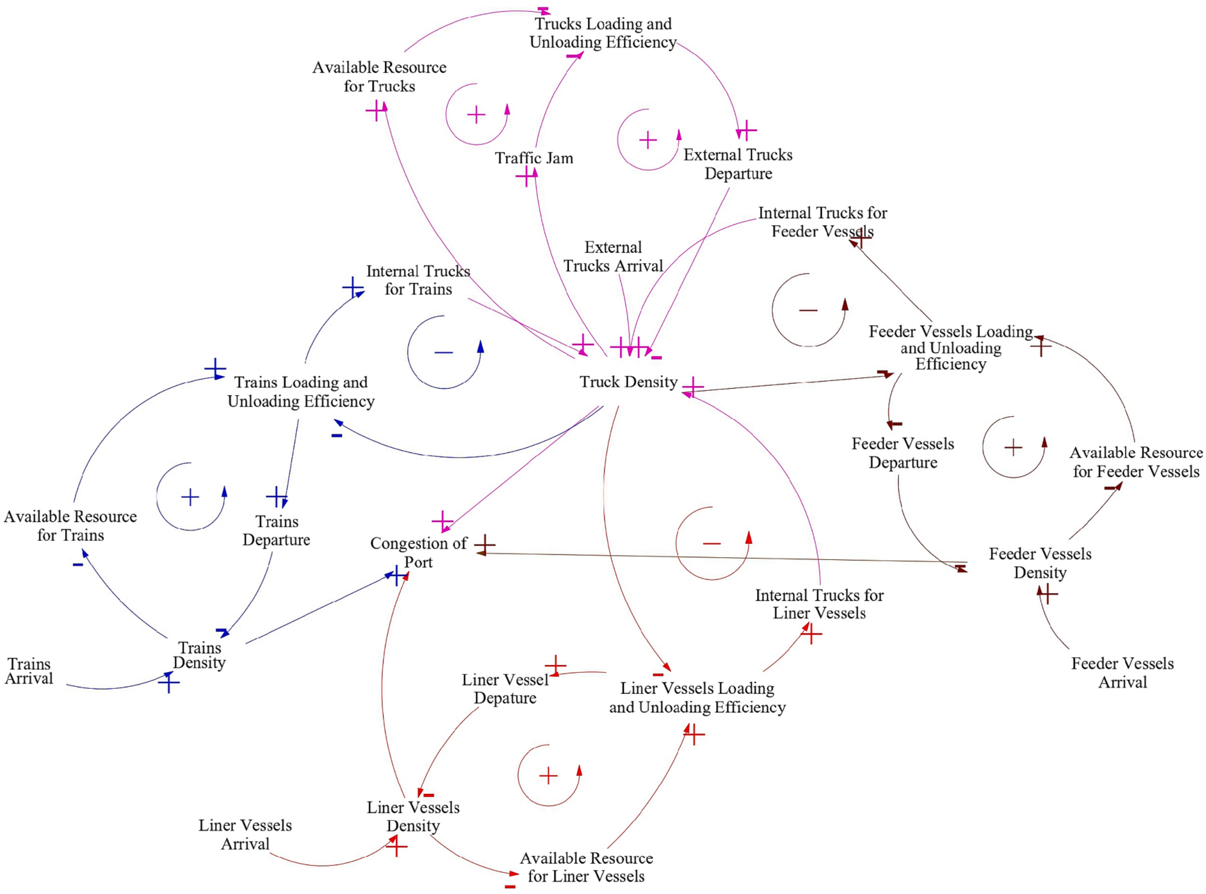


Fig. 2. Causal loop diagram.

waiting vessels and releasing more available resources. R2 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 unwanted delays, extending internal trucks' turnaround time and reducing operational efficiency. Without adequate support from internal trucks, liner vessels' loading and unloading efficiency will diminish. Similarly, R3 (feeder shipping), R5 (railway), and R7 (trucking) share the same logic as R1. R4 (feeder shipping) and R6 (railway) share the same logic as R2.

R8 shows the cyclic relationship of how truck density affects the loading and unloading efficiency of external trucks and internal trucks. Truck operations at a container terminal are divided into external trucks and internal trucks based on their operational scope. External trucks conduct delivery or pick-up services between the port and the hinterland, requiring 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 turnover time and dampening their working efficiency. As a result, the departure rate of external trucks slows down, causing a continuous accumulation within the container yard and leading to a further increase in the density of container trucks.

As a key variable, truck density influences not only the operations of external trucks through R7 and R8 but also the efficiency of other transportation modes through R2 (liner shipping), R3 (feeder shipping) and R6 (railway) via the operations of internal trucks.

3.4. 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 Figs. 3-7. These specific, quantifiable variables are derived from past literature, field research and expert opinions, as depicted in Table 5-6.

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 summarised in Table 5 serve as outputs. Constant variables, also known as input variables, are listed in Table 6, while the remaining variables are classified as intermediate variables.

To assess how operational disruptions affect port efficiency across various transportation subsystems, KPIs are selected to capture delays (e.g., queue length), efficiency (e.g., turnaround time), and capacity stress (e.g., container volume), as shown in Table 5. These KPIs are drawn from a comprehensive literature review and authoritative industrial sources. Specifically, they include reports, indices, and public data provided by international organisations (The World Bank), consulting firms (Drewry), and port authorities (e.g., Port of Long Beach). Similarly, a set of exogenous variables are derived from field investigations and expert consultations from a major container terminal. To avoid redundancy, details about data collection, including their values and sources, typically covered in Section 4.1, are outlined in Table 6 instead. Variables are included if they (1) directly influence operational bottlenecks or resource constraints; (2) participate in at least one feedback loop; or (3) represent quantifiable port efficiency. Transportation modes are denoted as $m = \{l, f, r, t, i\}$ which stands for liner shipping, feeder shipping, railway, external trucks and internal trucks.

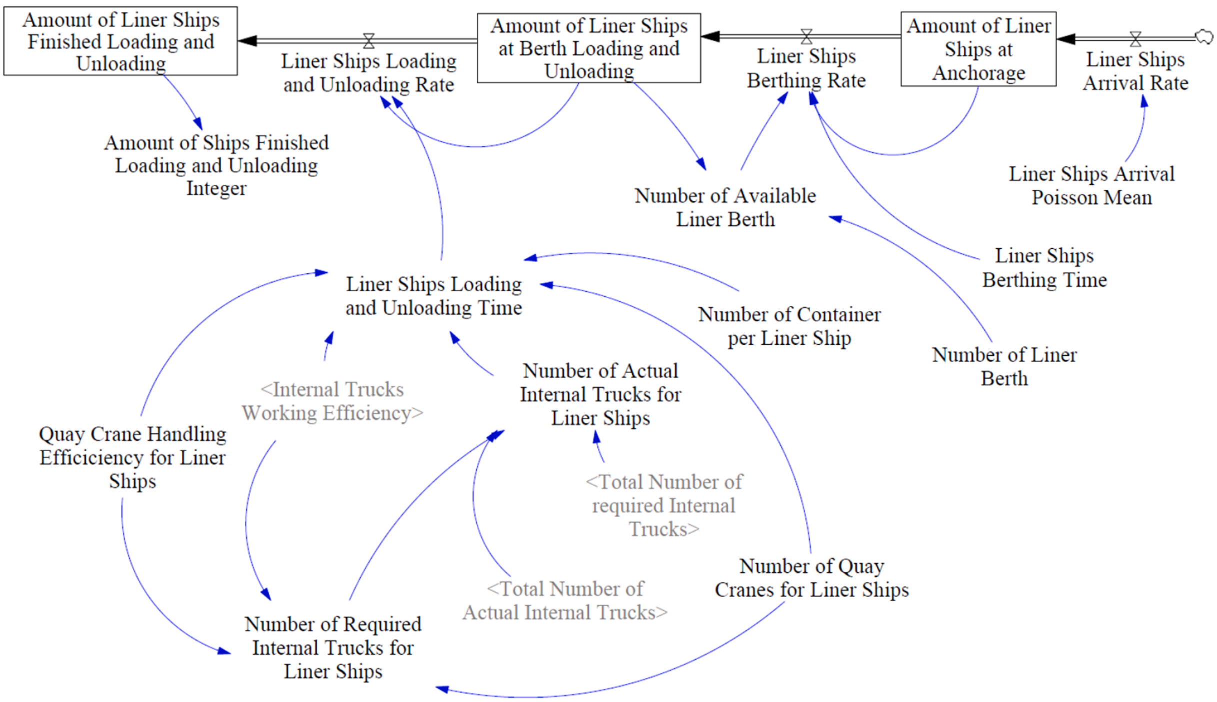


Fig. 3. Liner shipping subsystem.

