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Evaluation of the seaport-fulcrum supply chain risk for an archipelagic country from the perspective of Indonesian stakeholders

A Dissertation
Submitted to the Department of Transdisciplinary Science and Engineering
Graduate Major in Global Engineering for Development, Environment, and Society
in Partial Fulfilment of the Requirements of the Degree of
Doctor of Philosophy

Muhammad Reza Do. Bagus
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Al-'Alim, for Him most knowledgeable who makes all good things possible.

ABSTRACT

In past decades, a multitude of event related to supply chain disruption (e.g., the earthquake in Japan 2011, global economic crises in 2011, and current Covid19 case) have occurred in succession, causing greats loses to enterprise or even the national scale. Seaport, under global economic and supply chain integration, is also vulnerable on this event and sometime generating a domino effect to the entire supply chain network. The vulnerability of seaport thus needs to be addressed to ensure the functionality of seaport and enhance supply chain resilience. The primary goal of this study is to develop a framework that can be useful to understand: the phenomena of interdependency of the conditional risk in the seaports; and risk appetite from their entities too. This study investigated Indonesian seaport operation related the supply chain disruption. In realization, this research started with observing the extensive literature review and risk document related supply chain disruption from the Indonesian seaport. Furthermore, this research finds that there are 10 dimensional threats factors and 61 seaport risk factors that have clear implication to disrupt supply chain continuity – not only Indonesia but also somewhere seaport. From both variables, this study generates four topics to narrow down the objective as follows.

The first study proposes the model to understand the central tendency in the conditional seaport risk attributes as observed variables with semi-quantitative evaluation from the perspective of port authority, seaport operator, and seaport user. A rough set-based genetic algorithm (RSGA) is proposed to investigate the central tendency of conditional seaport risk factors implied by supply chain threats through a questionnaire evaluation. A risk score is employed in the algorithms to observe the level of clarity in terms of risk probability, showing that the lower the score an attribute obtains, the more likely it is that seaport risk implies supply chain disruption. As the results, the research finds 24 risk attributes, which threaten the ten-dimensional factors, based on their risk scores. Furthermore, the results show that the lack of storage risk planning, low punctuality of delivery goods, shortage of port capacity, congestion in waterways, and the lack of distribution risk planning, are the "best five" of the seaport-fulcrum supply chain risk (SSCR), in the context of Indonesian seaport firms. These discovered risk factors not only help seaport management detect possible risks related with supply chain interruption, but they also improve their capacity to evaluate resilience to supply chain difficulties. Thus, the proposed model serves as a universal guide in assisting port management in managing port-related disruptions – whether planning or technical level – and seeks to reduce the risk occurrences of seaport-related supply chain disruption.

The second study relates with the first study, where the purpose is to reveal the tendency phenomena of threat factors and conditional seaport risk attributes into a utility function using conjoint measurement. The topic also aimed to fill the gap to reduce the dimensionality problem in conjoint analysis (CA). To ensure supply chain continuity, it is important to understand the interdependency between seaport risk factors and the threat of supply chain disruption, from an economic and risk management perspective. This study understands the threat utility of seaport-fulcrum supply chain risk disruption (SSCRD). The RSGA model in the first study is used to solve the complexity among conditional seaport risk attributes and adopts the hybrid-conjoint analysis concept to generate the threat utility function. The threat utility means the sum of the level of disruption by the conditional seaport risk attributes influencing the satisfaction of SSC continuity. Based on 153 samples of experts' evaluation, the rough set model highlights 24 conditional seaport risks as central tendency risk factors and classifies them into ten-dimensional threat factors. The results show that the seaport service process threat is the primary source of the supply chain issue in Indonesia; it reduces utility satisfaction to 32.2%, in the 100% utility estimation. This is followed by the relationship and planning process threats with 28% and 26.6% utilities, respectively. Hence, this study presents a framework to analyze SSCRD in relation to utility satisfaction and demonstrates the need for an integrated plan to enhance resilience.

The third study expand more further about the correlation among the conditional seaport risk variables. The goals are to understand the interdependency factors amid the SSC using multivariate analysis of variance (MANOVA) and analyze to what extent the rough set model can explain the independency of the conditional seaport risk attributes. The results show the 39 conditional seaport risk attributes in this investigation depended on 21 predictor features. This correlation is built into the multiple linear regression model as a predictive model. Moreover, 15 features are considered to pose the highest potential risk to SSC continuity. Breakdown of port information system had the highest implication but the lowest interdependency degree, whereas low-efficiency operation had the lowest implication but the highest interdependency degree. In the middle was lack of supply chain strategic risk planning, which had the highest correlation among the seaport risk features, referring to the decision protocol as the highest risk level.

Lastly, the fourth study fills the gap for the developing model of the seaport-fulcrum supply chain risk disruption integrating the risk appetite of the decision makers within the interdependency risk network. Risk appetite can be described as an organization's risk capacity, or the maximum amount of residual risk (expected utility value) it will accept after controls and other measures have been put in place. In this sense, this study measures a risk aversion from the stakeholders' risk appetite with the assumption that the stakeholders have different preferences about the conditional seaport risk towards the supply chain continuity without interfering with each other. Then, the risk aversion model can be optimized with two different types of rules, called sporadic risk case and repetitive risk case, using mix integer linear programming model. In the result, assuming the percentage of highest risk is between 0 – 20%, then every decreasing the degree of risk accepted is reduced 20% from the utility value. Hence, lack of distribution risk planning, deficiency of berth allocation risk planning, less timeliness of port customs clearance, and less cash flow are considered as the high risk to be unacceptable risk by port authorities (Seaport-management and seaport-operator) either in sporadic risk case and repetitive risk case. They indicated that the degree of risk accepted by the port-authority should not exceed 40% from 100% of their utility value. Meanwhile, whatever risk case for seaport-users, shortage of IT and advanced technology should not exceed 60% of their utility value. Moreover, the highest unacceptable risk is less efficient cost in feeder link for port-authority in repetitive case, which should be below 20% from the utility. The result shows that the seaport user's optimal strategy depends on risk aversion rather than the seaport management's (port-authority and seaport operator), which means that the seaport management more risk taker or risk-seeking rather than seaport in the sporadic and repetitive risk case.

Therefore, the findings in this dissertation conclude that understanding seaport entities' related supply chain is essential to formulate the policy at the planning level and technical levels. This dissertation presents the framework analysis of how to compute the interdependency of conditional seaport risks phenomena that is not only related to supply chain threat but also a correlation among the risks. Furthermore, the risk behavior of seaport stakeholders showed the risk appetite of the SSC entities. The results related to conditional seaport risks and dimensional threats of Indonesian seaports indicated that the SSC disruption sources from seaport service threats. As a result, maritime logistics efficiency may be less efficient and leads to a market imbalance for the shipping industry. In the risk analysis and assessment, the breakdown of the port information system has the highest implication when occurring yet the lowest coupling effect to induce other conditional seaport risks, while low-efficiency seaport operation has the lowest implication but the highest coupling effect to affect the other conditional seaport risks.

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LIST OF ABBREVIATIONS

ACA	:	Adaptive Conjoint Analysis
AHP	:	Analytical Hierarchy Process
CA	:	Conjoint Analysis
CBCA	:	Choice-based Conjoint Analysis
DT	:	Decision Table
ETA	:	Event Tree Analysis
EUT	:	Expected Utility Theory
FAHP	:	Fuzzy Analytical Hierarchy Process
FRF	:	Fuzzy Risk Frequency
FRS	:	Fuzzy Risk Severity
FTA	:	Fault Tree Analysis
MANOVA	:	Multivariate Analysis of Variance
MCDM	:	Multi Criteria Decision Making
MILP	:	Mixed Integer Linear Programming
NP-hard	:	Non deterministic Polynomial-hard
Pelindo	:	Pelabuhan Indonesia
RSGA	:	Rough Set-based Genetic Algorithm
RST	:	Rough Set theory
SCRM	:	Supply Chain Risk Management
SSC	:	Seaport-fulcrum Supply Chain
SSCR	:	Seaport-fulcrum Supply Chain Risk
SSCRD	:	Seaport-fulcrum Supply Chain Risk Disruptions
WASPAS	:	Weighted Aggregated Sum Product Assessment

CHAPTER 1: Introduction

1.1 Background

1.1.1 Seaport supply chain network integration

Over a decade ago, various scholars such as Morash and Clinton (1997), Harding and Juhel (1997), Taylor and Jackson (2000), Notteboom and Winkelmans (2001), and Robinson (2002), recognized the essential role of seaports in aligning their functions and operations with global supply chains and logistics. This integration has been associated with intermodalism and organizational integration (Bichou and Gray, 2004; Panayides and Song, 2009). The former relates to container seaport management issues (UNCTAD,1995), while the latter directly impacts multimodal capabilities (Morash and Clinton, 1997). Robinson (2002) argued that the key aspect in organizational integration appears to be the additional value that ports can provide. According to a UNCTAD monograph (1995), third-generation ports are defined as those offering 'value-added' services. Additionally, customer relationships, satisfaction, and the information and communication regarding supplied services have been identified as crucial parameters for providing added value (Carbone and De Martino, 2003).

In terms of efficiency and effectiveness, Paixão and Marlow (2003) have applied the concepts of leanness and agility within the seaport context. This integration can be achieved through the use of communication technology for information exchange, as well as the incorporation of value-added activities and cost-saving measures. A seamlessly integrated seaport in the supply chain is characterized by effective communication, waste elimination, operational cost reduction, interconnectivity and interoperability of modal infrastructure, and the provision of value-added services, leading to increased customer satisfaction. However, Bichou and Gray (2005) argue that in the current globalized environment, ports must be considered as integral components of supply networks, with a crucial role in supporting supply chain integration. This includes serving and enabling multimodal transportation crossings, acting as logistics hubs, creating value, linking flows, and generating distinct supply chain patterns and procedures.

Bichou and Gray (2004) indicate that applying logistics and supply chain management principles can significantly improve the assessment of seaport efficiency, particularly regarding the logistics, channel, and supply chain processes within seaports. However, despite the widely recognized importance of viewing seaports as essential components of logistics and supply chain management, empirical research on the integration of ports and terminals within comprehensive supply chain networks has been limited. Expanding our understanding of how seaports can be more fully integrated into broader supply chain systems remains an important area for further study and analysis.

Moreover, many of the disruptions that occurred in seaport supply chain integration are knotted at international trade and transportation and result in its performance directly. This also has implications for all the countries around the globe making the countries more open in international trade terms. Proximity amongst the place of production resources to the center of industrialization encourages to the shortest of business cycle time – giving a positive impact to shipment of raw material or semi-finished goods become more effective and cheaper. This means that the trade circulation of raw material and/or semi-finished goods are becoming more global to produce finished goods and multinational's trading with cost and time-window competitively. Hence, seaport becomes primary key in the supply chain networks and we defined the seaport supply chain integration depicted in Figure 1.1.

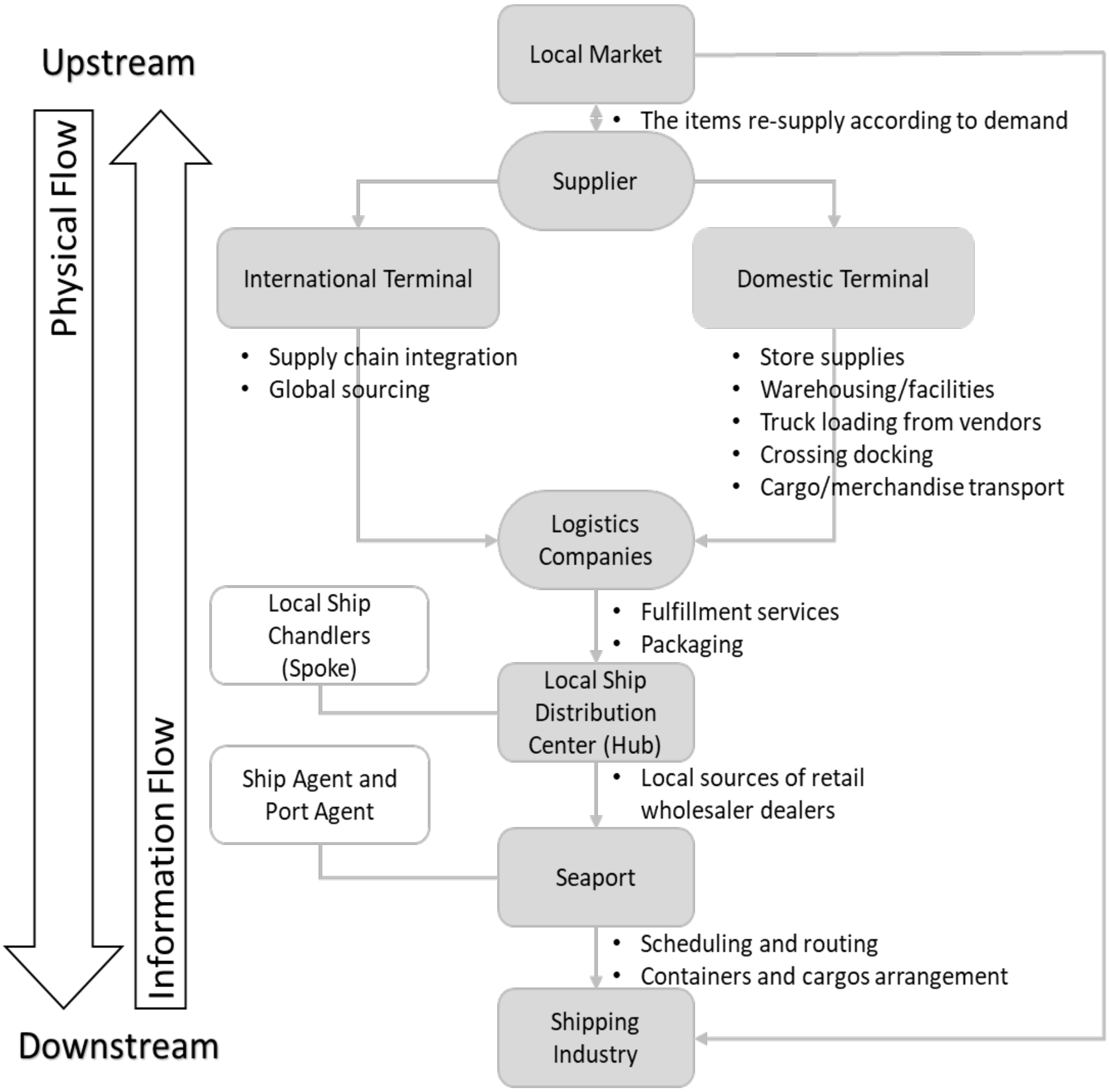


Figure 1.1 Integration seaport to supply chain network.

Talking about the integration seaport to supply chain in Figure 1.1. Seaports play a vital role as intermediaries in supply chains by facilitating the interaction between global supply networks and local production and consumption markets. The increasing complexity of global supply chains places demands on the logistics sector to enhance cost efficiency, performance, and the ability to withstand disruptions simultaneously. Like conventional supply chains, the physical flows of goods and services are most of the time from providers (upstream) to customers (downstream). In contrast, information flows are dominantly in the reverse direction since they relate to purchasing orders. Consumables ordered based on past consumption patterns require on-time delivery. Doing so in a seamless manner, local ship chandlers and suppliers will integrate with logistics providers and regional/global distribution centers. While shipping lines pursuing a profit-maximization focus on occupation rate per vessel, seaport focus on sustainable long-term contracts to utilize their facilities in terms of the total number of annual cargo and passengers served.

In the context of containerization's brief resupply window, it is essential for shipping lines to establish enduring and dependable relationships with service providers such as seaports, logistics companies, and freight forwarders. This helps minimize uncertainty, the need for increased flexibility and customization, and the overall risk in the supply chain. Managing the supply chain effectively relies on the collaborative engagement of all involved parties, encompassing interactions with external suppliers, internal departments, external distributors, and customers. Successful supply chain management, aimed at reducing coordination challenges, is influenced by factors like customer expectations, globalization, technological advancements, government regulations, competition, and sustainability considerations.

1.1.2 Interdependence between seaport risk event and supply chain vulnerability

In the era of global economic integration, seaports have evolved from being standalone nodes into integrated supply chain service centers, departing from their traditional roles as transportation or distribution hubs. Some major seaport enterprises in certain countries now aim to enhance the seaport supply chain through both horizontal and vertical integration. The heightened significance of seaports exposes them as vulnerable nodes, as disruptions in one seaport can trigger a cascading effect throughout a network of supply chains. Notable instances include the giant ship blocking the Suez Canal in Egypt in 2021 and the ship backlog in Southern California due to the pandemic, leading to substantial shipment delays and financial losses.

Internationally, seaports are recognized as gateways to global trade, particularly in maritime nations such as Indonesia. Developing maritime countries, like those in the developing world, strive to maximize seaport revenue and appeal to ship owners and shippers by enhancing seaport infrastructure, improving service quality, and mitigating the risk of supply chain disruptions related to seaport bottlenecks. The competitive landscape among seaports, especially those offering similar services, complicates the decision-making process for seaport selection, making disruptions a source of heightened uncertainty in supply chain risk.

Seaports occupy a vital role in supporting economies and global supply chain networks. Yet, their strategic positioning in low-lying areas along rivers and coastal regions renders them susceptible to the impacts of climatic extremes and natural disasters, including powerful waves, cyclones, and earthquakes. Disruptions to seaports have wide-ranging consequences, leading to substantial economic losses for maritime transportation and global supply chain networks that rely on seaports for facilitating trade. Recent research by Verschuur et al. (2023) highlights the risks that extreme weather events pose to supply chains, global production, and consumption. The specific risks associated with seaports, as shown in Figure 1.2, encompass three types of impacts: physical damage to port infrastructure, harm to critical infrastructure near the port, and additional logistical losses incurred by port operators, carriers, and shippers due to downtime or the need to reconstruct assets that exceed operational capacities.

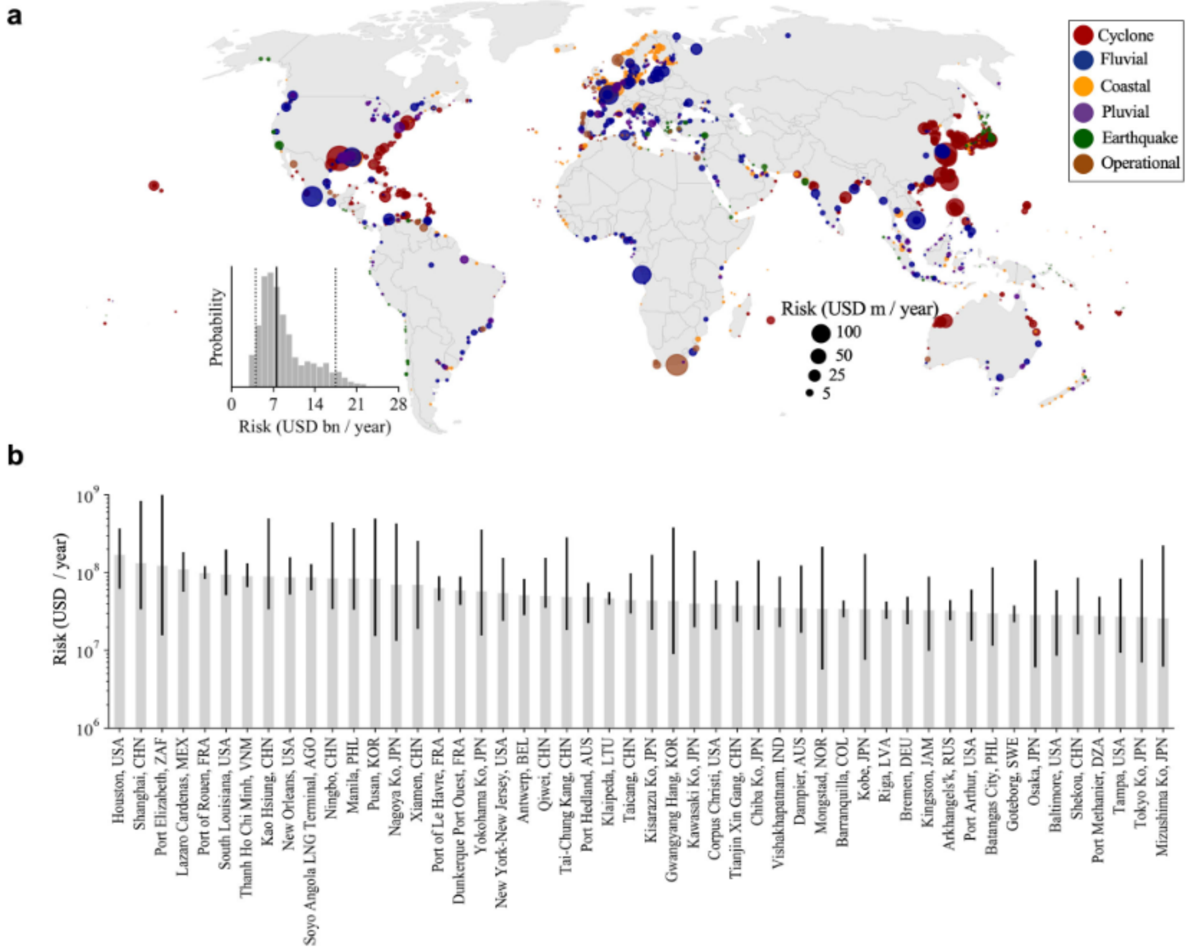


Figure 1.2 Global footprint of seaport-specific risk (Sources: Verschuur et al. (2023))

Many ports worldwide are vulnerable to disruptions from various extreme and natural events. Around 40.1% of the 1340 ports examined are exposed to harsh marine conditions beyond their operational norms. The majority of ports face multiple natural hazards, with half susceptible to four or five. Flood risks, both fluvial and pluvial, are the most common, affecting 80.4% and 84.3% of ports, respectively. Figure 1.2a highlights regions such as Japan, the U.S. West Coast, Middle America, New Zealand, Taiwan, and parts of mainland China that face diverse hazard exposures. Conversely, Figure 1.2b depicts regions like South America, parts of Northern, Western, and Eastern Africa, and Northern and Eastern Europe that face two or fewer threats. Given the multiple hazards, port infrastructure must account for considerations like robust quay wall foundations in earthquake-prone areas, resilient breakwater designs for extreme waves and surges, and adequate drainage systems to mitigate fluvial and pluvial floods.

Figure 1.2a visually depicts the anticipated seaport-specific risk, with the dot color indicating the predominant hazard. The accompanying histogram reveals that the median seaport-specific risk is $7.6 billion per year, spanning a range of $4.0 to $17.4 billion per year. Among the hazards, tropical cyclones pose the greatest median port-specific risk at $2.4 billion per year, followed by fluvial flooding at $1.9 billion per year, coastal flooding at $0.8 billion per year, and pluvial flooding as well as operational exceedances at $0.7 billion per year.

The significance of these hazards varies by geographic region. Tropical cyclones are the predominant threat for 25.2% of ports globally. In Western and Northern Europe, fluvial floods and coastal flooding are the primary concerns. Factors such as river locations, severe coastal water levels, flood protection regulations, and terminal freeboard influence the risk profiles of ports from flooding. While earthquakes generally pose a relatively low risk, they are the principal hazard for 10.8% of ports, with concentrated hotspots in Chile, parts of the Mediterranean, and Northern Japan. Notably, distinct major risks are observed across countries like India, the United States, and Australia, underscoring the need for a localized risk analysis that incorporates diverse hazards within a comprehensive framework.

The presentation shows the top 50 worldwide ports that are most vulnerable to predicted port-specific risk in Figure 1.2b. Notably, Asian ports, notably those in mainland China and Taiwan (China), the Gulf of Mexico, and Western European ports, have the highest port-specific risk. Houston (United States, 169.0 USD million per year), Shanghai (mainland China, 133.2 USD million per year), Port Elizabeth (South Africa, 123.4 USD million per year), Lazaro Cardenas (Mexico, 110.9 USD million per year), and Rouen (France, 98.7 USD million per year) are the top five at-risk ports, ranked by port-specific risk.

The article highlights the vulnerability of certain seaports to various natural hazards. Houston faces a combination of cyclone winds, pluvial flooding, and fluvial flooding, rendering it particularly susceptible. For Shanghai, cyclone winds pose the greatest threat, while fluvial flooding is the primary concern for Rouen and Lazaro Cardenas. The port-specific risk at Port Elizabeth is largely driven by operational threshold exceedances, particularly those caused by severe wave heights. Notably, over half of the world's ports confront an annual risk exceeding $1 million, with 160 ports facing a relatively high risk and 21 suffering a very high risk. The majority of the top 50 ports are distinguished by substantial freight volumes surpassing $10 billion per year, reflecting their expansive port areas and the significant potential for disruption.

Considering the above, operational deficiencies in every seaport process can lead to amplified unintended consequences in supply chains. In the current business environment, supply chain risk likelihood increases as disruptions originating from seaports have exacerbated effects. The ability of seaports to provide seamless services, operations, and cargo transfer is highly sought after. It is crucial to identify measures that port management can implement to minimize the impact of seaport-fulcrum supply chain risk disruptions (SSCRD) and reduce its threat occurrences. In this study, SSCRD threats are defined as inherent in seaport processes capable of disrupting the continuity of upstream to downstream supply chains, as shown in Figure 1.1.

1.1.3 Definition of seaport-fulcrum supply chain risk disruption

Given the integration of seaports with supply chains and the susceptibility of supply chains to seaport risks, this study defines a seaport-fulcrum supply chain network (SSCN) as a central node facilitating the connection between global supply chains and regional production and consumption markets. It is viewed as a value-enhancing transit point linking logistics nodes, industrial nodes, distribution networks, and the shipping industry. Consequently, the potential threat due to seaport risk event can be generated from the definition SSCN and it names as a seaport-fulcrum supply chain risk disruption (SSCRD).

