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Understanding Relationships Among Risk Factors in Container Port Operation Using Bayesian Network

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Abstract : *This study aimed to determine relationships among risk factors influencing container port operation using Bayesian network. Risk factors identified from prior studies were classified into five groups: human error, machinery error, environmental risk, security risk, and natural disasters. Panel experts discussed identified risk factors to fulfil conditional probability tables of the interdependence model. The interdependence model was also validated by sensitivity analysis and provided an interrelation of factors influencing the direction of each other. Results of the interdependence model were partially in line with results from prior studies while practices in the global port industry confirmed interrelationships of risk factors. In addition, the relationship between top-ranked risk factors can provide a schematic drawing of the model. Accordingly, results of this study can expand the prior research in the Korean port industry, which may help port authorities improve risk management and reduce losses from the risk.*

Key words : *seaport, container port risk assessment, risk factors analysis, Bayesian network, inter-dependency model*

1. Introduction

Maritime transportation is considered one of the most critical means of transportation. Ports are not just crucial nodes in the multimodal transport system, but also the important infrastructure that links water and land transportation, a gateway to international trade (Hossain, 2020). For instance, the shipping industry is responsible for the carriage of around 90% of international trade (Vista Oil & Gas, 2019). From the perspective of Korea, ports play a significant role in the economy, accounting for 99.7% of the total volume of international trade (Lee and Ha., 2022). However, the accidents in the port are increasing continuously as a larger volume of cargo is handled in ports with the total accident of 3,156 in 2020 which is almost a 6% increase compared to the previous year of 2,971 accidents (Korea Maritime Safety Tribunal, 2021). Unexpected risks can be the cause of serious damage or accidents, so it is critical to identify and understand the causes of these risks (Park et al., 2019; Sim et al., 2023). This is because risks also can have an impact on both international trade and regional economic development of the entire port system (Wang et al, 2022). Also, Wan et al. (2019) noted that the analysis of the risk factors is critical to the success of effective safety management because it can help identify the hazards, and understand where a risk may emanate from. In other words, the main objective of assessing risks is usually to prevent accidents or disasters. In response to avoid accidents, understanding of risk occurring and its background interrelation affecting reasons might be one of important and primary requirements (WPSP, 2020). However, the risks are often invisible and complicated to detect (Alyami et al., 2019).

To this end, this study aims to understand complex risk factors interrelation in container port operation in the level of identification and assessment by using Bayesian network (BN). For this, section 2 starts with a brief overview of previous works as a literature review. Then an adopted methodology is introduced in section 3. Next, section 4 presents the result of the analysis. Finally, section 5 is dedicated to discussion and conclusion.

2. Literature review

2.1. Identification of risk factors

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Seaport risk management plays an increasingly crucial role in ensuring port service resilience in the context of supply chain systems (Alyami et al., 2019). Different interpretations and customized steps exist, but the risk management process of an organization generally can classify into 4 steps involving identification, evaluation, control, and monitoring. Failure to set a specific risk management strategy can lead to a significant failure to adequately manage the risks faced by an organization (IRGC, 2015). Thus, a risk management study on port operation needs to provide the causal relations of the risk factors which influence the operational safety of container ports.

In response to the offer for complete risk management, risk identification should cover all sources of risk arising from the important activities within the organization (IRM, 2002; Lee and Ha, 2021). Mokhtari et al. (2012) explain that taking a corporate strategy perspective of risk management involves the greatest challenge for uncertainty identification, not least because the factors capable of influencing performance are so numerous. Lee and Ha (2021) have concretely reviewed previous literature in the context of risk management and risk assessment. Based on their study, this work classifies the risk factors into 2 categories shown below.