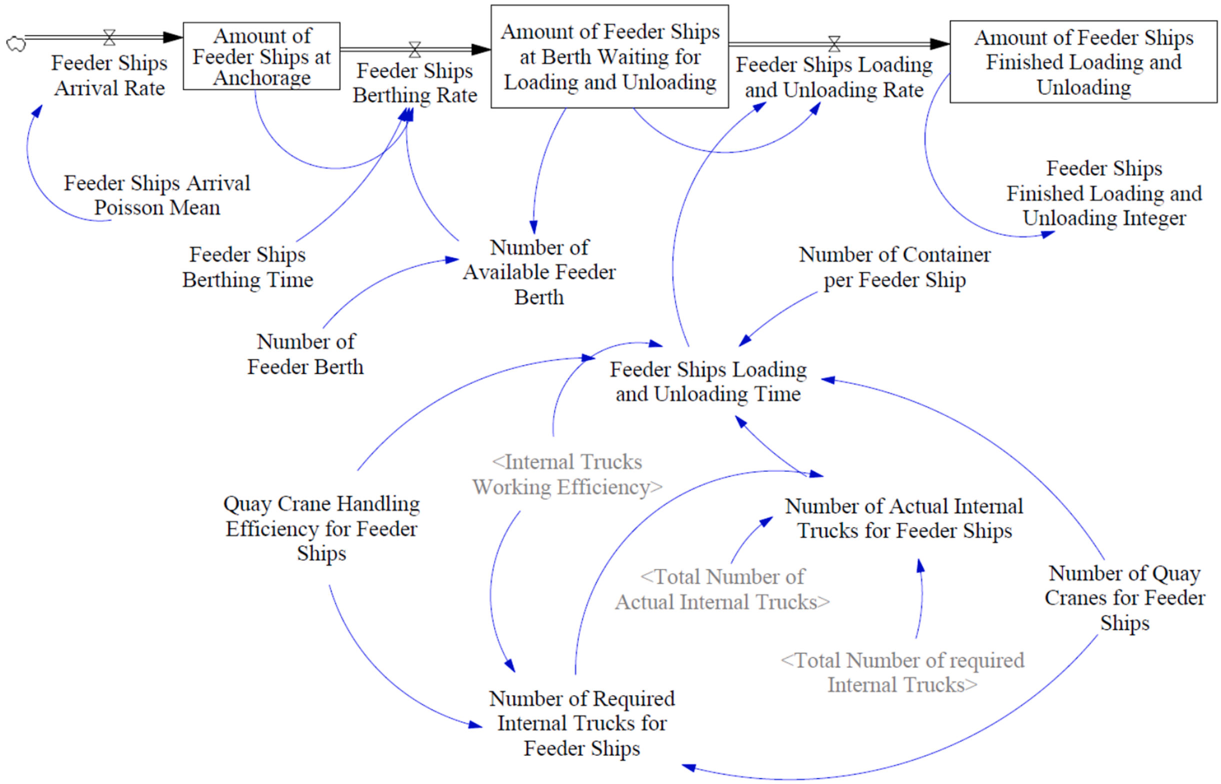


Fig. 4. Feeder shipping subsystem.

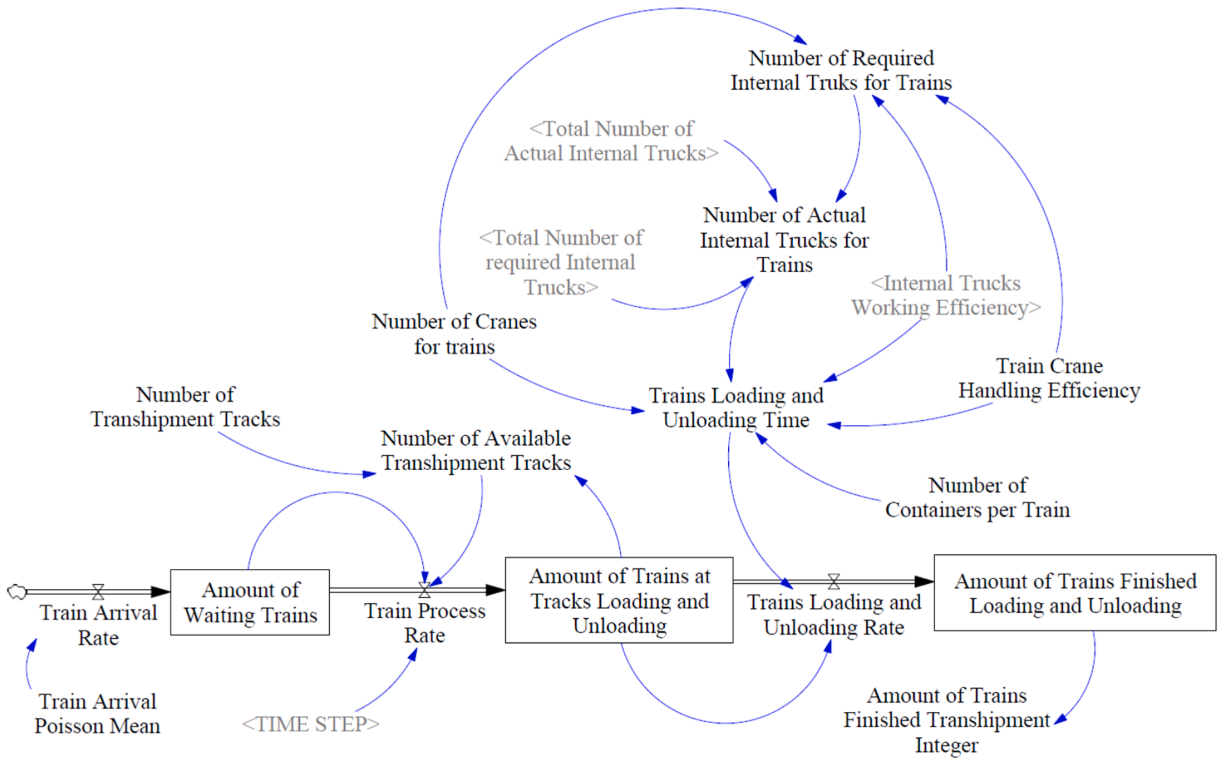


Fig. 5. Railway subsystem.

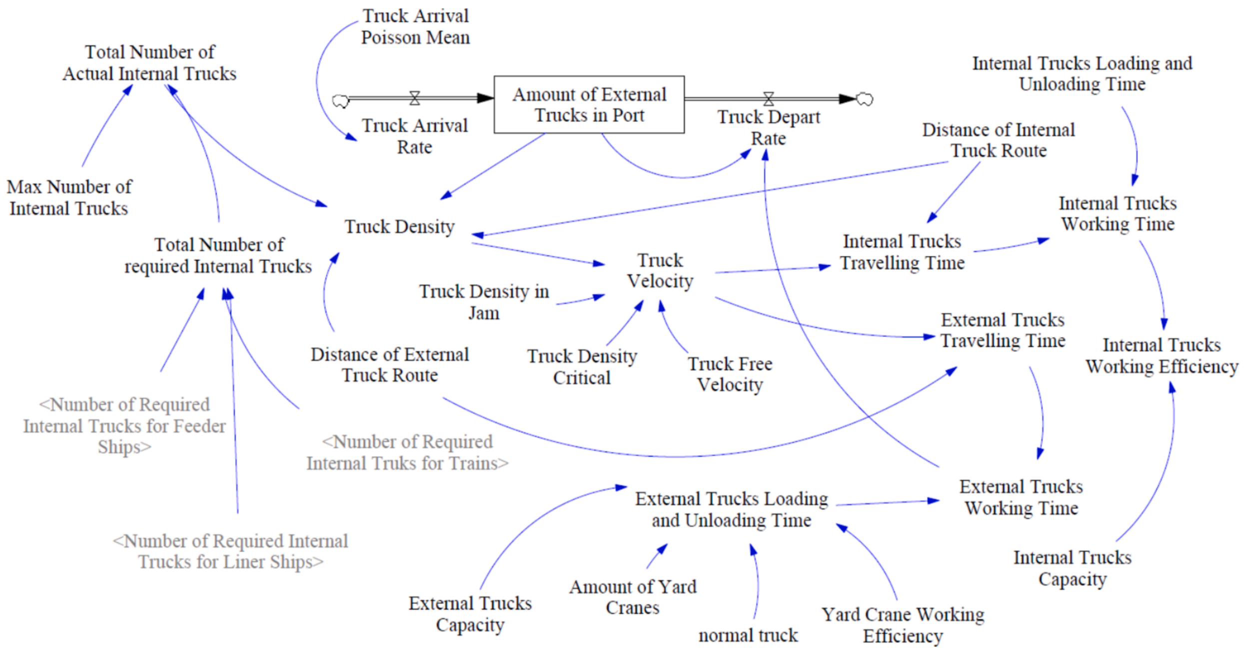


Fig. 6. Trucking subsystem.

3.4.1. *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 Fig. 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.

First, the stock variables represented by boxes are explained as follows. 1) The number of vessels waiting at anchorage gradually accumulates with the arrival of new vessels and diminishes through berthing. 2) The number of vessels engaged in unloading and loading operations at the berth is determined by the difference between vessels currently capable of berthing and those completing loading and unloading operations. 3) The number of departure vessels is accumulated with the rate of vessels finishing loading and unloading activities. These level variables are calculated by the integration of 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}). Therefore, the berthing rate can be calculated as follows:

$$P_l = \begin{cases} \dfrac{min(B_{al}, A_l)}{D_{lb}}, & B_{al} > 0, A_l > 0 \\ 0, & else \end{cases} \tag{1}$$

$$B_{al} = B_l - L_l \tag{2}$$

where B_l is the number of berths for liner vessels, L_l is the number of liner vessels at berthing under loading and unloading operations.