The SSCRD refers to the likelihood of undesirable events related to seaport risks that could interrupt the system, processes, or work cycles within the supply chain. Such disruptions can lead to accidents, losses, or damages that impact the supply chain and logistics business processes. The outcomes of these disruptions vary, with some being contained within the seaport and causing minimal impact on its users, while others can be severe enough to result in a breakdown of supply chain resilience. Loh and Thai (2015) have identified four potential threats to supply chain disruption arising from various conditional seaport risk attributes, including infrastructure threats, planning threats, manpower threats, and security threats. Furthermore, potential disruptions in the supply chain due to seaport risk events can affect terminal supply chain integration, leading to breakdowns in information and communication systems, reduced value-added services, and disruptions in multimodal systems and operations (Russell et al., 2020; Donnan et al., 2020; Wendler-Bosco & Nicholson, 2019).

The consequences of a port-related supply chain disruption can be significant, as evidenced by the West Coast port lockout in the US in 2002, which caused a loss of approximately US$19.4 billion (Hall, 2004). These disruptions can lead to various undesirable effects, such as cargo quality issues, timing differences, financial losses, and dips in market share. (Loh & Thai, 2014) The magnitude of these consequences underscores the crucial role of ports in supply chains and the imperative to address potential threats and implement effective measures to mitigate and contain the impact of port-related supply chain disruptions, ensuring the resilience of the supply chain (Loh & Thai, 2014; Loh & Thai, 2015a and 2015b).

Effective information and communication systems are essential for the smooth functioning of supply chain operations (Khanuja & Jain, 2019). These systems facilitate seamless communication, enabling the efficient execution of supply chain activities and the achievement of key supply chain goals. Information sharing and smooth communication systems are vital components of robust supply chain partnerships, fostering high levels of supply chain integration and enhancing reliability, dependability, and responsiveness (Domínguez et al., 2019). These systems also have a significant impact on overall supply chain performance in terms of both cost and service quality metrics.

The provision of value-added services within ports, such as procurement, pre-assembly, distribution, continuous replenishment, and specialized services, is increasingly viewed as a crucial factor in the future development of seaports and their integration into supply chain networks (Okorie et al., 2015; Verhoeven, 2009; Tran et al., 2012). However, recent scholarly research has indicated that these value-adding activities may have the unintended consequence of reducing the overall throughput capacity and operational efficiency of major seaports (Sdoukopoulos & Boilé, 2021). While value-added services can enhance the role of ports in logistics chains and provide benefits to supply chain partners, the potential trade-off between these services and port throughput capacity is an important consideration for port authorities and supply chain managers (Notteboom & Haralambıdes, 2020). Carefully balancing the provision of value-added services with maintaining efficient port operations will be essential to ensuring the resilience and competitiveness of seaport-based supply chains.

These undesirable effects underscore the significance of seaports in supply chains and highlight the amplified scope of their influence. Consequently, there is a need to identify potential threats and implement measures to mitigate and contain the consequences of SSCR. Drawing on concepts from Jiang et al. (2018), Loh and Thai (2015a), and Panayides and Song (2009), a new framework has been developed to comprehensively understand the SSCRD phenomenon. After screening potential supply chain threat factors resulting from conditional seaport risk attributes, discussions with experts in Indonesia were conducted to gain clarity within the context of the archipelagic country. As a result, 10 potential supply chain threat factors were identified and formulated in Table 1.1. In the context of SSCRD, three parameters define risk: implication (undesirable outcome), threat (probability of the risk event occurring), and feasibility (conditional probability that the risk event, if it occurs, will induce other risks).

Table 1.1 The definition of potential threat in the SSCRD model

Dimension of threat supply chain disruption	Definition
Planning Process threats	Planning process threats refer to any external or internal factors that could negatively impact the effectiveness or efficiency of a seaport's planning processes. These threats can hinder the development and implementation of strategies, policies, and initiatives crucial for a seaport's long-term success. The more comprehensive the plan, the easier it is to follow the established direction with reduced uncertainty, leading to successful achievement of objectives. The seaport enterprise planning process encompasses internal planning process risks and supply chain planning process risks. Internal plans include strategic, berth, ship, handling, storage, transfer, and distribution plans. Supply chain plans primarily consist of a strategic plan and a risk prevention plan.
Infrastructure threats	Infrastructure threats in seaports refer to external or internal factors that can compromise the integrity, functionality, or security of a port's physical assets. These threats can disrupt operations, lead to financial losses, and pose risks to personnel and cargo safety. Maintenance issues or technological advancements within the port often cause these "infrastructure threats," which impact port productivity. Addressing these problems requires local-level action, making it crucial for seaports to take initiative. Problems like congestion and resource insufficiency also stem from inadequate planning and forecasting. Collaborating and coordinating with external entities can help mitigate these threats.
Seaport Service Process threats	A seaport service process threat is any factor that can negatively impact a port's service efficiency, disrupting supply chain activities. These threats can hinder the timely and reliable movement of goods, leading to delays, increased costs, and potential cargo damage. Seaport operations include loading, unloading, storage, transfer, and distribution. The risk in these service processes is linked to seaport berth allocation, operational efficiency, and the effectiveness of handling, storage, transfer, and distribution. As the core of the seaport supply chain, service process risk directly impacts the overall supply chain operation. Significant risk in the

	seaport service process can greatly disrupt the entire port enterprise supply chain, causing adverse effects.
Distribution Process threats	Distribution process threats are external or internal factors that can negatively impact the effectiveness or efficiency of distributing goods from the port to their final destinations. These threats can hinder timely and cost-effective cargo delivery, leading to delays, increased costs, and potential damage. Seaport-specific risks can undermine logistics performance within the supply chain. A key component of logistics-related supply chain risks is the distribution process, encompassing hazards like transportation route and equipment selection, logistics provider selection, port departure and entry, delivery, customs clearance, and product defects. The first three hazards influence logistics cost control, while product defects impact logistics quality. The remaining hazards affect overall logistics efficiency.
Relationship Process threats	Relationship process threats are external or internal factors that can negatively impact the relationships between the port and its stakeholders, disrupting supply chain activities. These threats can hinder collaboration, communication, and trust, leading to delays, increased costs, and potential disruptions in the flow of goods. Seaport risk is often attributed to human error, which can disrupt coordination among supply chain entities. Changes in a seaport's supply chain services closely follow modifications in logistics processes, and any seaport risk event directly impacts supply chain logistics operations. Key risks involve enhancing coordination mechanisms, optimizing interest distribution, sharing responsibilities and exit strategies, and addressing information asymmetry among members. Risks associated with manpower threats relate to port workers' soft skills, making them susceptible to governmental pressures. Mitigating these threats is unlikely to be achieved through independent efforts alone.
Nuclear-enterprise financial threats	A nuclear-enterprise financial threat is any factor that could negatively impact the financial performance of a port or its related enterprises, disrupting supply chain activities. These threats can lead to financial losses, reduced profitability, and potential insolvency, hindering the port's ability to invest, maintain operations, and support the broader economy. Conditional seaport risk decreases profits and increases debt for entities within the supply chain. The port enterprise's supply chain involves various flows, including information, logistics, services, and capital. The financial risk of the core enterprise's capital flow significantly impacts the operational risk of the entire supply chain. Key financial risks for the core enterprise include profit, debt, operational, development, and cash flow risks.
Monetary threats	Monetary threats are external or internal factors that can negatively impact a port's or related enterprises' financial performance, leading to losses or reduced profitability. These threats can disrupt supply chain activities by limiting the port's ability to invest, maintain operations, or provide adequate services. Seaport disruptions can increase transportation costs due to currency fluctuations in the supply chain. These risks extend to the broader global supply chain and are linked to expenses incurred by shipping lines during transshipment. Monetary

	threats are also associated with deviation costs, which are expenditures incurred by shipping lines when deviating from the main sea route to reach hub ports, and port costs, which include container handling fees, navigation dues, pilotage, towage, and other related expenses. Additionally, the cost of transporting cargo between hub and feeder ports is known as the feeder link cost.
Location threats	Location threats are external or internal factors that can negatively impact a port's strategic positioning, disrupting the supply chain. These threats can reduce the port's accessibility, competitiveness, and economic viability, hindering its ability to attract and retain cargo traffic. The location of a seaport is crucial in global supply chain networks, as shipping companies often aim to minimize the number of ports they call on to maximize market coverage, often by being situated near growing markets. Key factors include the port's relationship to competing hubs, their proximity, and the growth potential of the port region. The study also examines elements like tides and water depth that influence port accessibility, as well as the growth potential and cargo volume of the connected feeder market.
Security threats	A security threat is any external or internal factor that could compromise the safety, security, or integrity of the port or its operations, thereby disrupting supply chain activities. These threats can lead to financial losses, reputational damage, and potential harm to personnel or the public. The occurrence of conditional seaport risk introduces unpredictability into supply chain operations. Risks associated with security primarily involve economic risk, political risk, and risks related to the natural environment. Economic risk stems from domestic and international macroeconomic activities, fluctuations in exchange rates, and international trade dynamics. Political risk encompasses factors like wars that can escalate costs and, in extreme cases, result in the breakdown of the supply chain.
Environmental threats	Environmental threats encompass any external or internal factors that could adversely impact the environment or human well-being, thereby disrupting supply chain operations. These threats can lead to regulatory penalties, reputational harm, and operational interruptions. Natural risk events can suspend seaport activities and directly obstruct the continuous flow of the supply chain. Risks associated with the natural environment primarily originate from the influence of natural disasters on seaport enterprises, directly tied to the geographical positioning of port enterprises and the selection of transportation routes.

In order to understand the performance of seaport supply chain integration when the risk event occurred, we proposed as SSC model referring some potential threat in Table 1.1. Unlike the supply chain-based manufacturing risk model, the SSCRD model proposed ten aspects that depicted in Figure 1.3. The ten aspect is defined SSCR factors and each factors pose conditional seaport risk attributes differently – name as SSCR attributes. The SSCR attributes will be examined the Indonesian seaport supply chain structure as study case. Furthermore, the SSCRD model are defined as follows:

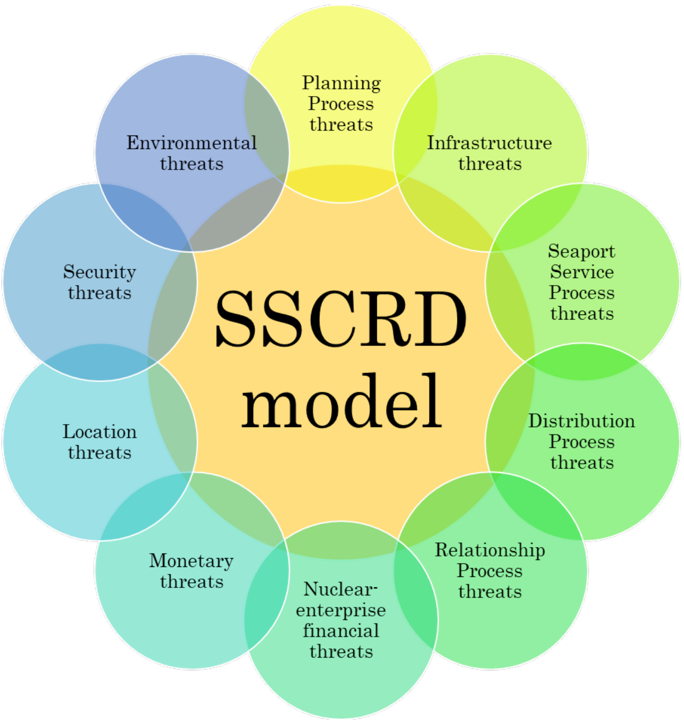


Figure 1.3 Seaport-fulcrum supply chain risk model.

1.1.4 Interdependency SSCRD phenomena in archipelagic country

Referring to the integration of seaport supply chains (Section 1.1.1) and the risk factors associated with SSCs (Sections 1.1.2 and 1.1.3), the interconnected nature of these phenomena significantly influences global and regional economic activities. Seaports, serving as central hubs in these phenomena, play a pivotal role as global transport facilitators in both inbound and outbound supply chains, contributing to the overall economic activities on a global and regional scale. A seaport that adapts to the evolving requirements of supply chain management ensures the competitiveness of its value chain system, enabling the hinterlands within the system to achieve comparative and competitive advantages. Moreover, the seaports play an essential role in the effective and efficient management of cargo movements across the supply chain. However, disruptions affecting any seaport along the supply chain can directly impact the chain's ability to sustain operations, deliver goods to market, and provide services to customers.

In an increasingly interconnected global supply chain, disruptions at any stage can trigger a cascading effect across other participants, potentially spanning multiple continents. Seaports and shipping, crucial components of trade and supply chains, contribute significantly to uncertainties (Sanchez-Rodrigues et al., 2010). Compared to other transportation contexts, seaports and shipping are more international and have more interfaces with other stages and members in the supply chain, making them potential weak points. However, research on related risk issues has been limited, especially in archipelagic countries.

The characteristics of archipelagic countries, as defined by UNCLOS (United Nations Convention on the Law of the Sea), introduce new challenges to SSC operations. The operation of the SSC in archipelagic countries introduces uncertainties in interdependency risk events and potential disruptions.

While there are limited studies on seaport disruptions in archipelagic countries, such as those by Loh and Thai (2015a and 2015b), Loh et al. (2017a and 2017b), and Amin et al. (2021), the overall understanding remains incomplete.

Additionally, Chang (2000) analyzed the impact of the 1995 Kobe earthquake on Japan's seaport traffic, revealing significant disruptions. Economic studies by Rosoff and von Winterfeldt (2007) and Park (2008) demonstrated that seaport disruptions caused substantial economic losses and trade interruptions between states. Gurning and Cahoon (2011) focused on estimating the costs of major accidents in port areas but did not specifically examine how seaport disruptions affect various stages and parties in a supply chain. Given the increasing complexity of global supply chain networks and their dynamic behavior in association with risks, this study aims to shed light on these phenomena using Indonesian seaports (an archipelagic country) as a case study.

1.1.5 Indonesians' seaport effectiveness and efficiency in supply chain network

Indonesia's maritime infrastructure operates through a structured hierarchy, comprising approximately 2,439 seaports. Among these, 111, including 25 designated as strategic, serve as commercial seaports managed by the Port of Indonesia Company (Pelindo). These seaports play a crucial role in facilitating the movement of people, goods, and services across islands, contributing significantly at national, regional, Asian, and international levels. Despite being an archipelagic nation, Indonesia has emerged as the 16th largest GDP country globally, registering a substantial US$1,186,093 million (World Bank, 2021). Notably, during the 2008-2009 global economic crisis, Indonesia sustained an impressive 5.5% economic growth (IMF, 2021).

However, the inadequate state of infrastructure nationwide poses a hindrance to economic growth and contributes to escalating domestic logistics costs. This circumstance diminishes Indonesia's competitiveness as a business hub in Southeast Asia, as underscored by benchmarking studies like the Logistic Performance Index, where Indonesia lagged globally at the 61st position in 2023, significantly trailing behind Southeast Asian counterparts that secured the 4th position (Hamid, 2018). The pronounced centralization of economic activities in Java is closely linked to these high domestic logistics costs. Furthermore, these challenges impact access to consumer goods for Eastern Indonesia and hinder the accessibility to commodities sourced from this region.

The majority of ports fall under the management of PT. Pelabuhan Indonesia (Pelindo), a government-owned port agency. The regional authority of PT. Pelindo IV extends across the central and eastern parts of Indonesia, overseeing 21 ports spanning 11 provinces, which collectively cover 45.76 percent of Indonesia's total area. Between 2005 and 2010, the annual growth rate of commodity flow through these ports averaged 9.66 percent, with container throughput experiencing an average annual growth of 13.42 percent during the same period. Notably, the Makassar port, the largest in the region, saw container throughput increase from 23.83 to 39.84 percent.

In the current era of heightened global competition, organizations grapple with informed and demanding stakeholders, altering the competitive landscape based on asset investment and management capabilities. Efficient performance demands not only data collection and evaluation but also the development, utilization, and implementation of data in the company's strategy and vision. Competing effectively necessitates the creation of a competitive advantage, differentiating a company from its rivals. The ability to establish a competitive advantage enhances a company's long-term positioning in business competition. Five dimensions, as defined by Li et al. (2006), gauge the quality of a company's competitive advantage: price, quality, dependable delivery, production innovation, and time to market. Quality and productivity, according to Helms (1996), serve as strategic tools to achieve a competitive advantage.

Globalization intensifies competition in the services sector, requiring companies to navigate challenges in managing business assets. Pelindo, a state-owned enterprise, plays a crucial role in providing port facilities and infrastructure. The background outlined above reveals challenges in the effectiveness and efficiency of Indonesia's supply chain and logistic networks, complicating the realization of the hub-spoke concept. Consequently, the demand between seaports and the cost from trucking industrial centers to seaports become more uncertain.

Concerning effectiveness and efficiency, maritime logistics takes center stage. Studies such as Sutomo and Soemardjito (2012) assessed port efficiency in western Indonesia, highlighting Tanjung Priok-Jakarta's port as the most effective and efficient. Aqmarina and Achjar (2017) affirm the determinants of port performance in four main ports. Fahmiasari and Parikesit (2017) demonstrate the efficiency of container transport networks, with the Sea Toll-way proving to be 8% more efficient than Nusantara Pendulum. Gena et al. (2020) formulates strategies to bolster Indonesia's port industry competitiveness. Mappangara et al. (2015) recommend developing a short-distance shipping network in certain Sulawesi corridor coastal areas. Kusumastanto (2020) estimates logistics costs at approximately 20–30% of Indonesia's GDP due to its archipelagic nature, resulting in higher logistics costs induced by inter-island connectivity. The efficiency of maritime logistics is crucial for island areas to stimulate local economic growth. Amin et al. (2021) shed light on maritime logistics issues in the eastern part of Indonesia, focusing on North Maluku, an archipelagic province grappling with irregular ship schedules, high sea transportation costs, and inadequate transportation modes. The ports in North Maluku, including Ternate, Tidore, Morotai, Tobelo, Buli, Weda, Babang, and Sanana, play a pivotal role in facilitating goods flow in surrounding areas and periphery islands with limited accessibility. Enhancing maritime logistics efficiency in these islands is a concerted effort to achieve equitable development across territories, particularly in eastern Indonesia.

1.1.6 Management disruption towards supply chain threat in Indonesia

Over the last two decades, the management of supply chain risk has become a pivotal element contributing to the competitiveness and efficiency of firms. Most companies have dedicated considerable efforts to enhance both their individual and supply chain performances, with a predominant focus on refining the effectiveness of supply chain operations. Cousins et al. (2004) proposed that certain measures taken by companies to boost the efficiency of their supply base might inadvertently elevate their exposure to technological and strategic risks, as they intensify their reliance on the remaining pool of suppliers. Thus, understanding risk management as an integral facet of supply chain management proves beneficial in comprehending supply chain disruption as a multifaceted phenomenon (Christopher et al., 2004). The assessment of risk in supply chains has evolved into a significant subject within supply chain management, gaining prominence due to various industry trends. These trends include an upswing in firms strategically outsourcing and depending on suppliers for specialized capabilities and innovation. Such trends are evident in the increased outsourcing and offshoring of manufacturing and research and development activities, sourcing from low-cost countries, and fostering collaboration with international supplier partners. While these trends expand strategic possibilities for firms, they concurrently heighten the likelihood of encountering adverse events in supply chains that pose substantial threats to the normal business operations of firms within those supply chains. Alongside the surge in these initiatives, there has been a simultaneous escalation in both the potential and scale of supply chain risks (Blackhurst et al., 2008).

In the case of the Indonesia supply chain, there are several factors that it indicates disruption-management in the seaport who significantly affluent to all entities and even inflicting the state loses directly. Based on the statistical data from the Inspectorate General Ministry of Transportation of Republic Indonesia, the disruption-management is summarize into caused – impacted factors and it leads to the risk in the seaport more unforeseeable. In the chart 1, it has eleven factors as resulted of port disruption management which is as follows from left hand side to right hand side: 1) Non-compliance with regulatory that inflict losses on state finance; 2) Non-compliance with regulatory that potentially losses on state finance; 3) Non-compliance with regulatory that inflict deficiency on state finance/regional or state-owned enterprise/regions: 4) Non-compliance with administrative regulations; 5) Indications of non-compliance with regulatory offenses; 6) Weakness accounting controls and reporting systems; 7) Weakness of the implementation of control systems revenue and expenditure budget; 8) Weakness of the internal control structure; 9) Uneconomical; 10) Inefficiency; 11) Ineffectiveness.

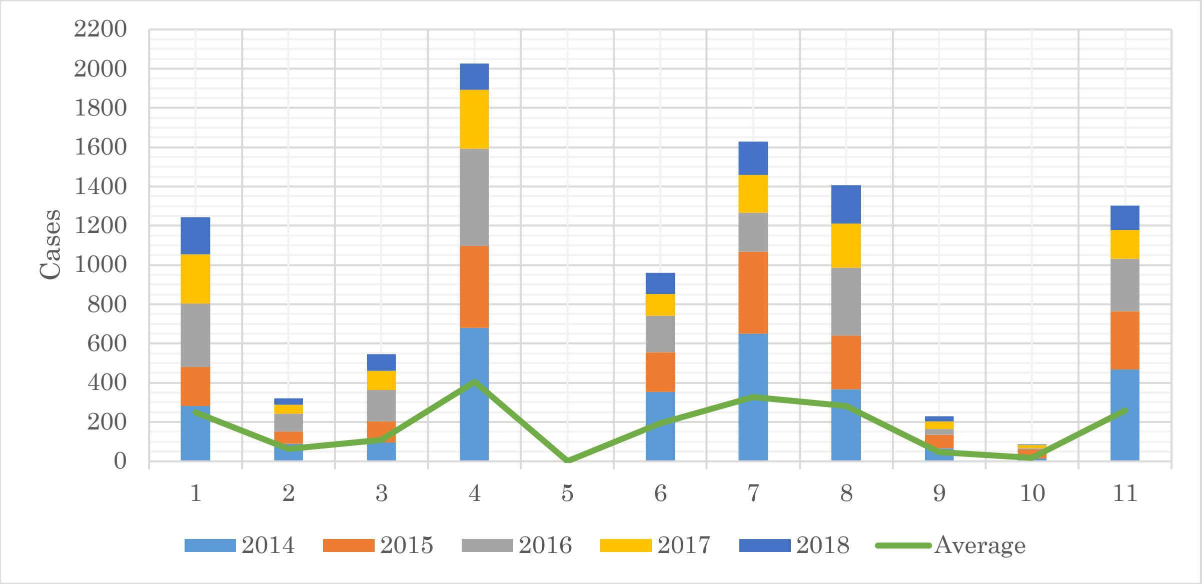


Figure 1.4 The impact of disruption-management in the seaport in periods 2014 to 2018 (Sources: The Inspectorate General Ministry of Transportation, Indonesia)

In the Figure 1.4, it is clearly seen that the non-compliance with administrative regulations was significantly impacted by the disruption-management in seaport-focal supply chain with more than 2,000 cases in total during 2014 – 2018. In otherwise, there was no indication case for disobedience on regulatory offenses through all periods. Moreover, even the seventh factor of the impact of disruption-management stood at in the second place but either the fourth and seventh shared the similar number of cases in 2014. The former and the later factor indicated that the disruption-management effect give more high risk to the supply chain in the Indonesia's seaport. The disobedience on administrative regulation and the weakness of implementation of control systems from the former and the later factors give direct impact to the seaport operational, such as bottleneck, long duration for turnaround ship, and so on. This unsought matter of disruption is good for decision maker no longer only if none of protective-measurement to catch information how much and significant the disruption can be effect the seaport-focal supply chain risk as well as seaport resilience.

In the same resources furthermore, the eleven factor impacted by disruption-management in the seaport was coming from ten reason during five years period respectively, such as 1) weakness in organization, 2) weakness in policy, 3) weakness in the plan, 4) weakness in procedure, 5) weakness in record-keeping and reporting, 6) weakness in human-development, 7) weakness in internal control or intern review, 8) extern barrier project, 9) extern duty fluency, and 10) service from government employee of state-owned enterprise. Such as the disruption management was depicted in Figure 1.5 respectively from the left hand side to the right hand side.

