Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen
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doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P5616-cd

Operational Resilience Assessment of Multimodal Container Ports: A Systematic Sensitivity Analysis

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Evaluations of port operational resilience currently focus on risks from individual components and/or sub-systems as an isolated entity, often overlooking the ripple effects across the components (e.g. the various transportation modes) within a port. Essential components such as liner shipping, feeder shipping, railways, and trucking form the operational backbone of a multimodal container port. As port functionality becomes more complicated to meet the development of new technologies, the need to accurately assess, measure, and sustain port operational resilience has intensified. However, the ripple effect of disruptions poses significant challenges in assessing this from a global systematic perspective. In response, a resilience assessment framework is newly designed specifically for multimodal container ports. This framework comprises four main elements: a System Dynamics (SD) simulation for simulating the operations of a multimodal container port; a resilience quantification model that translates system performance into a resilience metric based on three key criteria; an Evidential Reasoning (ER) based evaluation model that aggregates the resilience of various subsystems into an overall port resilience level; and a Global Sensitivity Analysis (GSA) technique, which employs Sobol sampling and Sobol sensitivity analysis to quantify the impact degree of both individual and combined disruptions. A series of disruptive scenarios, informed by historical failures and field investigations, are investigated to quantify port resilience extent at different levels to guide the rational countermeasure development. The experimental findings highlight the impact of traffic congestion, yard crane incidents, and liner quay crane accidents on port resilience. It is also evident that most significant disruptions are not formed by failures from individual components at a local level; rather, they interact with each other, causing ripple effect. This framework, for the first time to the authors' best knowledge, offers crucial insights for bolstering long-term resilience in container port operations from an overall port systematic perspective.

Keywords: Container Supply Chain, Port Disruption, Ripple Effect, Resilience, Global Sensitivity Analysis.

1. Introduction

Ports, as vital transshipment hubs in global container supply chains, play a pivotal role in facilitating international trade and economic growth. However, their distinctive geographical locations, political and economic stability, and environmental issues expose them to a range of uncertainties (Jiang et al., 2021). Previous literature has demonstrated that a variety of risk types, such as global pandemics, natural disasters, labor strikes, political conflicts, and economic imbalances, can all disrupt port operations (Zhang and Lam, 2015, Cao and Lam, 2018). Additionally, the transshipment functions of ports require seamless coordination across various transportation modes, including liner shipping, feeder shipping, railways, and trucking. Disruptions in one part of this interconnected network can trigger a cascade of impacts, known as the ripple effect (Verschuur et al., 2022). Recent studies demonstrate that the indirect losses resulting from the ripple effect often far surpass the direct damages (Afenyo et al., 2022).

Consequently, incorporating the ripple effect into port risk management strategies is essential for maintaining robust and resilient operations.

Numerous studies have focused on port resilience, among which the most rigorous defines its fundamental aspects into three criteria: (i) overall reliability, (ii) average robustness, and (iii) average recovery ability (Cheng et al., 2022). In contrast to other metrics employed to assess systems' responses to disruptions, the concept of resilience provides a comprehensive representation of the system's capabilities during both performance degradation and recovery phases within the observation period. A critical step in maintaining and enhancing port resilience involves the application of robust scientific methods to determine the impacts of various disruptions.

Although the analysis of the ripple effect in port disruptions has attracted significant attention from both industry and academia, much of the existing literature continues to treat the port as a singular entity, failing to account for the interdependence of diverse transportation modes within the port. This is reflected in the strategy of port skipping (Achurra-Gonzalez et al., 2019), the redistribution of container cargo flows (Cao et al., 2025), the construction of port infrastructure, and its relationship with the surrounding areas (Hossain et al., 2020), as well as the impact of ports on trade lanes (Bell et al., 2023). This oversight leads to an underestimation of the ripple effect of operational disruptions on port efficiency across different modes within multimodal transportation systems.

