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Exploring the Failure Mechanism of Container Port Logistics System Based on Multi-Factor Coupling

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Abstract: Container ports are prone to delays, congestion, and logistics interruptions under the perturbation of uncertain events inside and outside the system. This not only affects the service quality of the system but also brings a serious blow to the whole transportation network. Therefore, this paper aims to develop a hybrid Bayesian network (BN) model to investigate the failure mechanism of the container port logistics system. Considering the complex coupling relationship between failure risks, the DEMATEL and ISM methods are presented to thoroughly analyze the interdependence and hierarchical structure of system failure factors. The failure evolution mechanism of the system is then analyzed using BN reasoning ability. The suggested hybrid model can identify the main failure factors, examine how factors are coupled, and produce the main propagation path resulting in system failure. The findings indicate that the risks associated with technology, facilities, and equipment are the most significant and immediate in the system; human risks affect all system components by acting on other factors; organizational management risks have a fundamental impact on the stability of the system; additionally, the uncertainty of external risks has greatly increased the variability of each logistics link. This study provides useful insights for port logistics risk management.

Keywords: container port logistics system; failure risk; failure mechanism; risk coupling; DEMATEL-ISM model; hybrid Bayesian network model

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1. Introduction

The maritime industry plays an increasingly important role in international trade, and about 80% of the global trade volume of goods is completed through maritime transport [1]. Container shipping is the main type of international transport service [2,3]. As a crucial sector of the supply chain network, the port logistics system is a complex system that organically combines logistics links such as ship entry and exit, loading and unloading, transportation, storage, consolidation, and information services with the port as the central platform [4]. Therefore, the safe and efficient operation of the port logistics system is a necessary condition to guarantee the high-quality service of marine transportation. However, to adapt to the rapid development of modern logistics, the scale and business service capacity of the port is expanding, and its system exhibits the characteristics of complexity, environmental uncertainty, and dynamics, as well as the coupling of internal factors. Once hit by catastrophic (uncertain) events such as natural disasters, man-made disasters, and mechanical accidents, ports are often unable to operate normally and are plunged into delays, disruptions, or even interruptions [5]. For example, the port labor dispute at the U.S. West Coast Port led to the closure of the port for 11 days in 2002; the “8.12” Tianjin Port explosion caused serious economic losses and casualties in 2015; the typhoon “Meranti” in 2016 caused huge damage to the infrastructure and equipment of Kaohsiung Port. It is shown that any disruption of the port logistics system can result in serious societal economic losses, has an immediate impact on the global supply chain [6], and can even bring a catastrophic impact on the whole industry as the risk of disruption spreads.

Hence, how to analyze and determine the port disruption risk and effectively control the impact of the risk is of great significance in the field of maritime logistics and has received extensive attention from scholars. The commonly used risk analysis methods include failure mode and effects analysis (FMEA), risk matrix, comprehensive evaluation method, fault tree analysis (FTA) method, bow-tie model, etc. For example, Pallis [7] used the risk matrix approach to assess port operation risks under the framework of a comprehensive security assessment (FSA); Loh et al. [8] used the fuzzy integrated evaluation method to study the risk of port-centered supply chain disruption; Mokhtari et al. [9] established a bow-tie model to conduct a risk assessment for seaport operations management and identified the causes, impacts, and consequences of seaport risks. However, given that traditional risk analysis methods cannot effectively deal with the uncertainty (incompleteness and ambiguity) of risks, uncertainty analysis methods such as Bayesian Network (BN) [10] and Evidential Reasoning (ER) [11] are gradually explored, and applied by scholars. For instance, Alyami et al. [12] developed an improved FMEA model based on the fuzzy rule-based Bayesian network to quantitatively analyze the security risk problem of container ports and then combined with ER methods to aggregate the impact of each hazardous event on the safety of the port, and proposed dynamic decision support for container port operation system from the system perspective [13]. In summary, the current research on port risk analysis and quantitative risk assessment techniques are relatively systematic, and fruitful results have been achieved in the risk management of port operations. Nevertheless, risk factors are often interdependent, and existing studies rarely systematically explore the coupling relationship between the failure risk factors of the port logistics system and the impact of the interaction mechanisms among multiple factors on the system risk evolution. Therefore, this paper fully considers the coupled correlation relationship of failure risk factors and studies the failure mechanism and failure probability of the container port logistics system under the action of multi-factor coupling.

To comprehensively understand the potential risk factors of port failure and the mechanism of inter-factor interaction, this research takes the CPL system as the research objective and studies the failure mechanism of the system after being disturbed by uncertain events inside and outside the system in a series of logistics activities on the port. First, based on the literature review and expert knowledge and experience, the failure risk factors of the CPT system are systematically identified in five dimensions, including human risk, facility and equipment risk, technology risk, organization and management risk, and external risk. The second objective is to explore the coupling relationships among the risk factors and to determine the system risk hierarchy. The decision-making trial and evaluation laboratory (DEMATEL) method is used to analyze the interdependencies among the system components and identify the key risk factors [14]. Based on this, the interactions between system risk factors are further explored in combination with the interpretive structural modeling (ISM) to determine the direct and indirect causes of system risk and finally obtain a multi-level recursive structural model of risk factors [15]. The DMEATEL-ISM integrated model cannot only reflect the coupling degree between factors but also visually express the hierarchical structure relationship between factors, which can sort out the coupling relationship between failure risk factors of the system at a deeper level. The third objective is to construct a failure risk evolution model. The BN is invoked to further quantify the strength of coupling correlations among each factor, and its inference ability is used to output the failure probability of the system and the possible failure propagation path of the system. Moreover, to overcome the problem of insufficient objective data on maritime risks, the Noisy-or Gate model is introduced to approximate the conditional parameters of the BN [16]. The combination of DEMATEL-ISM and BN methods can both portray the complex coupling relationships between failure risk factors and also realize the failure deductive reasoning process of the system under the action of multi-factor coupling as a whole. The research idea and hybrid research method proposed in this paper enrich the existing port logistics literature and help port managers to identify system critical failure factors and system failure risk transmission paths so as to effectively manage port risk events and mitigate the losses caused by port disruptions.

The remainder of the paper is organized as follows: Section 2 reviews the literature related to port logistics risk management and summarizes the deficiencies in current research; Section 3 introduces the research framework and specific methodological steps for port logistics failure mechanism analysis; in Section 4, model validation is conducted to bring in actual data to derive the results; Section 5 is a discussion based on the data analysis results; finally, Section 6 concludes with an analysis of the overall contribution and limitations of the article.

2. Literature Review

To fully understand the current research on risk in the field of port logistics, in this section, a summary review of articles on risk management in port logistics is presented, including risk analysis methods and progress in the application of BN methods. Then, all uncertainties and possible threats related to port logistics failures are summarized. Finally, the progress and shortcomings of the existing research are summarized. Based on the results of current researchers, new ideas and research methods are proposed.

2.1. Research of Risk Analysis Methods for Port Logistics

Ports are an important interface between water and land transportation and an important hub node in the global supply chain. Risk management in seaports plays a crucial role in ensuring the resilience of port operations services in the supply chain [13]. The current research on port risk management is continuously enriched and deepened, and researchers have proposed qualitative, quantitative, and comprehensive risk analysis methods to enrich the system of maritime risk management. A review of risk analysis methods is summarized below.

2.1.1. Risk Analysis Methods in the Port Area

There are many methods regarding port risk management, among which the traditional risk analysis tools are the analytic hierarchy process (AHP) method, risk matrix, risk map, fault tree analysis (FTA), and event tree analysis (ETA). For example, Mokhtari et al. [9] conducted a risk assessment of seaport operations management by constructing a risk analysis framework of the Bow-Tie model, FTA and ETA methods were integrated for analyzing port-related risk factors, and fuzzy set theory was used to overcome the traditional probabilistic representation methods. Pallis [7] proposed an approach to port risk management based on the formal safety assessment (FSA) framework for systematic risk management, where port risks are assessed by using a risk matrix approach to describe the likelihood of occurrence and severity of consequences. Then, based on accident data from a major container terminal in Indonesia over five years (2014–2016), Budiyanto et al. [17] analyzed the accidents and potential risks occurring in container terminals using the FTA method and risk matrix to assess the level of risk. Chang Chia-Hsun [18] identified the risk factors of container shipping and port operations based on the logistics perspective and then assessed the potential risk factors using risk maps. However, due to the characteristics of port operation risks, such as complexity and uncertainty, these methods show a lack of capability in terms of uncertainty issues during practical application.

Therefore, to adequately cope with the uncertainty of risk data in port operations, methods such as fuzzy set theory, evidential inference (ER), and Bayesian networks (BN) have been applied to risk management. For example, Ding and Tseng [19] used a fuzzy risk assessment approach to assess the security operational risk of a dedicated container terminal in Kaohsiung, Taiwan. Loh et al. [8] invoked a fuzzy comprehensive evaluation approach to analyze the port-centric supply chain disruption risks to address the uncertainty problem. Mokhtari [11] used ER and fuzzy set theory to determine the risk level assessment of the entire port and terminal. Secondly, to effectively address the uncertainty in seaport operations, Jhon et al. [10] combined fuzzy AHP, ER, and expected utility theory to propose a new integrated assessment model to improve the resilience of the overall port operation system. Additionally, combining the fuzzy rule-based BN method, Alyaim et al. [12] proposed an improved failure mode and impact analysis (FMEA) method to assess the severity of hazardous events in container terminals, using the probabilistic inference of BN to update the assessment results. Based on this, ER method was proposed to be incorporated in a complementary way into an improved FMEA model to perform risk assessment analysis from a system perspective [13]. Moreover, Khan [20] used BNs for risk factor inference and analysis for dangerous cargo transportation in ship berthing scenarios and combined the binary logistic regression and expert judgment method for dangerous cargo risk factor identification.

On the other hand, with the research on the risk of the port operation process, the coupling and dynamic characteristics of risk factors have gradually attracted the attention of scholars. For instance, Sarkar and Shankar [4] proposed a hierarchical system model, the total interpretive structural modeling (TISM), to rank port logistics barriers and explain the interdependencies between barriers and then cited the MISMAC method to classify the factors. In response to the complex coupling and dynamic evolutionary characteristics of ship pilotage operation risks, Guo et al. [21] combined the functional resonance analysis method and dynamic Bayesian network to analyze the risk factors during ship port calls and pilotage and then used DBN combination with historical and observed data to analyze the spatial and temporal evolutionary patterns of collision risks in specific operation scenarios.

2.1.2. Application of Bayesian Network Model

The Bayesian network (BN) technique, which combines graph theory and probability theory, can integrate domain knowledge and statistical data to achieve network learning and probabilistic inference compilation. It can be used to examine the significance of risk variables and the interrelationships between them due to its advantage of causal reasoning [22]. Through the review of the above-related port risk analysis methods, it is shown that BNs have been fully applied in port operations. In addition, BN technology has been used in the context of shipping and supply chain networks and has been continuously enhanced and expanded. Hanninen, M [23] analyzed the benefits of applying the BN model in preventing maritime traffic accidents and modeling challenges. Garvey, Myles D et al. [24] established a supply chain network disruption risk propagation model based on the BN method to fully reflect the interdependencies among risks and the structural characteristics of supply chain networks. For assessing maritime supply chain risks, Wang et al. [1] constructed a fuzzy rule-based Bayesian network model (FRBN) and fused it with the FMEA method, which can effectively handle the uncertainty problem and enable probabilistic reasoning. Fan et al. [25] proposed a method for human factor analysis and maritime accident prevention by incorporating BN and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with a multi-criteria decision system. Zhou et al. [2] combined three models, FMEA, ER, and FRBN, to perform a risk assessment of container shipping services. Chen et al. [26] proposed an evidence-based FBN approach to build a maritime accident risk analysis model and quoted the Noisy-or Gate model to implement parameter learning.