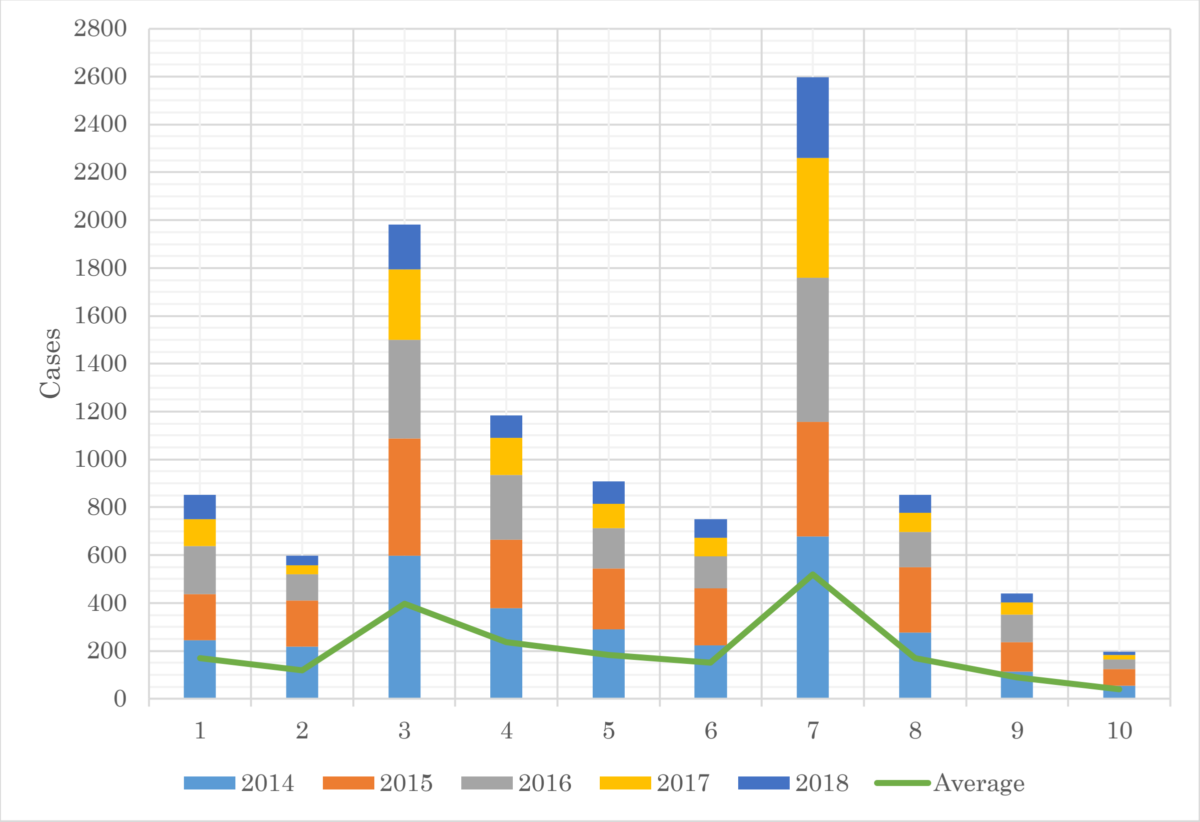


Figure 1.5 The disruption-management in the seaport in periods 2014 to 2018 (Sources: The Inspectorate General Ministry of Transportation, Indonesia)

The Figure 1.5 provides the information regarding disruption seaport management from 2014 to 2018. Based on the chart, it is shown that the weakness in internal control and review gave significant effect to the seaport-focal supply chain management about 2,500 case occurred. While the service from the employee was has low cases in seaport disruption management. So, it is not surprisingly if the bottleneck in every port Indonesia still have high percentage. This is also lead to lose the state finance in term of supply chain indirectly.

In order to evaluate whether the seaport disruption-management is have direct impact to seaport-focal supply chain management, this study proposes 10 dimensional threats factors with 61 conditional seaport risk attributes, 5 value or scaled indicates risk occurrence, and a decisional factor as seaport-focal supply chain evaluation into a decision table that shown in appendix. The dimensional threat is coming from literature review in this study and the real situational on Indonesia supply chain disruption based-statistical reported aforementioned before.

1.2 Research questions and objectives

The goal of this dissertation is to introduce a new SSCR framework considering the interdependency between the conditional seaport risk attributes and threat factors of supply chain disruption, and its stakeholder behavior that is suitable for a country with archipelagic geography.

However, there are four research questions that this dissertation considered to develop supply chain risk management (SCRM) framework referring to the interdependency and risk appetite of stakeholders as follows:

1. How can we develop and operationalize a SCRM framework that captures interdependency between risks, multiple (potentially conflicting) objective, and risk mitigation strategies specific to the risk appetite of a decision-maker?
2. How to route the risk conduction mechanism in order to analyze the interdependency - especially the SSCRD through study case?
3. What are the merits and challenges associated with the implementation of the proposed process?
4. How to assess the SSCRD according to its entity and its correlation (interdependency) as well?

In doing so, the study aims to develop models that take account of the trade-off relationship between different objective, qualitative attributes, multiple decision-makers, challenged faced by the decision-makers during the conditional seaport risk event period.

To achieve this purpose, the following specific objective are drawn:

1. To develop an optimization algorithm which has an ability to handle multiple attributes and incorporate risk-agent's preferences in the optimization to obtain the best trade-off design. (shown in Chapter 3)
2. To develop some trade-offs among the conditional seaport risk attributes is considered individually by the SSC entities and reveal the impact risk factors on a decision-maker satisfaction into a utility function. (shown in Chapter 4)
3. To reveal the interdependency factors amid the SSCR attributes. (shown in Chapter 5)

4. To determine the risk tolerance and risk appetite model taking account of expected utility value and average potential revenue loss to ease decision-making steps. (shown in Chapter 6)

1.3 Outline

The dissertation comprises of seven chapters as shown in Figure 1.6. Each chapter from Chapter 3 until Chapter 6 is started with features assumption as follows: Ch. 3 is multiple-path dependency analysis without correlation; Ch. 4 is complex-path dependency analysis without correlation; Ch. 5 is multiple-path dependency analysis with correlation; Ch. 6 is single-path dependency analysis with correlation. Further information regarding each chapter is presented as follows:

Chapter 1 introduces this dissertation's background, research questions and objectives, outline, scope of the study, and contributions.

Chapter 2 reviews related previous studies on the following topics: (a) the integration seaport on supply chain, (b) types of dimensional threat factor on supply chain related seaport, (c) conditional seaport risks and their effects, (d) seaport-fulcrum SCRM in Indonesia context, (e) RST, (f) CA, and (f) summary.

Chapter 3 presents the SSCR attributes that divided by ten dimensional threats, e.g. planning process threats, infrastructure threats, seaport service process threats, distribution process threats, relationship process threats, nuclear-enterprise financial threats, monetary threats, location threats, security threats, and environmental threats, and each of the threats have some conditional seaport risk attributes. This chapter also presents the data from field survey referring the 61 conditional seaport risk attributes. A questionnaire survey was conducted to reveal the central tendency of conditional seaport risk attributes in Indonesians' seaport context as well as the feasibility of the threat dimension factor possess. The central tendency is defined as the highest potential conditional seaport-risk factors to threat the supply chain. In this dissertation, the potential risk factors are generated from the intersection of attribute reduction sets of rough set. We proposed rough set based-genetic algorithm to solve the Non-deterministic Polynomial-hard (NP-hard) problem to find which attributes possess higher value of dependency and to estimate the feasibility of threat variables.

Chapter 4 is extension from the Chapter 3. The data from the previous chapter was used to determine the utility estimation – in a term of satisfaction – from conditional seaport risk attributes toward the thereat factors into the part-worth utility model. The model incorporates properties deemed suitable for archipelagic scenarios. The model is then applied to the Indonesians' seaport. The conjoint measurement was proposed to reveal the trend of the selected attribute sets from Chapter 3 toward risk level. Furthermore, this chapter generate the segmentation of conditional seaport risks referring to their exposure.

Chapter 5 solves the interdependency phenomena among the conditional seaport risk. The goals are to understand the interdependency factors amid the SSC using MANOVA and analyze to what extent the rough set model can explain the independency of the conditional seaport risk attributes. This chapter shows the expected sign (+/-) among the conditional seaport risk variables in the predictive model. The significancy each conditional seaport risk model is represented by the hypothesis test.

Chapter 6 proposed the risk appetite model to understand the risk aversion from the SSCR entities, e.g. port-authority (seaport-management, and seaport operator) and seaport user. Risk appetite can be described as an organization's risk capacity, or the maximum amount of residual risk (expected utility value) it will accept after controls and other measures have been put in place. In this sense, this study measures a risk aversion from the stakeholders' risk appetite with the assumption that the stakeholders have different preferences about the conditional seaport risk towards the supply chain continuity without interfering with each other. Then, the risk aversion model can be optimized with two different types of rules, called sporadic risk case and repetitive risk case, using mix integer linear programming model.

Chapter 7 summarizes this dissertation's results and findings and proposes future scopes.

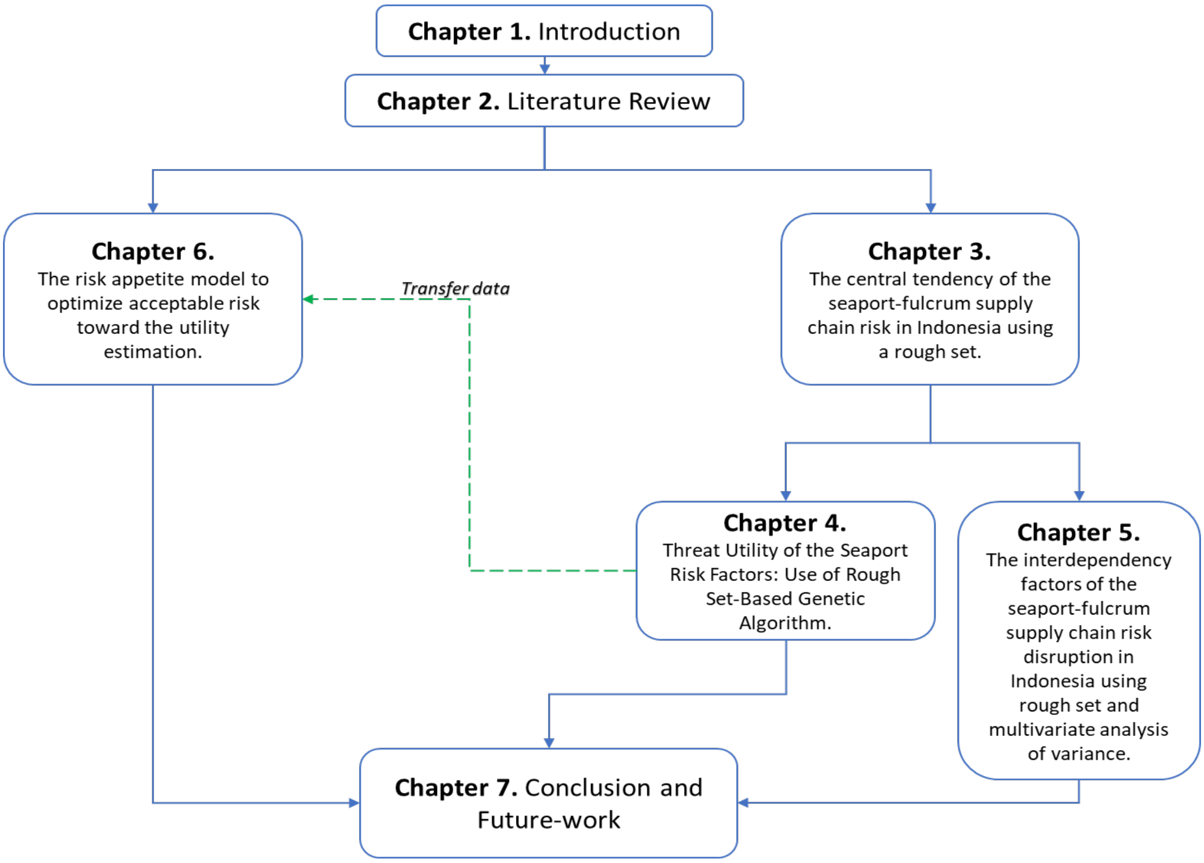


Figure 1.6 Organization of dissertation

1.4 Scope of the study

This dissertation does not include the hinterland factors, e.g. changes in transport policy and the cost structure of inland transportation modes, in the assessment of the SSCR. Furthermore, human factors defined as cause of the many seaports risk is not presented. However, the output of human factors, e.g. occupational accidents, collisions, congestion, and so on, is depicted into conditional seaport risk attributes. Hence, the scope in this dissertation includes the logistics network, industrial node, shipping network, and international trader (exporter and importer) in assessment.

1.5 Contributions

This dissertation has contributed to three aspects. Firstly, this study has presented a new framework for multi-criteria decision-making (multi-attributes optimization) applicated to the SSCR assessment and evaluation according to the dependency and interdependency variable. This relation is depicted in the Chapters 3 to 5. Secondly, the term SSCR is highlighted to present a new perspective in the supply chain risk assessment field – that is commonly manufacturing-based. Foreign and domestic trade in relation to logistics and transportation networks is sometimes not fully covered in many supply chain risk assessments. Thus, the SSC model was proposed to identify and assess the conditional risk phenomena in the supply chain corresponding to the distribution chain focused on the seaport. Thirdly, this study proposed a model to calculate risk aversion from the risk appetite of SSC stakeholders. Moreover, the detailed contributions of this dissertation are explained as follows.

In the Chapter 3, the SSCR model was developed from the literature review, accident report from the case study, and discussion with the experts. Hence, the SSCR model sourced from the ten threat factors depicted in Figure 1.3. Every threat factor owned conditional seaport risk attributes that directly affects seaport functionality and further disrupt supply chain continuity. From a seaport enterprise's perspective, the operations and development of the SSC are closely related to the import and export trade. Hence, the proposed risk model is used to investigate the association between the conditional seaport risk attributes and threats of supply chain disruption by expert evaluation.

In the Chapter 4, it contributed to reveals the interdependency between conditional seaport risk attributes and the threat of supply chain disruption referring the economic and risk management perspective into part-worth utility function. The results can assist policymakers engaged in the seaport management related conditional seaport risk attributes by serving as methodological references for developing resilience strategies related supply chain disruption. In relation to the threat utility, the study highlights the areas where each SSC operation can lead to supply chain disruption related to the potential threat. Given this, the study identifies a list of threat utility functions as indicators applicable to the archipelagic country.

In the Chapter 5, it revealed the interdependency pattern among the conditional seaport risk attributes into predictive model and evaluated the potential conditional seaport risk. In addition, the prediction and interdependency diagnosis of the conditional seaport risk probabilities are carried out in a dynamic manner based on the information available in practical operations between port authorities and shipping lines. Thus, the results of this study pioneer the inclusion of different types of conditional seaport risks as key factors in the seaport risk resilience model.

In the Chapter 6, it minimized potential revenue loss from the SSC stakeholders' behavior by selected relevant conditional seaport risk attributes associated with a set of threat utility estimations. The study contributes to introduce a risk appetite model as the evaluation criterion in the threat utility estimation model and to analyze which conditional seaport risk attributes contributed the most in the potential loss with two perspective, e.g. sporadic risk and repetitive risk. The results can assist policy makers to understand the stakeholders' attitude and his optimal decision according to the shipping line, freight forwarder, logistics company, and seaport operator toward the conditional seaport risk attributes.

CHAPTER 2: Literature review

Fundamental concepts of SSCRD from existing literatures are reviewed as starting point. The succeeding sections tackle the following: 2.1) the importance of seaport in supply chain networks globally; 2.3) studies on the interdependency phenomena between conditional seaport risks and supply chain threats; 2.4) analysis tools of SCRM; 2.5) risk analysis of supply chain models referring stakeholders' behavior. Lastly, Section 2.5) presents the gaps in literature which this study intends to fill.

2.1 Seaport supply chain integrations

Numerous studies delve into the role of seaports within supply chains, recognizing their evolving significance in network structures. An exploration of seaport functions across three generations has been proposed in various studies. For instance, Bichou and Gray (2005) outline the historical progression, highlighting the transformation of seaports from simple cargo storage providers to essential hubs for distribution, packing, and processing in second-generation seaports. Loh and Thai (2015a) shift the focus to third-generation seaports, emphasizing the growing importance of cooperation, information sharing, and technological advancements in facilitating communication among stakeholders. These seaport generations have experienced shifts in ownership, development strategies, and the scope of activities.

Seaports serve as integral systems for coastal cities and global supply chains, contributing significantly to the import, export, and transportation of goods. They comprise a noteworthy aspect of a city's appeal and offer essential infrastructure, including containers, cranes, and ships, for the seamless movement of goods and people (Nevins et al., 1998). Recognized as critical elements for coastal cities and maritime nations, seaports, as highlighted by Mokhtari et al. (2012), impact a country's cost structure, industrial competitiveness, and living standards. Seaports also play a pivotal role in trade networks, influencing channel control and ownership dynamics. Additionally, they serve as connectors for process flows, fostering new work patterns, and contribute to the overall enhancement of supply chain performance (Bichou and Gray, 2005).

The growing attention on the evolving role of seaports within supply chains is notable (Notteboom & Haralambıdes, 2020). Historically, seaports had limited involvement in hinterland integration and collaboration with the broader port community. The transformation of seaports from standalone entities to supply chain-integrated logistics hubs has involved them becoming value-generating centers through diverse customer-focused activities (Sdoukopoulos & Boilé, 2021), adapting to become more agile (Notteboom et al., 2020), and evolving into knowledge-based global supply chain management centers focused on delivering and capturing value (Gruchmann et al., 2018). Yet, as ports strive for deeper integration, they encounter new challenges, such as a lack of synergies, resistance to fostering partnerships, losing control over service provision, absence of contractual relationships with partners, and discrepancies in expectations between port authorities and port users (Song, 2003).

In the same way, the transformations in supply chain patterns and practices are driving a deeper integration of seaports (Mangan et al., 2008). Noteworthy shifts in supply chain dynamics, including a focus on economies of scale, outsourcing, globalization, flexible logistics, cost optimization, and the shift to e-business, exert a considerable influence on seaports (Lugt & Langen, 2005). As a result, these changes have an effect on how seaports are positioned within supply chains, leading to implications for circumstances such as multi-modal connectivity and integration initiatives, value-added services, agility and adaptability, communication and information exchange, port efficiency, and port security (Vitsounis & Pallis, 2012; Woo et al., 2012).

The evolving functions and responsibilities of integrated ports emphasize the close connection between ports and supply chain networks. As a result, understanding the implications of seaports' positions within supply chains provides valuable insights into the potential consequences of disruptive events originating from ports, underscoring the risk of disruptions centered around seaports. In summary, seaports are increasingly becoming essential to the continuity of supply chains, rendering them vulnerable to harm in the event of a disruptive incident. From the perspective of seaport enterprises, the operations and development of the supply chain centered around seaports are closely linked to import and export trade. Consequently, seaports face both external environmental risks and internal operational risks.

2.2 Conditional seaport risks and supply chain threats

Seaports, serving as pivotal points in the global movement of goods and people, have become essential for the effective assessment and management of SSCRD. This involves safeguarding people and the environment while upholding quality and performance standards. Container shipping operations, recently acting as the backbone of the global supply chain, have given rise to various operational risks impacting other components of the supply chain (Nguyen et al., 2022). In Chapter 5, we illustrated that inefficient maritime security inspections, leading to low punctuality in delivering goods, expose entities to liabilities under their contract of carriage. Maritime security checks at sea causing delays result in increased shipping expenses, encompassing rescheduled services, pilotage, class inspections, and planned maintenance.

Another dimension of threat pertains to organizing and planning processes, which play a crucial role in SSC operations. However, these processes are susceptible to disruptions from various seaport risks, potentially compromising the resilience of the seaport supply chain. For instance, Siswanto et al. (2018) emphasized the challenge of storage planning, specifically the inventory routing problem, in the fertilizer product supply chain. The inventory routing issue leads to demurrage in the loading port, diminishing the ship's utility and increasing operational costs. A comprehensive planning process can assist port-centric supply chain organizations in navigating their established direction with reduced uncertainty (Jiang et al., 2018).

The service process within seaports represents a significant dimension of threat. Commonly discussed risks related to SSCRD include breakdowns in seaport equipment (Mennis et al., 2018; Gurning et al., 2010) and inadequate handling of equipment at seaports (Lloyd et al., 2019). Both factors lead to reduced productivity and efficiency in seaport operations, posing potential hazards and losses for cargo (Loh et al., 2017). These hazards may eventually contribute to seaport accidents, diminishing cost efficiency and thereby significantly impacting the overall transport costs borne by supply chain parties (Hassanzadeh et al., 2013). In the context of SSC operations, Jiang et al. (2018) noted that the risk associated with the seaport service process pertains to port services and distribution facilities. This includes the rationality of port berth allocation, operational efficiency in production (e.g., ship, crane, and container), and effectiveness in handling, storage, transfer, and distribution. These factors are closely linked to the design of yard, dock, and warehouse spaces (Kim and Lee, 2015).

Another dimension of threat is related to distribution. The transportation of hazardous goods, such as chemical spills, is considered a distribution threat (Mansouri et al., 2010). John et al. (2014) explored potential hazards associated with such distributions, highlighting that handling hazardous goods or petroleum products could lead to cargo spillages. Similarly, Alyami et al. (2014) and Alyami et al. (2019) identified specific hazardous events related to various sources, including collisions due to crane and trailer breakdowns, potential substance leakage, ignition resulting from the distribution of hazardous products, and contamination of premises. These hazardous events, along with delays and inefficiencies stemming from inadequate infrastructure, contribute to 10% of the cost of imported goods, according to 2010 data from the World Bank (Adewole, 2019).

In the Indonesian scenario, an imbalance in cargo distribution, encompassing infrastructure availability, shipping patterns, and the supply and demand of maritime transport, including port connectivity, presents a challenge in SSCRD. This challenge is evident between the developed economic region in the western part and the developing economic region in the eastern part. Chapter 4 highlights the issue of high logistics costs and price disparities between these regions, which have a clear impact on Gross Regional Domestic Product per capita in certain areas of the developing economic region.

Addressing natural disasters, Mansouri et al. (2010) conducted an analysis of the port of Boston, revealing that Category 3 and 4 hurricanes, along with snowstorms, can result in significant economic and social consequences. In a specific examination of seismic events, Na and Shinozuka (2009) reported that the Kobe port in Japan suffered direct physical damage due to an earthquake, amounting to more than USD 9 billion within the initial nine months following the event in 1995. These studies underscore that seaports are particularly susceptible to extreme threats, giving rise to various risks in terms of operations, environment, nature, security, technology, and organization (John et al., 2014; Arisha and Mahfouz, 2009).

The literature shows that seaports play a key role in supply chain continuity, given the increasing integration of seaports into supply chains. However, there is no explicit risk model to explain the interdependency between conditional seaport risk attributes and potential threat of the supply chain, or to what extent the satisfaction level of seaport operation is due to the causal connection. Hence, a disruptive event originating at the seaports can hurt other interdependent businesses and alter the range as well as complexities of seaport service operations with other supply chain entities. An understanding of the seaport risk factors having a relationship with supply chain threats is necessary to elucidate on the characteristics of supply chain concerns, particularly the presence of numerous ports' dangers. Given this, Table 2.1 shows the issues potentially impeding seaport functioning and undermining supply chain continuity.

Table 2.1 Supply chain disruption threats under seaport risk events

No.	Conditional seaport risk events	Threat to supply chain disruption
1.	Stakeholder coordination (Loh and Thai, 2015a; Bichou and Gray, 2005)	• Ownership profile and leasing structures of terminal operators experienced conflicts of interest, hindered the decision-making processes, and disintegrated the supply chains.
2.	Cargo throughput imbalance (Amin et al., 2021; Rumaji and Adiliya, 2019)	• Lowers port performance including infrastructure availability, reduces the level of competitiveness, and makes visible the bullwhip effect vulnerabilities in the supply chain. • Reduced container demand in developing Indonesian regions increases sea transportation costs, diminishes port performance, and raises maritime logistics expenses.
3.	Maritime security inspection (Dewi and Purnamasari, 2021; Komarudin et al., 2017)	• Too many agencies involved in maritime security with no clear division of responsibilities leads to corruption. • These value-added services can cause operational delays, lower ship productivity, increase voyage costs, and increase exposure to liabilities under contracts of carriage.
4.	Port strikes (Loh et al., 2017)	• Delayed, duplicated or lost shipments of supplies, delayed shipments to customers, inventory build-up. • Inability to meet customer orders, broken contracts, and harm to manufacturing, retail, and food industries.
5.	COVID-19's effect and natural disaster on the seaport operation (Notteboom et al., 2021; Vousdoukas et al., 2017)	• Last-mile vulnerabilities in distribution became visible because of the lower availability of the workforce (e.g., absenteeism in trucking from major seaport).
6.	The interdependency of disrupted events (Nguyen et al., 2022)	• The creation of a domino effect that spread conditional seaport risk and increased the uncertainty of seaport operations resilience. • The lockdown disrupted the workforce and industrial activities from mid-January to early March 2020.

		- A disruption in demand that propagates backwards through the supply chain.
7.	Organizational planning process (Siswanto et al., 2018; Jiang et al., 2018)	- Decline in the ship's utility and increase in its operational cost owing to demurrage in the loading port. - Storage planning issues, especially for fertilizer supply chains.
8.	Seaport infrastructure breakdown (Mennis et al., 2008; Gurning et al., 2010; Loh et al., 2017; Hassanzadeh, 2013)	- Decline in ports' cost efficiency and a consequential increase in the total transport cost borne by the supply chain parties. - Reduced productivity and efficiency in seaport operations. - Potential exposure of cargo to risks and losses.
9.	Operational inefficiency in terminal (Jiang et al., 2018; Loh et al., 2017; Kim and Lee, 2015)	- Impact on the availability of equipment and workforce. - Implications for the planning and management of existing infrastructure and resources.
10.	Inadequate cargo handling equipment for hazardous goods (John et al., 2015; Mansouri et al., 2010; Alyami et al., 2014; Alyami et al., 2019; Adewole, 2019)	- Increase in the cost of imported goods. - Accidental releases of cargo, particularly hazardous materials or petroleum, during handling operations. - Collisions resulting from equipment failures involving cranes, rail-mounted equipment, and transport vehicles.