a. Human error-related risk factors: In respect of marine accidents, it is not surprising that it has been estimated approximately 80% of shipping accidents are caused by human factors. Human errors lead to incidents, losses and damages to people, ships and cargo (Makhtari et al., 2012). According to Allianz (2022), almost 15,000 marine liability insurance claims between 2011 and 2016 show human error is a primary factor in 75% of the value of all claims analyzed which is equivalent to over $1.6 billion of losses. Given the role of human error in so many incidents, the quality of crew and ship owners' overall safety culture is increasing importance to risk assessment (Expert risk article, 2019). On the other hand, increasing human error can be affected by other risk factors. For instance, according to Allianz, 2022, it is likely to be linked to the commercial pressures that container ships have to keep to a tight schedule, which may lead to an increase in the risk of human error. Besides, commercial pressure is not the only reason for the tight schedule of vessels.

b. Non-human error-related risk factors: Based on the part of the human error-related risk, the rest of non-human related risk accounts for 4-25% of total hazards covering other risk sources, e.g., safety-related risk, machinery error-related risk, operational risk, security related risk, natural disaster-related risk, environmental risk, contract or legal error related risk. In the context of this part of risks relate to various sources, for example, one of the causes of machinery error can be a human error (Hossain et al., 2020). That is why, it is not just important to identify and evaluate what are the main risk factors in the operation of the container terminal, but also there is a requirement of understanding what relationships between which factors are existing.

2.2. Assessment of risk factors

Previous studies adopt different methodologies of risk assessment in diverse situations. The risk assessment is often divided into a qualitative and a quantitative part. Qualitative methods for exploring risks could be influence diagrams, e.g., showing interrelations between regulatory, operational and organizational influences, etc. while quantitative methods include fault and event trees and Bayesian Belief Networks, in which barriers that prevent incidents from occurring or mitigate consequences are normally included (Berle er al., 2011; Pallis, 2017).

Nagi et al. (2021) choose a multiple-method design which is built by a network of survey data, communication intensity values, network analysis, community detection and plausibility check to detect the community of stakeholders at the port of Hamburg in which communication intensity in activities related to risk management. Olba et al. (2019) develop an assessment methodology for the nautical port risk index to evaluate the potential risk of vessel traffic in the ports. Pallis (2017) presents a port risk management methodology in a container terminal. Kwak et al. (2018) apply Interpretive structural modelling (ISM) for a holistic understanding of risk interaction influence supply chain management. John et al. (2014) adopt a novel fuzzy risk assessment approach which consists of a fuzzy analytical hierarchy process (FAHP), an evidential reasoning approach and a fuzzy set theory, to facilitate the treatment of uncertainties in seaport operation. Bazaras et al. (2017) present conceptual provisions and multi-criteria analysis for potential emergency risk management. Mokhtari et al. (2012) use fuzzy set theory and evidential reasoning to support a framework for risk management in seaports and terminals.

Furthermore, several works of literature adopt the Bayesian network (BN) as a powerful tool to support causal inference for the understanding of what are the most important indicators of accidents and where is the relationship connections between factors. For example, Yang et al. (2021) review literature which adopts BN applications in maritime-related risk management. According to the review, to mention for the core research classification into the occurrence of ship-ship collisions, navigational safety in shipping, maritime accident evaluation and prevention, oil spill accidents & recovery in the maritime field, offshore & port safety analysis, maritime autonomous surface ships, risk of ships and PSC inspections. From this part of global research relating context of risk, it is shown that it tends to understand holistically risk conception.

On the contrary, according to Lee and Ha (2022), the aspect of literature related to port risk assessment in Korea adopts several approaches of methodologies except for the BN. They also mention that domestic researches relate maritime risk management relatively less than compared to foreign literature and conduct two levels of series research for evaluating container port risks using methodologies of Analytic hierarchy process (AHP) in 2021 and fuzzy evidential reasoning which combines AHP based on FER algorithm and Utility techniques in 2022. However, applying the risk factors under a discrete condition based on multi-criteria decision-making (MCDM) approach is challenging to understand the interdependency among the factors. If we understand the relationships among the risk factors, it may deliver a better understanding for port managers and policy-makers to manage related risks in container terminal operations.