1. 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

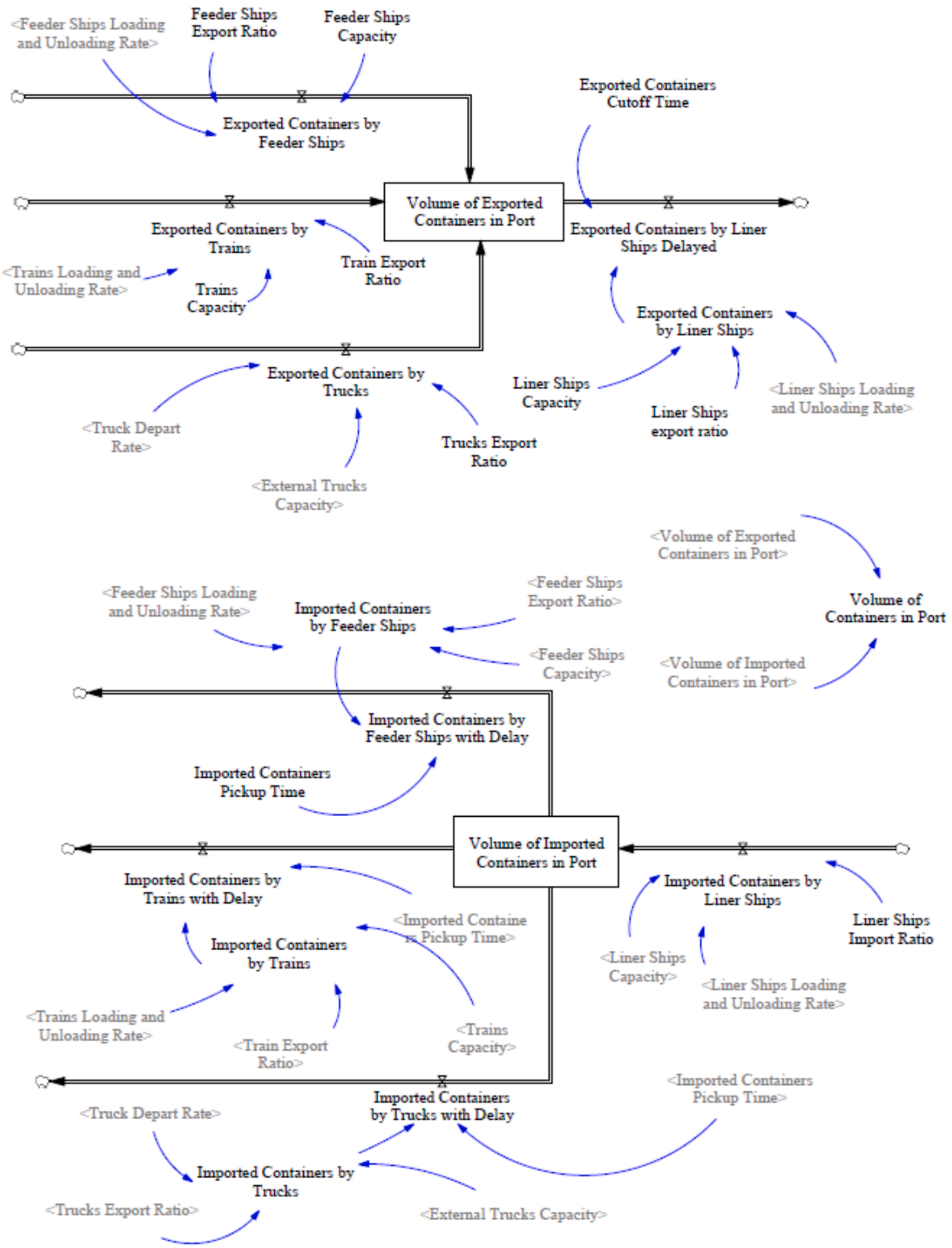


Fig. 7. Containers inventory subsystem.

follows:

$$D_{ll} = max(\frac{C_l}{\eta_l E_l}, \frac{C_l}{AI_l \eta_i}) \tag{3}$$

where C_l is the volume of containers requiring loading and unloading, E_l is the number of quay cranes, η_l is the efficiency of quay cranes operations, AI_l is the number of actual internal trucks, and η_i is the efficiency of internal truck operations. The loading and unloading rate for liner vessels can be modelled as:

Table 5
KPIs. (Output variables).

Category	Notation	Corresponding index	Unit	Literature	Industry
Liner vessels	A_l	Number of Liner Ships at Anchorage	Vessels	(Liu et al., 2023a, Zhou et al., 2022)	(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_t	Number of External Trucks in Port	Trucks	(Liu et al., 2023a, Xu et al., 2021, Li et al., 2018)	(The World Bank, 2023, Port of Long Beach, 2025)
	D_{tw}	External Truck Working Time	Hour	(Li et al., 2018, Sun et al., 2022)	(The World Bank, 2023, Port of Long Beach, 2025)
Containers	V	Volume of Containers in Port	Containers	(Liu et al., 2023a, Lin et al., 2022, Xu et al., 2021)	(Port of Long Beach, 2025)

$$\mu_l = \begin{cases} \dfrac{L_l}{D_{ll}}, & L_l > 0 \\ 0, & else \end{cases} \tag{4}$$

3.4.2. *Feeder shipping subsystem*

Feeder vessels transport containers between neighbouring ports, forming a hub-and-spoke structure, thus facilitating collection and distribution services for liner vessels. Due to the different positions in the transportation network structure, they are simulated in different sectors. However, the operational dynamics of the feeder shipping system and its impact on other modes of transportation parallel those of the international shipping subsystem. To avoid redundancy, the formulas related to feeder shipping are not reiterated, and only the diagram is provided as shown in Fig. 4.

3.4.3. *Railway subsystem*

A significant volume of containers is transported by railway via train tracks. Fig. 5 shows the details of the railway subsystem. The railway subsystem operates under the discipline of train arrival, potential waiting periods if no transhipment tracks are available, transhipment processes, and departure.

1. Train process rate **(**P_r)

Different from shipping, the transit time of a container train from the waiting area to its designated loading and unloading track is very short, rendering it negligible. Thus, the equation for calculating the process rate can be expressed as follows:

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

$$B_{ar} = B_r - L_r \tag{6}$$

where P_r is train process rate, B_{ar} is the number of available transhipment tracks, A_r is the number of waiting trains, B_r is the number of transhipment 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_f), and the number of trains finished loading and unloading (F_r) is the same as explained in section 3.4.1. The loading and unloading rate for trains (μ_r) follows the same logic as Equation (4) in the liner shipping subsystem.

3.4.4. *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 Fig. 6.

3.5. *Truck velocity (v)*

Traffic speed is depicted based on the fundamental road traffic theory, including traffic flow, traffic density, and vehicle speed (Greenshields et al., 1933), as shown below:

Table 6
Exogenous variables (Input variables).