2.3 Seaport-fulcrum supply chain risk management

Supply Chain Risk Management (SCRM) is a collaborative approach that aims to identify and manage risks within supply chains with the goal of reducing overall vulnerability (Polemi, 2017). Various SCRM frameworks have been developed, but they generally involve five consecutive stages: risk identification, assessment, analysis, treatment, and monitoring (Tummala & Schoenherr, 2011). Effective SCRM can enhance supply chain robustness and agility, thereby improving customer value and business performance (Wieland & Wallenburg, 2012). Given their strategic positioning as nodes that connect land-based transportation infrastructure with maritime shipping routes, seaports occupy a pivotal role within global supply chains, with their operational reliability and resilience being essential to the uninterrupted flow of goods around the world (Dhahri et al., 2022).

Scholarly investigations on supply chain risk identification have examined risk variables from diverse perspectives. Some researchers have approached the issue from the lens of supply and demand, categorizing supply chain risk into demand-related and supply-related risk (Rao & Goldsby, 2009; Tummala & Schoenherr, 2011; Punniyamoorthy et al., 2013; Gupta et al., 2014). Other scholars have identified risk factors based on the structural composition of the supply chain, classifying them as capital risk, information flow risk, and logistics risk (Wu et al., 2006; Punniyamoorthy et al., 2013; Louis &

Pagell, 2018). Expanding on this, a comprehensive supply chain risk typology has been developed, encompassing environmental risks (e.g., natural disasters, political instability), industry risks (e.g., market fluctuations, technological disruptions), organizational risks, problem risks, and decision-making risks (Dhahri et al., 2022).

Existing research on supply chain risk identification has explored risk variables from diverse standpoints. Some scholars have examined risk from the supply and demand perspective, categorizing it as demand-related risk and supply-related risk (Pfohl et al., 2010). Other researchers have identified risk factors based on the structural composition of the supply chain, classifying them as capital risk, information flow risk, and logistics risk (Heckmann et al., 2015). Mandal (2011) has suggested that supply chain risk is chiefly driven by the unpredictability of demand within the supply chain and the inefficient organization of the supply chain itself.

Academic research on supply chain risk assessment has explored various analytical approaches. Some scholars have utilized well-established methodologies such as the Analytical Hierarchy Process and Fuzzy Comprehensive Evaluation to evaluate risk (Samvedi et al., 2012). Meanwhile, other researchers have introduced innovative techniques (Ganguly & Guin, 2013). For instance, Loh and Thai developed a structured modeling framework to prioritize seaport terminal risks, demonstrating its application in a real-world case study (Dhahri et al., 2022). The heterogeneous body of literature on supply chain risk assessment has uncovered a diverse array of risk factors affecting seaports, including port service process risk, operational risk, port relationship process risk,and external environment-associated risk (Jiang et al., 2018).

In the field of supply chain risk prevention and control research, some scholars have focused on managing risks within the internal supply chain (Yue & Zhang, 2008; Liew & Lee, 2012; Jiang et al., 2017; Jiang et al., 2018; Wan et al., 2019). They have examined the causes of risk occurrence and analyzed the relationship between risk factors and overall risk. Other researchers have approached risk control from the perspective of the entire supply chain, viewing it as an adaptive system (Tummala & Schoenherr, 2011). This research has emphasized integrating all risk variables as components of the total risk. Additionally, some scholars have explored risk control by addressing mechanisms for risk prevention and improving risk management practices (Raghuram et al., 2020).

The existing body of research on supply chain risk management appears to have primarily concentrated on the manufacturing industry and enterprises. Furthermore, this scholarly work has explored SCRM from both economic and managerial viewpoints. However, there remains an opportunity for further investigation, particularly given the limited theoretical research that addresses the interdependencies within the service supply chain of seaport enterprises. To address this research gap, a seaport-centric SCRM framework should encompass three key elements: assessing the impact of seaport-specific risks on overall supply chain disruption, modeling the interdependencies of risks within the seaport service supply chain, and understanding the risk appetites of stakeholders within this chain. The solution methods for addressing these elements can be broadly classified into various analytical approaches.

2.3.1 Risk assessment method

The uncertain nature of disruptions stemming from diverse hazard sources and risk factors presents a significant challenge. As noted earlier, an effective risk assessment approach should encompass information on potential hazards, anticipated threats, and the scope of risks, including their ramifications. Risk assessment methods have become integral to the decision-making process, with managers or authorities sometimes withholding approval and implementation until a comprehensive risk assessment is completed. This underscores the critical importance of striving for optimal performance while mitigating unfavorable outcomes.

Seaports, as strategic hubs that undergird the global supply chain, play a pivotal role in catalyzing the transnational movement of goods, people, and information, serving as indispensable conduits that power the engine of international commerce (Verschuur et al., 2023). However, the very importance of seaports also renders them vulnerable to a wide range of threats, from natural disasters to human-induced disruptions, necessitating the implementation of robust risk assessment frameworks to safeguard these critical assets (Dias et al., 2019; Verschuur et al., 2023; United Nations Conference on Trade and Development, 2020).

One prominent approach to risk assessment in seaports is the multi-hazard risk framework (Verschuur et al., 2023; Lam & Lassa, 2016; Olba et al., 2019), which seeks to holistically account for the diverse threats facing port infrastructure and operations. This framework not only considers the physical damage to port assets that can result from natural hazards such as tropical cyclones, earthquakes, and coastal flooding, but also the operational disruptions that may arise from the impacts of extreme weather conditions, including high winds, waves, and temperatures. Moreover, by integrating port-level trade network data, this risk assessment framework can provide valuable insights into the cascading effects of seaport disruptions, quantifying the trade and logistics losses that may ensue. In doing so, it underscores the strategic economic importance of enhancing the climate resilience of ports and other critical coastal transport infrastructure, given their pivotal role in the global trading system. (United Nations Conference on Trade and Development, 2020)

Table 2.2 presents an overview of the quantitative and semi-quantitative risk assessment approaches used in seaports, based on a survey of the literature. Depending on the risks and hazards that have been discovered, these strategies' goals, traits, and techniques change.

Table 2.2 Risk assessment methods used in seaport.

Authors	Methods	Short description
McIntosh & Becker, 2017.	Meta-analysis of multi-port	The paper starts by emphasizing the value of a "multi-port" approach for assessing port operations. It then explores the key components of climate vulnerability assessments and presents examples of diverse methodologies.
Alises et al., 2013.	Overtopping risk management	This paper presents a risk assessment methodology that is integrated into an overtopping risk

		management framework to address safety issues in port operations. The overtopping risk value is determined by combining the probability of an undesirable event's occurrence with its consequences, which are estimated in terms of costs or delays and based on the vulnerability of the affected port system.
Zaloom et al., 2019.	A semi-quantitative risk matrix	This study identified commonly transported chemicals in the port of Houston and assessed the overall risk of each chemical based on its potential public safety and environmental health impacts in the event of exposure.
Hsu et al., 2017.	A risk matrix based on a Fuzzy Analytical Hierarchy Process (FAHP) approach	A risk matrix based on a fuzzy Analytical Hierarchy Process approach was proposed to assess the risk factors. The research model was then empirically investigated using the oil tanker fleet of the Chinese Petroleum Corporation in Taiwan.
Hsu et al., 2017.	A revised risk matrix based on fuzzy AHP (Analytic Hierarchy Process)	This study aims to assess the operational safety risks of dangerous goods in air freight. The relevant literature was reviewed to identify the risk factors. A revised risk matrix based on fuzzy Analytic Hierarchy Process was proposed to assess the risks of these factors. Finally, the model was validated through an empirical investigation of dangerous goods air freight operations in Taiwan.
John et al., 2016.	Bayesian belief networks	This paper presents a modelling approach that uses Bayesian belief networks to represent the influencing variables in a seaport system. The hierarchical structure of Bayesian belief networks enables collaborative design and modelling of the system.
Olba et al., 2019.	An Analytic Network Process (ANP)	The Analytic Network Process was used to determine the risk perception weights for each criterion, based on survey data from expert navigators. The consequences associated with each

		nautical risk were then identified in consultation with risk experts.
Mokhtari et al., 2011.	A generic bow-tie based risk analysis framework	This study integrated a generic bow-tie based risk analysis framework into the risk assessment phase as the backbone. Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) were used to analyze the risk factors associated with port operations. This process enables port professionals and risk managers to investigate the identified risk factors in greater detail. To address the vagueness of the data, Fuzzy Set Theory (FST) and the possibility approach were employed to overcome the limitations of conventional probability-based approaches.
Ventikos and Giannopoulos, 2013.	A qualitative measures	The researchers utilized qualitative measures of frequency and severity to assess and quantify mortality rates. However, a key limitation of this approach was the exclusion of specific environmental hazards, which undermined the overall reliability of the findings.
Sunaryo and Hamka, 2017.	Hazard Identification and Risk Assessment (HIRA)	The method is used to determine the type, cause, and impact of potential risks based on the activity sequences. A risk matrix is then employed to obtain the risk level. Additionally, the Fault Tree Analysis method is utilized to investigate the root causes of the highest-risk activities.

An alternative perspective on risk assessment in seaports emphasizes the need to consider these assets within a broader, multi-port context, recognizing that the vulnerabilities and interdependencies of individual ports within a regional or global network can have significant implications for the overall resilience of the system (McIntosh & Becker, 2017). This "multi-port" approach complements the more common single-case study approach, offering a more nuanced understanding of the complex web of risks and interdependencies that shape the risk landscape of seaports.

Alises et al. (2013) developed a comprehensive model to assist port authorities in assessing and managing the risks associated with overtopping in port infrastructure. The model incorporated key factors such as the probability of overtopping occurrences, the potential consequences, and the vulnerability of port systems. The likelihood of overtopping was calculated by analyzing the interplay of various meteorological elements that could contribute to such hazards. The researchers employed advanced analytical techniques, including mathematical formulations, propagation and prediction models, and climate data analysis, to derive the relevant risk variables. The vulnerability assessment focused on quantifying the exposure that could result in catastrophic events, utilizing a non-dimensional index ranging from 0 to 1. Additionally, the model incorporated the evaluation of overhead costs associated with material items or activities using weighted sets of linguistic characteristics. The authors recommended the use of this comprehensive port risk management tool to facilitate a thorough analysis of the identified risk characteristics and support informed decision-making by port authorities.

Zaloom et al. (2019) examined the risk of oil spill contamination at the port of Šibenik due to scenarios involving collision, impact, and grounding incidents. The researchers utilized a semi-quantitative risk matrix that incorporated both numerical and linguistic elements to assess the potential impact and likelihood of these hazards. Additionally, they evaluated the influence of weather conditions on ship operations and developed risk indicators to reflect the level of tolerance. The authors emphasized the necessity of employing the GNOME pollution spread modeling tool to simulate these scenarios, as it provided valuable insights into the potential environmental consequences of oil spills within the port area. The software was supplied with data on the type of oil, seawater parameters, currents, wind and wave conditions, leak specifics, and cleanup processes. This semi-quantitative approach enhanced the understanding of the environmental risks associated with oil spills in the port setting.

A semi-quantitative risk assessment approach, based on the International Maritime Organization's formal safety assessment framework, was proposed by Hsu et al. (2017). This method utilized a risk matrix, with the columns representing the likelihood of risk effects and the rows denoting the severity levels. The authors employed frequency and severity indices that combined verbal and numerical values to capture the varying degrees of relevance for the risk factors. This technique was then applied to analyze the cargo terminal operations at the Greek port of Thessalonica, where historical accident data was used to assess the frequency and impact on both human and environmental resources.

Hsu et al. (2016) utilized a fuzzy framework to represent and analyze risk variables. Risks were identified through an extensive literature review and in-depth discussions with senior port management. The authors then investigated and assessed fuzzy hazards. To manage ambiguous data, linguistic variables and a risk matrix model were employed, which were later expanded into a fuzzy risk matrix. In the subsequent stage, the linguistic sets of fuzzy risk frequency and fuzzy risk severity were analyzed for each risk factor. The resulting fuzzy risk values, obtained by multiplying the fuzzy risk frequency and fuzzy risk severity, were then evaluated, and the average fuzzy risk value for the risk factors was calculated. Finally, the risk values were integrated into the risk areas of the risk matrix using the Similarity Measure technique. The key advantage of this semi-quantitative risk assessment approach was its ability to convey complex information and handle unclear terminology.

A semi-quantitative risk assessment framework was developed to incorporate novel seaport risk data (John et al., 2015). The framework utilized a Bayesian belief network to hierarchically model the contributing factors. Additionally, the Fuzzy Analytic Hierarchy Process was employed to determine the relative importance of each variable. This approach effectively addressed the ambiguity and uncertainty inherent in the assessment process. Furthermore, the findings were validated through a sensitivity analysis, which examined the impact of changes in input parameters on the overall risk evaluation.

Olba et al. (2019) developed a methodology to assess the potential risk of accidents in port areas on an aggregate level by creating a 'Nautical Port Risk Index'. They first identified the primary nautical risks in ports, then used the Analytic Network Process to derive risk perception weights for each criterion based on survey data from expert navigators. The consequences associated with each nautical risk were determined through consultation with risk experts. By combining the risk perception values and the consequences of each criterion over a time period, the Nautical Port Risk Index was calculated. A case study on the Port of Rotterdam was presented, and the method was validated by comparing the results with assessments from experts on nautical port risks at the Port of Rotterdam Authority. This approach can be applied to evaluate new port designs, the performance of different vessel traffic management interventions, changes in fleet composition, or existing ports using Automatic Identification System data.

According to Mokhtari et al. (2011), the FAHP technique was advocated for hazard identification and prioritization of operational risks in seaport and offshore terminal management. The researchers employed a cause-and-effect diagram to determine the top event. Fuzzy set theory was utilized to address the linguistic assessments of risk variables' sources and consequences by experts, which were then converted into membership functions to represent fuzzy numbers. Subsequently, FTA was used to identify the sources of undesirable occurrences, while ETA was employed to depict the potential consequences that could lead to damage or operational shutdown. This semi-quantitative bow-tie framework serves as a powerful predictive tool, highlighting the importance of evaluating past incidents to prevent future undesirable situations. This approach provides a concise, integrated perspective on the causes and effects of hazardous circumstances.

A study by Ventikos and Giannopoulos (2013) performed a port risk assessment for two Greek ports, utilizing historical accident data from 2008 to 2011 and taking into account both human and environmental factors. The researchers employed qualitative measures of frequency and severity to assess and quantify mortality rates. However, a notable limitation of this approach was the exclusion of specific environmental hazards, such as chemical contamination and the transportation of hazardous materials, which compromised the overall reliability of the findings.

Sunaryo and Hamka (2017) proposed the application of HIRA, in combination with FTA, as a means to evaluate safety in container port loading and unloading operations. This assessment methodology involved the collection of data through on-site inspections, interviews, and the compilation of accident records from three different ports. The researchers utilized Fault Tree Analysis to investigate the underlying sources of risks, and employed a risk matrix that integrated both qualitative and quantitative measures to assess the associated risk levels.

2.3.2 Interdependency modelling of supply chain risks

The prolific growth and interconnectedness of contemporary global supply chains have rendered organizations increasingly susceptible to a multitude of risks, including disturbances in material and information flows, financial volatility, and geopolitical uncertainties - a phenomenon that has been extensively documented in the literature (Skipper & Hanna, 2009; Faisal, 2009; Calvo et al., 2020; Thomas & Helgeson, 2022). Firms have come to recognize that their survival is no longer contingent upon competing against individual organizations, but rather against entire supply chains (Putu et al., 2019). This heightened awareness of supply chain risk has led to a growing impetus for the adoption of robust risk management practices, which can yield continuous improvements in supply chain operations.

Researchers have proposed various models to analyze the interconnections among supply chain risks (Yu, 2012; Burns, 2017; Pfohl et al., 2010; Katsaliaki et al., 2021). For instance, Interpretive Structural Modeling, a hierarchical technique, establishes the order and direction of complex relationships within a system's elements (Jiang et al., 2017; Pfohl et al., 2011; Qiao & Ryan, 2020). This approach has been applied to identify causal linkages between risk mitigation strategies and supply chain risks. Other causal mapping methods, such as the fishbone diagram, also uncover cause-effect relationships among risks. Additionally, Social Network Analysis represents a supply network as an interconnected web of nodes, recognizing critical supply nodes. However, these techniques lack the ability to assess the strength of interdependence between risks (Wagner & Neshat, 2009).

In contrast, system-oriented approaches, like System Dynamics, model the complex, dynamic interactions among supply chain risks by capturing feedback loops, time delays, and nonlinear relationships (Guertler & Spinler, 2014) . By quantifying the magnitude and direction of risk propagation through the network, these models can inform organizational decision-making and contingency planning. The literature emphasizes the importance of developing a comprehensive understanding of the complex interdependencies among supply chain risks as a crucial prerequisite for designing and implementing effective mitigation strategies (Faisal, 2009; Schmitt & Singh, 2009).

Interdependency in maritime transportation, the seaports comprise interconnected structural and infrastructural nodes that constitute a framework supporting the functionality of the global supply chain system. However, catastrophic maritime accidents have serious social and economic effects on the sustainability of this system (Akyuz 2015; Celik et al. 2020; Heiji et al. 2011). These effects have been dramatically demonstrated in events such as the Amoco Cadiz oil tanker spill that leaked 230,000 tons of crude oil and had a serious negative impact on local tourism-related businesses (Wang et al. 2021), and ground-shaking and soil liquefaction from earthquakes (e.g. Port-au-Prince, Haiti, 2010; Maule, Chile, 2010; Tohoku, Japan, 2011; Samara, Costa Rica, 2012; Kaikoura, New Zealand, 2016) that resulted in severe damage to seaport structures (Conca et al. 2020). Furthermore, Mokhtari et al. (2012) argue that these infrastructure systems may affect a country’s cost structure, industry competitiveness, and living standards. Thus, potential disruptions may trigger a domino effect that influences the performance of the entire supply chain system, including the overall well-being of society.

Mota et al. (2016) have previously investigated the impact of cascading failures in complex infrastructure systems that clearly affect the entire transportation system, including its supply chain network. Further, Adiliya (2019) addresses the issue of high logistics costs and price disparity in Indonesian seaport operations. Moreover, Amin et al. (2021) posits that shipping costs harm the gross regional domestic product per capita in some developing economies due to the imparity discussed above. Whereas some of the developed region in Indonesia is still struggling with the dwelling time, inefficient maritime security inspections at sea reduce ship productivity, leading to charges and contract cancellation, and an increase in voyage costs (Dewi and Purnamasari 2021; Zaman et al. 2015; Komarudin et al. 2017).

Recognizing the critical role of maritime transportation in global supply chains, a comprehensive assessment of the interdependent risks within seaport systems is crucial for strengthening the resilience of the overall supply network. While researchers have proposed various models to examine the connections between different risk management strategies and their impact on performance measures, these models have yet to fully address the complex interdependence of risks in seaport operations. A deeper understanding of the intricate relationships and feedback loops among various risk factors, such as infrastructure vulnerabilities, operational inefficiencies, and geopolitical uncertainties, is essential for developing effective mitigation strategies that can enhance the stability and continuity of maritime transportation and the broader supply chain ecosystem.

2.3.3 Risk appetite of a decision maker

Supply chain networks operate within a tightly integrated environment, where interdependent organizations and their associated risks are intricately intertwined, leading to complex chains of interaction even at the individual firm level (Jabbarzadeh et al., 2016; Guertler & Spinler, 2014; Wang et al., 2017). Extensive research has identified distinct risk categories, which aids the risk identification phase of supply chain risk management. However, to capture the interdependent relationships between risks across the entire supply network, the involvement of diverse stakeholders in the risk identification process is necessary. Current risk classification approaches and methods that focus on the optimal treatment of individual risks may be suboptimal if correlations exist between risks and mitigation strategies. As suggested by Kumar et al. (2014), examining the combined impact of such risks can enhance supply chain management compared to addressing each risk type in isolation. Nevertheless, empirical research quantifying the correlations between risk factors and corresponding risk types, or the probability of occurrence of specific risk types associated with their factors, remains limited (Hou & Zhao, 2020).

Effective supply chain risk management requires a comprehensive understanding of the risk factors, their impacts, and the decision-maker's risk appetite. Risk appetite, defined as the amount and type of risk an organization is willing to take in pursuit of its objectives, is a crucial factor in shaping risk management strategies (Aven, 2012; Damodaran, 2010; Merna & Merna, 2004; Tarawneh & Ajmi, 2020; Sanusi & Johl, 2019). Previous studies have examined factors influencing risk appetite, such as organizational culture, leadership, and past experience. Additionally, the decision-maker's risk attitude, which reflects their willingness to take risks, can also impact the overall risk management approach.

Assessing and managing supply chain risks necessitates consideration of the decision-maker's risk appetite, as this influences the selection and implementation of appropriate risk mitigation strategies. As demonstrated by (Tran et al., 2018), supply chain risk assessment has become an active area of research, with a focus on developing robust methods to support decision-making. By incorporating the decision-maker's risk appetite into the supply chain risk assessment process, organizations can formulate tailored risk management strategies that align with their overall risk tolerance. The level of tolerance for accepting risks is significantly influenced by the decision maker's risk appetite, highlighting the need to integrate risk appetite into the decision-making framework.

According to (Sun et al., 2020), the decision maker's risk appetite influences their tolerance for the degradation of target values in supply chain management. Risk-averse managers are inclined to accept only minor deviations from efficiency-based goals, preferring adherence to or improvement in effectiveness-oriented objectives. Conversely, risk-seeking decision makers are willing to accept higher degrees of value degradation for a specific goal in exchange for progress on a competing objective. In contrast, risk-neutral supply chain managers do not exhibit a strong preference towards either type of goal.

Risk-averse decision makers in supply chain management are willing to accept lower expected profits in exchange for lower variability in outcomes. This implies that supply chain managers may choose to hold higher inventory levels or accept higher procurement costs to reduce the potential for stockouts and lost sales. (Mauro et al., 2020) This preference for stability over profitability maximization can have significant consequences for supply chain performance. Incorporating the decision-maker's risk appetite into supply chain risk assessment and optimization models can lead to more robust and practical solutions.

A concept of coordination for a supply chain with risk-averse actors, extending beyond the usual definition applied in risk-neutral scenarios, was proposed by Li and Zhang (2023). The deployment of a supply contract to coordinate a supply chain between a risk-neutral supplier and a downside-risk-averse retailer was investigated by Li and Zhang (2023). Within the conditional value-at-risk framework, Li and Ou (2021) explored the impact of missed sale penalty costs and the degree of risk aversion on the optimal ordering quantity for a risk-averse retailer. An objective function defined as a coherent risk measure in an extension of the standard multi-period, single-item, linear cost inventory problem was examined by (Jaarsveld & Arts, 2021). The reduction of conditional value-at-risk in the well-known single-period newsvendor problem was investigated by (Li & Ou, 2021), who demonstrated the tractability of downside risk measures such as CVaR due to their convexity feature. However, the integration of the decision-maker's risk attitude into supply chain risk management frameworks has been limited, and existing approaches often treat hazards as independent. To the authors' knowledge, the development of a risk management framework within a network of interacting hazards that incorporates the decision-maker's risk appetite has not been examined in prior research.

2.4 Rough set theory

2.4.1 Basic of rough set theory

The Rough Set Theory (RST), introduced by Zdzislaw Pawlak in 1982, is an evolving framework. Its methodology is focused on the classification and examination of imprecise, uncertain, or incomplete information and knowledge, marking it as one of the initial non-statistical approaches in data analysis (Pawlak, 1991). This theory provides a novel approach to dealing with vagueness and uncertainty in information systems, offering tools for the discovery of hidden patterns and decision rules within datasets. Furthermore, central to rough set theory is the notion of approximating a set, where the goal is to represent a set as precisely as possible using the available information (Mani, 2020).

At the core of rough set theory is the concept of an "information system", which is a tabular representation of structured data. This information system consists of a set of objects (rows) and a set of attributes (columns) that describe the properties of those objects. The key idea in rough set theory is to approximate sets of objects using two boundary regions: the "lower approximation" and the "upper approximation". The lower approximation contains all objects that definitely belong to the set, while the upper approximation contains all objects that possibly belong to the set. The formation of these approximations is based on the notion of "indiscernibility", which is a binary relation that groups together objects with the same attribute values.

Let us describe this problem more precisely. Suppose we are given a set of objects U called the universe and an indiscernibility relation $R \subseteq U \times U$, representing our lack of knowledge about elements of U. Indiscernibility relation is an equivalent relation. The equivalent relation is defined by a set of attributes. Formally, let I = (U, A) be an information system. $\forall R, R \subseteq A$, define an associated binary relation $I(R)$ on $U{:}I(B) = \{(x_1, x_2) \in U \,.\, U \mid \forall a \in R, a(x_1) = a(x_2)\}$, which is called R-indiscernible. If $(x_1, x_2) \in I(R)$, then we say x_1 and x_2 are indiscernible with respect to R. The equivalent class of the R-indiscernible are denoted by $R(x)$ or $[x]_B$.

For simplicity, let's assume that *R* is an equivalence relation. Consider a subset *X* of *U*. Our aim is to characterize the set *X* in relation to *R* using the fundamental concepts of RST outlined below:

1. The lower approximation of set *X* with respect to *R* comprises all objects that can definitely be classified as *X* with respect to *R*.
2. The upper approximation of set *X* with respect to *R* consists of all objects that can possibly be classified as *X* with respect to *R*.
3. The boundary region of set *X* with respect to *R* includes all objects that cannot be classified definitively as either *X* or not-*X* with respect to *R*.

Now we are ready to give the definition of rough sets as follow: (a) Set *X* is crisp (exact with respect to *R*), if the boundary region of *X* is empty. (b) Set *X* is rough (inexact with respect to *R*), if the boundary region of *X* is nonempty.

Now, we can present the definition of rough sets as follows: (a) A set *X* is crisp (exact concerning *R*) when the boundary region of *X* is empty. (b) A set *X* is rough (inexact concerning *R*) when the boundary region of *X* is nonempty.