This study introduces a novel framework to assess the impact of disruptions on container terminal operations, identifying key factors and their ripple effects across different transportation modes, thereby making new contributions as follows:

(i) Considering the dynamic and intricate nature of port operations during disruptions, System Dynamics (SD) is employed to capture the complex interactions and potential ripple effect within port operations. Compared with other simulation methods, such as Discrete event simulation (DES), agent-based modeling (ABM) and Monte Carlo Simulation (Ghadge et al., 2022), SD is chosen for its ability to represent intricate causal relationships via feedback loops, dynamic behaviors, and handle uncertainties in various scenarios.

(ii) Based on previous research, resilience metrics are classified into three categories: topological, attribute-based, and performance-based (Wang and Yuen, 2022). Among these, performance-based metrics are favored for their ability to capture the dynamic changes of a system over time and their applicability across varying system characteristics. Among performance-based metrics, the refined resilience triangle (Ayyub, 2014) is chosen for its comprehensive coverage of the three key attributes of resilience outlined previously.

(iii) Port efficiency is reflected through distinct sets of KPIs corresponding to different transportation modes. Therefore, the effective integration of these indicators and the clear presentation of the outcomes are crucial. Evidential Reasoning (ER) (Yang and Singh, 1994) is selected as the method for aggregating these KPIs. In contrast to other integration methods such as the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Decision Making Trial and Evaluation Laboratory (DEMATEL), ER does not depend on subjective input, thereby enhancing the objectivity and precision of the results. Furthermore, ER enables the display of middle-level variables within the constructed integration model, providing significant advantages for subsequent analyses. item one

(iv) Investigating the extent to which disruptions affect port operation efficiency, specifically how changes in model input parameters influence model outputs, falls within the scope of sensitivity analysis (SA). Among various SA methods, such as local, Morris, regression, and metamodel approaches, Sobol (Saltelli et al., 2010) is selected. Recognized as one of the most robust global SA methods, Sobol is particularly effective for complex systems and nonlinear relationships. This method not only determines the impact of individual parameters on model outputs but also assesses the joint effects of multiple parameters. Such capabilities are essential for understanding the ripple effect, as risk propagation within the port can result in cumulative impacts.

The remainder of the paper is structured as follows. Section 2 details the structure of the proposed methodology, including SD, the resilience calculation method, ER, Sobol SA and model validation, supplemented by necessary diagrams, tables, and equations. Section 3 presents experimental results, discussion and practical implications. Section 4 concludes the paper with directions for future research.

2. Methodology

This section provides a detailed exposition of the methodology employed to identify key disruption factors that impact the resilience of multimodal container ports through ripple effects. Illustrated in Fig. 1, the approach begins with simulating port operation using SD under normal conditions as the baseline, as elaborated in Section 2.1. This section also includes the identification and characterization of various disruptive sources based on expert opinions and field studies. Meanwhile, KPIs for port operations are selected. Resilience values for each KPI are computed by comparing outcomes from normal and disruptive scenarios, following the three predefined resilience criteria specified in Section 2.2. Subsequently, the overall resilience of the port, reflecting the performance across all KPIs, is aggregated using the ER method based on a three-tier hierarchy. Lastly, Sobol SA quantifies the relative contribution of each disruption factor on port operational resilience, involving the determination of Probability Density Functions (PDFs) for each factor and employing Sobol sampling to generate a quasi-random sample within the multidimensional input space, as discussed in Section 2.4.