	Notation	Variable	Unit	Estimation	Source	Reference
Liner Shipping system	λ'_l	Liner Ships Arrival Poisson Mean	Vessels/Hour	1.5	Real data	(Bell et al., 2023)
	B_l	Number of Liner Berths	Vessels	16	Real data	(Liu et al., 2023a, Zhou et al., 2022, Lin et al., 2022, Xu et al., 2021)
	E_l	Number of Quay Cranes for Liner Ships	Cranes	6	Real data	(Liu et al., 2023a, Xu et al., 2021)
	C_l	Number of Containers per Liner Ship	Containers	RANDOM UNIFORM (1000, 3000)	Statistics representation derived from real data	(Zhou et al., 2022, Emde and Boysen, 2016)
	η_l	Quay Crane Handling Efficiency for Liner Ships	Containers/ Hour/Cranes	30	Real data	(Liu et al., 2023a, Lin et al., 2022, Jin et al., 2021)
	D_{lb}	Liner Ships Berthing Time	Hour	1	Real data	(Zhou et al., 2022)
Feeder shipping system	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., 2023a, Zhou et al., 2022, Lin et al., 2022, Xu et al., 2021, Lee and Jin, 2013)
	E_f	Number of Quay Cranes for Feeder Ships	Crane	3	Real data	(Liu et al., 2023a, Xu et al., 2021)
	C_l	Number of Containers per Feeder Ship	Containers	RANDOM UNIFORM(500, 1000)	Statistics representation derived from real data	(Zhou et al., 2022, 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., 2023a, Lin et al., 2022, Jin et al., 2021)
	D_{fb}	Feeder Ships Berthing Time	Hour	1	Real data	(Zhou et al., 2022)
Train system	λ'_r	Train Arrival Poisson Mean	Trains/Hour	1.2	Statistics representation derived from real data	(Schulz et al., 2021)
	B_r	Number of Transhipment Tracks	Trains	4	Real data	(Schulz et al., 2021)
	E_r	Number of Cranes for Trains	Cranes	4	Real data	(Liu et al., 2023a)
	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., 2021, Schulz et al., 2021)
	η_r	Train Crane Handling Efficiency	Containers/ Hour/Cranes	30	Real data	(Liu et al., 2023a)
Trucking system	λ'_t	Truck Arrival Poisson Mean	TEU/Hour	500	Real data	(Sun et al., 2022, Li et al., 2018)
	s_t	Distance of External Truck Route	Km	5	Real data	(Li et al., 2022)
	s_i	Distance of Internal Truck Route	Km	3	Real data	(Lee and Jin, 2013, Li et al., 2022)
	ρ_j	Truck Density in Jam	Trucks/Km	60	Average real data	(Greenshields et al., 1933)
	ρ_c	Truck Density Critical	Trucks/Km	20	Average real data	(Greenshields et al., 1933)
	v_f	Truck Free Velocity	Km/Hour	30	Average real data	(Greenshields et al., 1933)
	D_{il}	Internal Trucks Loading and Unloading Time	Hour	0.05	Average real data	(Sun et al., 2022, Li et al., 2022)
	E_y	Number of Yard Cranes	Cranes	48	Real data	(Liu et al., 2023a, Xu et al., 2021, Li et al., 2018)
	η_y	Yard Crane Working Efficiency	Containers/ Hour/Cranes	30	Real data	(Liu et al., 2023a, Li et al., 2018)
	C_t	External Trucks Capacity	Containers/ Trucks	2	Real data	(Li et al., 2022)
	C_i	Internal Trucks Capacity	Containers/ Trucks	2	Real data	(Li et al., 2022)
	E_i	Max Number of Internal Trucks	Trucks	60	Real data	(Li et al., 2022)
	a_t	Coefficient	Dimensionless	−1.5	Real data	(Huynh et al., 2004)
	b_t	Coefficient	Dimensionless	0.0045	Real data	(Huynh et al., 2004)
Container import and export system	α	Exported Containers Cutoff Time	Hour	72	Average real data	(Li et al., 2023)
	β	Imported Containers Pickup Time	Hour	RANDOM UNIFORM(72, 120)	Statistics representation derived from real data	(Jin et al., 2021)
	x_f	Feeder Ships Export Ratio	Dimensionless	0.5	Average real data	(Lin et al., 2022)

(continued on next page)

Table 6 (*continued*)

Notation	Variable	Unit	Estimation	Source	Reference
x_r	Train Export Ratio	Dimensionless	0.5	Average real data	(Lin et al., 2022)
x_t	Trucks Export Ratio	Dimensionless	0.5	Average real data	(Lin et al., 2022)
x_l	Liner Ships Export Ratio	Dimensionless	0.35	Average real data	(Lin et al., 2022)
y_f	Feeder ships capacity	Containers/ Vessels	RANDOM UNIFORM(500, 1000)	Statistics representation derived from real data	(Zhou et al., 2022)
y_r	Trains Capacity	Containers/ Trains	RANDOM UNIFORM(100, 150)	Statistics representation derived from real data	(Xu et al., 2021, Schulz et al., 2021)
y_l	Liner Ships Capacity	Containers/ Vessels	RANDOM UNIFORM (1000, 3000)	Statistics representation derived from real data	(Zhou et al., 2022)

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

In the equation, v represents the current truck velocity, v_f 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.

3.6. Truck departure rate (μ_t)

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_{tl}) is calculated based on the number of cranes, their efficiency, and truck capacity. Preview studies (Huynh et al., 2004) provide empirical data and models that describe how changes in yard equipment availability or efficiency can affect D_{tl}, this relationship is characterised as follows:

$$D_{tl} = \frac{1}{a_t + b_t E_y \eta_y} C_t \tag{8}$$

where C_t 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_t and b_t are the coefficients. Subsequently, the total working time (D_{tw}) is calculated by adding together the loading and unloading time with the travel time (D_{tt}) within the terminal. The travel time is determined by the distance travelled (s_t) and the speed of the external trucks. Finally, the departure rate of external trucks (μ_t) is defined as the ratio of the number of trucks to their total working time, assuming that trucks are present. The equations are as follows:

$$\mu_t = \begin{cases} \frac{A_t}{D_{tw}}, & A_t > 0 \\ 0, & else \end{cases} \tag{9}$$

$$D_{tw} = D_{tt} + D_{tl} \tag{10}$$

$$D_{tt} = \frac{s_t}{v} \tag{11}$$

where A_t represents the number of external trucks in the port.

3.7. Number of actual internal trucks (AI_i)

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

$$RI_m = \frac{\eta_m E_m}{\eta_i}, \forall m = \{l, f, r\} \tag{12}$$

$$RI_i = \sum_{m=l,f,r} RI_m \tag{13}$$

where RI_i is the total number of required internal trucks. However, the resource of internal trucks is constrained by a maximum value E_i:

$$AI_i = min(E_i, RI_i) \tag{14}$$

where AI_i is the total number of internal trucks, and E_i is the maximum number of internal trucks available. Then, the actual number of available internal container trucks is allocated to various subsystems based on their demands. Therefore, the actual number of internal trucks in each subsystem can be modelled as follows:

$$AI_m = \frac{AI_i RI_m}{RI_i}, \forall m = \{l, f, r\} \tag{15}$$

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

3.8. Internal truck working efficiency (η_i)

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

$$\eta_i = \frac{C_i}{D_{iw}} \tag{16}$$

$$D_{iw} = D_{it} + D_{il} \tag{17}$$

$$D_{it} = \frac{s_i}{v} \tag{18}$$

where s_i 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.

3.9. 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:

$$\rho = \frac{A_t + AI_i}{max(s_t, s_i)} \tag{19}$$

The truck density will be further utilised in calculating the velocity of trucks in Equation (7), forming a cyclic feedback loop. The SIMUTENOUS and ACTIVE INITIAL functions in Vensim PLE are used to indicate the dynamic changes in values.

3.9.1. Container inventory subsystem

The investigated port is a pivotal hub, bridging international liner shipping routes with domestic multimodal transportation networks. Therefore, this model examines container inventory from both import and export perspectives, as shown in Fig. 7.

3.9.2. Volume of exported containers (V_{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:

$$V_{out} = \int (O_f + O_r + O_t - O'_l)dt \tag{20}$$

$$O'_l(t) = O_l(t - \alpha) \tag{21}$$

$$O_m = x_m \mu_m y_m, \forall m = \{l, f, r, t\} \tag{22}$$

where V_{out} is the volume of export containers, O_m represents the volume of exported containers under transportation mode m, O'_m is the volume of exported containers by transportation mode m considering the cutoff period, α is the cutoff time for the exported container, and x_m and y_m represent the export ratio and capacity of each transportation mode m.

3.9.3. Volume of imported container (V_{in})

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

$$V_{in} = \int (Q_l - Q'_f - Q'_r - Q'_t)dt \tag{23}$$

$$Q'_m = O_m(t - \beta), \forall m = \{f, r, t\} \tag{24}$$

$$Q_m = (1 - x_m)\mu_m y_m, \forall m = \{l, f, r, t\} \tag{25}$$

where V_{in} is the volume of imported containers, Q'_m is the volume of picked up imported containers after storage time β and Q_m is the volume of imported containers.

3.9.4. Volume of containers in port (V)

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

$$V = V_{in} + V_{out} \tag{26}$$

4. Numerical experiments and results

4.1. Experiment preparation

4.1.1. Data collection and processing

To test the precision and reliability of the proposed SD model, a world-leading multimodal container port (i.e. top 20 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 transhipment 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

Table 7
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 8 and Fig. 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 9.
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.
Sensitivity analysis	Yes	Pass	Shown in Section 4.2.
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.

Table 8
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 Transhipment Tracks	Truck Arrival Poisson Mean
Base condition result	1.5	30	4	500
Extreme condition result	15	1	1	5000