Therefore, a set is considered rough (imprecise) if it possesses a nonempty boundary region; otherwise, the set is crisp (precise). This concept aligns with the notion of vagueness introduced by Frege. For a more precise definition of approximations and the boundary region, additional notation is necessary. The equivalence class of *R* determined by an element *x* will be denoted as $R(x)$. The indiscernibility relation, in a certain sense, characterizes our limited knowledge about the universe. Granules generated by *R*, which are equivalence classes of the indiscernibility relation, signify elementary portions of knowledge that we can perceive due to *R*. Therefore, when considering the indiscernibility relation, our ability to observe individual objects is generally limited, and we are compelled to reason only about the accessible granules of knowledge.

Formal definitions of approximations and the boundary region are as follows:

1. *R-lower* approximation of *X*

$$R_*(x) = \cup_{x\epsilon U}\{R(x): R(x) \subseteq X\} \tag{2.1}$$

2. *R-upper* approximation of *X*

$$R^*(x) = \cup_{x\epsilon U}\{R(x): R(x) \cap X \neq \emptyset\} \tag{2.2}$$

3. *R-boundary* region of *X*

$$RN_R(X) = R^*(x) - R_*(x) \tag{2.3}$$

As evident from the definition, approximations are articulated in the context of knowledge granules. The lower approximation of a set is the combination of all granules entirely encompassed by the set, while the upper approximation is the combination of all granules that have a non-empty intersection with the set. The boundary region of the set is the disparity between the upper and lower approximations. This conceptualization is visually represented in Figure 2.1.

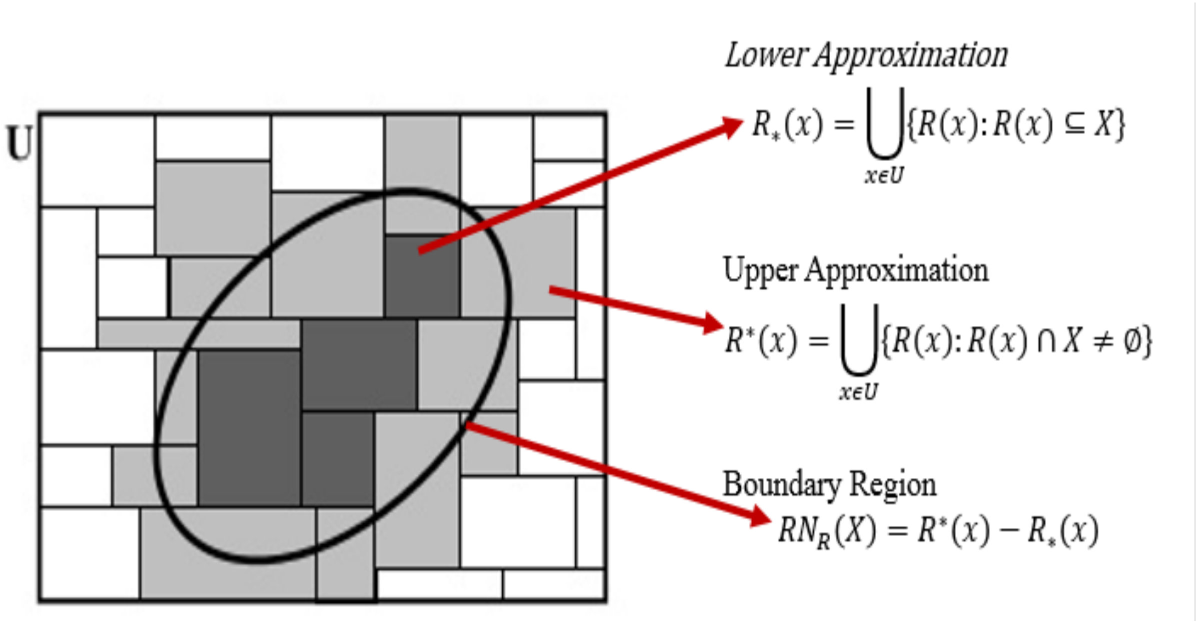


Figure 2.1 Definition approximation of Rough Set

It is intriguing to draw comparisons between the definitions of classical sets, fuzzy sets, and rough sets. A classical set is a fundamental concept, defined either intuitively or axiomatically. Fuzzy sets, on the other hand, rely on the fuzzy membership function, incorporating sophisticated mathematical structures, numerical values, and functions. Rough sets, in contrast, are defined through approximations, necessitating the utilization of advanced mathematical concepts.

Approximations have the following properties:

- $R_* (X) \subseteq X \subseteq R^* (X)$
- $R_* (\varnothing) = R^* (\varnothing) = \varnothing$; $R_* (U) = R^* (U) = U$
- $R^* (X \cup Y) = R^* (X) \cup R^* (Y)$
- $R_* (X \cap Y) = R_* (X) \cap R_* (Y)$

- $R_*(X \cup Y) \supseteq R_*(X) \cup R_*(Y)$
- $R^*(X \cap Y) \subseteq R^*(X) \cap R^*(Y)$
- $X \subseteq Y \rightarrow R_*(X) \subseteq R_*(Y)$ & $R^*(X) \subseteq R^*(Y)$
- $R_*(-X) = -R^*(X)$
- $R^*(-X) = -R_*(X)$
- $R_*R_*(X) = R^*R_*(X) = R_*(X)$
- $R^*R^*(X) = R_*R^*(X) = R^*(X)$

It is evident that the lower and upper approximations of a set correspond to the interior and closure of that set in the topology created by the indiscernibility relation. Four fundamental classes of rough sets, signifying four distinct categories of vagueness, can be defined as follows:

- A set X is *roughly R-definable*, if $R_*(X) \neq \emptyset$ and $R^*(X) \neq U$.
- A set X is *internally R-undefinable*, if $R_*(X) = \emptyset$ and $R^*(X) \neq U$.
- A set X is *externally R-undefinable*, if $R_*(X) \neq \emptyset$ and $R^*(X) = U$.
- A set X is *totally R-undefinable*, if $R_*(X) = \emptyset$ and $R^*(X) = U$.

The intuitive meaning of this classification is the following.

A set *X* is considered roughly *R-definable* when, with respect to *R*, we can determine that certain elements in *U* belong to *X* and others belong to *–X*. If a set *X* is internally *R-undefinable*, it means that with respect to *R*, we can determine that certain elements in U belong to *–X*, but we cannot decide for any element of *U* whether it belongs to *X*. On the other hand, a set *X* is externally *R-undefinable* when, with respect to *R*, we can decide that certain elements in *U* belong to *X*, but we cannot decide for any element of *U* whether it belongs to *–X*. Finally, a set *X* is considered totally *R-undefinable* if, with respect to *R*, we cannot decide for any element of *U* whether it belongs to *X* or *–X*.

Rough sets can also be defined using a rough membership function, as proposed in Skowron et al. (2002). In classical set theory, an element either belongs to a set or does not, represented by the characteristic function taking values 1 and 0, respectively. However, in rough sets, membership is different. The rough membership function measures the degree of relative overlap between the set *X* and the equivalence class *R(x)* to which *x* belongs. Thus, rough sets can be alternatively defined using rough membership, as shown in the equation below, instead of relying on approximations:

$$\mu_X^R : U \rightarrow \langle 0,1 \rangle \tag{2.4}$$

where,

$$\mu_X^R(x) = \frac{|X \cap R(x)|}{|R(x)|} \tag{2.5}$$

and $|X|$ denotes the cardinality of *X*.

The rough membership function signifies the conditional probability that x belongs to *X* given *R*, representing the extent to which *x* is considered to belong to *X* based on the information about *x* conveyed by *R*. The interpretation of the rough membership function is illustrated in Figure 2.2.

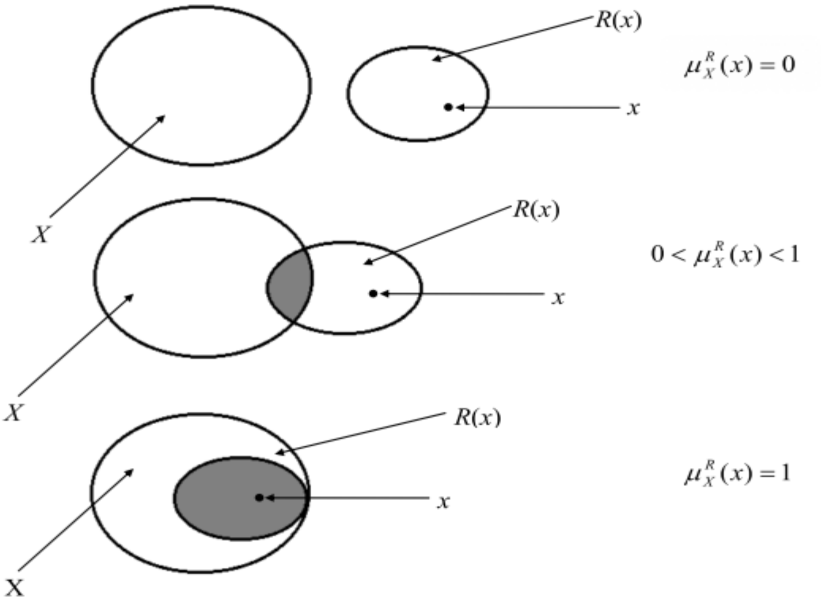


Figure 2.2 Rough Set membership function. Source: Pawlak (1991)

The rough membership function can be used to define approximations and the boundary region of a set, as shown below:

$$R_*(X) = \{x \in U: \mu_X^R(x) = 1\}, \tag{2.6}$$

$$R^*(X) = \{x \in U: \mu_X^R(x) > 0\}, \tag{2.7}$$

$$RN_R(X) = \{x \in U: 0 < \mu_X^R < 1\}. \tag{2.8}$$

It can be shown that the membership function has the following properties:

$$\mu_X^R(x) = 1 \; if \; x \in R_*(X) \tag{2.9}$$

$$\mu_X^R(x) = 0 \; if \; x \in U - R^*(X) \tag{2.10}$$

$$0 < \mu_X^R < 1 \; if \; x \in \; RN_R(X) \tag{2.11}$$

$$\mu_{U-X}^R(x) = 1 - \mu_X^R(x) \; for \; any \; x \in U \tag{2.12}$$

$$\mu_{X\cup Y}^R(x) \geq \max(\mu_X^R(x), \mu_Y^R(x)) \; for \; any \; x \in U \tag{2.13}$$

$$\mu_{X\cap Y}^R(x) \leq \min(\mu_X^R(x), \mu_Y^R(x)) \; for \; any \; x \in U \tag{2.14}$$

The distinctive features outlined above highlight a fundamental difference between rough membership and fuzzy membership. Properties (2.13) and (2.14) indicate that, unlike fuzzy sets, the membership for the union and intersection of sets cannot be straightforwardly computed from the membership of their constituents. Formally, the rough membership is considered a generalization of fuzzy membership. Additionally, the rough membership function, unlike its fuzzy counterpart, carries a probabilistic essence.

The formulae for the lower and upper set approximations can be generalized to some arbitrary level of precision $\pi \epsilon \left(\frac{1}{2}, 1\right)$ by means of the rough membership function in the following way:

$$R_*^\pi(X) = \{x \in U: \mu_X^R(x) \geq \pi\} \tag{2.15}$$

$$R_\pi^*(X) = \{x \in U: \mu_X^R(x) > 1 - \pi\} \tag{2.16}$$

Please note that the lower and upper approximations, as originally devised, are derived as a special case when π = 1.0. The construction of concept approximations is contingent on background knowledge, and concepts are inherently linked to previously unseen objects. Consequently, it is advantageous to introduce parameterized approximations, where parameters are fine-tuned during the process of seeking approximations for concepts. This concept is pivotal in the application of rough set methods for constructing concept approximations. For further details regarding parameterized approximation spaces, readers are directed to Skowron et al. (2002). Through rough sets, it becomes possible to provide approximate descriptions of sets encompassing patients, risk events, outcomes, etc., which might otherwise pose challenges in delineation.

2.4.2 Representation attributes analysis in decision tables

The study of the rough set theory has gained significant attention in the field of decision-making and data analysis, particularly in the context of decision tables. The rough set framework offers a unique approach to handle uncertain and imprecise information (Tekkali & Karthika, 2023), which is commonly encountered in real-world applications. Identifying and analyzing the representation attributes, which are the features that best describe the decision-making process within a given decision table, is a critical component of rough set analysis (Geng & Zhu, 2003; Pawlak, 2002; Wu et al., 2004).

One of the key advantages of the rough set theory is its ability to handle incomplete or inconsistent data, which is often the case in decision tables. Previous studies have explored the use of rough sets in decision table analysis, highlighting its potential in areas such as attribute reduction, decision rule extraction, and knowledge discovery (Tekkali & Karthika, 2023; Geng & Zhu, 2003; Pawlak, 2002; Wu et al., 2004).

A decision table is a fundamental structure in rough set theory, as it represents the relationship between objects, attributes, and decisions. In this context, the representation attributes are the features that best capture the decision-making process, and their analysis is crucial for understanding the underlying patterns and dependencies within the data. Information systems in decision tables often contain redundant information, including repeated rows, indiscernible rows, and dependent attributes that can be induced from other attributes. Inferring a more concise equivalent information system is valuable in practice. The equivalent information system, with fewer rows and columns, is considered a pattern of the original one (Zhou et al., 2021; Liu et al., 2020). In RST, this pattern is referred to as a reduct. The process of obtaining reducts is based on two concepts: 1) indiscernibility relation, which addresses row redundancy, and 2) set of approximation, which handles column redundancy.

The paper by Geng and Zhu (2003) introduces the concept of a rough correlativity matrix, which can be used to analyze the relationships between attributes and decisions in a decision table. This approach allows for the identification of the most important attributes, as well as the degree of certainty and coverage associated with the decision rules. In addition to the traditional rough set-based methods, researchers have explored the integration of rough set theory with other computational techniques, such as machine learning and neural networks, to enhance the analysis of decision tables (Tekkali & Karthika, 2023; Geng & Zhu, 2003). For example, the paper by Tekkali and Karthika (2023) proposes a rough set-based deep neural network model, which combines the strengths of rough sets and deep learning for improved classification accuracy.

As per Pawlak's framework (1991), a decision table structure serves as a guide outlining the actions to be taken when specific conditions are met. Furthermore, this decision table proves to be a valuable instrument for facilitating decision-making. Consequently, the illustration of the decision table structure is provided in Figure 2.3 below.

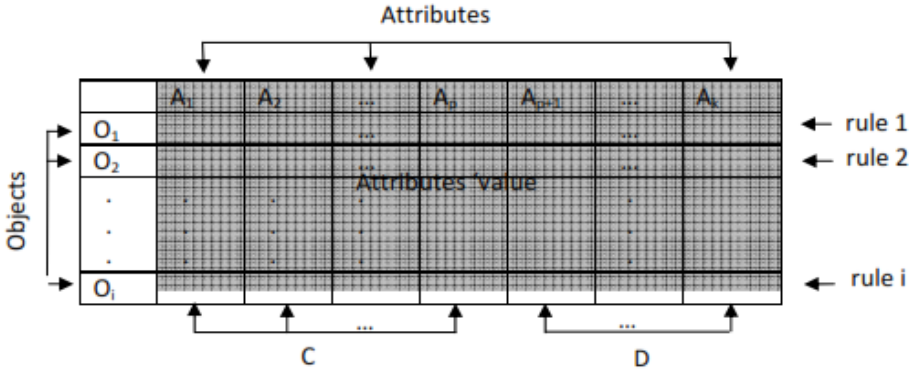


Figure 2.3 Decision table structure

The depiction of the decision-making process, utilizing RST and taking into account the decision table structure shown in Figure 2.3, is outlined in Table 2.3.

Table 2.3 Patients with symptoms of cold

Patient	**Runny nose**	**Headache**	**Fever**	**Fatigue**	**Cold**
P1	Yes	No	Yes	Slightly	Yes
P2	Yes	Yes	No	Slightly	Yes
P3	Yes	Yes	Yes	Heavy	Yes
P4	No	Yes	No	Normal	No
P5	No	No	Yes	Slightly	No
P6	No	No	No	Slightly	No
P7	Yes	Yes	No	Slightly	No
P8	No	Yes	No	Normal	No

Example 2.4.1

A decision table is an information system that classifies attributes into two groups, namely condition attributes and decision (action) attributes. These attributes define partitions within the universe of the decision table. The goal is to approximate the partition defined by the decision attributes using the partition defined by the condition attributes. In Table 2.3, attributes like Runny nose, Headache, Fever, and Fatigue can be regarded as conditional attributes, while Cold is considered a decisional attribute. A decision table with condition attributes denoted as C and decision attribute as D is symbolized as $DT = (U, C, D)$.

Each row in a decision table represents a decision rule, specifying the actions to be taken when the conditions indicated by the condition attributes are satisfied. Objects within a decision table serve as labels for decision rules. In the example provided in Table 2.3, Decision rules *P2* and *P7* share the same conditions but have different decisions. Such rules are labeled as inconsistent, nondeterministic, or conflicting; otherwise, rules are deemed consistent, certain, deterministic, or non-conflicting. Occasionally, consistent decision rules are referred to as sure rules, while inconsistent rules are termed possible rules. Decision tables containing inconsistent decision rules are labeled inconsistent, nondeterministic, or conflicting, whereas tables with consistent rules are considered consistent, deterministic, or non-conflicting.

As a starting point, RST initiates by establishing an indiscernibility relation. The definition of this relation is exemplified in Table 2.3. Let R = {Runny nose, Headache, Fever, and Fatigue}; then *IND(R) = {{P1}, {P2, P7}, {P3}, {P4, P8}, {P5}, {P6}}*. If we consider only Runny nose and Headache, *IND(R1) = {{P1}, {P2, P3, P7}, {P4, P8}, {P5, P6}}*. Alternatively, let *R2 = {Fever, Fatigue}*; then *IND(R2) = {{P1, P5}, {P2, P6, P7}, {P3}, {P4, P8}}*.

Set approximation, a fundamental concept in RST, relies on the indiscernibility relation. It explores the relationship among different partitions within the same set of objects. Various indiscernibility relations within an information system may yield different partitions of a universe. One can "imprecisely" represent one partition with another. In Table 2.3, patients can be categorized into two groups based on the attribute Cold: those with a cold and those without. Additionally, patients can be grouped according to a set of attributes in Table 2.3 (e.g., Runny Nose, Headache). If both approaches result in the same partition of the universe, a doctor may use the former to diagnose patients as having a cold or not, providing a natural diagnostic approach for the doctor.

After defined the indiscernibility relation, the set approximations are determined referring Equations (2.1 and 2.2). Consider *R1* and *R2* above, Representation *R1-approximation* and *R2-approximation* of catching cold group (i.e., *X1 = {P1, P2, P3},* non-catching cold group *X2 = {P4, P5, P6, P7, P8}* separately).

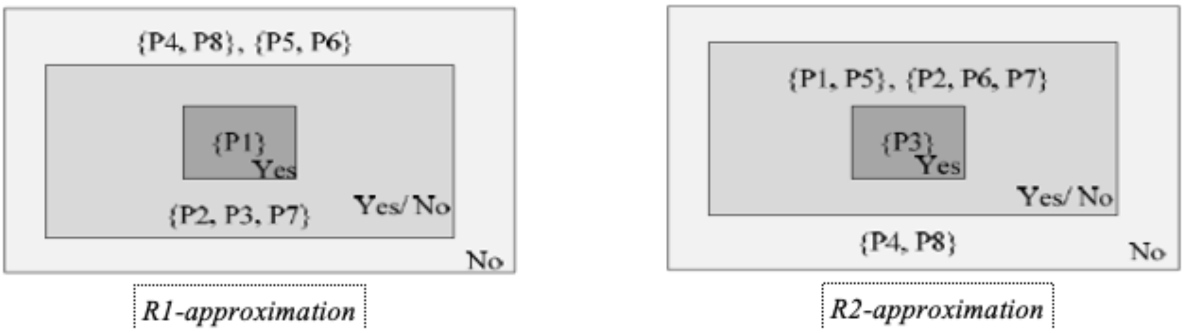
$\underline{R1}(X1)$ = *{P1},* $\overline{R1}(X1) = \{P1, P2, P3, P7\}$;

$\underline{R1}(X2)$ = *{P4, P5, P6, P8},* $\overline{R1}(X2) = \{P2, P3, P4, P5, P6, P7, P8\}$;

$\underline{R2}(X1)$ = *{P3},* $\overline{R2}(X1) = \{P1, P2, P3, P5, P6, P7\}$;

$\underline{R2}(X2)$ = *{P4, P8},* $\overline{R1}(X2) = \{P1, P2, P4, P5, P6, P7, P8\}$;

Four approximation is depicted into subset in Figure 2.4.



R1-approximation *R2-approximation*

Figure 2.4 Approximation of subsets

To determine the consistency of each approximation, the calculation involves the use of a dependency degree. Consider an information system represented as *DT = (U, A)*, where *C* and *D* are subsets of *A*, denoted as the condition and decision attributes, respectively. The computation of the dependency degree is performed using Equations (2.17) and (2.18).

$$\boldsymbol{\gamma(C,D)} = \frac{|\boldsymbol{POS_C(D)}|}{|\boldsymbol{U}|} \tag{2.17}$$

where,

$$\boldsymbol{POS_C(D)} = \cup_{\boldsymbol{X \epsilon U/I(D)}} \boldsymbol{C_*(X)} \tag{2.18}$$

The expression $POS_C(D)$, called a positive region or lower approximation in Equation 2.1.

2.4.3 Application of rough set

Rough set theory, pioneered by Zdzislaw Pawlak in the 1980s, offers a unique mathematical approach for the examination of imprecise, uncertain, or incomplete data, and has since found widespread applications in various fields (Pawlak, 2002). At its core, the rough set theory provides a framework for the analysis and representation of knowledge, particularly in the context of decision-making processes. Rough set theory is commonly used as a complementary approach to other methods, not as a standalone replacement. Its ability to handle raw and inconsistent data with minimal prerequisites, as well as generate useful outputs like reducts, core, attribute relevance, and decision rules, have made it a compelling choice for real-world applications and decision support purposes (Ziarko, 1999).

One key application of rough set theory is in the realm of decision-making. The theory provides a means to handle vague and uncertain data, which often arises in real-world decision-making scenarios (Skowron & Dutta, 2018; Pawlak, 2002; Shen & Jensen, 2007; Greco et al., 2001; Pawlak, 2000; Aggarwal, 2017; Remesh & Nair, 2016). By introducing the concepts of lower and upper approximations, rough set theory allows for the derivation of three distinct regions: the positive, negative, and boundary regions. This three-way decision-making approach has been successfully applied in areas such as credit scoring analysis and biometric recognition, where the refinement of the boundary region can lead to more deterministic decisions (Wang et al., 2019).

Another notable application of rough set theory is in the field of data analysis and knowledge discovery (Pawlak, 2002; Shen & Jensen, 2007). The theory has been applied in a wide range of domains, including medicine (Pattaraintakorn & Cercone, 2007), engineering (Shen & Jensen, 2007), banking (Shyng et al., 2005), and environmental management (Matarazzo, 2018), to uncover patterns, extract rules, and gain insights from complex and often incomplete data. Moreover, the rough set approach has been integrated with other techniques, such as machine learning and fuzzy logic, to enhance its capabilities and expand its applicability (Zavareh & Maggioni, 2018).

Rough set theory has also found applications in the field of intelligent systems and artificial intelligence (Zhang et al., 2016). The theory's ability to handle vagueness and uncertainty aligns well with the challenges faced in areas like knowledge acquisition, decision support, and pattern recognition (Skowron & Dutta, 2018; Zhang et al., 2016; Pan et al., 2008; Shen & Jensen, 2007). Researchers have successfully employed rough set methods in the development of expert systems, rule-based systems, and intelligent data analysis tools, contributing to the advancement of these fields.

Rough set theory relates to various mathematical frameworks that address specific types of uncertain or imperfect data. It is often compared to techniques like discriminant analysis, fuzzy sets, and evidence theory. Tables 2.4 and 2.5 provide a concise comparison of the rough set approach with traditional statistical analysis and the fuzzy set approach according to Greco et al. (1999). The widespread adoption and successful integration of rough set theory across diverse disciplines underscores its significant impact and the continued relevance of this powerful mathematical framework in addressing complex real-world problems.

Table 2.4 Statistical analysis versus the rough set approach

Issue	Statistical methods	Rough set approach
Objective	Clarifying a classification scheme by determining and estimating structural model parameters.	Classifying objects, reducing redundant attributes, and generating decision rules.
Representation of data	Two-entry table representing a sample.	Information table.
Type of attributes	Convert numeric features and qualitative attributes to binary form.	Categorical and discretized numerical features.
Requirement of data	The data sample should be representative and well-balanced across decision classes.	Rough set theory enables the analysis of complex real-world data with reduced dimensionality without prerequisite of data.
Operator for data aggregation	Average values, covariance matrices, statistical tests.	No operator; the indiscernibility relation operates on original data.
Reduction of data	Selection of the most discriminating attributes; standard statistical tests.	Attribute subsets that preserve classification quality.
Final results	Discriminant analysis or decision tree classifier.	Rough set theory generates decision rules in the form of logical statements.

Table 2.5 Fuzzy sets versus rough set theory

Issue	Fuzzy sets	Rough sets
Semantics of uncertainty	Proximity, partial information, or level of fulfilment.	Inconsistency or ambiguity following from granularity of knowledge.
Additional information	Membership functions that depend on the context and specify the degree to which an object belongs to a set.	It can discretize quantitative attributes and determine the degree to which an object belongs to a set from the available information.
Mathematical modeling	Sets with imprecise boundaries; generalization of sets, relations, and logical operators to a continuous domain.	It involves partitioning data, approximating sets, and analyzing attributes.
Processing of uncertainty	"Exact", using the membership functions.	"Approximate", using the lower and upper approximations.
Its primary application is in image processing.	Level of grey (degree of membership).	Size of the pixels (granularity).