2.2. Risk Factors Associated with Port Logistics

In general, port logistics describes the logistics and distribution services provided to goods arriving at the port, including cargo handling, storage, transportation, customs clearance, and other logistics activities [4]. Safe and orderly port logistics activities are the basic guarantee for maintaining the continuity of the supply chain network. However, due to the complex coupling of the internal environment of the port logistics system and the uncertainty of the external environment, there are various threats in the process of port operation, such as loading and unloading accidents, worker strikes, mechanical failures, network disruptions, natural disasters, terrorist attacks, etc. The present research on the identification and analysis of risks related to port logistics is constantly enriched, and based on the existing research, the risk factors are summarized from the internal and external environments of the system. Among them, this paper defines the internal risk as the risk that exists in the entire port operation system and the external risk as the external natural and social environment of port operation.

2.2.1. Internal Risk Factors of the Port Logistics

Port operations face complex internal risk factors, which have been studied in many studies. First, port logistics is a labor-intensive activity, and human factors are key factors in causing port accidents, where unsafe behaviors such as lack of personal competence, poor supervision, lack of safety awareness, and irregularities are important factors that threaten the normal and safe operation of ports [4,17,25,27]. For example, Fan et al. [25] concluded that human factors are the main cause of maritime accidents; Budiyanto et al. [17] believed that human factors, especially due to human work negligence in operating vehicle equipment, are one of the most important factors causing accidents in terminal container operations; Zhang et al. [28] found that human factors are the primary influencing factors in port ship pilotage accidents, and discussed their impact on accident risks by studying the coupling effects between the human organizational factors and system factors. Furthermore, port workers' ability to apply new technologies, work operations, and safety awareness is closely related to professional training and safety education, indicating that management variables are also a major source of dangerous human behavior [27,29,30]. Next, facilities and equipment are critical materials for ensuring the smooth operation of ports. On the one hand, port infrastructure such as quay berths, warehouses, power supply systems, and information network facilities are necessary for delivering services such as ship access and cargo transit. According to Loh et al. [27], port information system failure is a highly important infrastructure threat that causes port disruption. On the other hand, aging, failure, and inadequacy of handling and transportation equipment are also significant causes of port dangers. Several studies determined that port equipment efficiency and adequacy are key elements affecting port operations, which not only lower port productivity but also may cause port accidents [7,8,12,29].

Additionally, the effective maintenance of port facilities and equipment is another prerequisite for guaranteeing the port's regular operation. John [9] and Alyam [13] pointed out that a lack of facilities and equipment maintenance capabilities is an important technical risk factor during terminal container operations, which may result in facilities and equipment failure and thus cause terminal operation accidents. Therefore, timely maintenance and inspection of facilities and equipment can effectively reduce the risk of system failure, improve service quality and operational efficiency, and thus boost the reliability of system operation. Moreover, the port management organization system is also a crucial component of the port logistics system. It has been suggested that proper organizational management is a significant element in maintaining the order of the port and guaranteeing the continuity of the system due to the complex environment of the port system and the closely related activities of each link; otherwise, it will cause problems such as congestion and even collision and conflict [4,10,30].

Moreover, the port is an open infrastructure resource, and the orderly operation of the port logistics operation system is inseparable from information technology and connectivity and coordination inside and outside the port. Gui et al. [31] believe that the risk of "Interruption of railways/barges services" on the land side of the port may bring collection and distribution problems, which lead to serious "stacking" problems and cause port congestion. Furthermore, a proper port management system needs to have integrated information and communication technology, which can improve the reliability of port operations [4]. This paper also pointed out that proper coordination and information sharing in port logistics are necessary to effectively improve port performance [4]. Hu et al. [32] concluded that port authorities and terminal operators should focus on sharing resources and coordination, and flexible outbound railway schedules and inter-terminal transportation will help improve container integration. In short, effective coordination and communication, information resources, and a complete collection and distribution system are important guarantees for port operations; otherwise, problems such as detention, delays, and congestion may occur.

The analysis presented above focuses primarily on the risk factors affecting the reliability of the port logistics system from the system's internal environment. These elements interact with one another in various ways, and when a risk event surpasses the system's resilience, the system will collapse.

2.2.2. External Risk Factors

Due to the dynamic changes in the environment that might have a more negative influence on the port, it is also thought that the external objective environment of the port logistics system is one of the most significant causes of uncertainty impacting the correct operation of the system [33]. Much recent research categorizes environmental influences primarily in two broad categories. One category is the natural environment, which includes things such as natural disasters [2,34,35], sudden climatic changes [2,36], severe weather [7], etc. Zhou et al. [2] defined such environmental factors as unpredictable natural risks that have a direct impact on the dependability of container transport services. Lam et al. [35] analyzed the interruption events of Asian ports since 1900 and concluded that natural disasters are the main cause of port interruptions, except for port strikes. Natural disasters and other emergencies can cause port disruptions that affect the stability of the global supply chain network and cause serious economic losses, such as typhoon Meranti in 2016, which severely damaged port infrastructure and equipment. The other category is the objective social environment in which the port logistics system is situated, such as port management policies [2], legal regulations [9], and the socio-economic trade environment [37]. The port transportation industry may be directly impacted by changes to the objective transportation environment, which would damage the logistics stability of the whole shipping sector.

In addition, public health events, such as COVID-19, have received the attention of many researchers in recent years. During the epidemic, due to international security measures and national control management, ship entry procedures became more complicated, causing congestion, which has seriously affected the efficiency of port operation systems and even led to global supply chain disruptions [2]; Notteboom et al. [38] compared COVID-19 with the 2008 global economic crisis to study the impact of the epidemic on container ports and the container shipping industry, and the evolution of their resilience and adaptability. Finally, some other scholars analyze the security risk factors faced by ports and consider smuggling, smuggling, theft, and terrorist incidents as important risk factors that threaten the security of port operations [7,27]. According to Niamat et al. [39], cyber-attacks may also pose a threat to shipping navigation, yard operations, container handling, and gate operating systems in port logistics systems. Port logistics systems are more vulnerable to these external threats, and maintaining system resilience is more difficult.

In summary, this study defines the risk elements of the port logistics system from both internal and external perspectives. The internal factors are divided into four categories: human factors, facilities and equipment factors, technical factors, and organizational management factors, and the external factors are divided into two categories: natural environment factors and objective social environment. Research now focuses more on the occurrence likelihood of the risk and the severity of consequences and then determines the risk value. However, these risk factors are not simply linear or independent relationships, and numerous studies have overlooked the close interaction between systemic risk factors. Moreover, there is a complex and dynamic non-linear correlation between these elements rather than a simple coupling. On the one hand, internal factors can interact with one another, resulting in an unmanageable situation and internal system dysfunction. On the other hand, internal and external elements may also be related, exposing the system's susceptibility and leading to operation system functional failure. Simply said, as soon as a risk emerges in the system, it spreads and superimposes itself due to the coupling effect between components until it eventually exceeds the risk threshold of the system node. This may cause transportation delays, congestion, conflicts, work accidents, etc., disrupting the normal operation of the entire system and even causing a port business interruption.

2.3. Research Gap

Although the research on port logistics risk analysis has achieved fairly good results, there are still some shortcomings in risk analysis techniques and research ideas. Mainly include: (1) Traditional risk analysis methods focused more on assessing risk factors to determine the risk level of each risk, that is, a single-factor risk assessment method. However, fewer studies focused on the interdependence among port logistics risk factors. (2) The Bayesian network is widely used in maritime risk assessment, which can consider the inter-causal relationship among factors to achieve probabilistic reasoning. However, in the absence of objective data, especially for complex topological networks, relying on expert scoring to obtain network models is a method with low efficiency, low accuracy, and high workload. (3) When studying the failure risk of port logistics systems, it is not only necessary to identify the system's influential larger failure factors but also to study the evolution mechanism of system failure risk. This can effectively control system failure both at its source and along the conductance path.

Because of the shortcomings in the current research, this paper proposes an improved Bayesian network failure mechanism analysis model with the container port logistics system as the research object. Under the coupling conditions of numerous internal and external risk factors, the container port logistics system's failure mechanism is examined, and the key factors and the main propagation paths of its failure risks are identified. Finally, the system failure mechanism is reasoned out using the GeNIe simulation software.

3. Methodology

In this paper, risk identification is performed through a detailed literature review and pertinent accident reports in maritime logistics. Then a port logistics security risk analysis method is chosen to explore the failure risk generation mechanism and evolution path of the CPL system. Through the summary of relevant risk assessment techniques in the literature review mentioned above, a Bayesian network risk analysis method based on DEMATEL-ISM is proposed in this paper. The Bayesian network approach is being utilized extensively in early warning, decision-making, and risk management. Bayesian network, an uncertain causal association model, is an important tool for uncertainty inference and data analysis of complex networks, which can efficiently obtain the network structure and network parameters from the data set by autonomous learning [40,41]. However, there is currently no complete risk case library for port accidents. This method still relies on domain knowledge, and building a network model is still a complex task. Therefore, to ascertain the interaction between system failure risk variables and create a multi-level recursive structure model, this research offers the DEMATEL-ISM system structure analysis approach. The network structure is then obtained by mapping the system's hierarchical structure to BN. Next, the network parameters (prior probabilities and conditional probability tables) are learned. Under the premise of insufficient data, expert judgment is an important basis for determining the conditional probability distribution of nodes. However, a huge number of parameters are needed when there are many nodes and a complicated network topology, which significantly increases the workload of experts. Therefore, this paper adopts the Leaky Noisy-or Gate extended model to approximately determine the conditional parameters of the Bayesian network based on expert evaluation. Finally, the Bayesian network simulation is performed using GeNIe software. The positive causal reasoning of the BN method is used to simulate the change of port logistics failure risk probability and the coupling relationship between factors when multiple risks emerge, and reverse reasoning is applied to investigate the possible propagation path of the system failure risk.

The proposed method consists of four parts in total, and the relationships between these steps, as well as the research questions corresponding to the method and the research objectives achieved, are shown in Figure 1. For the specific research steps of the hybrid approach, see the following subsections.