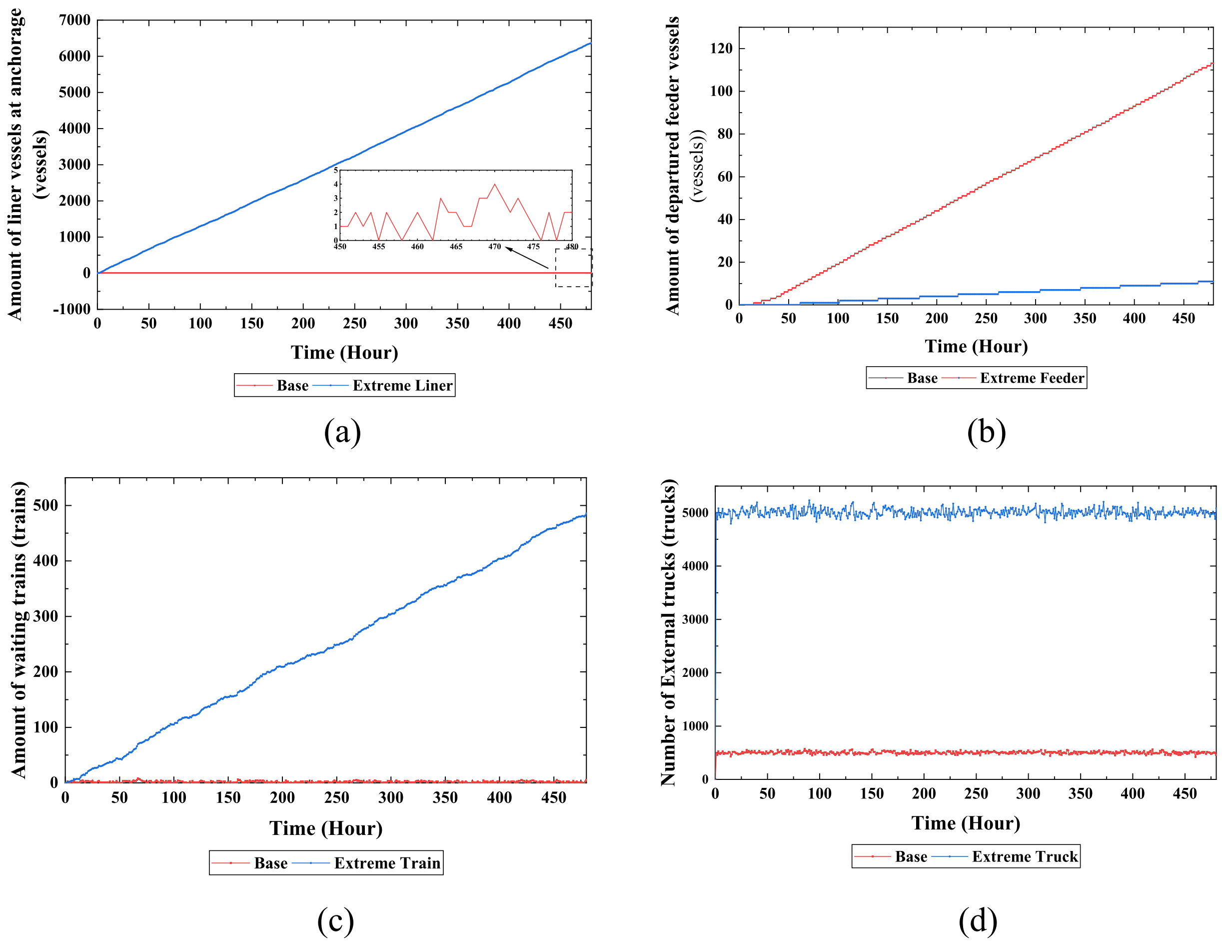


Fig. 8. (a) Number of liner vessels at anchorage when the arrival rate increases by 10 times; (b) number of departure feeder vessels when quay crane efficiency decreases to 1; (c) number of waiting trains when the number of train tracks decreases to 1; (d) number of external trucks when the arrival rate increases by 10 times.

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 variables (shown in Table 6) and KPIs (shown in Table 5), the quantification of relationships between variables and subsystems, the choice of disruptive scenarios (shown in Table 10), and the model validation (shown in Appendix A). (3) Internal accident reports of port accidents from 1998 to 2021 are used to identify representative disruptions and quantify disruptive scenarios (shown in Section 4.1.3).

Table 9
Result 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	102,107.5	110,000	7%
Container throughput per hour	1,251	1,157	8.1%

Table 10
Disruption scenario selection.

Disrupted sectors	Disrupted component	Scenario name	Occurrence Rate	Severity	Typicality
Liner shipping	Quay crane	D1	Highest	High	Yes
Feeder shipping	Quay crane	D2	Highest	High	Yes
Railway	Train tracks	D3	Low	High	Yes
	Train crane	D4	Low	High	Yes
Yard	Yard crane	D5	Highest	High	Yes
	Traffic density (scale)	D6	High	High	Yes
	Traffic density (duration)	D7	High	High	Yes

4.1.2. *Model verification and validation*

Previous literature (Sterman, 2010, Qudrat-Ullah, 2012) has systematically established validation methods for SD models, which are concisely listed in Table 7, 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 sensitivity analysis, the extensive scenario analysis in Section 4.2 serves the same purpose and yields comparable insights. Moreover, similar terminology has been adopted in other studies, where scenario-based approaches are recognised as a form of sensitivity analysis.

(1) Extreme condition test.

Several extreme conditions are set in Table 8. Results demonstrate that the model's behaviours are predictable, as illustrated in Fig. 8. For instance, the number of waiting vessels in the anchorage exhibits exponential growth in response to an unreasonably high arrival rate.

(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., 2023a), 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., 2024, 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 9.

(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., 2023a). 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.

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

To design disruptive scenarios, a multi-criteria approach based on occurrence rate, severity and representativeness is developed, and real-world data and expert judgment are used for assessment. Real data are used to quantify the occurrence rate (see Fig. 9) and severity (see Fig. 10), while expert input is employed to assess the representativeness. As illustrated in Fig. 9, equipment failure, traffic accidents, and container structure damage are among the most frequently occurring incidents in ports. Within the category of equipment failure, yard cranes, quay cranes, and container trucks are most affected. However, since the damage costs associated with container trucks and containers are relatively low, they are excluded. In terms of severity, equipment failure, traffic accidents, and personal injuries account for the majority of severe incidents. Specifically, personal injury incidents, although severe, are rare and fall outside the research boundary of this study and are therefore excluded. The detailed selection criteria and results are presented in

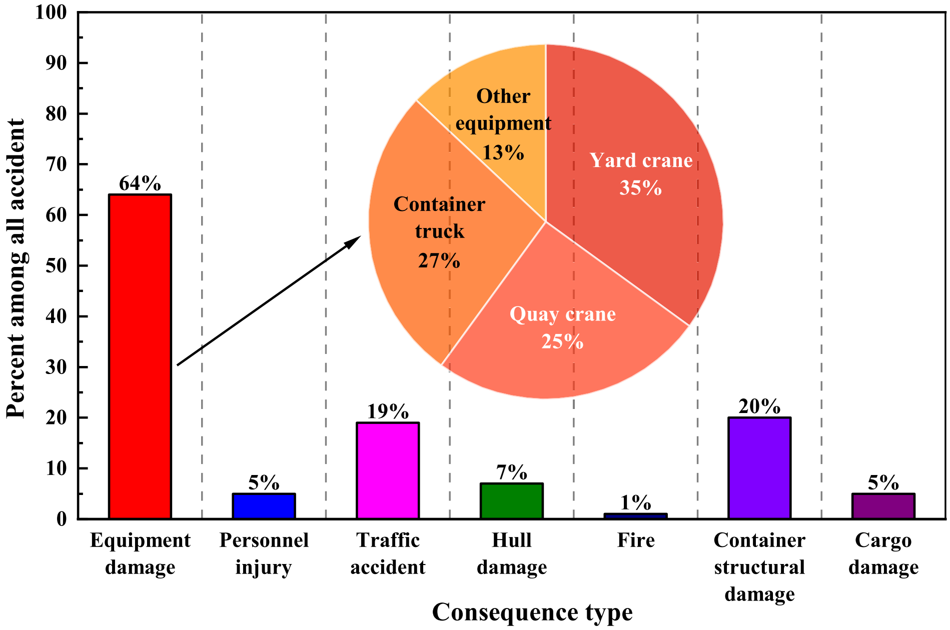


Fig. 9. Percentage of the consequence occurrence rate.

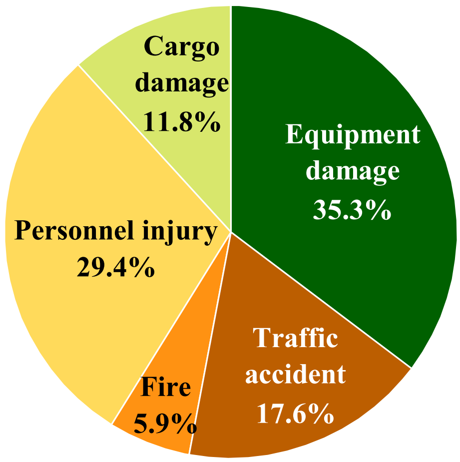


Fig. 10. Percentage of accidents involving major consequences.

Table 10.

Mathematically, different types and degrees of disruptions are illustrated through the various values of variables specified in Eq. (27) with the specific variable names and values detailed in Table 11. The entire simulation is set to last 480 h to reflect the cyclical nature of container shipping, all disruptions are scheduled to occur at the 200-hour mark when the variables are stable. The disruption's lasting time spans multiple periods: 8 h (one shift), 24 h, 48 h, 72 h, 120 h, 240 h and 280 h (the end of the simulation).

Table 11
Parameters of different scenarios.

Disruption name	X	Δx	Δt
D1	E_l	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
D2	E_f	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
D3	E_r	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
D4	B_r	-1	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
D5	E_y	-4	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$
D6	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
D7	ρ	0.5ρ	$\Delta t \in \{8, 12, 24, 48, 72, 120, 240, 280\}$

$$X(t) = \begin{cases} x, & t \leq 200 \\ x + \Delta x, & 200 < t \leq t + \Delta t \\ x, & t + \Delta t < t \leq 480 \end{cases} \tag{27}$$

where $X(t) \in \{E_l, E_f, E_r, B_r, E_y, \rho\}$, each combination of Δx and Δt represents a different scenario.