One domain where rough set theory has demonstrated significant potential is multi-criteria decision making (MCDM). The original rough set approach, however, was not able to handle preference-ordered attribute domains and decision classes, which posed a challenge for its application in multi-criteria decision analysis (MCDA) (Greco et al., 2000; Greco et al., 2001). To address this limitation, researchers have developed extensions and hybridizations of the rough set model, enabling its integration with other decision-making methodologies and the incorporation of preferential information (Dembczyński et al., 2008; Hassan et al., 2002; Shen & Tzeng, 2016).

The importance of applying rough set theory to MCDA stems from the nature of the input and output of such decision problems. The rough set approach is well-suited for situations where the decision-maker's preferences are available in the form of examples or decision rules, which is a common scenario in MCDA. Furthermore, rough set-based MCDA methods can provide insights into the decision-making process by extracting decision rules that explain the underlying logic and rationale behind the choices made (Słowiński et al., 2012). In addition, Singh et al. (2023) provided a comparison of the relative advantages and disadvantages of various multi-criteria decision making (MCDM) methods in Table 2.6.

Table 2.6 Brief overview of common MCDM tools

Methods	Strength	Weaknesses
AHP	1. Simple and unambiguous computation. 2. Flexible and utilizing. 3. Every criterion is taken into account individually. 4. Easy comprehension is made possible by stepwise analysis.	1. The analysis relies on experiential data, which may be unpredictable. 2. Interdependencies among alternatives and objectives limit impartial analysis and cloud the actual outcomes. 3. Weights assigned to criteria are determined solely by personal opinions, complicating the true representation.
Weighted product method	1. Effective for decision-making issues that involve criteria of a similar nature. 2. Relative values are employed to address the issue of bias.	Undesirable for problems with many outliers.
Technique for order preference by similarity to ideal solutions (TOPSIS)	1. Maximizes the effective utilization of the available information. 2. Independence of information is not a requirement.	1. The calculations of various distances ignore the sign of the values due to the Euclidean measurement.

		2. The attributes exhibit a monotonic increase or decrease.
Eliminating and choice translating reality (ELECTRE)	1. Functions with both qualitative and quantitative data. 2. Outcomes are authenticated through practical experience. 3. Manages heterogeneity.	Requires a comprehensive grasp of the objective, particularly concerning quantitative aspects.
Case-based reasoning (CBR)	1. It does not require extensive data and can be adjusted to accommodate changes. 2. Performance enhancement can be achieved with minimal maintenance.	1. Proficiency in the domain is essential for the user. 2. Highly responsive to inconsistent information. 3. Many cases are needed to attain a generalizable result.
Preference ranking organization method (PROMETHEE)	1. Decision-making at the group level. 2. Addresses both qualitative and quantitative information. 3. Model uncertain information.	1. The objective function lacks a comprehensive model. 2. Relies on decision-makers to assign weights. 3. The complex algorithm restricts the user base.
Data envelopment analysis (DEA)	1. There is no limitation on specifying the mathematical form of the production function. 2. Capable of managing multiple inputs and outputs. 3. Individual bottlenecks and constraints of different entities can be identified. 4. Through the dual of the problem, it can be determined which entity is assessing itself against other entities.	1. The outcomes are significantly influenced by the selection of inputs and outputs. 2. Adjusting the weights of inputs and outputs can easily change the efficiency score of an entity.
Weighted sum method	1. The computational demands are straightforward. 2. Demonstrates efficiency for problems with a single dimension.	1. Provides a basic approximation of the objective function.

		2. Ineffective for models that encompass multiple preferences.
VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)	An enhanced iteration of TOPSIS that mitigates the influence by rationing positive and negative ideal solutions.	The effectiveness is constrained in scenarios involving conflicts and real-time data.

Source: Singh et al. (2023)

Therefore, RST has been widely documented and applied across various fields over the past two decades, including medicine, economics, finance, business, environmental engineering, intelligent control, signal and image analysis, software engineering, decision analysis, social sciences, molecular biology, and pharmacy (Wu et al., 2004). While some of these applications have achieved significant success, the fundamental rough set approach has limitations in handling diverse problem domains. To address more specific needs, researchers have developed enhanced rough set methodologies. An important trend in rough set applications is the integration of this theory with other computational techniques, such as fuzzy sets, neural networks, support vector machines, expert systems, and statistical analysis, resulting in hybrid approaches. These hybrid strategies offer tailored solutions for complex problems and specific application challenges. The collaborative integration of these approaches leads to the creation of more intelligent and robust systems, as well as user-friendly and cost-effective technological solutions.

2.5 Conjoint analysis for estimating expected utility

Conjoint analysis is a widely used statistical technique in marketing research and consumer behavior studies, which aims to understand consumer preferences and the trade-offs they make when considering various product or service attributes (Houtven et al., 2011; Song et al., 2008; Choi et al., 2007; Jedidi & Zhang, 2002). This technique can also be applied to the field of risk analysis, specifically in estimating the expected utility of different decision alternatives under uncertainty (Razu & Takai, 2010; Choi et al., 2007; Myung et al., 2007; Kirkwood, 2004; Kahneman & Tversky, 1979). One important application of conjoint analysis in risk analysis is to understand the trade-offs that individuals are willing to make between various attributes of a risky outcome (Houtven et al., 2011). For example, a person may be willing to accept a lower probability of a positive outcome in exchange for a higher potential payoff. Conjoint analysis can be used to estimate these trade-offs and develop a more nuanced understanding of how individuals value different aspects of a risky decision (Wilson et al., 2014).

Prospect theory, an alternative to expected utility theory, has shown that people do not always behave in a way that is consistent with the axioms of expected utility theory (Kahneman & Tversky, 1979). Specifically, prospect theory suggests that people tend to overweight outcomes that are considered certain, relative to outcomes that are merely probable. Conjoint analysis can be a useful tool for exploring these deviations from expected utility theory and developing more accurate models of decision making under risk (Houtven et al., 2011). Furthermore, prospect theory posits that individuals' risk preferences are influenced by the framing of outcomes, with losses being weighted more heavily than gains of equal magnitude (Kahneman & Tversky, 1979).

Over the past several decades, the broad methodology of conjoint analysis has been advanced by numerous researchers, leading to the emergence of four primary conjoint analysis techniques. These include the traditional method that relies on stated preference ratings, choice-based conjoint analysis which utilizes stated choices, adaptive conjoint analysis developed to address challenges associated with a large number of attributes, and the self-explained conjoint analysis approach that follows a bottom-up framework (Knudsen & Johannesson, 2018; Bridges et al., 2011; Razu & Takai, 2010; Rao et al., 2009; Song et al., 2008). The first three methods are known as de-compositional methods because they break down stated preference or choice data to create part-worth functions (Rao et al., 2009; Netzer et al., 2008). The fourth method is classified as a compositional method, as it generates a preference score by combining assessments of attribute levels and the relative relevance of characteristics (Steiner et al., 2016; Scholz et al., 2010).

In the context of risk analysis, conjoint analysis can be used to elicit individuals' preferences for different outcomes and the probabilities associated with those outcomes (Houtven et al., 2011; Rao et al., 2009; Green & DeSarbo, 1978). For example, a conjoint analysis task may present respondents with various commuting options that differ in terms of travel time, cost, and reliability, and ask them to indicate their preferences for these alternatives. This information can then be used to estimate the expected utility that individuals derive from these different commuting options, which can inform the design of transportation policies and interventions aimed at encouraging a shift from private car use to public transit (Redmond & Mokhtarian, 2001; Khulbe et al., 2022).

One of the key advantages of using conjoint analysis for estimating expected utility is that it allows researchers to capture the complex trade-offs and heuristics that individuals use when making decisions under uncertainty (Cai et al., 2022; An et al., 2021). In contrast to the assumptions of traditional expected utility theory, which posits that individuals make decisions through a rational assessment of the probabilities and utilities associated with different outcomes, conjoint analysis acknowledges that real-world decision-making often involves the use of simplifying heuristics and satisfying behaviors, rather than the comprehensive evaluation of all possible alternatives (Pleskac et al., 2015). By incorporating these behavioral factors, conjoint analysis can offer a more realistic and nuanced perspective on how people actually make decisions in the face of risk and uncertainty.

Incorporating conjoint analysis into risk analysis enables researchers to develop more nuanced and behaviorally-informed models of decision-making under uncertainty (Weber & Bottom, 1990; Blesch & Eisenhauer, 2021). By capturing the complex trade-offs and heuristics that individuals employ in their decision-making processes, conjoint analysis can provide a more realistic understanding of how people actually respond to risk and uncertainty (Pleskac et al., 2015; Kahneman & Tversky, 1979; Blesch & Eisenhauer, 2021; Izhakian, 2016). This can lead to more accurate predictions of how individuals and organizations navigate various risk management strategies and interventions, resulting in more effective and tailored risk mitigation and management practices. The integration of conjoint analysis into risk analysis facilitates the development of risk management approaches that are better aligned with real-world decision-making processes, ultimately enhancing the efficacy of risk management efforts and leading to improved decision-making and outcomes in the face of risk and uncertainty (Rampini et al., 2019; Sols, 2018; Bai & Jin, 2016). Conjoint analysis allows researchers to explore the subjective factors and cognitive biases that influence how people perceive and respond to risks, enabling the design of more user-centric and psychologically-grounded risk management strategies.

The fundamental premise of conjoint analysis is that the value or utility an individual derives from a product or service is determined by its various attributes (Green et al., 2001). By exposing respondents to hypothetical scenarios featuring different combinations of these attributes, researchers can estimate the relative importance or "part-worth" of each attribute in contributing to the overall utility (Rao et al., 2009). This information can then be leveraged to forecast consumer responses to various product or service offerings, and to optimize the design and positioning of these offerings.

Conjoint analysis ultimately yields a utility function, which is crucial for decision-making under uncertainty. In this context, risk can be linked to a utility function that reflects the decision maker's preferences regarding potential losses or consequences associated with a decision (Kirkwood, 2004; Meyer, 2008). As Stefánsson and Bradley (2017) explains, if X represents the possible outcomes and $u(X)$ denotes the utility function, then the expected utility $E[u(X)]$ serves as a decision criterion. This process involves assigning probabilities and a utility function to the array of outcomes, and a rational decision maker will choose the action that maximizes the expected utility value as follows (Aven, 2012):

$$Risk - netural: E[u(X)] = u(E[X]) \tag{2.17}$$

$$Risk - averse: E[u(X)] < u(E[X]) \tag{2.18}$$

$$Risk - seeking: E[u(X)] > u(E[X]) \tag{2.19}$$

Conjoint analysis provides a flexible and powerful technique for estimating expected utility functions in the context of risk analysis. To further explore the development of utility functions, prior research by Kainuma and Tawara (2006) can be referenced. While expected utility theory offers a standardized normative framework for decision-making under uncertainty, its practical implementation is often constrained by the challenges in assigning utility values to all possible outcomes. Additionally, decision-makers may aim to identify satisfactory solutions rather than solely maximizing expected utility. The literature frequently cites the use of cost-benefit analysis and risk matrix-based tools. These approaches map risks onto a two-dimensional plane, considering associated probability and loss values, rather than utilizing a range of utility values for every possible outcome. The focus is placed on managing risks through cost-benefit analysis by balancing costs and benefits. The proposed method seeks to enhance the risk matrix and cost-benefit analysis approach by incorporating interdependencies between supply chain risks and strategies, in alignment with the risk appetite of decision-makers.

2.6 Summary

The existing literature underscores the pivotal role of seaports in ensuring the continuity of supply chains, given their growing integration into these networks. However, numerous SCRM models tend to focus on the manufacturing sector and individual enterprises, overlooking the critical significance of seaports within global supply chains as shown in Figure 2.5. There appears to be a need for further investigation to elaborate on the nuances of supply chain threats, with a specific emphasis on the multitude of risk factors associated with seaports. Additionally, there is currently no explicit risk model that elucidates the interdependencies among these seaport risk factors and their potential impact on the overall threat landscape of the supply chain. The extent to which the operational satisfaction level of seaports is causally connected to these factors remains unexplored. Consequently, a disruptive event originating from seaports has the potential to adversely affect other interconnected businesses, leading to shifts in the scope and intricacies of seaport service operations with other entities in the supply chain. A comprehensive understanding of the seaport risk factors and their relationship with supply chain threats is crucial for shedding light on the characteristics of supply chain concerns, especially in the context of the numerous risks associated with seaports.

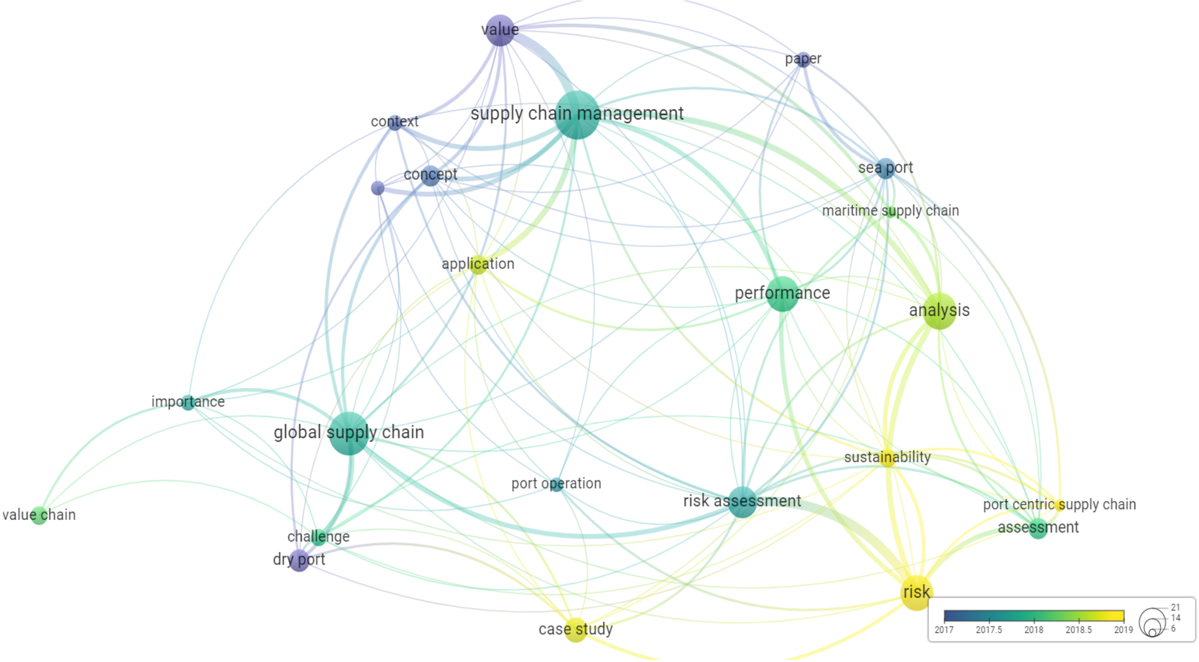


Figure 2.5 Seaport-fulcrum supply chain risk management (bibliography analysis)

According to the reported references, there are four major research gaps (specifically in methodology gap) that necessitate immediate attention:

Gap 1: The current SCRM framework downplays the significance of maritime transportation, specifically the role of seaports.

Gap 2: Many SCRM approaches lack a comprehensive analysis of the central tendency of numerous conditional seaport risk attributes.

Gap 3: There is a lack of analysis in SCRM approaches regarding the causal connections among conditional seaport risk attributes and the potential threat they pose to disrupted supply chain activities.

Gap 4: The existing SCRM research has limitations in modeling the interdependencies of risks.

Gap 5: Decision-makers' risk appetite is not explicitly considered in general when prioritizing risks and developing risk mitigation strategies in the seaport-fulcrum supply chain.

Hence, this research aims to elucidate the causal connections among various conditional seaport risk attributes and their potential impact on disrupting supply chain activities. It introduces a proposed framework for generating a utility function, which proves valuable in understanding the satisfaction level regarding the relative importance of these conditional seaport risk attributes. Specifically, Chapter 3 addresses Gap 1 and delves into Gap 2 by assessing central tendency, which has significant implications for supply chain threat factors. Chapter 4 centers on Gap 3, estimating the utility value of conditional seaport risk and the relative importance of supply chain threat factors. Chapter 5 primarily focuses on Gap 4, unveiling the interdependencies among conditional seaport risks and estimating seaport-fulcrum supply chain risk in terms of threat, implication, and feasibility degrees. Finally, Chapter 6 addresses Gap 5 by calculating the potential loss associated with decision-makers' behavior. Table 2.7 illustrates the position of this dissertation in relation to previous studies.

Table 2.7 The position of this dissertation in previous studies

Authors	Method/approach	Focus-targeted	Analysis					
			a	b	c	d	e	f
Alises et al., 2013.	Overtopping risk assessment	Seaport infrastructures		✓	✓	✓		
Alyami et al., 2014.	Advanced Failure Mode and Effects Analysis	Container seaports		✓	✓	✓		
Amin et al., 2021.	Survey and Stochastic Frontier Analysis	Cargo throughput imbalance		✓		✓		✓
Aqlan and Lam, 2015b.	Bow-tie analysis	Supply chain-based manufacturing firm	✓	✓	✓			✓
Bichou and Gray, 2005.	Operational, organizational, and strategic management approaches	Stakeholder coordination					✓	✓
Celik et al., 2020.	Risk simulation and modelling	Seaport infrastructures	✓	✓	✓			✓
Dewi and Purnamasari, 2021.	Interview and survey	Maritime security inspection		✓			✓	✓
Faisal, 2009.	Fuzzy-AHP	Small and medium enterprises (SMEs)		✓	✓	✓		
Jiang et al., 2017.	Interpretative Structural Model	Maritime Supply Chain System	✓	✓		✓		
John et al., 2016.	Bayesian Belief Network	Cargo handling		✓	✓	✓		✓
Loh and Thai, 2015a.	Interview	Management disruption by seaport						✓
Loh et al., 2017a.	Interview and survey	Port-centric supply chain disruptions threats					✓	✓
Loh et al., 2017b.	Fuzzy comprehensive evaluation	Port-centric supply chain disruptions threats		✓	✓		✓	✓
Mokhtari et al., 2011.	Generic bow-tie risk analysis framework	Operational seaport risk		✓	✓	✓		

McIntosh & Becker, 2017.	Meta-analysis of multi-port	Seaport Climate Vulnerability Assessment				✓	✓	✓
Olba et al., 2019.	An Analytic Network Process (ANP)	Defining the Nautical Port Risk Index		✓	✓			
Qiao & Ryan, 2020.	An Interpretive Structural Modeling	Business processes	✓	✓				✓
Sunaryo and Hamka, 2017.	Hazard Identification and Risk Assessment	Seaport safety		✓	✓	✓		
Thomas & Helgeson, 2022.	Spatiotemporal model	Natural Hazard Damage on Manufacturing Value Added		✓	✓	✓		
Ventikos and Giannopoulos, 2013.	A qualitative measures	Marine Accidents		✓			✓	
Verschuur et al., 2023.	An asset-level risk analysis of global port infrastructure from multiple hazards	Physical asset damages and logistics services		✓		✓		✓
Wagner & Neshat, 2009	Graph Theory	The vulnerability of supply chains	✓			✓		✓
Zaloom et al., 2019.	A practical risk assessment framework	Handling a wide variety of chemicals in ports		✓			✓	✓
This dissertation	Rough set based-genetic algorithm, conjoint analysis, and mix-integer linear programming	Seaport-fulcrum supply chain risk disruptions.	✓	✓	✓	✓	✓	✓

Noted:					
a)	Interdependency	c)	Threat/probability	e)	Risk appetite
b)	Implication/impact	d)	Feasibility/vulnerability	f)	Implication to supply chain disruption

CHAPTER 3: The central tendency of the seaport-fulcrum supply chain risk in Indonesia using a rough set

3.1 Introduction

The exchanges and relationships between a seaport and its peripherals generate globalization and supply chain continuity. Seaports' role in the global production and distribution system accounts for more than 80% of international trade (Hall, 2007). As an intersection between the worldwide mobility chain of goods and people, seaports have become critical to effectively and efficiently evaluate as well as manage SSC factors and risk attributes, protect the people and the environment, and maintain quality and performance. Disruptive events at the seaport spread to various SSC stakeholders and dimensions. The identification of seaport risk attributes involves understanding the supply chain threats due to disruptive events. Correctly identifying those risks contributes to the logistics industry by increasing seaport resilience and ensuring business sustainability. Therefore, this chapter present an optimization algorithm as an integrated part of risk assessment and evaluation framework that involved various elements related to the maritime industry, such as ships, facilities, and other objects.

Enhancing the awareness of seaport risks and concerns helps achieve seaport resilience. Although some studies in the Chapter 2 investigated such phenomena, research on the dynamics between large numbers of seaport-fulcrum supply chain disruption factors and the correlated risk attributes is scant. Therefore, this study aims to provide an approach for identifying the central tendency in supply chain risks and elaborating the impact of seaport risk on the threats to supply chain continuity. To this end, it investigates the current practices of seaport operations, where disruption management by seaport firms significantly affects the SSC.

We select Indonesia as a case study referring to Subsection 1.1.6. The data from Kementerian Perhubungan R.I. (2020) shows at least 9,755 cases of disruption management in Figures 1.4 and 1.5. Typical causes of disruption are "disobedience" in terms of operational rules, administrative regulations, and ministry decrees; weakness in the control systems, such as accounting and financial control; and policy. Both directly and indirectly, these factors relate to the export and import trade, as well as supply chain continuity and accidents with victims (either infrastructure or people). These phenomena reduce the seaport risk predictability.

The SSCR model in Subsection 1.1.3 have ten-dimensional threat factors and every factor poses some conditional seaport risk attributes. This study defines risk as the probability of a risk event in seaport operation, multiplied by the impact of that risk (Aqlan & Lam, 2015a). Threats are situations that may trigger a hazardous source, generate disruptive events, and raise the risk probability in the supply chain (Singh, 2017). Thus, we define the SSCR as the potential effect of seaport risk on supply chain disruption.

We utilize a rough set-based genetics algorithm (RSGA) to reduce uncertainty and deal with many conditional seaport risk attributes. RST provides valuable tools for understanding data, and quantifying and handling uncertainty, knowledge discovery, and vagueness in risk data. Wu et al. (2004) stated the useful applications of RST as: pattern recognition and information processing, business and finance, industry and environmental engineering, and intelligent control systems. Moreover, the combination of rough set with other methodology was also used in medical research (Sudha, 2017), which integrated a RSGA with a neural network to diagnose disease from clinical data sets. We use heuristic information, such as the genetic algorithm, to determine the central tendency of the conditional seaport risk attributes and obtain a ranking of SSC threat factors. Thus, the proposed RSGA handles the complexity between the seaport risk factors and its supply chain entities.

3.2 Multiple criteria decision-making problem description

3.2.1 Risk assessment problem

The data is used in this dissertation is based on expert evaluations, which they are asked to evaluate large number of conditional seaport risk attributes. During their making decision, the decision makers often need to handle large amount of information (conditional seaport risk attributes) to reach rational decision. Such information can be incomplete, uncertain, and even contradictory (inconsistent) to each other.

The uncertainty comes from subjective evaluation from the decision-makers for two aspects, such as the evaluation among conditional seaport risk attributes and their correlation. The representation of data in this MCDM problem is based on the lower and upper value approach in Equations (2.1) and (2.2) respectively. The goal is to estimate a certain set from multiple combination sets among the conditional seaport risk attributes and decision-maker evaluations, where decision variables are discrete/categorical.

In this Chapter, MCDM is used in risk assessment to evaluate and prioritize SSCR factors and analyze potential SSCR attributes, which SSCR factors defines as threat dimensions and SSCR attributes defines as conditional seaport risk attributes. Moreover, MCDM assist in prioritizing risk factors by considering multiple attributes or criteria. Thus, the final score of potential SSCR factors and SSCR attributes (conditional seaport risk attributes) are presented to help SSC stakeholders to act in their business operations. While MCDM offers valuable tools and methodologies for dealing with complex decision problems, it also faces several challenges and limitations. Besides the subjectivity and bias as mentioned above, MCDM often requires data on multiple criteria (attributes) and alternative (decision-maker evaluations) but obtaining reliable and comprehensively data can be challenging. Data may be inconsistent which can be undermine the accuracy and reliability of decision outcomes.

Furthermore, the complexity of risk factors is also challenging task. Risks – SSCR factors and their attributes – often stem from multiple interconnected factors and attributes. Evaluating and prioritizing these factors using MCDM methods can be difficult due to their complexity and interdependencies.

Based on the key problem associated with using MCDM in this risk assessment above, this chapter present a framework to handle those issues as follows:

1. *Complexity of SSCR factors and attributes*: Due to their complexity and interdependencies, we proposed RSGA to select and reduce the number of SSCR attributes. By identifying redundant, irrelevant, or less informative attributes, RSGA help simplify decision problem, improve model interpretability, and enhance computational efficiency. It is provided in Sub-subsections 3.3.3.1 – 3.3.3.3.

2. *Risk prioritization*: After solving the interdependency problem by using RSGA, we proposed a calculation of importance degree to rank the SSCR factors and attributes using risk score as a final evaluation. It is provided in Sub-subsection 3.3.3.4.
3. *Decision support for complex system*: The concept of RST can also extract decision rules from decision data, providing decision support and insight into decision-making process. These rules represent patterns and relationship among SSCR attributes, helping decision-makers understand the implications of different choice and predict outcomes under various scenario. It is provided in Sub-subsection 3.3.3.5.