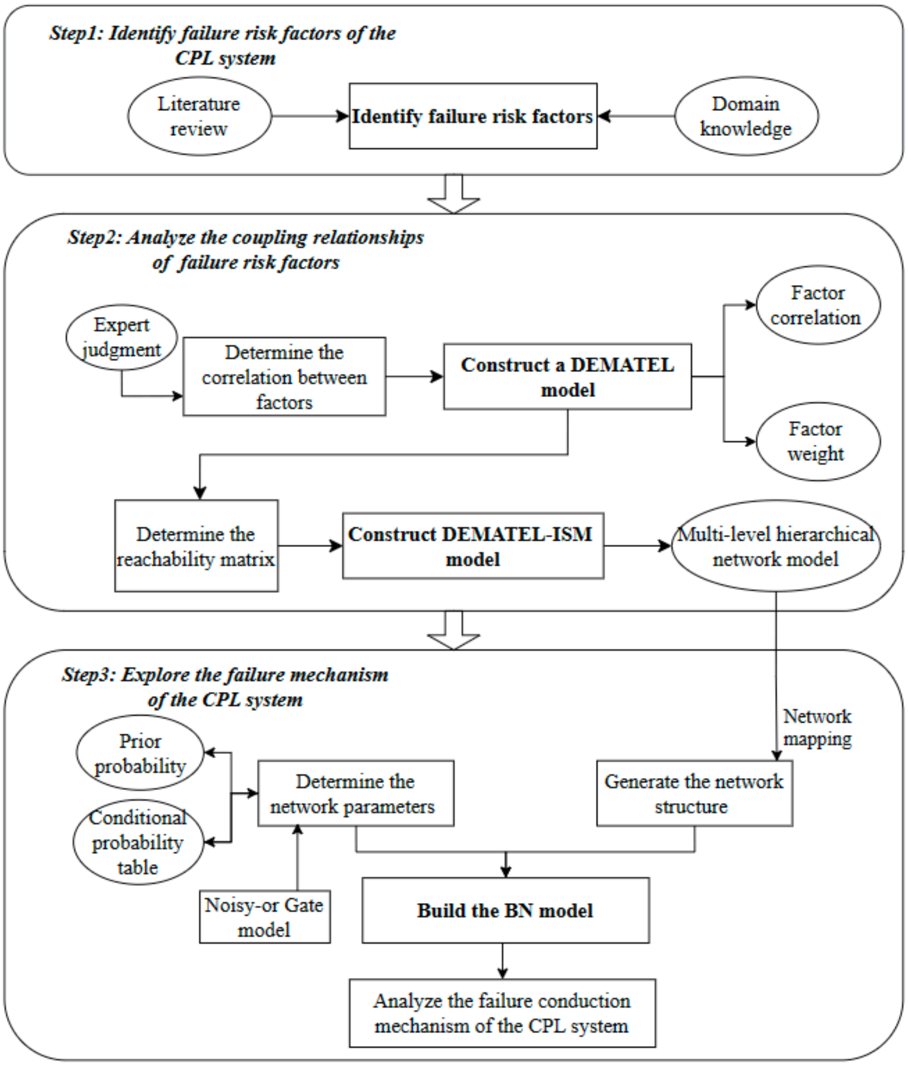

Figure 1. The Process diagram of the proposed hybrid model.

3.1. Risk Identification

Typically, the risk is described as a combination of hazard, consequence, and uncertainty [15,42]. Risk factors can contribute to the occurrence of various emergencies, increase their occurrence likelihood, or expand their loss. Then, failure is a functional state, and system failure denotes either a complete loss of original function, reduced functionality, or the presence of hidden dangers within the system. It is first required to define the term "failure risk" to more fully and precisely identify relevant risk factors. This paper proposes that container port logistics system failure, in a broad sense, can be understood as the interruption of the port logistics system, specifically referring to the situation in the container terminal, yard, and other port scenarios where the equipment, personnel, network, and other risk issues make abnormalities occur in logistics links such as cargo in and out, loading and unloading, transportation and storage abnormal, which leads to the inability of the system to operate as originally planned, with delays, congestion, and functional interruption, etc. Based on this, the failure risk of the CPL system is defined as the potential risk factors in the port-centered logistics activities in the system that may affect the normal operation efficiency and cause system function failure or port operation interruption. Concerning relevant literature and relevant port accident cases, risk factor indicators are determined by combining relevant expert recommendations. Finally, a multidimensional risk evaluation index system is constructed from five dimensions: human, facilities and equipment, technology, organization and management, and external risks, with a total of 20 risk factors, as detailed in Table 1.

Table 1. The identified failure risk factors.

Category	Description	Code	Risk Factors	Remark	References
Human risks (H)	Port activities are labor-intensive, this paper considers human activities that may lead to abnormal system operation as human risks.	H_1	labor shortages	shortage of in-port workers (dock or warehouse workers), shortage of truck drivers; port labor strikes	[4,9,13,17,27,30,36]
		H_2	operating errors	improper operation due to misunderstanding of instructions, negligence of personnel, poor communication, poor condition of workers, etc.	
		H_3	lack of security awareness	lack of relevant security awareness among port workers and unsafe behavior during work resulting in operational accidents	
		H_4	insufficient professional knowledge and skills	insufficient maintenance ability of machinery, the port operation is not skilled.	
		H_5	poor supervision	lack of complete supervision and inspection of port operations	
Facility and equipment risks (F)	Facilities and equipment are important basic guarantees for port logistics operation systems. Facility and equipment risks can be explained as factors that cause the failure of operations, such as loading and unloading, transit, and warehousing.	F_1	lack of port equipment	inadequate handling equipment and transit equipment, such as cranes, forklifts, trailers, and trucks	[4,7,8,10,12,17,27,29]
		F_2	over-aging and defects of equipment	over-aged and defective port operation machinery and equipment	
		F_3	lack of warehouse/yard space	port warehouse or a yard full of cargo with no applicable inventory space	
		F_4	equipment breakdown	machinery failure, including cranes; in-vehicle equipment failure, such as trucks; the power supply equipment failure	
		F_5	port information technology (IT) system failure	failure of the port logistics information network system (navigation, communication, and dispatching system)	
Technical risks (T)	Technologies that may cause container operation failures or affect operational efficiency are defined as technical risks.	T_1	lack of maintenance technology	insufficient technical capacity for the maintenance of port infrastructure and machinery equipment, and IT system.	[7,9,10,29]
		T_2	mismatch between technological innovation and system capabilities	immaturity of the technology required for technological innovation in the port, the lack of corresponding facilities and equipment Inadequate	
Organization and management risks (O)	Management organization refers to the activities that maintain the safety and order of port operations	O_1	poor organization of port production scheduling	improper organization and command of port handling, pilotage, and other production scheduling may cause production delay, congestion, and other problems	[4,10,29,30]
		O_2	Imperfect management organization rules and regulations	sound rules and regulations are the guarantees of port operation; loopholes may lead to the disorganization of ports	
		O_3	lack of professional training or safety education	staff should master the necessary professional skills and safety knowledge to reduce accident injuries	
External risks (E)	External risks refer to the risks arising from changes in the port operating environment, mainly including political and economic environment, natural disasters, and emergencies.	E_1	port management policy	port security inspection policy, customs clearance rules, yard management policy, etc.	[2,4,7,9,10,27,29,34,36,37,43]
		E_2	economic and trade risks	trade policies, customs rules, global economic states, market freight rates, and labor costs of various countries	
		E_3	natural disaster/harsh climate	earthquake, tsunami, hurricane, and so on, heavy rain, storms, and other abrupt climate change	
		E_4	public health event	COVID-19	
		E_5	security threats	trafficking, smuggling, breaking in/theft, terrorist attacks, cyber attack, etc.	

From Table 1, it can be seen that human risks, facility and equipment risks, technical risks, and organization and management risks are the main internal influencing factors of port logistics activities. Moreover, external risks refer to those risks due to dynamic and uncertain factors in the external environment faced by port operations, mainly including port management policies, economic and trade environment, natural disasters, health emergencies, and security threats.

3.2. Data Collection

After identifying the systemic risk factors, the risk factor analysis is systematically carried out according to the five dimensions classified above to explore the coupling relationship between the various factors. This study adopts a subjective approach to this problem, which is mainly based on experts' expertise and experience in scoring. First, this paper designs a questionnaire on the influence degree of failure risk factors in port logistics and uses the Likert scale to assess the importance of system failure risk factors. The experts used a scoring system of 0–4 to determine the direct influence of the factors, where 0 means no influence and 1, 2, 3, and 4 mean low, medium, high, and very high influence, respectively, as shown in Table 2. The subjective opinions from multiple experts were then combined using arithmetic averaging.

Table 2. The scale of the degree of direct influence between factors.

Score	Impact Level	Description
0	No influence	Factor ihas no influence on factor j
1	Low influence	The occurrence of factor i has a low influence on factor j
2	Medium influence	The occurrence of factor i has a 50% probability of affecting factor j
3	High influence	The occurrence of factor i has a high influence on factor j
4	Very high influence	The occurrence of factor i will have the greatest influence on factor j

Then, after determining the network structure by the DEMATEL-ISM system hierarchical analysis, the subjective probability method was used to determine the probabilities of nodes and the relationship between the edges of nodes. A questionnaire was then used to collect data about the probabilities of the nodes.

3.3. The DEMATEL-ISM Method

The DEMATEL (decision making trial and evaluation laboratory) method is a crucial tool for visualizing complex causal relationships within a system through causal network diagrams [44]. The DEMATAL method can evaluate the interdependencies between factors and convert them into structural models, and it can find the key factors of complex structural systems through influence diagrams [45]. Furthermore, the DEMATEL technique can demonstrate the direct or indirect effects between different factors [46], which helps decision-makers to better understand the system structure. For example, Jiao et al. [47] combined DEMATEL models and BN to evaluate the direct and indirect coupling relationships among factors and generated BN models from the relationship matrix for inference analysis.

Additionally, the ISM (interpretive structural model) is considered an effective method for modeling system hierarchy. The ISM approach maps the system factor relationship into a directed graph by constructing the reachability matrix, revealing the system hierarchy [15,48]. This method is highly applicable to a system with many factors and complexity. Some studies have combined ISM with Bayesian networks to convert structural models into network structures to further analyze complex relationships among factors, such as Huang et al. [49], who used the factor hierarchy graph obtained by the ISM technique can be used as the topology of Bayesian networks to effectively deal with the causal relationships among risk factors, thus reducing the complexity of BN modeling.

Through the above analysis, the DEMATEL method can determine the degree of association between factors and identify the key factors in the system, but the method cannot effectively describe the coupling mechanism and hierarchical structure of factors within the system. Therefore, this paper proposes a system structure analysis method that combines DEMATEL and ISM models, which can both visualize the coupling relationship between factors and effectively identify the crucial factors in the system. By constructing a multilevel recursive structure model, the structural relationship of system risk factors can be analyzed visually. The procedure flow of the DEMATEL-ISM method is shown in Figure 2.

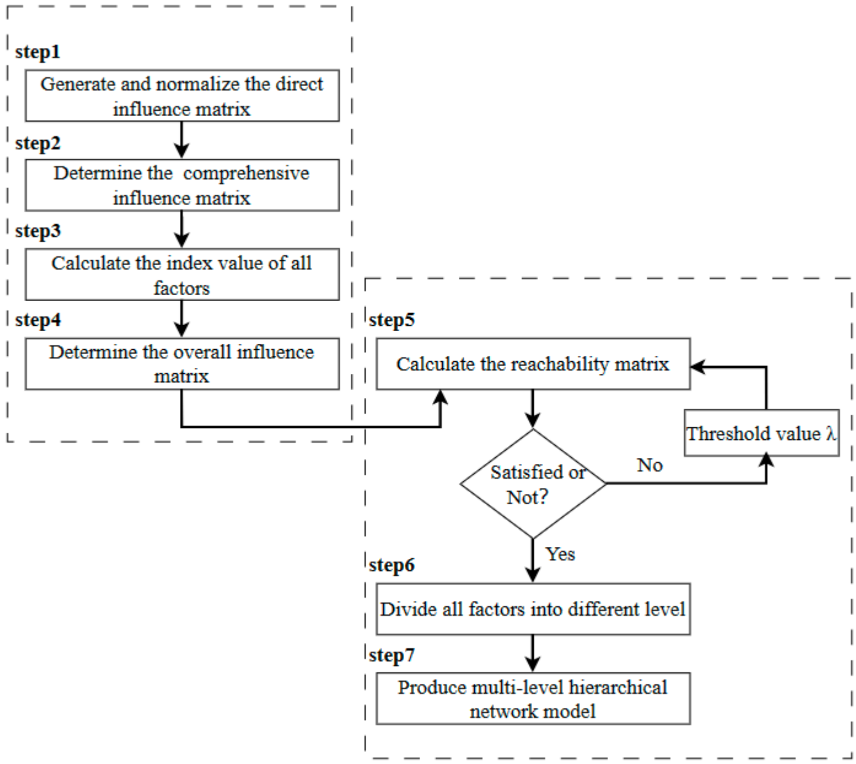

Figure 2. The production of the DEMATEL-ISM model.