The simulation steps of the model are as follows:

Step 1: Initialise the model using variables and values from Table 6.

Step 2: If the current time is less than the simulation termination time, then update the system state based on the equations in section 3.4. If the current time equals the start time of the disruption, then adjust the parameter values according to Table 10 and continue updating the system state.

Step 3: Compile and save the results of the simulation using the variables summarised in Table 5.

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

4.2. Experiment results

4.2.1. 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 Fig. 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 Fig. 11 (b). Impacts on other areas are minimal and are therefore not demonstrated. In Fig. 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 h. The same applies to the subsequent similar figures.

As the duration of the loss of a single quay crane extends, the number of ships at anchorage correspondingly increases. Fig. 11 (a) shows that when the disruption lasts less than 72 h, the increase in the number of ships is relatively small. However, after 120 h, 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 h. Besides, the result reveals that disruptions to quay cranes lasting more than 72 h 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 Fig. 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.

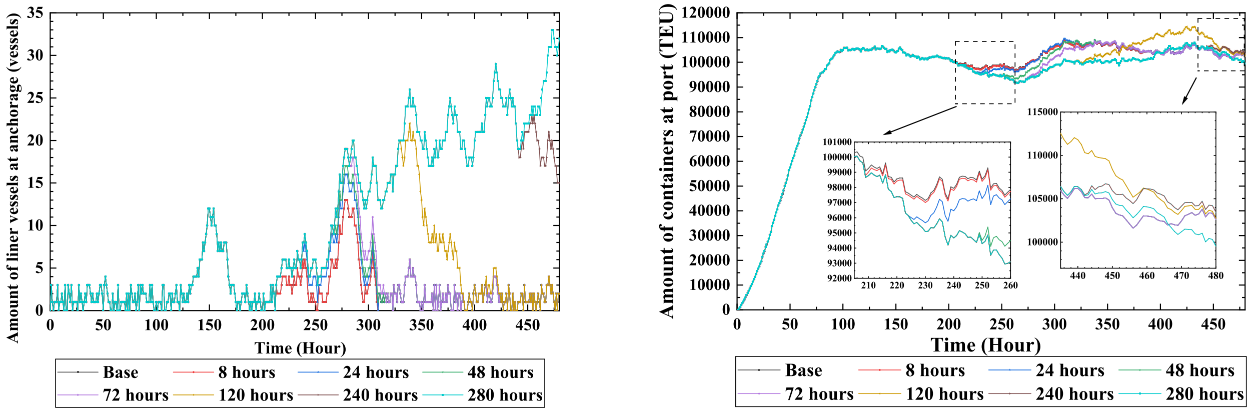
4.2.2. Feeder shipping disruption scenario

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. Fig. 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.

4.2.3. Railway area disruption scenario

The disrupted components in the railway area can be summarised into two main types: the inaccessibility of railway tracks (Fig. 13) and the malfunction of cranes conducting loading and unloading services (Fig. 14). Only the metrics with significant changes are demonstrated and analysed, others with minor changes are neglected due to their lack of relative importance.

It can be observed from Fig. 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 h, indicating a critical turning point between 72 and 120 h. 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 Fig. 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 h 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.



(a) (b)

Fig. 11. (a) Number of liner vessels waiting in anchorage; (b) number of containers stored in the yard when the liner quay crane is disrupted.

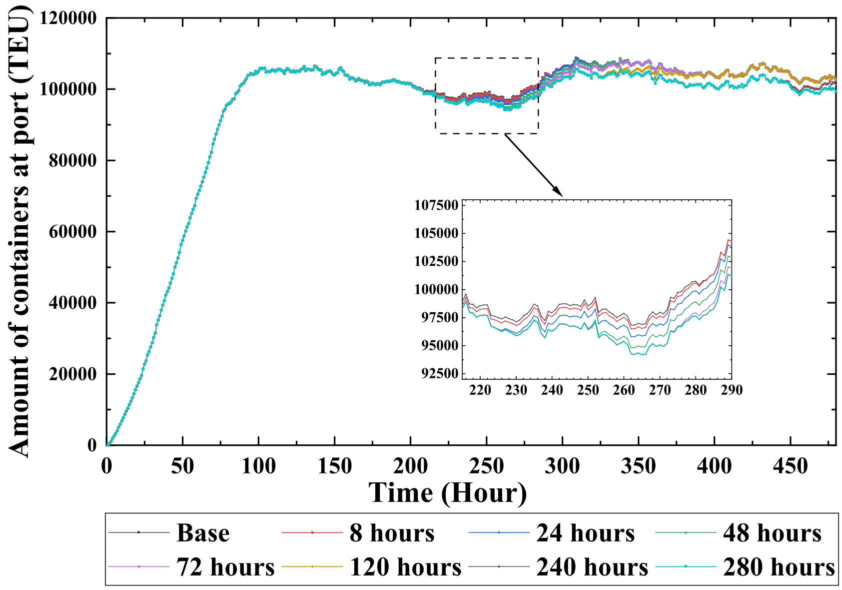


Fig. 12. The number of containers stored in the yard when the feeder quay crane is disrupted.

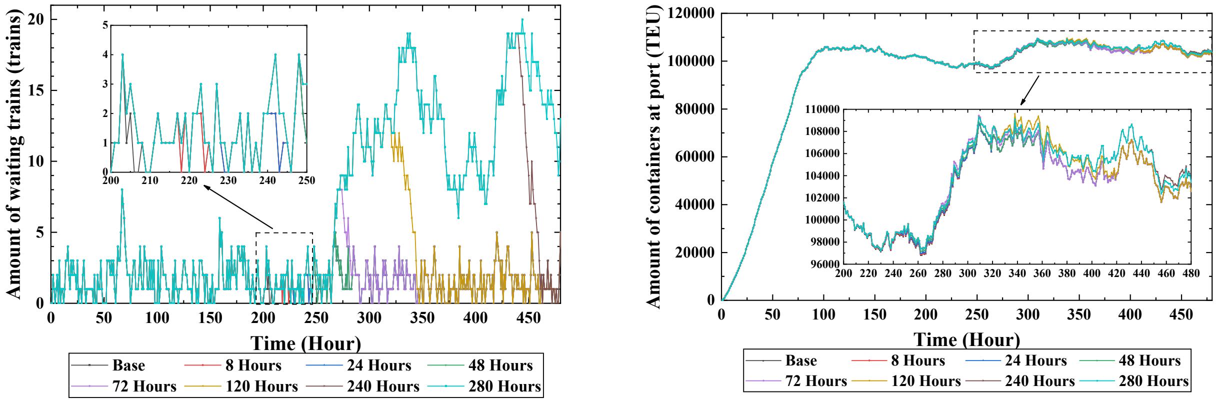
4.2.4. Yard area disruption scenario

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 (Fig. 15). However, as the scale of yard congestion escalates, the ripple effects extend to waiting liner vessels (Fig. 16). Moreover, prolonged yard congestion severely deteriorates port operation efficiency across all transportation modes (Fig. 17).

Fig. 15 illustrates that the turnaround time for external trucks escalates from 0.7 h to approximately 1 h 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 by others.

From Fig. 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 h 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 Fig. 16 (c), there is a noticeable increase in the number of waiting liner vessels. This increase is accompanied by a



(a) (b)

Fig. 13. (a) Number of waiting trains; (b) number of containers stored in the yard when the train tracks are disrupted.

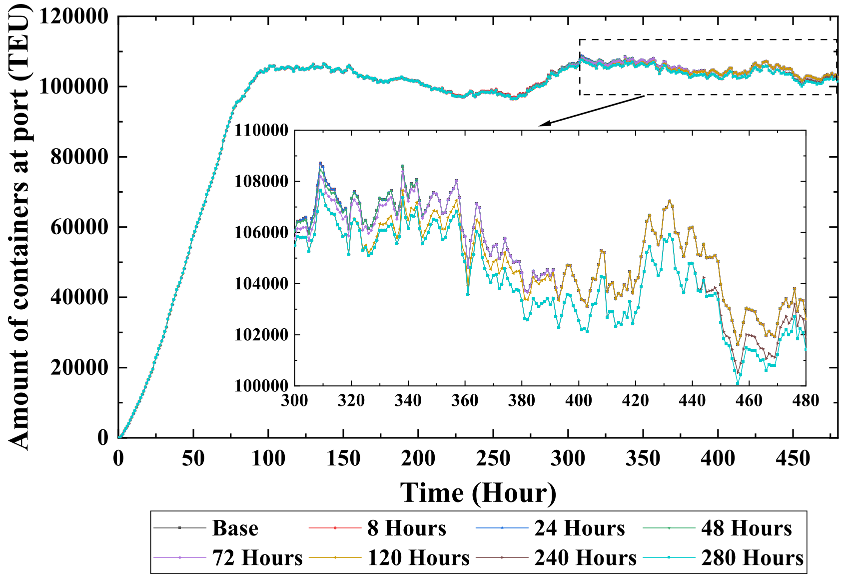


Fig. 14. The number of containers stored in the yard when the train cranes are disrupted.

substantial fluctuation in the container inventory, which reaches up to 4,000 TEUs as illustrated in Fig. 16 (d). These changes are primarily due to that port congestion restricts the mobility of internal trucks, which play a crucial role in facilitating coordinated transhipment 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.