3.2.2 The complexity problem of SSCR attributes

In MCDM, selecting relevant criteria (SSCR attributes) is crucial. RST can assist in identifying the most relevant SSCR attributes set by eliminating redundant or irrelevant ones. This process can simplify the decision-making process by reducing the dimensionality of the problem. The problem of finding attribute reduction set (reduct) is inherently combinatorial in nature. As the number of attributes increases, the total number of possible combinations grows exponentially, leading to computational challenges, especially for larger datasets. Thus, RST concept is also introduced to find minimal subset of SSCR attributes that retain the ability to distinguish between different decision-maker evaluations in a dataset. The discernibility relation in RST is based on the idea that if two decision-makers are indistinguishable with respect to a set of attributes, those features can be removed without affecting the ability to differentiate between those decision-makers. Therefore, a rough set-based attribute selection problems is addressed.

Hence, it is given a system information or decision table is expressed in $DT = (U, C \cup D)$, which is shown in Table 3.1, where DT is information system/decision table from U decision-makers denoted with $U = \{u_1,u_2,..u_i..,u_n\}$, C is conditional seaport risk attributes (SSCR attributes) denoted with $C = \{a_1,a_2,..a_j,..a_m\}$, and D is a decision attribute, x_{ij} is the decision variable of decision-maker u_i under conditional seaport risk attribute a_j, and y_i is the given value of decision-maker u_i under decision attribute D. Identifying the minimum set of conditional seaport risk attribute is important in risk assessment process.

The problem has the following elements:

u_i : decision-maker *i-th* such as seaport-user, seaport-operator, and seaport-manager.

a_j : conditional seaport risk attributes *j-th* (SSCR attributes).

x_{ij} : decision variable of the conditional seaport risk attributes *j-th* evaluated by the decision-maker *i-th*.

y_i : the given value of the decision-maker *i-th* under decision attribute D.

D : the percentage of risk implication towards SSCR attributes.

R : the equivalent relation on $U * x$ indicating whether a conditional seaport risk attribute is present for a decision-maker. It is defined as R_{ikj} and it explains in Sub-subsection 3.3.3.2.

$S_{ij}(R)$: the significance ratio of the *j-th* attribute for the *i-th* decision-maker.

$P_{ij}(R)$: the probability of the *j-th* attribute being significant for the *i-th* decision-maker.

$\bar{S}_{ij}(R)$: the average measure of significance related to the *i-th* decision-maker and the *j-th* attribute.
n : the number of decision-makers.
m : the number of conditional seaport risk attributes.

Table 3.1 A decision-making table

u_i / a_j	a_1	a_2	... a_j	a_m	D
u_1	x_{11}	x_{12}	...	x_{1m}	y_1
u_2	x_{21}	x_{22}	...	x_{2m}	y_2
⋮ u_i	⋮ x_{i1}	⋮ x_{i2}	⋮ ... x_{ij}	⋮ x_{im}	⋮ y_i
u_n	x_{n1}	x_{n2}	... x_{nj}	x_{nm}	y_n

The decision variables in this problem are binary/discrete variables x_{ij} and denoted as:

$$x_{ij} = \begin{cases} 1, if\ risk\ attributes\ j\ is\ selected\ by\ decision\ maker\ i \\ 0, otherwise \end{cases} \tag{3.1}$$

In rough set-based attribute selection problems, the objective function typically aims to optimize the selection of attributes while maintaining or improving the discriminatory power of the selected subset (Ślęzak and Stawicki, 2020; Greco et al., 2000). The objective function's goal is to find a subset of attributes that provides the best trade-off between attribute relevance and redundancy, ensuring that the selected features effectively discriminate between different classes or categories in the data. Thus, there are three objectives in this problem, such as discriminatory power, redundancy reduction, and complexity control. The objective is to maximize the significancy of the selected attribute and controlling the redundancy with the reduction rate between attribute pairs which denoted as follows:

$$max\ Z = \sum_{i=1}^{n} \sum_{j=1}^{m} S_{ij}(R) * x_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{m} P_{ij}(R) * x_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{m} \bar{S}_{ij}(R) * x_{ij} \tag{3.2}$$

At first, the first term in Equation (3.2) is discriminatory power that measures how well the selected subset of features can differentiate between different classes or categories in the dataset. It may involve calculating measures such as information gain, entropy, or Gini index to assess the ability of the selected attributes to discriminate between classes. We use significance degree referring attribute dependency (see Sub-subsection 3.3.3.1) to compute information gain. Since selecting redundant attributes can decrease the efficiency of the attribute subset, the objective function may include terms or penalties aimed at minimizing redundancy.

The computation redundancy in the second term is measured using reduction rate, which the process of simplifying the decision table by eliminating redundant attributes while preserving the discernibility ability of the elementary set. Reduction rate measures the degree of reduction achieved by the reduction process. It is calculated as the ratio of the number of attributes in the original decision table to the number of attributes in the reduced decision table. A higher reduction rate indicates a more effective reduction process.

The last term is complexity control which refers to managing the computational complexity – due to interdependencies – involved in the process of finding the most concise and effective representation of the decision table. This complexity arises primarily due to the combinatorial explosion of possibilities when dealing with large datasets and a high number of attributes. The objective function in Equation (3.2) is explained more detail in Sub-subsections 3.3.3.1 – 3.3.3.2.

3.2.3 Risk ranking problem

After addressing the problem of the attribute's complexity in previous subsection, the next problem is how to rank the selected SSCR attributes and SSCR factors. The SSCR attributes ranking involves assigning a numerical score of the core attributes (explained in Sub-subsection 3.3.3.4) to each risk based on a weighted sum of attributes. Suppose that a given risk ranking problem is defined on q decision-makers and m core attributes (SSCR attributes). Next, suppose that ω_i denotes the relative importance (weight) of the core attribute and V_{ij} is the risk value of decision-maker i when it is evaluated in terms of core attributes j. $V = 1, 2, \ldots,$ and 5 indicates the highest to the lowest risk level. The objective of risk ranking is typically to assign ranks to risks in such a way that the overall risk prioritization according to weighted sum (Zavadskas et al., 2014). The weighted sum is a linear combination of values, where each value is multiplied by a corresponding weight and then summed together. Mathematically, the weighted sum of a set of values V_{ij} with corresponding weight $\omega_1, \omega_2, \ldots, \omega_m$ is defined as:

$$\sigma_i = \sum_{j=1}^{m} \omega_j V_{ij}\,, \forall i = \{1, 2, \ldots, n\} \tag{3.3}$$

where, V_{ij} represent risk value of the *i-th* decision-maker score on the *j-th* core attributes, w_j represent the relative importance associated with the core attributes *j-th*.

The Weighted Sum Model aggregates the performance scores of each alternative across all criteria by applying the corresponding weights. The resulting overall score reflects the combined impact of each criterion on the decision, with higher weights indicating greater importance. The alternative with the highest overall score according to the Weighted Sum Model is typically considered the most favorable or preferred option (Zavadskas et al., 2014).

3.3 Methodology

3.3.1 Sampling data

In the sampling data, we select Indonesia as a case study due to some reasons. Firstly, there are many accidents reports both directly and indirectly to supply chain continuity based on the data from Kementerian Perhubungan R.I. (2020). The data shows at least 9,755 cases of disruption management. Typical causes of disruption are "disobedience" in terms of operational rules, administrative regulations, and ministry decrees; weakness in the control systems, such as accounting and financial control; and policy. This disruption management is shown in Section 1.1.6. Secondly, due to the archipelagic characteristic shown in Sections 1.1.4 and 1.1.5, the Indonesia seaport operation can be a good example to demonstrate the dependency among the SSCRD variables particularly on other archipelagic countries. Lastly, Indonesia is considered has potential market power and supply as well to the manufacturing node, export and import trade, and shipping industry (World Bank, 2021; Hamid, 2018).

Manufacturing organizations have a tendency to operate as closely as possible to their targeted market and reduce transportation costs. Exporters and importers try to make close relationships with the seaport and the shipping company. As a result, local ship chandlers and suppliers will integrate with logistics providers and regional/global distribution centers. While shipping lines pursuing a profit-maximization focus on occupation rate per vessel, seaport focus on sustainable long-term contracts to utilize their facilities in terms of the total number of annual cargo and passengers served. Meanwhile, due to the short resupply window (the time response pattern) in the shipping industry, it is crucial for shipping lines to establish stable long-term relationships with service providers (seaport, logistics companies, freight forwarders, and so on) to reduce uncertainty, increased requirements for flexibility and customization, and increased supply chain risk. Therefore, any tiny disturbance of the SSCRD factors in the seaport is clearly implicated to another seaport and related to the export and import trade, as well as supply chain continuity and accidents with victims (either infrastructure or people). These phenomena reduce the seaport risk predictability.

To begin with, this empirical study investigated the roles of supply chain entities to understand their patterns of dependency and interdependency. Thus, to collect primary data from SSC organizations in Indonesia, we used a stratified random sampling technique (Slovin's formula) in Equation (3.4) according to Susanto (2017) to invite 750 respondents to participate in an online questionnaire survey and face-to-face interviews with some top-level managers.

$$n = \frac{N}{1+Ne^2} \tag{3.4}$$

where n is sample required (questionnaire), N is population considering response rate (sample size), e is maximum error that tolerated (from 0.01 – 0.05)

We addressed some potential supply chain threats due to conditional seaport risk attributes before conducting a questionnaire survey by sending an email and official letter to make audiency and discuss further these. The audiency and discussion were held in Zoom on September 11, 2020, by three experts from PELINDO Regional 3. The expert names and positions are Dini Ayu Praditya as the head of human capital development, Arya Pradana Putra as a supervisor of the port terminal, and Daru W. Julianto as a senior manager. Based on the intensive discussion, we defined the SSCRD model in Section 1.1.3 to understand the interdependency phenomena between supply chain threat factors and conditional seaport risk events. After that, the survey began in January and ended in August 2021. The design of the questionnaire was such that the definition of each dimensional threat factor and conditional seaport risk attribute was clearly stated before the questions. Moreover, the definition of the scale in the subsequent Section 3.3.2 is also explained before the questions and is shown in Appendix A. This study classifies the SSC stakeholders into three main stakeholder categories that significantly impact the supply chain issues—seaport managers (10%), operators (40%), and users (50%).

Seaport manager is a seaport enterprise or state-owned enterprise, while a seaport operator is a stakeholder responsible for managing operational processes within the seaport, handling various cargoes such as containers, vehicles, liquids, and dry bulk. Seaport users are entities with a close working relationship with port operators and a direct interest in the transported cargo. This category encompasses cargo owners, freight forwarders, ship owners, and ship management companies. The target population considered for this study includes cargo owners, primarily sea-freight forwarders, and logistics companies, as they commonly act as representatives of cargo owners.

Referring to Shipping Law Number 17 of 2008, the Port Authority in Indonesia has outwardly returned the authority to manage state land and business activities at the port to a government agency under the Ministry of Transportation, replacing the state-owned enterprise [Perseroan Terbatas (PT)]. Pelindo (Persero) acted as an operator and regulator at the port prior to the enactment of the decree but only as an operator after. Thus, the Port Authority of Indonesia's seaport consists of two entities: a harbour master as the regulator and PT. Pelindo as the port operator. Hence, in this study, the seaport manager is the harbour master, whereas the seaport operator is a state-owned enterprise. Furthermore, seaport users such as PT. Temas Shipping and Kalla Lines are included in this study.

Precisely, the procedures of sampling data are explained as follows:

Step 1: Audiency by sending a letter, email, and phone call to the targeted seaport organizations in Indonesia to address the SSCR context.

Step 2: Determining the SSCRD model – as shown in Figure 1.3 – from extensive literature review in Chapter 2.

Step 3: Estimated population as many as 1000 with response rate 20% to generate sample size.

Step 4: 750 respondents were invited to participate in an online questionnaire survey and face-to-face interviews with some top-level managers.

Step 5: Calculating sample size by using Equation (3.4).

Step 6: Estimating strata from 150 targeted seaport organization by using stratified random sampling. Percentage of each targeted seaport organization from stratified random sampling is provided in Table 3.2.

During data collection, the background information related to conditional seaport risk attributes that ability to disrupt supply chain continuity was addressed to the respondents before they gave an evaluation. The information is defined in Table 1.1 to give a glance at information regarding the interdependency of the SSCRD. Furthermore, they would present some conditional seaport risk attributes and they were asked to give judgment on the conditional seaport risk attributes in relation to the risk implication in the supply chain continuity in a five-level ordinal scale. These risk levels have meaning (shown in Appendix B) that is also informed by respondents together with the background information of the SSCRD factors. After that, the stakeholders are then asked to allocate 0 - 100 points towards the whole of the conditional seaport risk attributes so as to reflect their relative importance. This relative importance is used in Chapter 4 to generate utility functions.

Table 3.2 Percentage strata from targeted seaport-organizations

Stratum	**Object Research**	**Total**
Population		1000
Estimated response rate		20%
Estimated sample size based on response rate		750

Strata I	Port Manager	10%
Strata II	Port Operator	30%
Strata III	Port Users	60%
Total Samples		150

Respondents were chosen based on their proficiency in risk management, encompassing both general risk management and SCRM or project risk management. Seventeen semi-structured interviews were carried out, involving key stakeholders of the seaport fulcrum supply chain, as outlined in Table 3.3. The duration of each interview averaged 90 minutes, with a range from 70 to 120 minutes. Additionally, three focus group sessions were conducted to facilitate the development and validation of the model, as well as to communicate the results. Each focus group session had an average duration of 2 hours.

Table 3.3 Sample demographic

No.	**Demographic Factors**		**Percentages**
1.	Gender	Male	70%
		Female	30%
2.	Object of research	Port-manager	11%
		Port-operator	43%
		Port-user	47%
3.	Duration of work	Below 5 years	4%
		Between 5 - 10 years	39%
		Over 10 years	57%
4.	Educational Degree	Diploma	10%
		Bachelor’s degree	61%
		Master’s degree	27%
		Doctoral’s degree	2%
5.	Occupation Position	Director	11%
		Manager/Division head	55%
		Supervisor	15%
		Others	19%

The optimal number of the expert evaluation does not follow sampling method. It means that the more data is the greater way to compute the model. However, in order to ensure a reliability of data set for the next step, we followed stratified random sampling with Slovin formula in Equation (3.4) that. Furthermore, the number of responses from the expert per region is depicted in Figure 3.1 as follows:

Figure 3.1 Number of responses to the questionnaire per region

The number of expert evaluation sources from Indonesia seaport-manager: Indonesian harbor master and Pelindo (Indonesia state-owned enterprise); seaport-operator: Pelindo Multi Terminal; Seaport-user: PT. Kalla Lines (shipping company), PT. Temas Lines (container shipping company), PT. Samudera Indonesia (shipping and logistics company), and PT. Trans Power Marine (bulk cargo transportation and handling company. This response rate for each stakeholder is depicted in Figure 3.2 as follows:

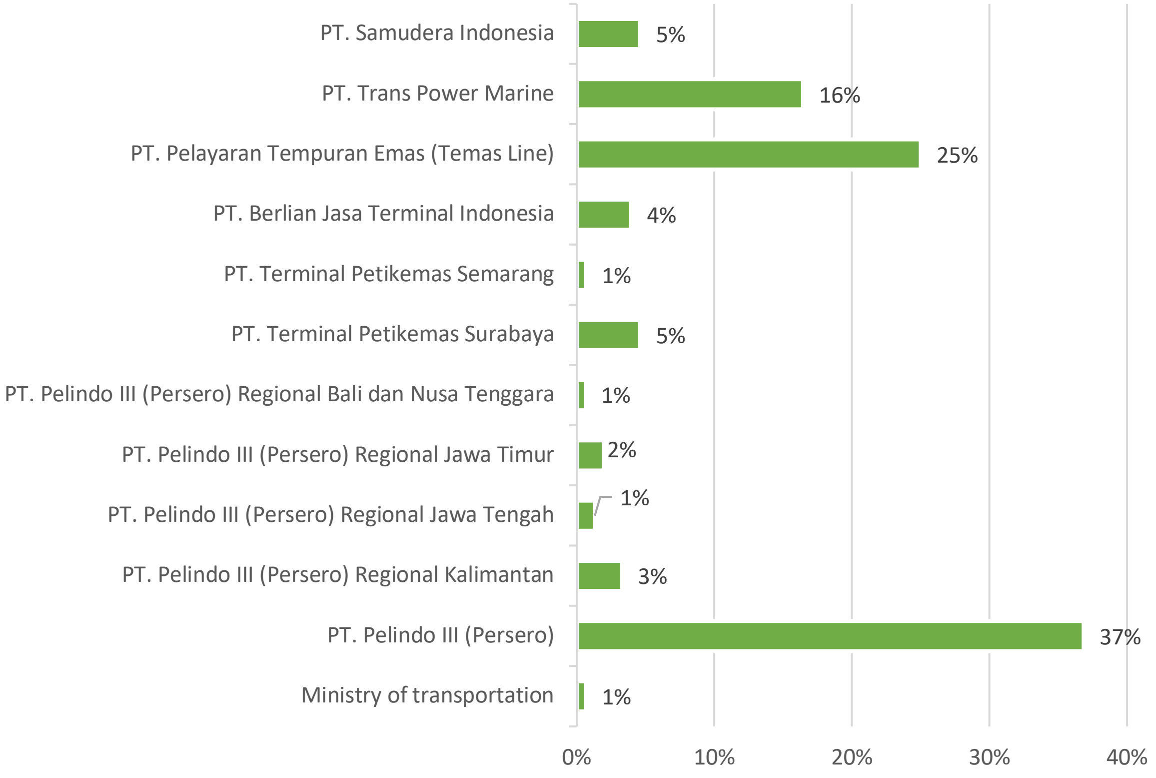


Figure 3.2 Number of responses per company

3.3.2 Selection of dimensional threats and risk attributes

We mainly identified SSCR factors and attributes, such as dimensional threat factors and conditional seaport risk attributes, from accident reports found in the literature review (shown in Chapter 1, Section 1.1.4 and Chapter 2). Accordingly, 61 risk attributes divided by 10 dimensional threats were identified as the result of an extensive examination of the relevant literature (e.g. Jiang et al. 2018; Loh et al. 2017; John et al. 2014; and Kavirathna et al. 2018) and discussions with some experts. Thus, we categorized the ten-dimensional threats in Table 3.4, which were sourced from 61 conditional seaport risks according to the four abovementioned studies. We then identified several indices to capture the different perspectives of domain experts. However, the dimensional threats variables have different conditional seaport risk attributes as seaport risk criteria. Thus, we created this threat categorization index to represent the degree/level of reaction to the danger in terms of ports monitoring, as well as to describe the breadth of measures that may be taken. Furthermore, the 61 conditional seaport risk attributes are divided by the ten-dimensional threats, as indexed and labelled in Table 3.4.

Table 3.4 Seaport-fulcrum supply chain risk factors and attributes

SSCR factors (dimensional threats)	***Index TF***	**SSCR attributes (conditional seaport risk attributes)**	**Index a_j**	**References**
Planning Process	TF_1	Lack of seaport-enterprise strategic risk	a_1	Jiang et al. (2018); Loh et al. (2017).
		Lack of berth risk planning	a_2	
		Lack of supply chain strategic risk planning	a_3	
		Lack of ship risk planning	a_4	
		Lack of handling process risk planning	a_5	
		Lack of storage risk planning	a_6	
		Lack of transfer risk planning	a_7	
		Lack of distribution risk planning	a_8	
		Deficiency of berth allocation risk planning	a_9	
Infrastructure	TF_2	Port equipment breakdown	a_{10}	Loh et al. (2017).
		Inadequate port cargo handling equipment	a_{11}	
		Occupational accidents	a_{12}	
		Power outages	a_{13}	
		Breakdown of vessel traffic management system	a_{14}	
		Breakdown of port information system	a_{15}	
		Collisions in the waterway	a_{16}	
Seaport Service Process	TF_3	Congestion in the waterway	a_{17}	Jiang et al. (2018); Loh et al. (2017).
		Congestion within terminals	a_{18}	
		Congestion at hinterland transfer	a_{19}	
		Less services calling at port	a_{20}	

		Less ship visits	a_{21}	
		Less load factors in captive cargo	a_{22}	
		Shortage of facilities or equipment	a_{23}	
		Shortage of port capacity	a_{24}	
		Shortage of IT and advanced technology	a_{25}	
Distribution Process	TF_4	Less timeliness of port departure and entry	a_{26}	Jiang et al. (2018); John et al. (2014); Loh et al. (2017).
		Low punctuality of delivery goods	a_{27}	
		Less timeliness of port customs clearance	a_{28}	
		Bad defect condition of goods	a_{29}	
		Low deviation time	a_{30}	
		Low efficiency of navigational services	a_{31}	
		Long time in feeder link	a_{32}	
		Less quality of logistics company	a_{33}	
Relationship Process	TF_5	Lack of member coordination	a_{34}	Jiang et al. (2018).
		Member exit mechanism	a_{35}	
		Port labor strikes	a_{36}	
		Less motivation of member interest distribution mechanism	a_{37}	
		Member information asymmetry	a_{38}	
Nuclear-enterprise financial	TF_6	Low revenue	a_{39}	Jiang et al. (2018).
		High debt	a_{40}	
		Low-efficiency operation	a_{41}	
		Low growth development	a_{42}	
		Less cash flow	a_{43}	
		Less growth of domestic and international macroeconomic operation	a_{44}	
Monetary	TF_7	Less efficient deviation cost	a_{45}	Kavirathna, Kawasaki, Hanaoka, and Matsuda (2018).
		Less efficient port cost	a_{46}	
		Less efficient cost in feeder link	a_{47}	
Location	TF_8	Short sailing time to the other hub ports	a_{48}	Kavirathna et al. (2018).
		Less accessibility of hub port	a_{49}	
		Long connectivity of feeder markets	a_{50}	
Security	TF_9	International trade-war	a_{51}	Jiang et al. (2018); Loh et al. (2017).
		War or terrorist attacks	a_{52}	
		Stowaway	a_{53}	
		Smuggling	a_{54}	
		Trafficking	a_{55}	

		Exchange rate	a_{56}	
Environmental	TF_{10}	Earthquake frequency	a_{57}	Jiang et al. (2018); Loh et al. (2017).
		Pandemics/epidemics occurrence	a_{58}	
		Typhoon frequency	a_{59}	
		Increasing sea-level in the seaport	a_{60}	
		Increasing sedimentary level in the seaport	a_{61}	
Decisional Factors	D	Implication of seaport risk to the potential threats of supply chain continuity. Respondents should allocate their evaluation from 0 – 100%.		

Additionally, each attribute is coded and assigned to the appropriate numerical value as follows: (1) 'highest level' indicates loss of ability to perform operations and/or meet customer requirements; (2) 'high level' indicates temporarily interrupting or stopping normal operations and/or delivery of goods and/or services to customers; (3) 'medium level' indicates postponement in force of regular operations, plans and schedules, and/or additional conveyance of products and/or services to customers; (4) 'low level' indicates deviation in transportation plans, costs, common operations, timetables, quality, and/or additional measures of conveyed merchandise (products) and/or services to customers; and (5) 'lowest level' indicates operations that remain unaffected or only experience a negligible effect. The five-risk value in Appendix B is estimated from the data of management disruption in the Indonesia seaport context based on Kementerian Perhubungan R.I. (2020).

3.3.3 MCDM based on RST procedures

The feature selection approach in the MCDM problem involves the utilization of RST. Within the MCDM framework, six distinct problem types exist, including choice problems, sorting problems, ranking problems, description problems, selection problems, and design problems (Mohamad et al., 2015). The selected features serve as a tool for decision-makers to comprehend the central tendencies of conditional seaport risk attributes. The advantages of RST are detailed in Section 2.4.2. The theory of approximation, integral to rough sets, proves beneficial in addressing various issues, making RST a preferred method for researchers dealing with MCDM problems due to its capability to handle uncertain and vague data.

Despite its utility, the original method proposed by Pawlak in 1982 has limitations in handling data and does not account for attributes with preference-ranked domains, such as criteria, choices, and selections (Huang et al., 2013; Chai and Liu, 2011; Shen & Tzeng, 2015). This limitation may result in impure results (noise or errors) during decision analysis tasks and is primarily restricted to the classification of work (Liou et al., 2010). Moreover, the combination problem, classified as an NP-hard problem in feature selection of RST (Skowron and Rauszer, 1992), prompted the introduction of a genetic algorithm to focus on selecting attributes with the highest dependency on the decision attribute.

One well-known rough set-based algorithm for feature selection is the Quick Reduct Algorithm (Chouchoulas and Shen, 2001; Cornelis et al., 2010). This algorithm calculates the dependency or quality of approximation for a single attribute concerning class labels or the decision attribute. It iteratively selects the best attribute and adds other attributes to enhance the overall quality. The addition of attributes ceases when the final subset reaches the same quality as the maximum possible quality of the dataset or when the quality of the selected attributes remains unchanged. Other notable algorithms in this domain include the discernibility matrix-based method (Pal and Skowron, 1999; Skowron et al., 2005) and dynamic reducts (Bazan et al., 1994). However, these approaches are computationally expensive.

Extensions of the original rough set-based knowledge representation include the Variable Precision Rough Set Model (Inuiguchi et al., 2009; Xie et al., 2008), Tolerance Rough Sets (Kim, 2001; Parthalain et al., 2009), and Probabilistic Rough Sets (Yao, 2008). Furthermore, various heuristic approaches based on RST have been developed for feature selection (Modrzejewski, 1993).