The specific steps of the proposed DEMATEL-ISM technique are as follows:

Step 1: Generate and normalize the direct influence matrix

Analyze the interactions between different factors and the degree of influence, and establish the direct influence matrix H. Experts score based on domain knowledge and their own experience. $H^k\left[h_{ij}^k\right]_{n\times n}$ is a direct influence matrix obtained by expert k (k = 1, 2, 3, . . . , m), where, h_{ij}^k denotes the degree of direct influence of the factor F_i on F_j as perceived by expert k. The arithmetic mean method was then used to fuse the opinions of each expert to finally obtain the direct influence matrix H.

$$H = \begin{bmatrix} 0 & \ldots & h_{1n} \\ \ldots & \ldots & \ldots \\ h_{n1} & \ldots & 0 \end{bmatrix} = \left[h_{ij}\right]_{n\times n} \tag{1}$$

where, $h_{ij} = \frac{1}{m}\sum\limits_{k=1}^{m} h_{ij}^k$, ($k$ = 1, 2, 3, . . . , m).

h_{ij} indicates the average degree of influence of the factor X_i on X_j, if $i = j$ and $h_{ij} = 0$.

Normalization:

The direct influence matrix H is normalized to obtain the normalized direct influence matrix G,

$$G = \mu \times H \tag{2}$$

$$\mu = \frac{1}{\max\limits \sum\limits_{1\le i\le n}^{n} h_{ij}}, i, j = 1, 2, \ldots, H \tag{3}$$

where $\max\limits_{1 \le i \le n} \sum h_{ij}$ is denoted as the row and the maximum value. It is known that $g_{ij} \in [0, 1]$ and $\max\limits_{1 \le i \le n} \sum h_{ij} = 1$.

Step 2: Determine the comprehensive influence matrix

The comprehensive influence matrix T can be obtained by adding up the direct and indirect influences between factors to determine the comprehensive influences between factors in the system.

$$T = G \times (I - G)^{-1} \tag{4}$$

Step 3: Calculate the index value of all factors

Based on the comprehensive influence matrix, determine the influencing degree of each factor on other factors and the influenced degree, and calculate the centrality and causality of each factor.

1. Influencing degree and influenced degree

The influencing degree D_i of the corresponding factor is obtained by summing the elements of matrix T by rows, and the influenced degree R_j of the corresponding factor is obtained by summing the elements of matrix T by columns. The calculation formula is as follows:

$$Di = \sum_{j=1}^{n} t_{ij}, i = 1, 2, \ldots, n \tag{5}$$

$$R_j = \sum_{i=1}^{n} t_{ij}, j = 1, 2, \ldots, n \tag{6}$$

2. Centrality and causality

The centrality and the causality of factor i are calculated by the influencing degree and the influenced degree of factor i. That is, $D_i + R_j$ indicates the centrality of factor i, the greater the centrality, the more significant factor i is. The causality, denoted by $D_i - R_j$, reflects how factor i affects other factors. If the value of $D_i - R_j$ is positive, factor i has a stronger influence on other factors and is called causal factor. If the value of $D_i - R_j$ is negative, factor i is influenced by other factors to a large extent and is called the result factor.

Step 4: Determine the overall influence matrix.

The comprehensive influence matrix T can only reflect the influence relationship between factors and the degree of influence without considering the influence of the factors on themselves. The overall influence matrix X reflects the overall influence relationship of system factors, including the mutual influence among factors and the influence of factors on themselves. The overall influence matrix X is expressed as

$$X = T + I \tag{7}$$

Step 5: Calculate the reachability matrix.

The key to obtaining the reachability matrix A is to determine the threshold λ based on the overall influence matrix T. The system structure of the influential factors is simplified by setting appropriate thresholds to remove the less influential factors [15]. Then reachability matrix is determined according to Equation (8).

$$\begin{aligned} A &= \left(a_{ij}\right)_{n \times n} \\ a_{ij} &= \begin{cases} 1, \; x_{ij} < \lambda \\ 0, \; x_{ij} \ge \lambda \end{cases} \end{aligned} \tag{8}$$

Step 6: Classify different levels based on the reachability matrix.

According to the reachability matrix, we determine the reachable set R, the prior set Q, and the intersection set M of each element. R represents the set of all factors that factor F_i can reach, and the Q denotes the set of all factors that can reach a factor F_i. Then there is the division of the hierarchy. When Equation (9) is satisfied, the factors satisfying the conditions are divided into the first level (I). After determining the first level, the next division is performed, and the corresponding row and column elements in the reachability matrix should be crossed out. The above steps are repeated until all elements are assigned to the corresponding hierarchical levels, and the iteration ends to produce the final hierarchical distribution.

$$R(a_i) = R(a_i) \cap Q(a_i) = M(a_i) \tag{9}$$

Step 7: Draw the directed graph.

Based on the division of factors in each level of the system, the skeleton matrix is extracted from the reachability matrix. If there is a strongly connected factor pair, one of the factors is selected as the representative element. Then, after removing the transitive binary relationship and the self-reachable binary relationship between elements in the reachability matrix, the skeleton matrix K is finally generated. Clarify the causal relationship among the factors, and finally, draw a multi-level hierarchical structure diagram of the failure risk factors of the CPL system.

3.4. Noisy-Or Gate Bayesian Network Model

3.4.1. Bayesian Network Model

Bayesian Network (BN) is a probabilistic network model and one of the effective theoretical models in the field of uncertain knowledge representation and inference. BN conducts a qualitative and quantitative analysis of the interdependence among factors through directed acyclic graphs (DAGs) and probabilistic correlation model and studies the event propagation mechanism through probabilistic reasoning methods [50,51]. The theoretical basis of BN model realization is the Bayesian theorem and conditional probability theory, in which the Bayesian formula can be expressed by Equation (10).

$$P(A|B) = \frac{P(A|B)P(A)}{P(B)} \tag{10}$$

Bayesian network is a combination of qualitative and quantitative analysis methods, and the modeling process includes network structure learning and network parameter learning. The two main parts are as follows:

(1) Construct the network structure S and express the relationship between each information element by determining the directed graph. It consists of a point variable set $V(V = \{V_1, V_2, \ldots, V_n\})$ and a directed edge set $L\left(L = \left\{V_iV_j\middle|V_i, V_j, \in V\right\}\right)$. Among them, the directed edge L represents the dependence or causality between variables V_i and V_j. The final network structure S is expressed as $S = (V, L)$.

(2) Determine the probability distribution of the node, including the prior probability of the parent node and the conditional probability table (CPT) of other child nodes. The degree of interaction between variables is expressed through the probability distribution among them. The conditional probability table distribution of node variables is expressed as Equation (11).

$$P = \left\{P\left(V_{i|}\middle|V_1, V_2, \ldots, V_{i-1}\right), V_i \in V\right\} = P\left(V_i\middle|V_{pi}\right) \tag{11}$$

where P represents all possible conditional probabilities of a node relative to its parent nodes and V_{pi} represents the set of parent nodes of the variable V_i.

3.4.2. Noisy-Or Gate Model and Leaky Noisy-Or Gate Model

Assuming that node variables have two states (Y and N), if child node i has n parent nodes, then the child node conditional probability is 2^n [26]. Moreover, complex network nodes not only increase the effort for experts but also, to a certain extent, decrease structural accuracy. However, the Noisy-or Gate (NG) model can solve such problems by clarifying the connection relationship between nodes. Therefore, when the network structure and expert knowledge are known, the NG model can be used to approximately calculate the conditional parameters of BN. The NG model mainly obtains the complete conditional probability distribution of nodes by describing the internal logical relationship between the child nodes and their corresponding parent nodes in BN [52]. Suppose a node V has n parent variables X_1, X_2, … , X_n, and the following conditions need to be satisfied for modeling analysis using the BN based on the NG model [16].

1. All variables have only two states, occurrence (Y) and non-occurrence (N);
2. The corresponding parent nodes of any node are independent of each other.
3. When any parent node X_1 is Y, and all other parent nodes are N, it is enough to make node V in Y state. At this time, the node connection probability is $P_i = P(V = Y|X_1 = N, X_2 = N, \ldots, X_i = Y, \ldots, X_n = N)$. Then other items X_p of conditional probability table (CPT) of node V determined by $P_1, P_2, \ldots, P_i, \ldots, P_n$, expressed as Equation (12).

$$P\left(V = Y \mid X_p\right) = 1 - \prod_{i:\ x_i \in x_n} (1 - P_i) \tag{12}$$

However, child node occurrences are not necessarily caused by parent node occurrences. A complex system is influenced by multiple factors, the node variables cannot cover all factors, and there may also be some unpredictable or unknown factors denoted by X_L [52]. In other words, Leak probability (P_L) exists when all parent nodes are in N state, but the probability of occurrence of child nodes is not zero. Therefore, the Leaky Noisy-or Gate extension model is proposed to determine the CPT of the nodes.

Suppose V has two parents: X_i and X_{all}, where X_{all} denotes all factors except X_i, and P_i and P_{all} denote the corresponding connection probabilities. From Equation (12), we can see that

$$P(V = Y \mid X_i) = 1 - (1 - P_i)(1 - P_{all}) = P_i + P_{all} - P_i P_{all} \tag{13}$$

$$P\left(V = Y \,\middle|\, \bar{X_i}\right) = P_{all} \tag{14}$$

Then P_i, denoted as Equation (15), is calculated by combining Equations (13) and (14)

$$P_L = \frac{P(V = Y|X_i) - P\left(V = Y \middle| \bar{X_i}\right)}{1 - P\left(V = Y \middle| \bar{X_i}\right)} \tag{15}$$

From Equation (15), the joint probability $P_1, P_2, \ldots, P_i, \ldots, P_n$ of all parents of node V can be expressed and then combined with the Leak probability P_L to obtain the conditional probability of V being in state Y, denoted as Equation (16).

$$P(V = Y) = 1 - (1 - P_L) \coprod_{i:\ X_i \in X_n} (1 - P_i) \tag{16}$$

3.4.3. Conduct the BN Model Based on the Leaky Noisy-Or Gate Model

According to the directed graph obtained by ISM, the multi-level hierarchical structure model is transformed into the network structure in BN by the mapping method. The factor nodes and directed edges in the ISM network graph are matched one by one to create the BN network structure model. Define the conditional probability table next. The prior probability of the parent node and the conditional probability of the connection between the parent node and the child node are determined by expert judgment. The node probability distribution of the whole network is then determined based on the extended NG model. The Leak probability of uncertainty is assumed to be 0.1. Finally, the complete Bayesian network model is obtained.