Hence, this research adopts the productive tool of BN methodology to effectively understand relationships between various risk factors which influence container terminals in Korea. The research methodology is developed in the following section.

3. Methodology: Bayesian network (BN)

This study uses Bayesian Network (BN) to identify and analyse the risk factors in port operations. The BN method was developed based on the well-defined Bayesian probability theory and networking technique. It employs a graphical display of probability and mathematical inference calculations to form a robust structure for expressing knowledge. This technique has been utilized to examine the significance of various risk factors and their interdependencies (Yang et al., 2021). Since BN is a graphical model of probability, it illustrates a group of random variables and their conditional relationships in a directed acyclic graph (DAG). The DAG includes nodes that represent random variables and edges that demonstrate the causal dependence among the variables in terms of probability (Li et al., 2014). BN is a valuable resource for calculating the probability distribution of unobserved variables based on certain observed variables, while encoding both quantitative and qualitative data in a probability format. These variables can take various forms, such as Boolean (yes/no), qualitative (low/medium/high), or continuous. The Conditional Probability Table (CPT) associated with each node outlines the relationship between the variables and their corresponding states, offering a quantitative component (Li et al., 2014).

Normally, the process of developing a BN model consists of four phases: data acquisition, variable identification, BN construction and conditional probability disruption and risk prediction (Yang et al., 2021; Yang et al., 2018).

In this research, the specific steps applied in this research are introduced as follows.

Step 1. Identification of factors: The factors influencing port operations were selected to form the prior research of Lee and Ha (2022). Based on the concrete literature review and face validity by port export, they already identified these risk factors which are the optimist in Korean container port systems. The 19 factors into five groups are shown in Table 1.

Step 2. Expert discussion: In this step, we invited 8 experts from the port industry who have been working for more than 10 years[1]. They confirmed that factors can represent risks that could occur in port operations. They discuss which factors connect with the others, in

1) Four experts from container terminals (one section head with BA, one head of department with MSc, two deputy head of department with BA and MSc, respectively), two experts from academia (professors in maritime studies) and two experts from the port authority (a head of department with MSc) and national research institute (a senior research with PhD), respectively.

other words, which factors can influence which factors and what is the conditional probability of risks when factors are connected. For example, what is the probability of machinery risk in a ship crash? (BayesFushion, 2022).

Step 3. Development of interdependency model & validation: BN can be structured by establishing the relationships between factors. The relationships between 19 elements were evaluated by pairwise comparison based on the brainstorming of experts. Because BN can obtain this option that can be used when in lack of data information. The possible likelihood of risk factors was fulfilled in the CPTs, and then the software calculates it by Bayesian theorem and shows what factors have an influence on which factors. In other words, the structural properties of BN, along with the conditional probability tables associated with their nodes allow for probabilistic reasoning within the model (BayesFushion, 2022). The model is constructed by the GeNIe software.

Step 4. Analysis of results: In this step, the result of the influence diagram can be explained as shown in the next section.

Table 1 Risk factors and their importance

No	Groups	Factors	ID	Local weight
1	Human Error (0.48)	Pilots related errors (ships crash when berth)	HE1	0.28
2		Poor maintenance & steering in port	HE2	0.34
3		Port operation errors from stevedores	HE3	0.16
4		Freight forwarding & storage (loss, demage)	HE4	0.23
5	Machinery Error (0.17)	Terminal equipment malfunction	ME1	0.5
6		Mechanical failure	ME2	0.16
7		System malfunction	ME3	0.34
8	Environmental Risk (0.18)	Greenhouse gas emission from ship	ER1	0.16
9		Marine pollution from oil seepages	ER2	0.51
10		Port pollution from ballast water release	ER3	0.25
11		Noise pollution from cargo handling	ER4	0.08
12	Security Risk (0.07)	Security risk from hacking	SR1	0.16
13		Security risk from smuggling, theft	SR2	0.39
14		Security risk from illegal trade	SR3	0.16
15		Security risk from illegal entry	SR4	0.29
16	Natural Disaster (0.10)	Strong wind	ND1	0.42
17		Heavy waves	ND2	0.24
18		High temperature, fog	ND3	0.21
19		Heavy rain, flood	ND4	0.14

Source: Lee and Ha. (2022)

4. Results

In this section, we discuss the two different types of analysis Influence diagram and sensitivity analysis. A total of 19 factors are used to build an influencing diagram which is drawn without considering element names but using elements IDs.