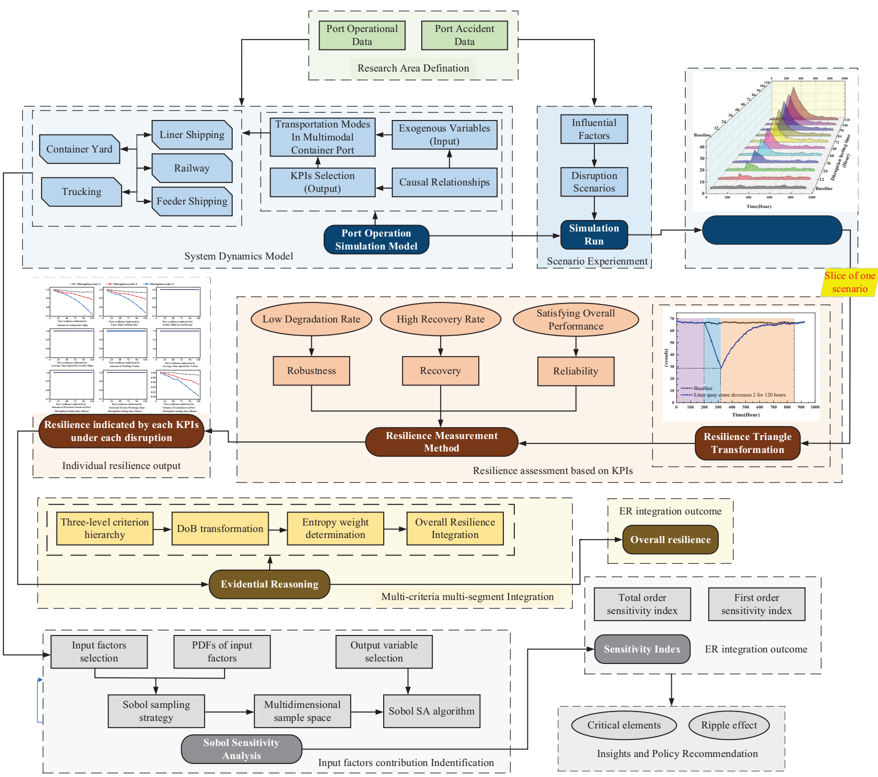

Fig. 1. Methodology framework

2.1. *Port operation simulation*

The development of the simulation model involves several key stages: (i) setting modeling assumptions, (ii) defining simulation protocols, (iii) choosing key elements, and (iv) determining KPIs.

2.1.1. *Modeling assumptions*

Before elaborating on the model, the following assumptions are assumed based on field research and prior studies (Liu et al., 2023, Li et al., 2022, Jin et al., 2021):

(i) The multimodal container port comprises four transportation modes: liner shipping, feeder shipping, railway, and trucking. Liner and feeder shipping are modeled separately to reflect their specific functions in container transshipment.

(ii) Inbound containers are imported by liner containerships and then distributed via feeder containerships, trains, and trucks, while outbound containers are gathered in yards by feeder containerships, trains, and trucks before being exported by liner containerships.

(iii) Internal trucks manage movements within the port, facilitating loading and unloading operations among all transport modes.

(iv) Yard operations involve both internal and external trucks, prioritizing internal ones to maintain efficiency regardless of external truck fluctuations.

(v) Port efficiency is constrained by the availability of resources such as berths, cranes, and other equipment.

(vi) Internal trucks cause the ripple effect within the port, as loading and unloading require coordinated operations of cranes and trucks across different subsystems, allowing inefficiencies in one area to affect others.

2.1.2. *Simulation protocols*

The SD model in this study utilizes a modular structure, encompassing five primary transportation modes (subsystems): liner shipping, feeder shipping, railway, trucking, and the container yard. It is essential to understand that these subsystems are interconnected, with inefficiencies in one potentially spreading to the others. The causal loop diagram is developed based on field research and previous studies, as shown in Fig. 2. A world-leading multimodal container terminal, renowned for its international influence, comprehensive operations, and risk management strategies, provides the data to formulate the quantitative part of the diagram. The terminal's standardized layout, common among many container facilities, ensures that the developed framework can be applied broadly across similar sites.

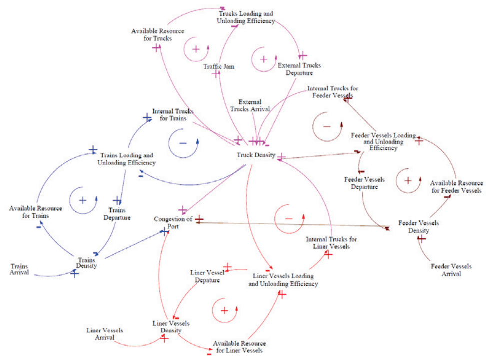

Fig. 2. Casual loop diagram of SD model.