4. Results

Firstly, 20 major failure risk factors of the CPL system were identified through a literature review, relevant accident reports, and expert consultation. Then, the coupling correlation of the system factors was analyzed. The questionnaire survey was used to determine whether the failure factors were correlated and to determine their direct impact on the degree of correlation. The structure analysis model, DEMATEL-ISM model, was conducted to analyze factor categories and criticality and generate the final hierarchical structure diagram. Based on the above system failure risk factor hierarchy analysis, the BN model was presented to explore the main formation causes of system failure and the main propagation mechanisms of failure factors. The hybrid model proposed in this paper was verified to analyze the coupling mechanism of system risk factors by using sample calculations, and the whole process of failure evolution of the CPL system is described visually through simulation. In this paper, five experts in port and maritime security risk analysis are selected to form an expert scoring team to determine the main parameters in the form of subjective scoring for container port logistics operations. The data collected from them were applied to the proposed model.

4.1. Coupling Analysis of System Failure Risk Factors

4.1.1. DEMATEL Model

The pairwise relationships of the failure risk indicators (Table 1) determined in this paper were assessed using the evaluation scale of the impact relationship in Table 2. Then, the opinions of each expert are aggregated and counted to derive the direct influence matrix of the system. The DEMATEL-ISM integrated model was represented using Python, and the data were substituted into the model. After calculation, the influencing degree, influenced degree, centrality, and causality of each factor are determined. Then the importance ranking and factor attributes of each factor are derived according to the index value, and the specific factor analysis results are shown in Table 3 and Figure 3. Next, based on the data results, the causality diagram of the failure risk factors is drawn, as shown in Figure 4.

DEMATEL technology not only determines the relationship and correlation degree among failure risk factors but also explores the importance of each factor within the system. The centrality index can reflect the importance of factors, and the larger the value, the more important the factor. As shown in Table 3, the centrality values of the 10 factors X_{12}, X_9, X_{10}, X_8, X_6, X_2, X_{13}, X_5, X_7, and X_{18} are larger and are therefore more significant in the system. The causality index is used to distinguish factor attributes, that is, how one element affects another. The causal factor is the factor that has more influence on other factors when the value is more than 0; the resulting factor is the factor that is more influenced by other factors when the value is less than 0. From the causality diagram (Figure 4), it's shown that the 12 factors, such as X_1, X_3, X_4, X_5, X_{11}, X_{14}, X_{15}, X_{16}, X_{17}, X_{18}, X_{19}, and X_{20}, are located in the first and second quadrants, which belong to the causal factors. The failure risk system of the CPL system is likely to affect other risk factors; factors such as X_2, X_6, X_7, X_8, X_9, X_{10}, X_{12}, and X_{13} are located in the third and fourth quadrants, which belong to the result factors and are easily affected by other risk factors in the failure risk system.

According to the results, the centrality of the failure risk in the CPL system was arranged in descending order to obtain 10 critical factors, including a mismatch between technological innovation and system capabilities, equipment breakdown, port IT system failure, lack of warehouse/yard space, lack of port equipment, operation errors, poor organization of port production scheduling, poor supervision, over-aging and defects of equipment, and natural disaster/harsh climate, etc., which are more important than other failure factors. Among them, the mismatch between port innovation technology and system capacities is the risk factor with the greatest impact on system failure. The results reveal that all five external risk factors in the paper are causal factors, which have an impact on other risk factors; facility and equipment risk factors belong to the result factors, which are easily affected by other risk factors in the system.

Table 3. The analysis results of DEMATEL.

Factors	Influencing Degree D	Influenced Degree C	Centrality M	Causality R	Weight	Rank	Factor Attribute
X_1	0.813	0.793	1.606	0.02	0.044	13	Cause
X_2	0.897	1.061	1.958	−0.164	0.053	6	Result
X_3	0.866	0.335	1.2	0.531	0.033	19	Cause
X_4	1.336	0.25	1.586	1.087	0.043	15	Cause
X_5	1.244	0.614	1.857	0.63	0.05	8	Cause
X_6	0.401	1.856	2.258	−1.455	0.061	5	Result
X_7	0.439	1.382	1.82	−0.943	0.049	9	Result
X_8	0.243	2.173	2.415	−1.93	0.065	4	Result
X_9	0.499	2.177	2.676	−1.678	0.073	2	Result
X_{10}	0.463	2.112	2.575	−1.648	0.07	3	Result
X_{11}	1.048	0.602	1.65	0.446	0.045	12	Cause
X_{12}	0.327	2.508	2.835	−2.181	0.077	1	Result
X_{13}	0.801	1.158	1.959	−0.357	0.053	6	Result
X_{14}	1.055	0.363	1.418	0.691	0.038	18	Cause
X_{15}	1.296	0.334	1.631	0.962	0.044	13	Cause
X_{16}	1.266	0.425	1.692	0.841	0.046	11	Cause
X_{17}	0.806	0.303	1.109	0.503	0.03	20	Cause
X_{18}	1.724	0	1.724	1.724	0.047	10	Cause
X_{19}	1.449	0	1.449	1.449	0.039	17	Cause
X_{20}	1.472	0	1.472	1.472	0.04	16	Cause

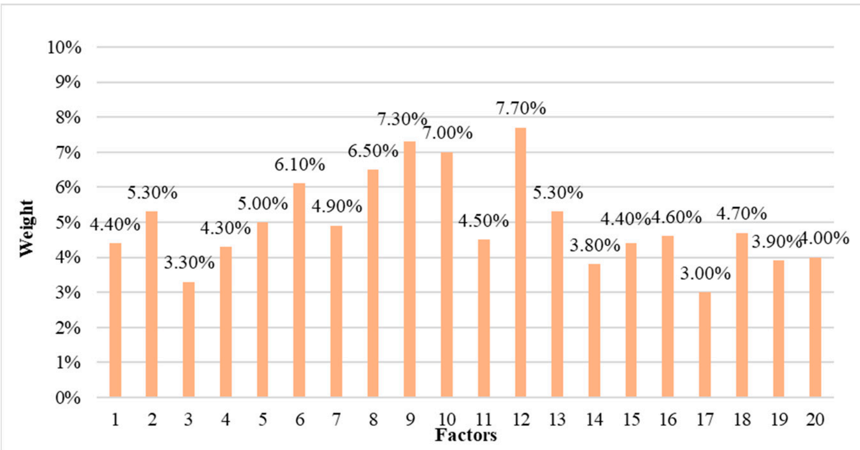

Figure 3. The weight graph of various failure risk factors.

4.1.2. ISM Model

According to the calculation steps of the hybrid model in Section 3.3, the ISM model is further solved using the comprehensive influence matrix T to determine the hierarchical relationships among the system failure risk factors. The threshold λ is then determined according to the data distribution characteristics to determine the reachability matrix. In the paper, the threshold λ is set to 0.11, 0.12, 0.13, and 0.14 for multi-value testing, and the node degree of each factor under different threshold conditions is calculated. Where the sum of the row and column of each factor in the reachable matrix is called the node degree of that factor, arrange the node degrees corresponding to each threshold in descending order to obtain the node degree distribution diagram, as shown in Figure 5. Then, by analyzing the node degree distribution graph, it is concluded that when the threshold

λ = 0.12, the distribution of node degree and centrality corresponding to the reachability matrix is similar, and the most suitable hierarchical structure of influencing factors can be obtained. The specific hierarchical division results are listed in Table 4 in detail. After that, the self-binary relationship and the leapfrog binary relationship in the sorted reachable matrix are processed to obtain the final simplified version of the skeleton matrix K, and based on this, the multi-level hierarchical structure diagram of the failure risk factors is drawn (Figure 6).

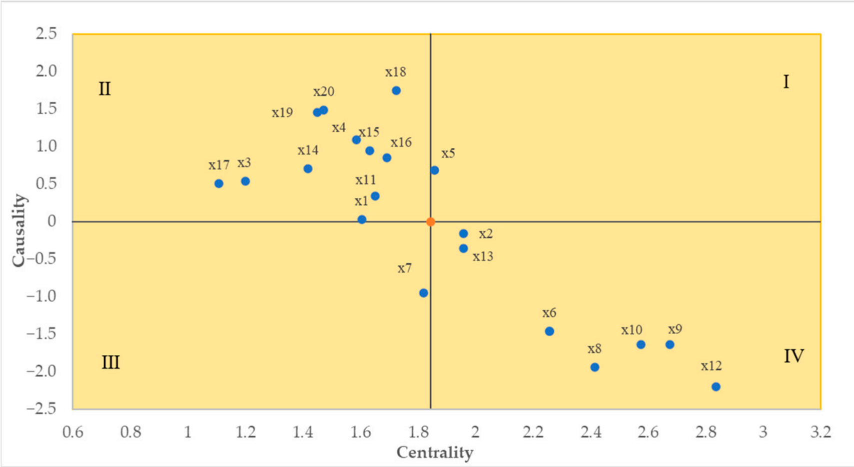

Figure 4. The causal graph of failure risk factors. The blue dots indicate the position of the nodes in the coordinate system, with the horizontal coordinates corresponding to the centrality and the vertical coordinates to the causality. The red dots are the central nodes, the average of the horizontal and vertical coordinates respectively.

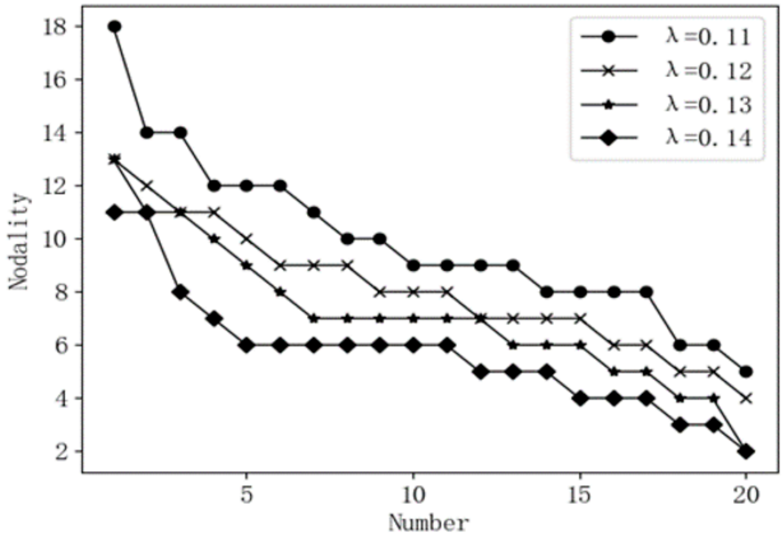

Figure 5. The distribution diagram of node degree with different thresholds.

Table 4. Results of factor hierarchy.