In Figure 1, 19 factors build the interdependency model. Hence, according to this result, HE1 (Ship crash) have the most parent elements, which means it is affected by the most factors that four factors of ND (Natural disaster), ME2 (Mechanical failure), ME3 (System malfunction) and HE2 (poor maintenance and steering in port). The next most influenced factor is ME2 (Mechanical failure) which is influenced by HE2 (poor maintenance and steering in failure), and also four factors of ND. But this ME2 is one of the parent nodes of HE1 (ship crush). In terms of affecting, the factors which have the most child nodes are ND1 (Strong wing), ND2 (Heavy waves), ME3 (System malfunction), and ME2 (Mechanical failure).

The greater influence of one node on another, the greater width of the link (BayesFushion, 2022). According to this representation, ME2 has a great influence on ER3 (Port pollution from ballast water release). Besides, there are only four parentless nodes exist – HE1, ER1, SR1, and SR2, which means they do not influence other factors.

In general, BN refers to risks of Natural disaster (ND1), Machinery risks (ME1, ME2, ME3), Human risks (HE1, HE2, HE3), and Environmental risks (ER2, ER3) have the highest likelihood, which estimated in the research of Lee and Ha(2021) and Lee and Ha (2022), in which factors of ND1 (29%), ER3 (27.25%), SR2 (27.25%), HE2 (0.27%), HE1 (26.25%) ranked highest that represent the port operation would not be sustainable.

In addition, Security risks (SR2, SR4) also ranked greater, which was confirmed in the Allianz(2022). The Allianz report mentioned that security risks increasing, for example, 44% of maritime professionals reported that their organization has been the subject of a cyber-attack in the last three years. The reason for this risk increase is ports are increasingly reliant on technology, where an interruption of service or cyber-attack could effectively close a port.

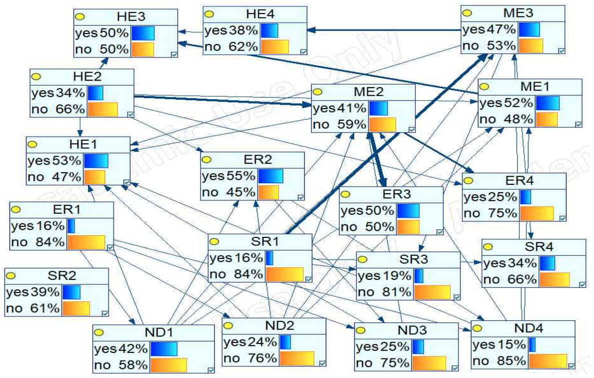

Fig. 1 Result of Bayesian network for scenario 1

In scenario 2 (Fig. 2), the higher probability of risk factor of ND1 was adjusted as no occurred risk when the amount of probability of all factors also changed except factor of SR2 which has no parent or child node. If it assumed that only risk ND1 would not occur, then the probability of remaining variables can reach under 50%, except ER2 (Marine pollution from oil seepages). The risk of ER2 also dropped from 55% to 51%.

Afterwards, the high likelihood of risk factor (HE1) from the Human error group was modified to that of not occurring would 100%. Also, except for the risk of ER2, remained all risk factors can reduce by under 50%. From this analysis, it was obvious that port authorities can not change weather conditions, but if they can focus only on one crucial risk factor, port operation sustainability would be influenced positively. As well, follow with the model, except for the SR2, there is no existence of risk factors just by themselves. Almost all risk factors have interrelations with each other. As exemplified, to reduce the probability of the HE1 factor, affecting factors of HE2, ME2, ME3, ND1, ND2, ND3, and ND4 need to be considered.