The truck density is designed to increase by 50%, a rate commonly observed during congestion in historical data. These disruptions not only directly impact truck operations but also spread their effects to nearly all other transportation modes. As shown in Fig. 17 (a), the turnaround time for external trucks reflects a consistent pattern of rise and fall, with each cycle lasting between 20 and 50 h. This indicates the system's effort to mitigate congestion, showcasing its capacity to maintain resilience. Consequently, the number of external trucks in the port also follows this pattern, ranging between 500 and 1,100 trucks, as seen in Fig. 17 (b).

Beyond the immediate impacts on trucks, the ripple effects are most severe in the liner vessels and container inventory subsystems, as evidenced by Fig. 15 (c) and (f). Trains also experience notable impacts, albeit to a lesser extent, as depicted in Fig. 17 (e). In contrast, the feeder sector remains largely unaffected, as shown in Fig. 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 h) leads to a systemic increase in

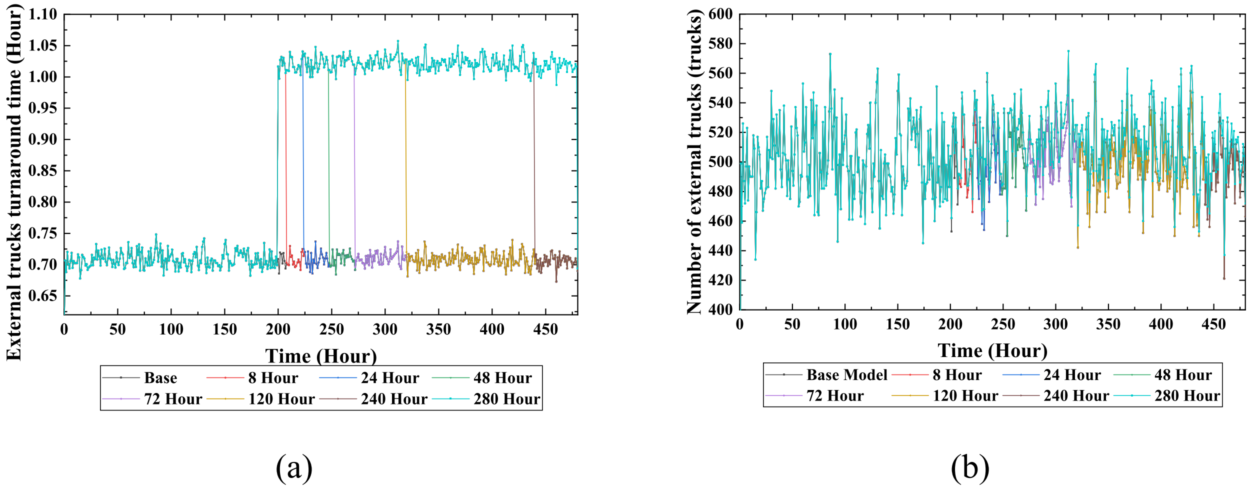


Fig. 15. (a) External truck turnaround time; (b) number of external trucks in port when the yard crane is disrupted.

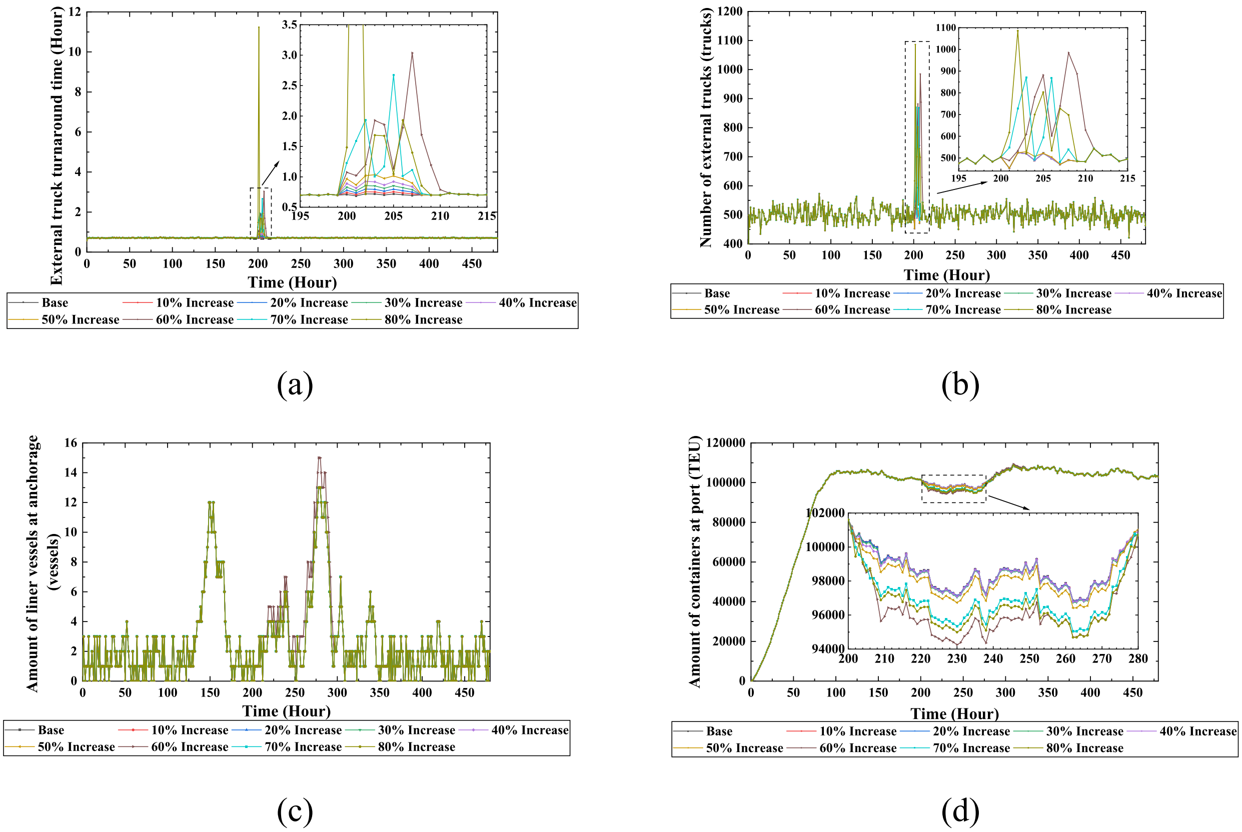


Fig. 16. (a) External truck turnaround time; (b) number of external trucks in port; (c) number of vessels at anchorage; (d) number of containers in port when truck density increases for 8 h.