Level L_i	Factors X_i
L_1	X_8, X_{12}
L_2	X_1, X_6, X_9, X_{10}
L_3	X_2, X_3, X_7, X_{16}, X_{20}
L_4	X_5, X_{11}, X_{13}, X_{17}, X_{18}
L_5	X_4, X_{14}, X_{19}
L_6	X_{15}

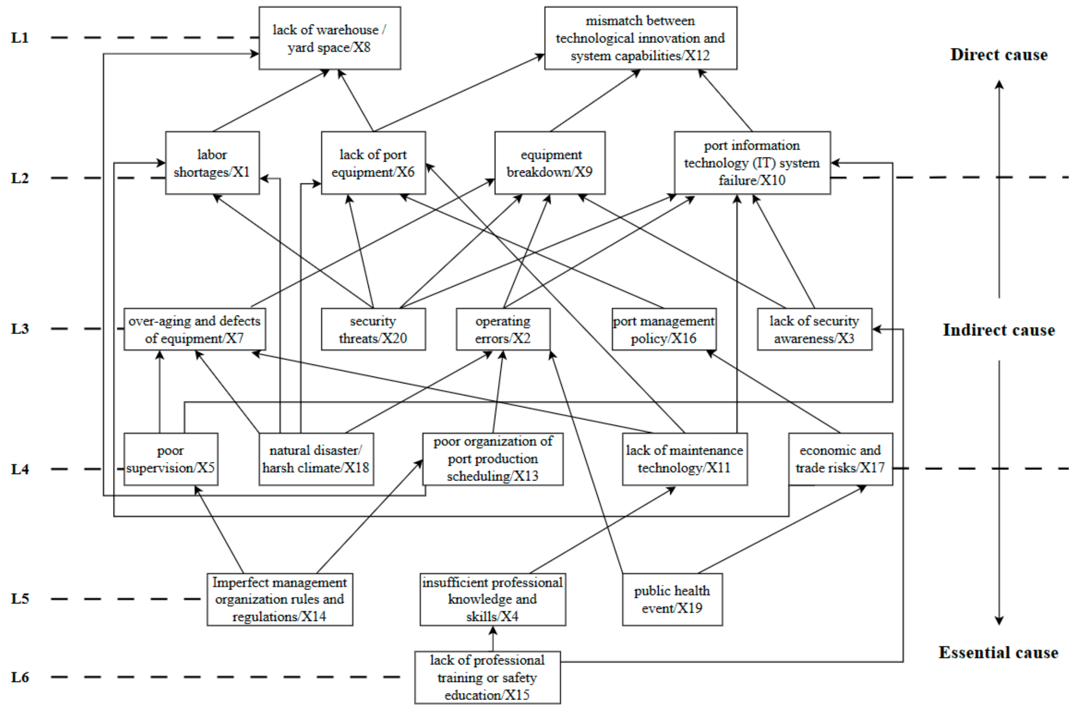

Figure 6. The hierarchical structure diagram of failure risk factors.

The failure risk factors of the CPL system are divided into six levels by ISM analysis, and each factor is classified into three parts: direct cause, indirect cause, and essential cause. As shown in Figure 6, the direct cause includes six factors such as X_8, X_{12}, X_1, X_6, X_9, and X_{10}, and the changes to these risk factors will have a more obvious impact on the system. The indirect cause includes 10 risk factors, such as X_2, X_3, X_7, X_{16}, X_{20}, X_5, X_{11}, X_{13}, X_{17}, and X_{18}, which indirectly affect the system by acting on the upper factors. Furthermore, the essential cause affecting the normal state of the system includes four factors, X_{15}, X_4, X_{14}, and X_{19}, which are the lowest-level factors of the system and easily affect other factors. Specifically, lack of warehouse/yard space and mismatch between technological innovation and system capacities are the top-tier factors. These factors, together with the other four risk factors, labor shortages, lack of port equipment, equipment breakdown, and port IT system failure, form the group of direct risk factors of the system. Moreover, the essential factors that affect the functional state of the CPL system include lack of professional training or safety education, insufficient professional knowledge and skills, imperfect management organization rules and regulations, and public health event. These factors are the bottom risk factors of the system, which will act on the system by influencing other factors. Other factors are indirect factors that connect the entire system.

4.2. BN Modeling

4.2.1. Establish the Network Structure and Network Parameter in the BN

Network topology and CPTs are the two main elements of Bayesian networks. In this study, the hierarchical network graph from the DEMATEL-ISM integrated model is translated to the BN network structure based on the mapping criteria in Figure 7, and the dependence links between variables are represented using directed graphs. Then the systematic network structure model of the failure risk of the CPL system is obtained through the GeNIe simulation software, as illustrated in Figure 8. The node states are set as binary states in the text, which are represented by *Y* and *N*, respectively; that is, *Y* represents the event that occurred, and *N* represents the event that did not occur. The next step is to determine the node parameters of the model, including the prior probability and CPTs. Specifically, (1) determine the prior probability of each root node and the probability of occurrence of child nodes under the condition of occurrence of the root node; (2) calculate the connection probability of the nodes by Equation (15) from Leaky-NG; (3) determine the Leak probability, P_L = 0.1, and calculate the conditional probability of each child node by the Equation (16).

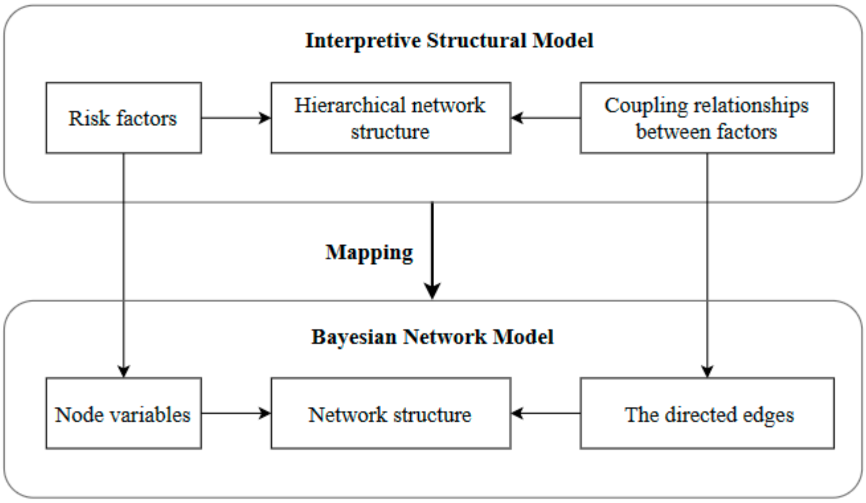

Figure 7. Structure-mapping technology of the BN model.

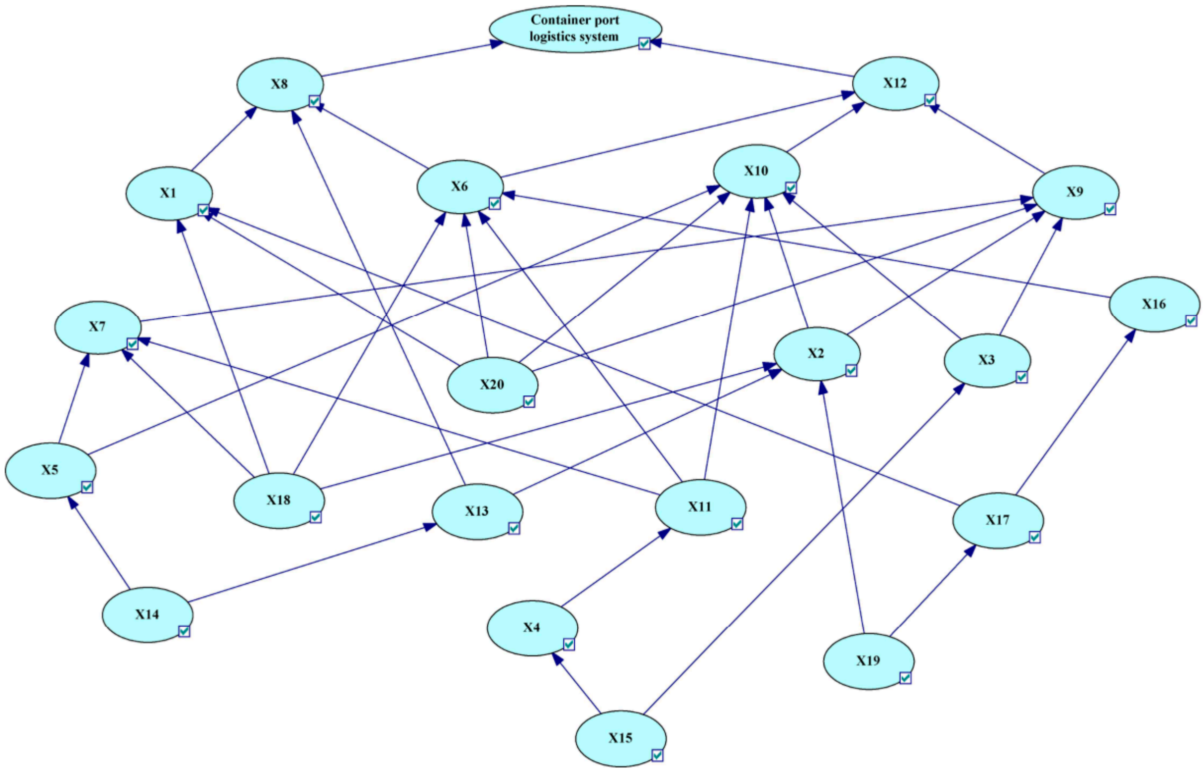

Figure 8. The Bayesian network structure of container port logistics system failure.

Taking the child node of X_7 as an example, the occurrence probability of X_7 under the influence of 3 root node states, X_5, X_{11}, and X_{18}, respectively, is first obtained based on subjective scoring. Then the extended NG model is invoked, and the connection probabilities of each node of X_5, X_{11}, and X_{18} are calculated according to Equation (15) as P_5 = 0.3214, P_{11} = 0.3571, and P_{18} = 0.7125, respectively. Then the conditional probabilities of X_7 are introduced by Equation (16) in combination with P_L = 0.1, as shown in Table 5. Similarly, the CPTs of other child nodes in the network are determined by the above calculation method. The prior probabilities of the parent nodes and the conditional probability values of each node are imported into the GeNIe network model, and the Bayesian network diagram of the CPL system's failure risk is finally generated after evidence learning (Figure 9).

Table 5. The CPT of the child node X_7.