Then how port management can consider Natural disasters, of course, have to be obtained weather forecasts and other predictions, besides Environmental risks can be affecting factors, unfortunately, it is not just the issue of Korean port authorities.

In the last analysis, sensitivity analysis (Fig. 3) are used to examine the validity of a simulation model by appraising its strength (Hossain et al., 2020). Sensitivity analysis is also a technique that can help validate the probability parameters of a Bayesian network. This is done by investigating the effect of small changes in the model's numerical parameters (e.g., prior and conditional probabilities) on the output parameters (e.g., posterior probabilities). Highly sensitive parameters affect the reasoning results more significantly. Identifying them allows accurate results of a Bayesian network model.

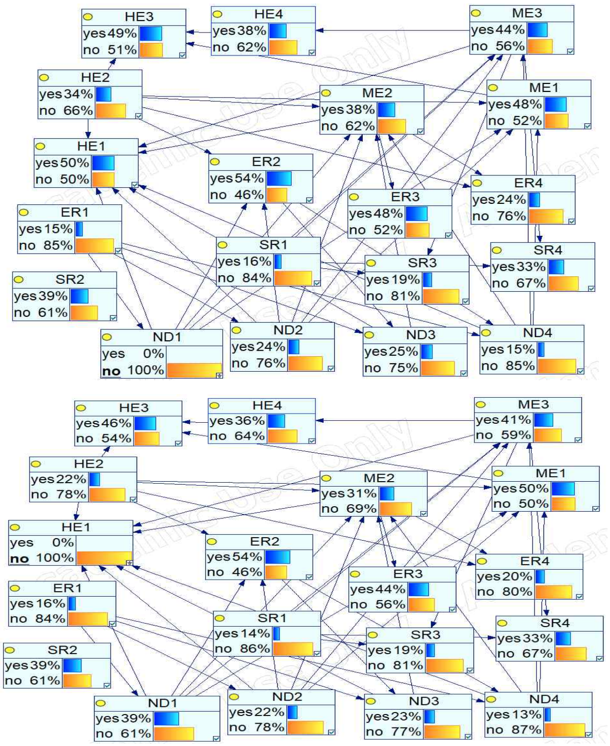

Fig. 2 Result of Bayesian network for scenario 2

To conduct sensitivity analysis, there is one target note required for at least the most affected nodes of HE1, and ME2 set as target notes. In Fig. 3, nodes coloured in red contain parameters that are important for the calculation of the posterior probability distributions in those nodes that are marked as targets. While, grey-coloured nodes do not contain any parameters that are used in the calculation of the posterior probability distributions over the target variables (BayesFusion, 2022).

Then Tornado icon shows the most sensitive parameters for the selected state of the target node sorted from the most to least sensitive (Bayes Fusion, 2022). As well the bar shows the range of node changes in the target state as the parameter changes in its range, in other words, the width of the bars corresponding to each sensitive node in the tornado icon, represents a measurement of the impact from that target node (Hossain et al., 2020).

Hence, selected target notes of HE1 and ME2 are not the most sensitive parameters, but the model gives HE2 as the most sensitive one, even though HE2 has not any parent nodes. Both target nodes are impacted by HE2, which means as the factor of HE2 occurred greatly, the amount of HE1 and ME2 is modified greatly.