2.1.3. *Key element selection*

The factors in the causal loop diagram are effectively quantified in the stock and flow diagram by selecting variables that embody the established logical relationships. These variables, as shown in Table 1, are selected based on past literature and expert insights and function as key elements.

Table 1. Key elements.

Subsystem	Factor
Liner shipping	Arrival and departure rate of liner containerships, loading and unloading resources (berths, cranes), handling efficiency, capacity
Feeder shipping	Arrival and departure rate of feeder containerships, loading and unloading resources (berths, cranes), handling efficiency, capacity

Railway	Arrival and departure rate of trains, loading and unloading resources (tracks, cranes), handling efficiency, and capacity.
Truck	Arrival and departure rate of external trucks, internal trucks, yard cranes, handling efficiency, traveling speed, capacity, traveling distance
Container Yard	Container volume, export rate, import rate, cutoff time

2.1.4. *KPIs selection*

The model selects industry-recognized port efficiency KPIs based on expert guidance to evaluate port resilience against disruptions, as shown in Table 2.

Table 2. KPIs.

Transportation modes	KPIs	Unit
Liner shipping	Amount of waiting liner containerships	Vessels
	Liner containerships waiting time	Hours
Feeder shipping	Amount of waiting feeder containerships	Vessels
	Feeder containerships waiting time	Hours
Railway	Amount of waiting trains	Trains
	Trains waiting time	Hours
Trucking	Amount of external trucks in port	Trucks
	External trucks' working time	Hours
Container yard	The volume of containers in the port	Containers

2.2. *Resilience measurement method*

This study introduces an innovative resilience assessment method that meets the resilience calculation standards by highlighting the core elements of resilience: reliability, robustness, and recovery, as illustrated in Eq. (1) and Fig. 3 (Ayyub, 2014). Its scientific accuracy and rigor have been well recognized and validated within the academic community, yet its use in evaluating port resilience is still to be explored.

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

$$F = \frac{\int_{T_i}^{T_f} f(t)dt}{\int_{T_i}^{T_f} P_0(t)dt} \qquad (1)$$

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

where R_e is the resilience of the system, the failure profile F can be considered as a measure of robustness and redundancy, and the recovery profile R is considered as a measure of resourcefulness and rapidity. The notation is defined in Table 3.

Table 3. Notations for resilience measurement method.

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

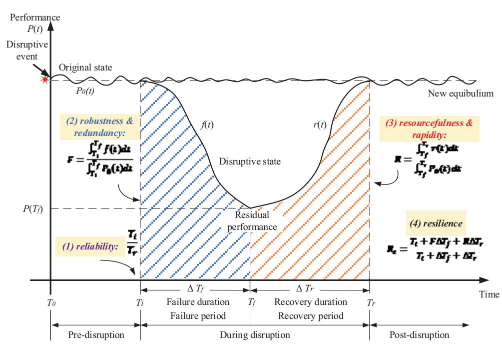

Fig. 3. Resilience quantification using KPIs.

2.3. *Resilience aggregation based on ER*

KPIs measuring port resilience from various perspectives should be integrated into an overall port resilience metric while preserving their distinct characteristics. The integration is conducted via these steps:

(i) Criteria hierarchy development: A hierarchy with three levels is formulated, including multiple KPIs at the bottom, transportation modes at the middle, and overall port resilience at the top, as shown in Fig. 4.

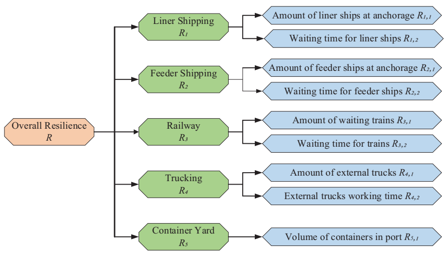

Fig. 4. The three-level hierarchy for port resilience aggregation.