X_5	X_{11}	X_{18}	X_7	
			Y	N
Y	Y	Y	0.88713	0.11287
		N	0.6074	0.3926
	N	Y	0.82442	0.17558
		N	0.38929	0.61071
N	Y	Y	0.83366	0.16634
		N	0.42143	0.57857
	N	Y	0.74125	0.25875
		N	0.1	0.9

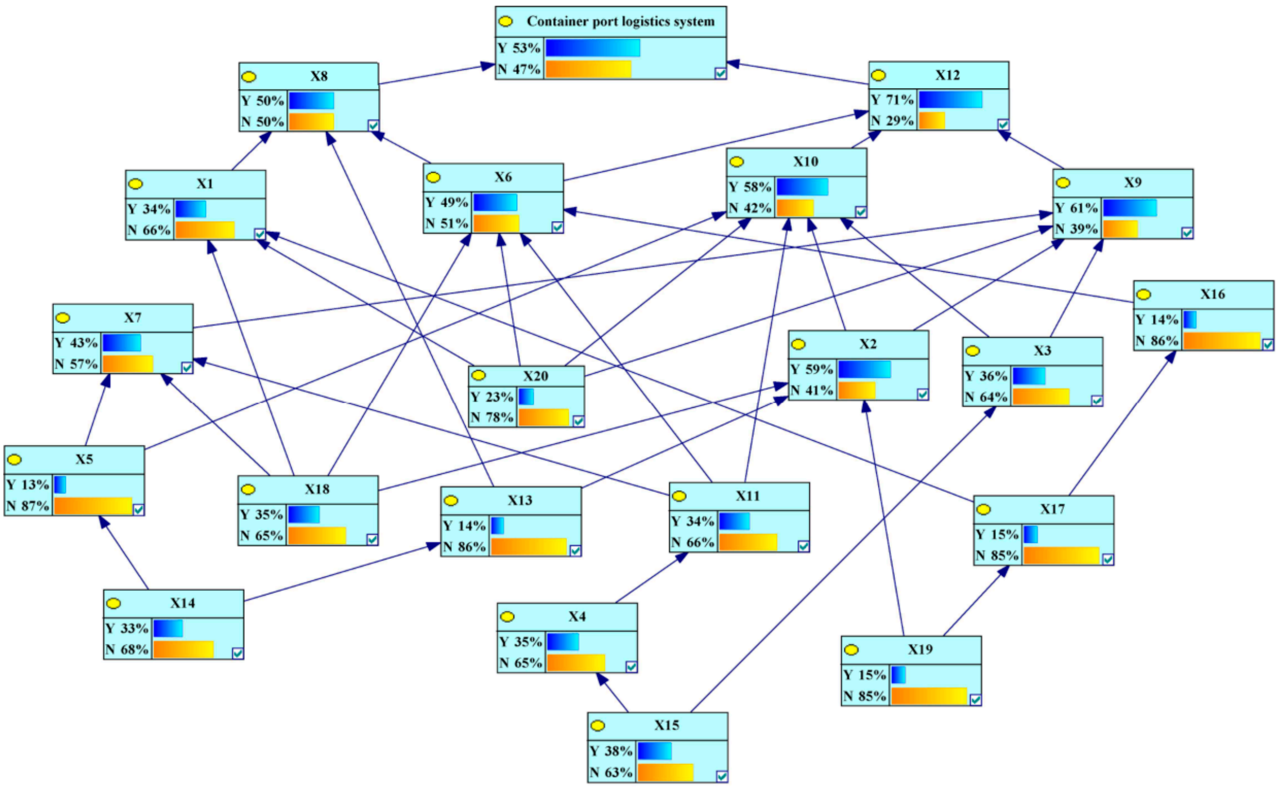

Figure 9. The results of the BN model. These nodes, e.g. X_1,X_2, represent failure risk factors in the CPL system.

4.2.2. Causal Reasoning Analysis

1. Positive causal reasoning

Positive causal reasoning in the BN refers to the examination of the likelihood of CPL system failure with evidence input. As can be seen from Figure 9, the failure probability distribution of each node in the network is inferred under the assumption that the parent node's prior probability is known, where the failure probability of the target node is 53%. This suggests that the system is about a 53% probability of operational disruption under the uncertain environment both inside and outside the system. First, the impact of single-factor changes on the system failure is analyzed. Based on the analysis of system failure factors in Section 4.1, X_8 (lack of warehouse/yard space) and X_{12} (mismatch between technological innovation and system capacities) are the direct causes within the system, where X_{12} is the most influential failure risk in the system. When the node X_8 event occurs, i.e., P_8 = 1, the failure probability of the target node is 72% by positive reasoning; when the node X_{12} event occurs, i.e., $P_{12} = 1$, the port failure probability is 64%. Second, given the complex coupling relationship between system failure risk factors, the influence on system failure is analyzed when multiple node factors within the system fail at the same time. For instance, Figure 10 is produced when the failure probability of nodes X_{12}, X_6, and X_2 are all 1. It's clear that the failure probability of the system becomes 70%, and the failure probability of nodes X_8, X_9, and X_{10} also changes greatly, increasing the occurrence probability by 30%, 21%, and 19%, respectively. This also illustrates the coupling relationship among failure risks, which describes how changes in one factor's state have an effect on other factors in the system.

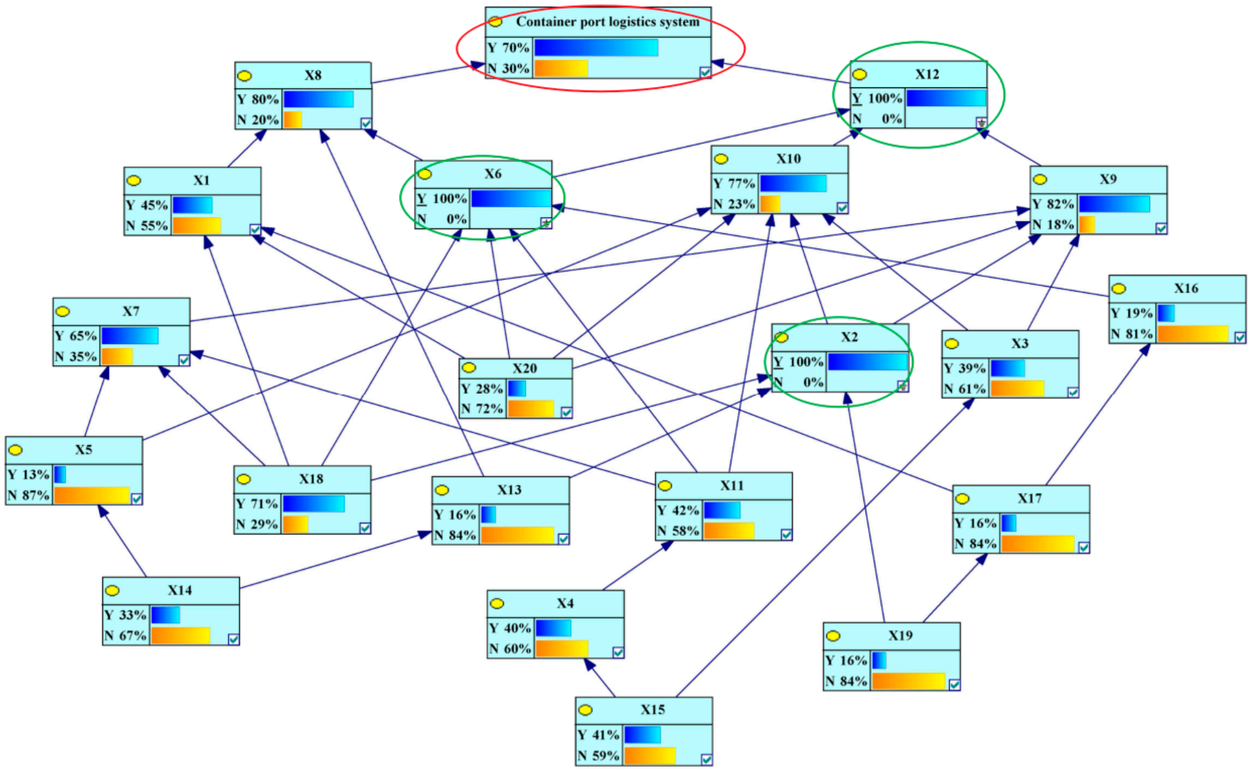

Figure 10. Results of positive causal reasoning in the BN model. These nodes, e.g. X1,X2, represent failure risk factors in the CPL system. In the figure, the red circle represents the target node "Container Port Logistics System"; The green circle represents the failed node, that is, the node X_{12}, X_6 is in a failed state.

2. Reverse Diagnostic Reasoning

The main purpose of this paper is to explore the failure evolution mechanism of the CPL system, and the main research idea is to determine the system failure risk coupling mechanism and the root cause of the system failure by building the BN model. Therefore, the reverse diagnosis in BN can be used to derive the possible failure propagation paths and failure factors when the system is disrupted by failure, i.e., $P = 1$, as shown in Figure 11. In the figure, the failure probabilities of nodes X_{12} and X_8 are 87% and 68%, respectively, and the failure probabilities of X_9 and X_2 in the second and third layer factors are higher at 67% and 65%, respectively. Moreover, the failure probability of the parent nodes X_{18} and X_{15} in the network is higher compared to the other parent nodes, with 42% and 40%, respectively. It is shown that the more likely propagation paths leading to system failure are: $X_{18} \to X_2 \to X_9 \to X_{12} \to P$; $X_{18} \to X_6 \to X_8 \to T$; $X_{15} \to X_3 \to X_9 \to X_{12} \to T$.

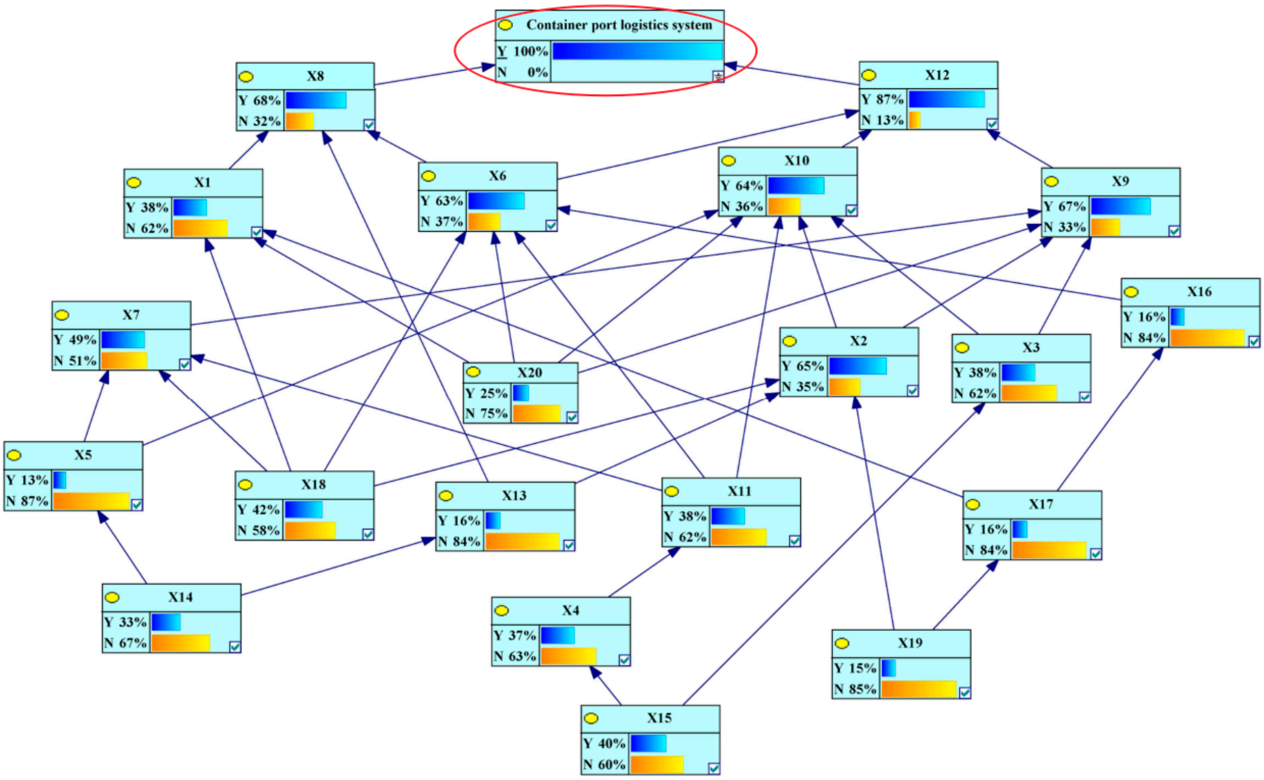

Figure 11. Results of BN reverse diagnostic analysis. These nodes, e.g. X1,X2, represent failure risk factors in the CPL system. The red circle indicates the target node, indicating the possible failure propagation path of the container port logistics system when it is in a failure state.