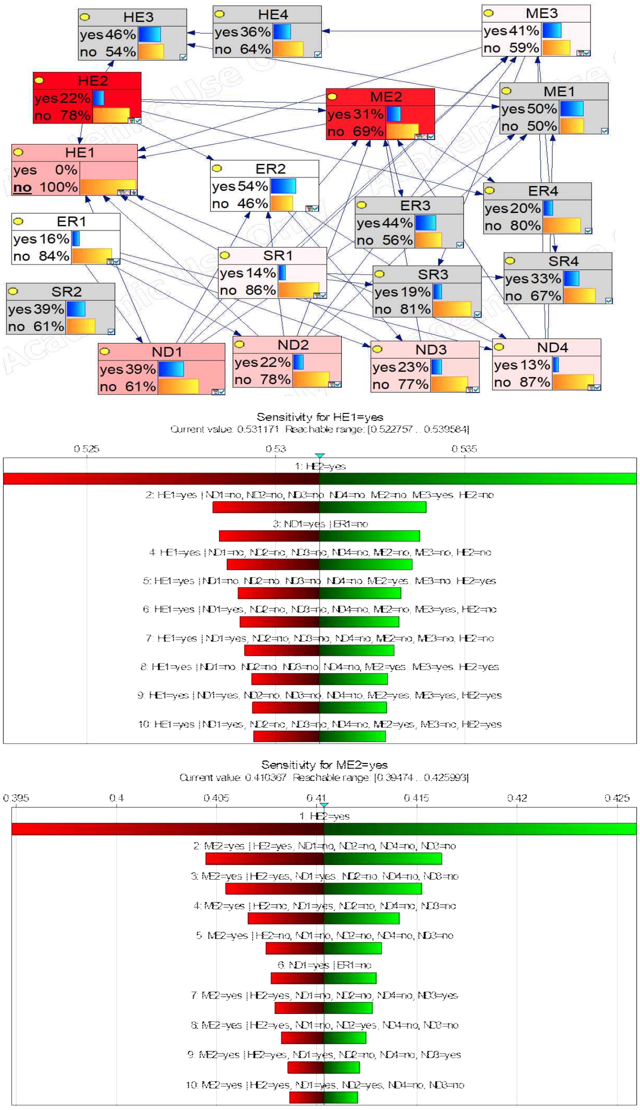

Fig. 3 Result of sensitivity analysis and tornado icon

5. Conclusion

This study identified the relationship among critical risk factors on port operation in Korea, and analysed their interrelations and influencing each other using the Bayesian network and conducting Genie software. The analysis of the BN-based model confirms that 19 risk factors influence port operation, and construct an interdependence model. In the last analysis, the interdependence model was validated by Sensitive analysis.

First, this study can confirm the source study of Lee and Ha (2022), in which the top five risk factors estimated that ND1, ER3, SR2, HE2, and HE1. While top five risk factors evaluated in this study are ER2, HE1, ME1, HE3 and ER3. As well factors of ND1, SR2, and ME3 are calculated after the top five.

Then what interrelation have these factors that ER2 have three parent nodes (ND1, ND2, HE2) and two child nodes. HE1 has only parent nodes which mean influenced by ND1, ND2, ND3, ND4, ME2, ME3, and HE2. While HE2 has no parent nodes, and six child nodes, which means HE2 can influence these child nodes (HE1, ER2, ER4, ME2, ME1, and HE3). The other type of risk factor ME2 has both parent and child nodes, which means, ME2 can be influenced by HE2 when it affects ME1.

In the end, the interdependence model was validated by Sensitivity analysis, which also confirms that most sensitive parameters are included in the top-ranked risk factors. Sensitivity analysis distinguished the risk factors of HE2, HE1, and ME2, respectively.

This study believes that assuming the risk factors independent and irrelevant to each other is not realistic in many cases to solve risk management problems in complex port activities and operations. Based on the results discussed above, therefore, this study offers an essential understanding of the cause-effect relationships among the risk factors for port managers and policy-makers in risk management practices.

However this study has some limitations, therefore, future research areas are suggested. This study only focused on the interrelations between risk factors' influence on the port operation and identified risk factors based on one prior literature by Lee and Ha (2022). Hence further study may need to expand to the risk factor source and to analyse how risk factors influence the loss of port operation or supply chain as a whole system.

Acknowledgements

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