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

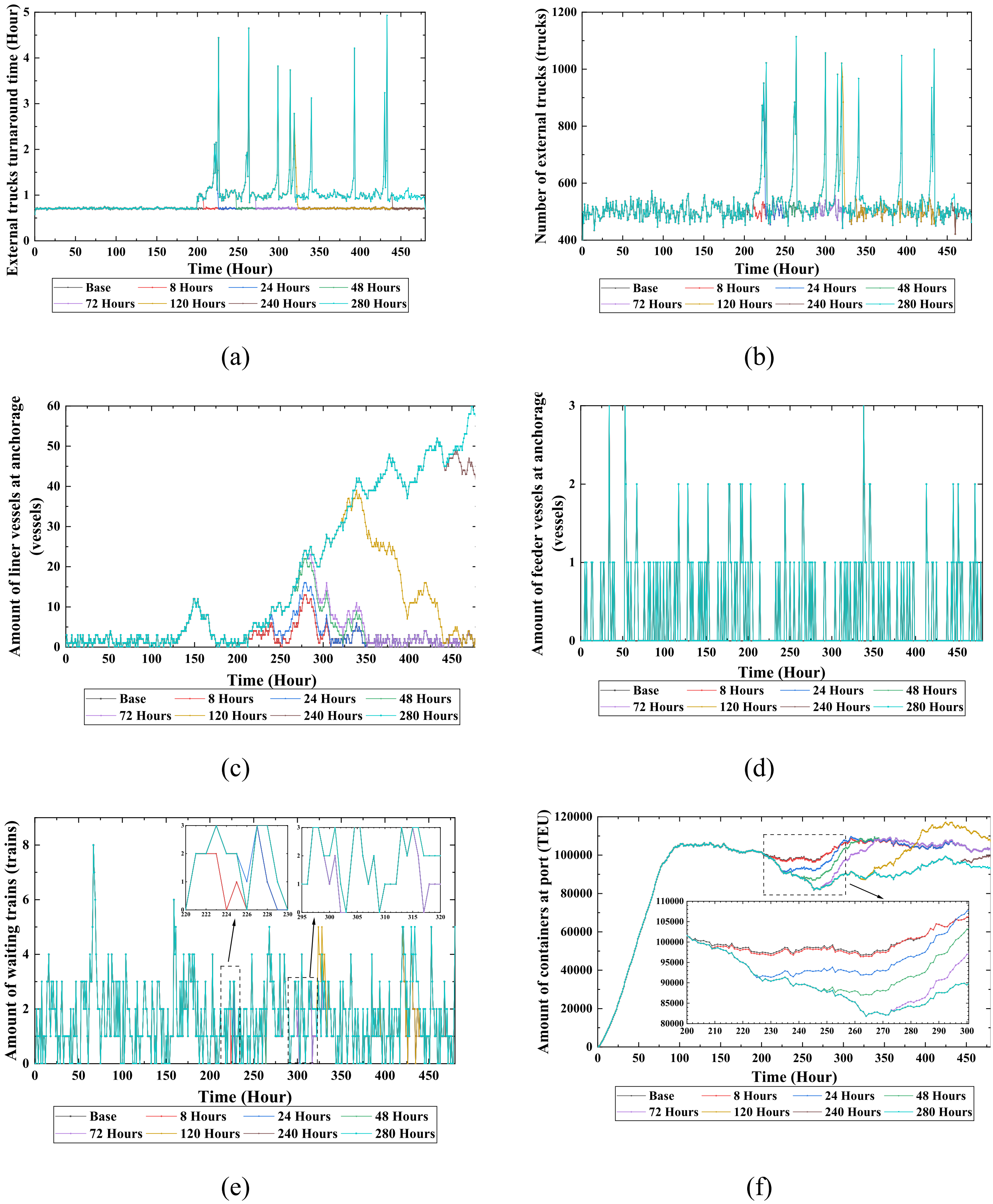


Fig. 17. (a) External truck turnaround time; (b) number of external trucks in port; (c) number of vessels at anchorage; (d) number of feeder ships at anchorage; (e) number of waiting trains; (f) number of containers in port when truck density increases by 50%.

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.

Table 12
Impact measurement index.

Subsystems	KPIs	Minor impact	Major impact	Critical impact	Catastrophic impact
Liner shipping	A_l	$\lvert A_l - A_{l0}\rvert \leq 1$	$1 < \lvert A_l - A_{l0}\rvert \leq 5$	$5 < \lvert A_l - A_{l0}\rvert \leq 10$	$\lvert A_l - A_{l0}\rvert > 10$
Feeder shipping	A_f	$\lvert A_f - A_{f0}\rvert \leq 1$	$1 < \lvert A_f - A_{f0}\rvert \leq 5$	$5 < \lvert A_l - A_{l0}\rvert \leq 15$	$\lvert A_l - A_{l0}\rvert > 15$
Railway	A_r	$\lvert A_r - A_{r0}\rvert \leq 1$	$1 < \lvert A_r - A_{r0}\rvert \leq 5$	$5 < \lvert A_r - A_{r0}\rvert \leq 15$	$\lvert A_r - A_{r0}\rvert > 15$
Trucking	A_t	$\lvert A_t - A_{t0}\rvert \leq 600$	$600 < \lvert A_t - A_{t0}\rvert \leq 800$	$800 < \lvert A_t - A_{t0}\rvert \leq 1000$	$\lvert A_t - A_{t0}\rvert > 1000$
	D_{tw}	$\lvert D_{tw} - D_{tw0}\rvert \leq 0.8$	$0.8 < \lvert D_{tw} - D_{tw0}\rvert \leq 1$	$1 < \lvert D_{tw} - D_{tw0}\rvert \leq 10$	$\lvert D_{tw} - D_{tw0}\rvert > 10$
Containers	V	$\lvert V - V_0\rvert \leq 100$	$100 < \lvert V - V_0\rvert \leq 1000$	$1000 < \lvert V - V_0\rvert \leq 10000$	$\lvert V - V_0\rvert > 10000$

Table 13
Consequences of port disruptions.

Consequence		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

5. Discussion, insights, and implications

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.

5.1. *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 carried out by comparing the differences in 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 12.

Based on Table 12, the influence of specific risks on the performance of each transportation sector is systematically outlined in Table 13. It provides an intuitive perspective on the consequences of each risk scenario, providing evidence for identifying bottlenecks and strategically prioritising resource allocation. Additionally, it supports the development of targeted risk mitigation strategies tailored to specific transportation sectors.

5.2. *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 14.

Table 14 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. 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;
(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;

Table 14
Behaviours 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

Table 15
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; Maintain spare parts and backup resources.
Government and public agencies	Long-term policy and port development	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).
Logistics companies	Depending on the port service for import and export	Collaborate with other stakeholders to minimise disruption impacts; Develop their own contingency plans under disruptive scenarios; Provide training for port-related staff.

(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.

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 15.

6. Conclusion

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

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.

Future research could investigate the coupling effects due to the simultaneous occurrence of multiple disruptions. For example, typhoon-induced damage to quay cranes may coincide with prolonged truck waiting times at terminal gates due to equipment malfunctions. When such disruptions co-occur, their combined impact can amplify port congestion and significantly degrade overall operational performance. Additionally, our study focuses on general containers, but the transportation of hazardous materials within ports is also important for future risk management. In addition, while considering the ripple effect in port operations can enhance risk mitigation, it may also lead to unintended consequences such as excessive redundancy or underutilisation of resources. Moreover, implementing external interventions, such as dynamic truck arrival times or rescheduling vessel calls may disrupt the original plans of shipping companies, trucking companies, or rail operators, thereby increasing operational uncertainty and communication costs. Future research is needed to assess the cost-effectiveness and long-term sustainability of such measures.

CRediT authorship contribution statement

Jinglin Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xuri Xin:** Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Zhigang Liao:** Validation, Resources, Investigation, Data curation. **Rameshwar Dubey:** Writing – review & editing, Supervision. **Trung Thanh Nguyen:** Writing – review & editing, Supervision. **Na Li:** Writing – review & editing. **Zaili Yang:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A

To evaluate the robustness and applicability of the proposed model, expert interviews are conducted with three senior professionals in the maritime and port sectors from China, the UK, and Iran. Each expert has 10–30 years of experience and is recognised for their contributions to port management through publications and practice.

The interviews address two core questions:

1. Whether the model adequately reflects the operations of a multimodal port.
2. Whether the model can be generalised to other ports with similar facilities.

Key insights from the experts are summarised as follows:

Table A1
Expert background and response for 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.

Appendix B

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. (2), we obtain the following equation regarding liner ships berthing rate P_l:

$$P_l = \frac{B_l - L_l}{D_{lb}} \tag{B.1}$$

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:

$$A_l = \sum\nolimits_{t=0}^{T}\left(\lambda_l - \frac{B_l - L_l}{D_{lb}}\right) \tag{B.2}$$

We assume that the efficiency of quay cranes is lower than that of internal trucks, which is $\eta_l E_l < A_{Il} y_i$, 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:

$$\mu_l = \frac{L_l}{D_{ll}} = \frac{L_l \eta_l E_l}{C_l} \tag{B.3}$$

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:

$$L_l = \sum\nolimits_{t=0}^{T}\left(\frac{B_l - L_l}{D_{lb}} - \frac{L_l \eta_l E_l}{C_l}\right) \tag{B.4}$$

Since our analysis primarily focuses on stable condition of the number of vessels operating at berth, the integral can be reasonably approximated by a product form during a stable period of Δt:

$$L_l \approx \left(\frac{B_l - L_l}{D_{lb}} - \frac{L_l \eta_l E_l}{C_l}\right)\Delta t \tag{B.5}$$

L_l can be expressed as:

$$L_l \approx \frac{B_l C_l \Delta t}{D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t} \tag{B.6}$$

By substituting Eq. (B.6) into Eq. (A.2), we can obtain:

$$A_l \approx \sum\nolimits_{t=0}^{T}\left(\lambda_l - \frac{B_l}{D_l b} + \frac{B_l C_l \Delta t}{D_{lb}^2 C_l + D_{lb} C_l \Delta t + D_{lb}^2 \eta_l E_l \Delta t}\right) \tag{B.7}$$

As shown in Eq. (B.7), a reduction in the number of quay cranes E_l leads to an increase in the number of vessels waiting in the port. Similarly, an increase in the vessel arrival rate λ_l also results in a higher number of waiting vessels. In the following, we further examine how changes in another key variable, the number of berths B_l, affect the number of vessels waiting in the port.

Eq. (B.7) can be reorganised as:

$$A_l \approx \sum\nolimits_{t=0}^{T}\left[\lambda_l + \frac{B_l}{D_{lb}}\left(-1 + \frac{C_l \Delta t}{D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t}\right)\right] \tag{B.8}$$

To determine the relationship between the number of berths B_l and the number of vessels waiting in the 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 $C_l \Delta t < D_{lb} C_l + C_l \Delta t + D_{lb} \eta_l E_l \Delta t$, thereby indicating that the coefficient is negative. This implies a negative correlation between the number of berths and the number of waiting vessels in the port.

Since the model in this study is constructed in a modular fashion and the formulation for the liner shipping area has been validated, the equations governing other subsystems can be considered valid as well.

Data availability

Data will be made available on request.

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