(ii) Calculation of resilience scores and belief distributions: The resilience is divided into four grades: "strong", "moderate", "minimal" and "weak" as identified in earlier research (Gu et al., 2023). For resilience values that do not exactly match a predefined grade, a linear distribution approach is used to distribute the scores into belief distributions.

(iii) Weight determination: The weight of bottom-level criteria on middle-level criteria is considered equal because both are equally important to stakeholders. The weight of middle-level criteria on top-level criteria is determined by the container throughput of each transportation mode.

(iv) Overall resilience integration: Utilizing the predefined criteria hierarchy, the model calculates the overall resilience of the port employing the ER approach. As the ER algorithm is a well-established approach, it is not detailed in this research.

2.4. *Sobol SA*

The Sobol method decomposes the total variance of a model into two primary components: the variance attributable to individual parameters and the variance arising from interactions between parameters (Saltelli et al., 2010). The formula for decomposing the model's variance is shown in Eq. (2)-(4):

$$V = \sum_{i=1}^{k} V_i + \sum_{i=1}^{k} \sum_{j>i}^{k} V_{ij} + \dots V_{1,2,\dots,k} \tag{2}$$

$$V_i = V[E(Y|x_i)] \tag{3}$$

$$V_{i,j} = V\left[E\left(Y|x_i x_j\right)\right] - V_i - V_j \tag{4}$$

where V represents the total variance of the model output, V_i denotes the variance associated with each input parameter x_i, and $E(Y|x_i)$ indicates the mean output value Y when the parameter x_i is constant. $V_{i,j}$ accounts for the variance due to the interactions between parameters x_i and x_j, and $V_{1,2,\dots,k}$ captures the collective variance among k parameters. These elements, referred to as Sobol's Sensitivity Indices (SIs), quantify the influences of each parameter and their interactions on the variance of the model output.

As shown in Eq. (5), the main sensitivity index S_i, represents the main effect of parameter x_i on the total variance of Y, excluding influences from interactions with other parameters:

$$S_i = \frac{V_i}{V(Y)} \tag{5}$$

The total-order sensitivity index S_{Ti} for any given parameter x_i reflects both its main variance effect and the variance due to interactions with other parameters, as shown in Eq. (6).

$$S_{Ti} = S_i + \sum_{i \neq j} S_{ij} + \cdots + S_{1,2,\dots,k} \tag{6}$$

These index values range from 0 (no influence), to 1 (strong influence).

The Sobol quasi-random method is employed for parameter space sampling, which ensures a uniform distribution throughout the probability space. It focuses on previously unsampled sections of the probability function rather than just generating random numbers.

2.5. *Model validation*

The proposed framework encompasses four methods, among which resilience measurement, ER, and Sobol SA are well-established and recognized in the existing literature. As a result, the primary focus of our validation efforts is directed towards the SD model and the comprehensive framework. SA is generally divided into two distinct types. The first type, employed for model validation, assesses the stability of the model by analyzing whether minor variations in input parameters result in significant changes in outcomes. This paper utilizes this type of SA for the model validation, and empirical testing has demonstrated that the model is robust. However, further details are not expanded upon due to space limitations. The second type, discussed in Section 2.4, is known as parameter impact analysis, which focuses on understanding how input variables contribute to the outputs.

3. Experience results

3.1. *Source of uncertainty*

Data is sourced from routine operational activities and reports of port accidents. Expert judgment and thorough data analysis have identified five key types of disruptions: liner quay crane, feeder quay crane, rail crane, yard crane, and traffic congestion. Each disruption type is evaluated for both duration and severity. Therefore, the input factors of the SA and their range of variations are shown in Table 4.

Table 4. Input factors and their range of variability.