Among them, we can find that if the port system fails, the five factors of mismatch between technological innovation and system capacities (X_{12}), lack of warehouse/yard space (X_8), equipment breakdown (X_9), operation errors (X_2), and lack of port equipment (X_6) pose a greater threat to the system and present a higher failure probability of the CPL system. In contrast, uncontrollable external factors such as natural disasters and terrorist attacks are not conducive to the stability of the CPL system. The two risk factors of mismatch between technological innovation and system capacities and lack of warehouse/yard space are the most immediate key factors contributing to the system. Natural disasters/harsh climates and lack of professional training or safety education are the most likely essential sources of system failure which will essentially increase the failure risk level of the CPL system by affecting the working condition of workers and the reliability of facilities and equipment.

5. Discussion

In this paper, to more systematically and comprehensively explore the coupling mechanism of failure risk factors in CPL systems, the DEMATEL-ISM integrated model is used to explore the key failure factors of the system and the coupling relationship between the factors. Then, the probabilistic reasoning capability of the BN is used to study the system failure evolution mechanism and determine the failure risk transfer mechanism. The key issues of this paper are analyzed and discussed in depth based on the results of the data analysis in Section 4.

The coupling analysis results of system failure risk factors indicate that technical risks, human risks, and facility and equipment risks play a crucial role in the CPL system. First, compared to much current research on port operation risk management [3,11,17], this study highlights that technical risks, particularly the risk of mismatch between technological innovation, pose the greatest threat to container port logistics systems. In the study by Loh et al. [8,27], the research argues that the efficiency of port operations depends on new technologies and advanced systems, as well as the ability of port technicians. Therefore, this factor is one of the most direct influencing factors of the system. When the system risk level is high, and stability is poor, the effective control of such factors can reduce the system instability level more significantly in a short period and improve the reliability of the system. Second, based on the proportion of the above factors, it can be found that facility and equipment risks and human risks are the second largest threat risk group for container port logistics services. This finding is consistent with existing literature on the risks of harbor operations [12,16,24,28]. For example, human factors, especially operational errors and equipment-related risks, are considered the most prominent risk factors in terminal container operations by Budiyanto et al. [16]. Additionally, this suggests that external risk factors such as natural disasters, security threats, and economic and trade risks will bring greater risk potential to the system. External risks have the characteristic of "small probability and large impact," seriously threatening the orderly operation of ports and increasing the danger to ports and goods themselves [10,53].

Secondly, this study not only judges the importance of the failure risk factor but also innovatively analyzes the correlation between the risk factors and determines the risk factor categories using the DEMATEL-ISM model. It shows that external risk factors are causal factors that have an impact on other risk factors because uncontrollable external factors not only affect the working condition of port workers but also endanger the facilities and equipment in the port. Zhou and Li [3] also pointed out the important role of external risk factors and specifically analyzed the threat effects of different risk factors on the resilience of container transportation services. Zhou et al. [3] did not analyze the relationships between risks and only derived the relative importance of the factors. Moreover, this study also emphasizes that the mismatch between technological innovation and system capacities, equipment breakdown, port IT system failure, lack of ware-house/yard space, and lack of port equipment are the main key result factors within the system. Poor supervision and natural disasters/harsh climate are the critical cause factors. Among them, human risk and external risk factors can affect the normal functional status of facilities and equipment. On the other hand, according to the hierarchical structure of the risk system, it has been shown that human factors and organization and management factors, including lack of professional training or safety education, insufficient professional knowledge and skills, imperfect management organization rules and regulations are the fundamental factors that affect the functional status of the CPL system. These factors are the bottom risk factors of the system, which will have direct or indirect effects on other risk factors, thus threatening the safety and reliability of the whole system. John [29] and Fan [25] also pointed out the serious threat of human and organizational factors to maritime safety, making important contributions in the field of maritime risk management. The findings of this research also conform to the research conclusions of the current top literature.

The key purpose of this paper is to explore the coupling mechanism of system failure risk factor and failure risk propagation path using the BN model. This is an important uniqueness of this paper. In practice, during the container port operation, the warehouse space problem in the port may cause congestion in the yard and terminal traffic areas, making it difficult to load and unload or transfer the terminal cargo in time. These may slow down terminal operations, leaving ships stranded, or substantially disrupt the logistics chain, which eventually leads to disruption of the whole port logistics system. On the other hand, the facilities and equipment capacity and technical capacity of the port are complementary. If the introduction of new port technology is not matched by the port transportation capacity, it may result in issues including low operational efficiency and confusion at the operation site, and even improper command, operational errors, and other work failures, which will destroy the continuity of the port logistics system.

In addition, one of the innovative viewpoints of this paper considers the coupling effect between factors and studies the failure mechanism under the coupling effect of multiple factors. The mutual coupling effect of multiple factors in the system will increase the possibility of system failure and enhance the impact consequences of failure risks. For example, when there is a capacity issue for technical innovation in the system, the problems of worker error and inadequate port equipment can further increase the likelihood of port failure. Moreover, it will bring more serious risk problems such as insufficient storage space, equipment breakdown, and port IT system failure. These could complicate internal system issues and make it harder to control risks. Budiyanto et al. [17] analyzed the causes of the seaport accident using the FTA model while only focusing on determining the relative importance of factors without considering the impact of multi-factor coupling on the system. Then, combining the key results in this study and relevant literature on risk analysis of container port operations [12,13], this research furthers explores the possible failure propagation paths during CPL operations. Thus, it can help container port enterprises participate in port operation and risk management from the perspectives of key nodes and propagation paths (points and lines).

In fact, previous research on risk management in seaports, especially those related to container shipping risks [6,9,31], has shown that human factors, facility and equipment factors, technical factors, organizational management factors, and external environmental factors have always been important objects of risk management, playing an important role in the safety and stability of port operations. On the one hand, this article further proves such conclusions and highlights the crucial role of technical risk factors in modern port logistics. It is worth noting that this study also comprehensively analyzes the coupling mechanism between internal and external risk factors in the system. Furthermore, compared to traditional risk analysis methods, this research studies the failure risk of the CPL system from a new perspective, the failure mechanism perspective. Therefore, this research achieves innovation in the research framework and model and proposes some unique conclusions. Moreover, container port risk management is still a research hotspot, and this paper has contributed to the enrichment and improvement of the theoretical basis of maritime risk management, as well as the safe development of container shipping.

In practical applications, it helps port managers to identify the main failure risk propagation paths and critical failure nodes and to propose targeted prevention and control strategies to reduce the impact of risk emergencies on the system. Based on the above discussion and results, this paper proposes the following risk management ideas from the perspective of port enterprise managers:

(1) For the key cause factors, port managers should cut off their influence transmission among other factors to control the risk propagation and evolution; for the key result factors, it is necessary to not only control the influence consequences of the cause factors but also pay attention to preventing the risk emergence from increasing due to the mutual coupling among risk factors.
(2) From the perspective of factor hierarchy and transmission, we should concentrate more on their subtle influence when managing the bottom risk factors; fundamentally eliminate the hidden problems and cut off the transmission path from the bottom risk factors to other high-level factors in a timely manner; and focus on the interaction between multiple factors and focus on time efficiency.

In summary, this study conducts an in-depth analysis and summary of key results and obtains the key content and innovation of the research through a comparative analysis of relevant literature. Then, the specific significance and contribution of the research results in theory and practice were analyzed. Constructive suggestions on control to port managers were provided. However, this paper focused less on the risk factors of connecting the internal and external environments in the CPL system in the risk analysis. Then, the output of the results depends more on expert opinions, and there are certain differences.

6. Conclusions

1. Conclusions and implications

This research proposes a hybrid BN method based on the DEMATEL-ISM integrated model to systematically analyze the failure risks of the container port logistics system and explore the coupling mechanism of system failure risk factors as well as the system failure evolution mechanism. First of all, this study identifies the main failure risks of CPL system by combining literature review, expert investigation, and relevant accident reports and determines 20 failure risk factors in five dimensions: human risks, facility and equipment risks, technical risks, organization and management risks, and external risks. Secondly, this paper investigates the coupling relationship between system failure factors and the system factor hierarchy using DEMATEL and ISM techniques and then finds out the system critical failure factors and the attributes of each factor. Afterward, the BN model is constructed to further quantify the coupling strength between the system failure factors and to mine the possible failure risk factor sets and failure propagation paths of the system. This paper highlights that technical risks and facility and equipment risks are direct threats to system stability, especially factors such as mismatch between technological innovation and system capacities, lack of warehouse/yard space, and equipment breakdown will increase the potential risk of system failure. Following this, human risks have an important position in the system and run through all aspects of the system, which can enhance the level of system failure risk by influencing other factors. Moreover, organization and management risks, such as imperfect safety education or technical training, incomplete management organization rules and regulations, etc., mainly have a subtle impact on the system in essence. Moreover, the whole container port logistics system is most sensitive to external environmental risks, and the changes in the external environment will increase the internal risk level of the system and result in internal risks emerging. Hence, this paper emphasizes that the complex coupling relationship between internal and external risks of the system and the strong coupling role of the internal system should be paid attention to in order to discover the risk potential in time, cut the risk connection, and develop risk response measures to ensure the safe and stable operation of the system.

On the whole, this research has important theoretical and practical implications. On the one hand, this research's theoretical contributions are multi-fold. First, the object of this study is to investigate port risk from the new perspective of system failure and provide important insights by considering the influence of multifactor coupling on the evolution of system failure and building a failure mechanism model. This provides a new analytical framework and research perspective. Second, this study enriches the failure risk index system of the port logistics system and strengthens the understanding of the complex coupling relationship between factors. Third, this paper constructs a new risk model to deeply explore the relationship between factors, effectively overcome data problems, and improve the accuracy and persuasiveness of the results. Furthermore, the model can achieve real-time updates of data, which helps with risk monitoring and control. In short, this paper compensates for the shortcomings in port risk management research, enriches the theoretical foundation of the maritime risk field, and promotes the development of this field. Moreover, the new analytical framework proposed in the article can be applied to risk management in other fields.

From a practical point of view, this research provides a theoretical basis for enterprise managers to carry out risk management, helps them propose targeted prevention and control strategies, and promotes the scientific decision-making of enterprise managers. Moreover, it can enable port companies, governments, and other stakeholders to grasp the risks of port operations and determine the direction of future changes and development. In addition, timely and effective risk control can reduce losses caused by port risk events and improve resource utilization. Finally, constructive suggestions are put forward in terms of organizational management, daily monitoring of facilities and equipment, technical management, and contingency response, such as sound port management rules and regulations, comprehensive risk monitoring, and early warning mechanism.

2. Limitations

However, there are some limitations to this study. First, this study mainly relies on expert assessment to obtain relevant data but lacks objective data. Second, to make the output network structure more aesthetically pleasing, this paper simplifies the association lines of factors on the graph when establishing the structural model, which makes the hierarchical structure not fully reflective of the direct connection between individual factors. There is still room for improvement regarding the methodological model used. Third, this research tends to be theoretical, and more comprehensive practical investigations can be conducted in the future to have a deeper understanding of the failure risk issues of typical ports and propose targeted risk management recommendations for specific ports. Therefore, in the future, the scale of expert review can be expanded and combined with objective statistics to improve the accuracy of the output results. On the other hand, the failure evolution of the port can be studied under different scenarios, and its feasibility can be proved. In the end, research on risk mitigation and control strategies for container port logistics can be continued based on the findings of this paper.

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