Disruption type	Factors	Notation	Lower bound	Upper bound	Unit
Liner quay crane	Number of equipment	x_1	1	3	Cranes
	Duration	x_2	12	120	Hours
Feeder quay crane	Number of equipment	x_3	1	2	Cranes
	Duration	x_4	12	120	Hours
Rail crane	Number of equipment	x_5	1	3	Cranes
	Duration	x_6	12	120	Hours
Yard crane	Number of equipment	x_7	4	24	Cranes
	Duration	x_8	12	120	Hours
Traffic congestion	Truck density increase	x_9	0.2	1.0	-
	Duration	x_{10}	12	120	Hours

These factors are modeled as independent random variables uniformly distributed within their possible variation range (unknown PDFs). This allows for continuous variations across a ten-dimensional space. A total of 1,500 simulation runs are conducted.

3.2. *Results, discussions and conclusion*

The SD model is implemented using Vensim DSS, while the ER analysis is performed with IDS software. The sampling method and SA utilize the open-source Python package SALib. Tables 5 and 6 present the total and first order SIs along with their confidence intervals.

Table 5. Total SIs and corresponding confidence intervals for each input variable.

Input variable	S_T	Confidence interval
x_1	0.111624	0.079606
x_2	0.258560	0.156554
x_3	0.134156	0.055574
x_4	0.125197	0.091074
x_5	0.357752	0.149737
x_6	0.615615	0.221557
x_7	0.539525	0.227035
x_8	0.716690	0.228283
x_9	0.588720	0.221067
x_{10}	0.765956	0.245637

Table 6. First order SIs and corresponding confidence intervals for each input variable.

Input variable	S_1	Confidence interval
x_1	0.100191	0.100000
x_2	0.056395	0.143647
x_3	0.098977	0.144395
x_4	0.059596	0.098982
x_5	0.033030	0.216786
x_6	0.003070	0.315797
x_7	0.045511	0.248548
x_8	-0.005884	0.324785

x_9	-0.034258	0.261282
x_{10}	0.105801	0.296292

According to the total order SIs in Table 5, the duration of traffic congestion significantly impacts port resilience. Yet, its influence appears less pronounced in the first order SIs, indicating that its interactions with other variables significantly affect resilience. Other factors, such as the duration of yard crane disruptions, the number of malfunctioning yard cranes, the duration of rail crane disruptions, the number of failed rail cranes, and the extent of traffic congestion, also critically influence port resilience and demand heightened attention for effective risk management.

Most first order SIs are minimal, with the exception of the number of malfunctioning liner quay cranes and the duration of traffic congestion. These findings suggest that these two factors alone significantly impact resilience. The result emphasizes the substantial influence of variable interactions on port resilience, highlighting the critical role of the ripple effect in resilience studies. This evidence underlines the importance of this research. Additionally, the data indicates that the duration of disruptions tends to have a greater impact than the severity of the disruptions, suggesting that rapid response and resolution of disruptions should be prioritized in port risk management strategies.

Moreover, identifying key disruptions and their ripple effects within ports benefits various stakeholders. Port operators can use this information to prepare for significant risks and vulnerabilities, anticipate the extent of ripple effects, and implement effective recovery measures. Shipping companies can leverage the proposed framework to inform their port selections. Meanwhile, carriers across different transportation modes can customize safety training for employees and adjust work schedules in response to port disruptions.

4. Conclusion and future work

A novel resilience assessment framework has been developed that integrates SD simulation, resilience evaluation, ER, and SA to assess the impact of diverse disruptions on the resilience of multimodal container ports. This methodology divides ports according to their transportation functions to investigate the ripple effects across these modes. The main contributions of this research are: 1) a practical framework that directs users in performing assessments to boost the entire port operational resilience; 2) an innovative SD simulation model that accounts for the ripple effects across various interconnected transportation modes; 3) a tailored SA method and sampling strategy designed specifically for assessing the impact of various disruptions. Experimental findings shed light on the impact of various types of disruptions, both individually and collectively, on port resilience. Future research will concentrate on employing a range of empirical data to validate the model described in this paper, while also exploring methods to enhance the framework's scalability. Additionally, incorporating more disruption factors, including environmental, social, and political elements, and expanding the experimental scope will also be beneficial.

Acknowledgement

This research was funded by a European Research Council project under the European Union’s Horizon 2020 research and innovation programme (TRUST CoG 2019 864724).

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