Moreover, the MCDM process commences with data collection through questionnaires. The sampling method involves assessing the potential for supply chain disruption as a threat dimension. Conditional risk factors, representing the risk implication in supply chain continuity, are generated using a five-level ordinal scale. Subsequently, a decisional factor is developed to evaluate this term and ascertain the impact of seaport disruption on SSCR. The evaluation of both risk factors is carried out by SSC stakeholders. A rough set model is employed to identify central dependencies among many attributes, such as 61 conditional seaport risk attributes, through a questionnaire survey. The proposed algorithm generates a reduced attribute set, facilitating the acquisition of a core attribute set. This set of core attributes is essential for comprehending the central tendency of SSCR. The workflow of the classification process is elucidated in Figure 3.3.

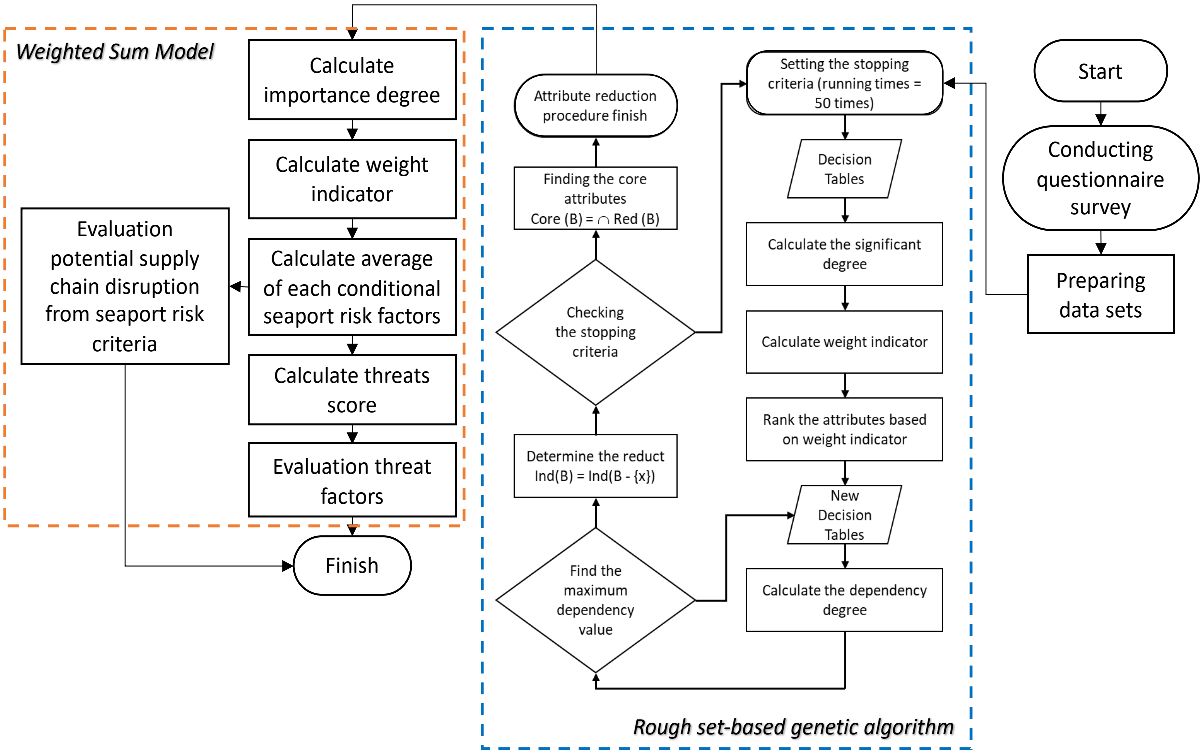


Figure 3.3 The flowchart for Chapter 3

3.3.3.1 Rough set model formulation

The RST, initially introduced by Pawlak in 1985 (Wu et al., 2004), is a mathematical approach for understanding and manipulating imperfect knowledge. It helps deal with many risk factors in risk assessment without losing classification capabilities and attribute reduction. We use a genetic algorithm based on the positive regions of a rough set to identify the core attribute and find a relatively minimal reduction with reduced computational time. Here, we provide the several definitions to formulize a reduct (reduction attribute set) problem as follows:

Definition 1 (decision system). A new data table is identified by the quadruple (4-tuples) $DT = (U, A, V_a, f)$, where U is a finite set of decision-maker evaluations; $A = C \cup D$; $\{a_1, a_2, ..., a_m\}$ is a finite set of attributes (conditional seaport risk attributes), C is conditional attribute set, D is decision attribute set, and $C \cap D = \emptyset$, $C \neq \emptyset$, $D \neq \emptyset$; V_a is the value set of attribute a, where $V = 1, 2, \ldots, 5$ indicates the highest to the lowest risk level, $V = \cup_{a \in A} V_a$; and $f: U \times A \rightarrow V$ is a decision table information function, such that $f(v,a) \in V_a$ for each $a \in A$, and $v \in U$ is called the information function. A string vector describes each decision-maker evaluation v of U. Thus, the description of v is expressed in terms of the evaluation of the attributes from A. It represents the available information about u, as:

$$A_{des}(u) = \{f(u_1, A),\ f(u_2, A), \ldots,\ f(u_n, A)\} \tag{3.5}$$

Definition 2 (lower approximation and positive domain). Consider a decision attribute divided into a domain $U/D = \{y_1, y_2, ..., y_n\}$, R is the equivalence relation of U, $U/R = \{v_{11}, ..., v_{21}, ..., v_{ij}..., v_{nm}\}$ and the lower approximation of u_i is defined as:

$$\underline{R}(y_i) = \cup \{v_{ij} | v_{ij} \subseteq y_i\} \tag{3.6}$$

v and y explained here:
where $i = 1, 2, ..., n; j = 1, 2, ..., m$.

The positive domain is defined as:

$$POS_R(D) = \cup_{y_i \in U/D} \underline{R}(y_i) \tag{3.7}$$

The lower approximation and positive domain are used to determine discernbility relation in problem formulation of RSGA in Sub-subsection 3.3.3.2. Thus, let $R \subseteq X$ be a subset of the risk attributes, and i and k are two different decision-makers. The discernibility relation with respect to R is defined as follows $R_{ijk} = \begin{cases} 1, if\ R_{ij} = R_{kj} \\ 0, otherwise \end{cases}$. This mathematical expression captures the discernibility between two decision-makers i and k based on the conditional seaport risk attributes in the subset R. If there exist at least one attribute in R for which the presence or absence similar between i and k, then $R_{ijk} = 1$, indicating that the decision-makers are discernible. Otherwise, if the discernibility is not affected by any feature in R, then $R_{ijk} = 0$.

Definition 3 (attribute dependency). As indicated in Definition 1, let the conditional attribute set be $C = \{a_1, a_2, ..., a_m\}$, for $R \subset C$, the dependency of decision attribute on R is defined as:

$$\gamma_R(D) = \frac{|POS_R(D)|}{|U|} \tag{3.8}$$

Specifically, when $R = \{\alpha\}$, the attribute dependency is defined as:

$$\gamma_{R-\alpha_j}(D) = \frac{|POS_{\alpha}(D)|}{|U|} \tag{3.9}$$

where |•| is the number of elements contained in •.

Equations (3.8) and (3.9) can also be defined as follow:

$$\gamma_{ij}(R) = \frac{|R_{ij}|}{n}; \forall j \in \{1,2,\dots,m\} \tag{3.10}$$

$$\gamma_i(R) = \frac{|Ry_i|}{n} \tag{3.11}$$

Definition 4 (significant attribute). For a conditional attribute $R \subset C$, for $\forall a_j \in R$, its significance to R is defined as:

$$S_{a_j}(R) = \gamma_R(D) - \gamma_{R-\alpha_j}(D) \tag{3.12}$$

$$S_{ij}(R) = \frac{|R_{ij}| - |Ry_i|}{n} \tag{3.13}$$

Theorem 1. Suppose $a_j \in B$, where B denotes the attribute reduction set. Then, $Max(\gamma_{a_j}(D))$, which follows the condition attribute a_j belonging to the condition set of attributes B (where $B \subseteq A$), is D-superfluous if it has no effect on the lower approximation of D. Otherwise, attribute a_j is D-indispensable in A.

Proof 1. As defined in Definition 1 and 5, for $\forall a \in C$, the $S_a(D) = \gamma_C(D) - \gamma_{C-\{a\}}(D)$; if $\gamma_C(D) = 1$, D depends entirely on C, the $S_a(D)$ becomes larger, and the $\gamma_{C-\{a\}}(D)$decreases, as mathematically defined by Equation (3.6). Furthermore, the smaller $|POS_{C-\{a\}}(D)|$, the greater the dependency of decision attribute D on attribute a, and the larger $\gamma_a(D)$, as mathematically shown in $\gamma_{C-\{a\}}(D) = \frac{|POS_{C-\{a\}}(D)|}{|U|}$, where $|U|$ is a fixed value. Owing to the addition of attributes in the order of significance, a reduction may be obtained, so that $Max(\gamma_{a_j}(D))$ $\forall a_j \in B$.

Definition 5. If every condition attribute in the decision table is not dependent on D, then the condition attribute set C is considered independent of D; otherwise, C is deemed dependent on D.

Definition 6. A subset B of the conditional attribute set C in the decision table $DT = (U, C \cup D, V_a, f)$ is regarded as independent of D, and if $POS_B(D)$ is equal $POS_C(D)$, then B is identified as a reduction of C.

Theorem 2. In the Equation (3.14), the larger $\bar{S}(R)$ is, the more likely R is to be reduction. It means that the more B is reduced, the larger the average of the significance attribute. This principle is reflected in the weight indicator in Equation (3.5).

$$\bar{S}_{ij}(R) = \frac{|S_{ij}(R)|}{|R|} \tag{3.14}$$

Proof 2. Let the conditional attribute set be C and R be a subset of C. As shown in Equations (3.12) or (3.13), for a_i element R, each attribute in R is independent of D (Definition 5), then $\bar{S}(B)$ becomes larger. Otherwise, $\gamma_{R-a_j}(D)$ becomes smaller than in Equation (3.12). Thus, *R* is more likely to be a reduction. Specifically, when $POS_R(D) = POS_C(D)$, *R* is the reduction in *C* according to the Definition (6).

Definition 7. (reduction rate). Let *U* be the information system of decision-makers *i* in the dataset. $C = \{a_1, a_2, ..., a_m\}$ be the set of original attributes. $B \subset C$ be the subset of attribute reduction set for optimization. U_i be the cardinality of the information system *U*. *R* be the cardinality of the indiscernibility relation induced by the subset of attributes $R \subseteq C$. Then, the reduction rate represents the proportion of reduction in the complexity of the data set achieved by selecting the subset *B* compared to the original attributes *A* referring Definition 6. According to Yang and Yang (2012), the reduction rate is defined: $\frac{|C|-|R|}{|C|}$, where $|C|$ is the number of original attributes (complete set of risk attributes *j*) and $|R|$ is the number of attributes in the reduced set after applying rough set-based reduction. Furthermore, Mohamed (2011) defined as the probabilistic relationships between concepts (object) and instances (risk attributes). Hence, the reduction rate in this study based on the significance degree of the attributes selected in the subset *B* is shown as follows:

$$P_{ij}(R) = 1 - \frac{S_{ij}(R)}{\overline{S_{\imath\jmath}(R)}} \tag{3.15}$$

The reduction rate in Equation (3.15) is depicted probabilistic relationships between concept and instance over discrete domains. The numerator part is represented all possible cases (concept) of generalization for all possible instances, while the denominator part is defined all possible combinations of conditional seaport risk attribute value in decision table.

3.3.3.2 Attribute reduction design of the RSGA

RST is effective when dealing with many seaport risks and find the attributes reduction set. The RSGA is built on MATLAB 2022 software. The RSGA improves individual metrics in the evolutionary process and avoids population diversity imbalance, by introducing a Hamming distance when initializing the population. As a result, the initial population may cover the entire solution space. Theorem 1 employs a constraint condition (reported in Appendix C); thus, we assign a value equal to one to the attribute reduction set position, according to the conditional attributes with the largest attribute dependence. To identify the variation in the population diversity in the evolutionary process of the algorithm, we reduce the decisional attributes using the adaptive method of the rough set-based genetic algorithm. We decided that the termination condition would be reach 200 iterations, to directly analyze algorithm diversity. As the initial population is randomly generated, the algorithm's initial population may not be the same, nor the evolutionary processes of the two attribute reductions.

According to Subsection 3.2.2, the objective of is to minimize the conditional seaport risk attributes and to optimize the selection of attributes while maintaining or improving the discriminatory power of the selected subset. This objective emphasizes simplicity by selecting the smallest subset of features that still satisfies the discernibility requirements. The discernibility measurement follows the concept of RST.

Hence, the decision variables are presented in Equation (3.1) where $x_{ij} = 1$ if the attribute a_j is selected for decision-maker *i,* and $x_{ij} = 0$ otherwise. Moreover, the index for this subsection is presented as follows:

C : the set of conditional seaport risk attribute a_j.

U : the set of decision-maker *i.*

R_{ikj} : the equivalence relation the *i-th* and the *k-th* decision-makers, and the *j-th* attribute indicating whether a conditional seaport risk attribute is present for a pair of decision-maker evaluation.

$S_{ij}(R)$: the significance ratio of the *j-th* attribute for the *i-th* decision-maker. This significance measure indicates how important the attribute *j* is for the decision-maker *i.*

$P_{ij}(R)$: the probability of the *j-th* attribute being significant for the *i-th* decision-maker.

$\bar{S}_{ij}(R)$: the average measure of significance related to the *i-th* decision-maker and the *j-th* attribute within a rough set framework.

i : indexed for the decision-makers, $i = \{1, 2, ..., n\}$.

j : indexed for conditional seaport risk attributes, $j = \{1, 2, ..., m\}$.

n : the number of decision-makers.

m : the number of conditional seaport risk attributes.

p : parameters.

Furthermore, the new objective function is set up according to Equations (3.5 – 3.15) and adjusting some adapive parameter to ensure correct reduction results with minimum reduction. The objective is to maximize the significancy of the selected attribute and controlling the redundancy with the reduction rate between attribute pairs:

$$max\ Z = \sum_{i=1}^{n}\sum_{j=1}^{m} S_{ij}(R) * x_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij}(R) * x_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} \bar{S}_{ij}(R) * x_{ij} \qquad (3.16)$$

Subject to:

$$\sum_{j=1}^{m} S_{ij}(R) \cdot x_{ij} \geq 1;\ \forall i \in \{1, 2, \dots, n\} \qquad (3.17)$$

$$\sum_{i=1}^{n} P_{ij}(R) \cdot x_{ij} \geq 1;\ \forall j \in \{1, 2, \dots, m\} \qquad (3.18)$$

$$\sum_{j=1}^{m} \bar{S}_{ij}(R) \cdot x_{ij} \geq 1;\ \forall i \in \{1, 2, \dots, n\} \qquad (3.19)$$

$$\sum_{j=1}^{m} x_{ij} < 61;\ \forall i \in \{1, 2, \dots, n\} \qquad (3.20)$$

$$\sum_{j=1}^{m} x_{ij} \geq 1;\ \forall i \in \{1, 2, \dots, n\} \qquad (3.21)$$

$$x_{ij} \in \{0, 1\}, \forall i \in \{1, 2, \dots, n\}, j \in \{1, 2, \dots, m\}; \qquad (3.22)$$

In the objective function in Equation (3.16), function of R in three terms represent the value of lower apriximation and positive region in Definition 2 that depend on discernbility relation, which a configuration to construct equivalent class. The equivalent class is used to determine the significance attribute *j* according to every decision-maker *i,* and the significance attribute is developed to compute reduction and complextity control as well. The objective function is formulated based on the significance degree in Equations (3.12 - 3.15). Three terms in the objective function in Equation (3.16) are defined as follows:

$S_{ij}(R)$: the ratio of the number of decision-makers correctly classified by the attributes in the relation *R* when the attribute is added in the set *R* to the total number of decision-makers in *U*. Hence, the selected attribute j for decision-maker i depends on configuratrion paramater *R* based on the significance degree and shown in Equation (3.13).

$P_{ij}(R)$: representation of the combined probability of attribute j for the decision-maker i within the parameter *R*. By substarcting this product from 1, the Equation (3.15) gives the probability that at least attributes *j* and decision-maker *i* pair in attribute reduction set *B* is significant with respect to the parameter *R*.

$\bar{S}_{ij}(R)$: the average measure of attribute j for decision-maker i within the parameter *R*. It is used to provide a comprehensive evaluation metric in the context of attribute reduction problems as shown in Equation (3.14).

Furthermore, the constraint for this problem consists of several constraints as follows:

Discriminatory power constraint in Equation (3.17):

The discriminatory power measure evaluates how well the selected subset of attributes can differentiate between different classes or categories in the dataset. The discriminatory power refers to significance degree that explain in Definitions 1 – 4. In the optimization process, this constraint guides the search for an optimal subset of attributes by ensuring that the selected subset maintains a sufficient level of discriminatory power, thereby contributing effectively to the classification or decision-making task.

Reduction rate constraint in Equation (3.18):

In this constraint, we consider the significance degree in Definition 7 where the formula calculates the reduction rate based on the significance degrees of the attributes selected in the subset *R*. The reduction rate represents the proportion of reduction in the complexity of the dataset achieved by selecting the subset *R* compared to the original feature set a_j. A higher reduction rate indicates a greater reduction in the dataset's complexity, implying that the selected feature subset effectively captures the essential information in the dataset. In the optimization process, this constraint guides the search for an optimal subset of features by ensuring that the selected subset achieves a sufficient reduction rate, thereby balancing complexity reduction with discriminatory power.

Complexity constraint in Equation (3.19):

The measure of complexity refers to significance degree that explain in Definition 6. In rough set-based attribute selection, the complexity constraint ensures that the selected subset of attribute maintains a certain level of simplicity or interpretability. This constraint is important for ensuring that the resulting model or decision rules are understandable and consistency.

Size constraint in Equation (3.20)

The constraint means that the selected attribute is at the most 60 attributes. If x_{ij} indicates whether an attribute j is selected for a decision-maker *i,* the constraint ensures that fewer than 61 attributes are selected for each decision-maker. These refers to the number of SSCR attribute (conditional seaport risk attributes) in Table 3.4. The goal of the selected attributes is to reduce unnecessary attributes from 61 attributes. By limiting the size of the selected attributes, size constraints help prevent the model from becoming overly complex, which can lead to overfitting and decreased generalization performance.

Selected attributes constrain in Equation (3.21)

This constraint ensures that for each decision-maker i (where i range from 1 to 153) can select at least one j-attribute (where j ranges from 1 to 61).

Binary constraint in Equation (3.22)

In these applications, binary constraints help model the discrete nature of decision-making and enable the formulation of optimization attribute reduction problems that accurately represent risk assessment considering the attribute correlation. They are fundamental in ensuring that solutions are feasible and reflect the binary decisions inherent in the risk assessment problems.

Optimization of attributes reduction in RST involves finding the most concise subset of attributes that preserves the discernibility of decision classes in the dataset. This problem is NP-hard due to its inherent combinatorial complexity and the need to evaluate all possible combinations of attributes to determine the optimal solution. There are few reasons why attribute reduction optimization is considered as NP-hard:

1. *Combinatorial complexity*

The optimization problem involves a minimal subset of attribute (reduct) from a given set attribute. The number of possible subsets grows exponentially with the number of attributes, making it impractical to evaluate all combinations in search of the optimal solution. For example, let decision table of Table 3.1 as $DT = (U, A = C \cup D, V)$, suppose an attribute set denoted by $C = \{a_j | j = 1, 2, ..., m\}$, the attribute a_j contains k_j values, the decision attribute d contains k_d values. In decision table, the number of alternatives with the form as $t = \wedge_{a \in C' \subseteq C}(a, v) \rightarrow s = (d, w)$ which could possibly generate various alternative are $(2^{\prod_{j=1}^{m}(k_j+1)} - 1) \cdot k_d$ (Jun et al., 2007).

2. *Discernibility requirement*

The chosen attributes reduction set must preserve the discernibility ability of the original set of attributes. In other words, the selected subset should be able to distinguish between different decision-maker evaluations based on their attribute values. Verifying whether a subset satisfies this discernibility requirement involves comparing pairs of decision-maker evaluations, and this comparison process can be computationally intensive. For example, let decision table as $DT = (U, A = C \cup D, V)$, V is the set of all possible values that attributes A can take. The problem is to find a minimal subset of attributes, called a reduct, $R \subseteq C$, such that: First condition, R preserves the discernibility of decision classes in the decision table DT, i.e., for any two distinct decision-makers *i, k in U, if i* and *k* cannot be distinguished to the same decision class. Second condition, R is minimal, meaning no proper subset of R satisfied condition 1. Mathematically, the problem can be expressed as finding a subset $R \subseteq C$ that satisfied the following conditions: First, $\forall u_i, u_k \in U, if\ u_i(R) = u_k(R), then\ u_i(D) = u_k(D), where\ u(R)$ denoted the restriction of object u to attribute in R. Second, $\nexists R' \subset R$ such that R' satisfied condition 1 (Skowron and Rauszer, 1992).

3. Reduct complexity

The problem is not just about finding any subset that satisfies the discernibility requirement; it's about finding a minimal subset of reduct. This introduces an additional level of complexity because it requires checking whether any proper subset of a candidate reduct also satisfies the discernibility requirement (Ślęzak and Stawicki, 2020).

The problem of finding a reduct in RST is known to be NP-hard (Ślęzak and Stawicki, 2020; Greco et al., 2000; Ke et al., 2008; Jun et al., 2007; Skowron and Rauszer, 1992). In the context of attribute reduction within RST, the decision variables usually pertain to the attributes themselves. These attributes are the variables considered when determining which ones to incorporate into the reduct, which is a minimal set of attributes preserving the discernibility and classification ability of the original set.

Additionally, the reduct problem is NP-hard because it involves exploring all possible combinations of attributes to determine which subsets satisfy the conditions of being minimal reducts. This involves evaluating the dependency and discernibility of the attributes in these subsets, which is a complex task. As the number of attributes increases, the number of potential attribute combinations grows exponentially, leading to the NP-hard nature of the problem.

Encoding

When employing the genetic algorithm, the initial considerations encompass the genetic representation (encoding) and the formulation of the fitness function. The former approach involves utilizing a fixed n-bit binary series, considering the actual characteristics of attribute reduction, as suggested by Luo et al. (2007). In the subsequent steps, a genetic algorithm is employed to derive a solution for the rough-set decision problem. Initially, an encoding of potential solutions to the problem must be determined. This encoding needs to be meaningful in the context of the problem and its corresponding solution. The problem at hand is to identify the minimum reduct of a decision table. To represent potential solutions, a natural choice is a bitmap, as illustrated in Figure 3.4. Following the definition of the reduct, the reduct representation is essentially a subset of attributes. Consequently, a binary string is created, with its length corresponding to the number of attributes in the decision table. Each bit of the string corresponds to one attribute in the decision table. If a particular bit is set to one, it indicates that the corresponding attribute belongs to the reduct. It is conceivable that, upon concluding the genetic algorithm, multiple solutions may emerge due to these strings having the same fitness score, a concept that will be elaborated upon later.

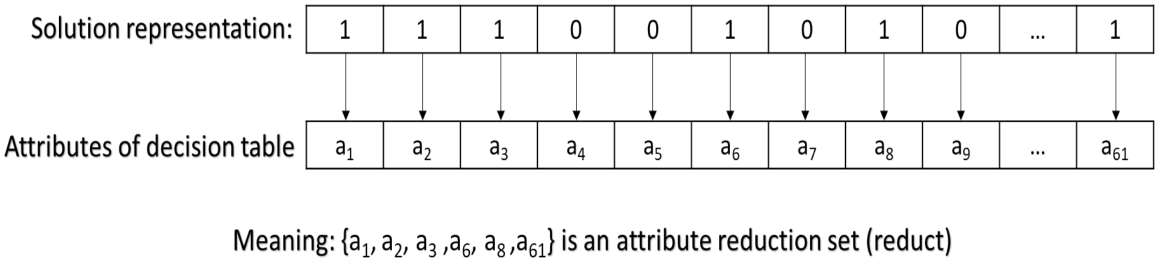


Figure 3.4 Solution representation of a reduct

Another aspect to consider is how to establish the first generation, which is contingent on the nature of the problem. In the case of the travelling salesman problem, for example, the initial population can be generated from any permutation of city numbers, each serving as an individual. However, the current scenario is more intricate. Initially, it is necessary to transform the decision table into a distinction table, as depicted in Figure 3.5 to illustrate the construction of a distinction table. A random selection of individuals is then made from the distinction table. Moreover, the distinction table becomes integral to the computation of the fitness score for each individual. This distinction table is represented as a binary matrix denoted as *B*. Let *b(j,(i,k))* be an element of *B* corresponding to the attribute *I* and pair *(u_i, u_k)*: For $j \in \{1, an\ M\}$: $b(j,(l,n)) = \begin{cases} 1, x_{ij} = x_{kj} \\ 0, x_{ij} \neq x_{kj} \end{cases}$ and $b(M+1,(i,k)) = \begin{cases} 1, y_i = y_k \\ 0, y_i \neq y_k \end{cases}$. To guarantee the diversity within the population, the Hamming distance, as outlined in Theorem 1 in APPENDIX C, is incorporated during the initialization of the population. This ensures that the initial population spans the entirety of the solution space. The findings from Theorem 1 are employed as a constraint condition, and the gene position corresponding to the attribute with the highest attribute dependence is designated as 1.

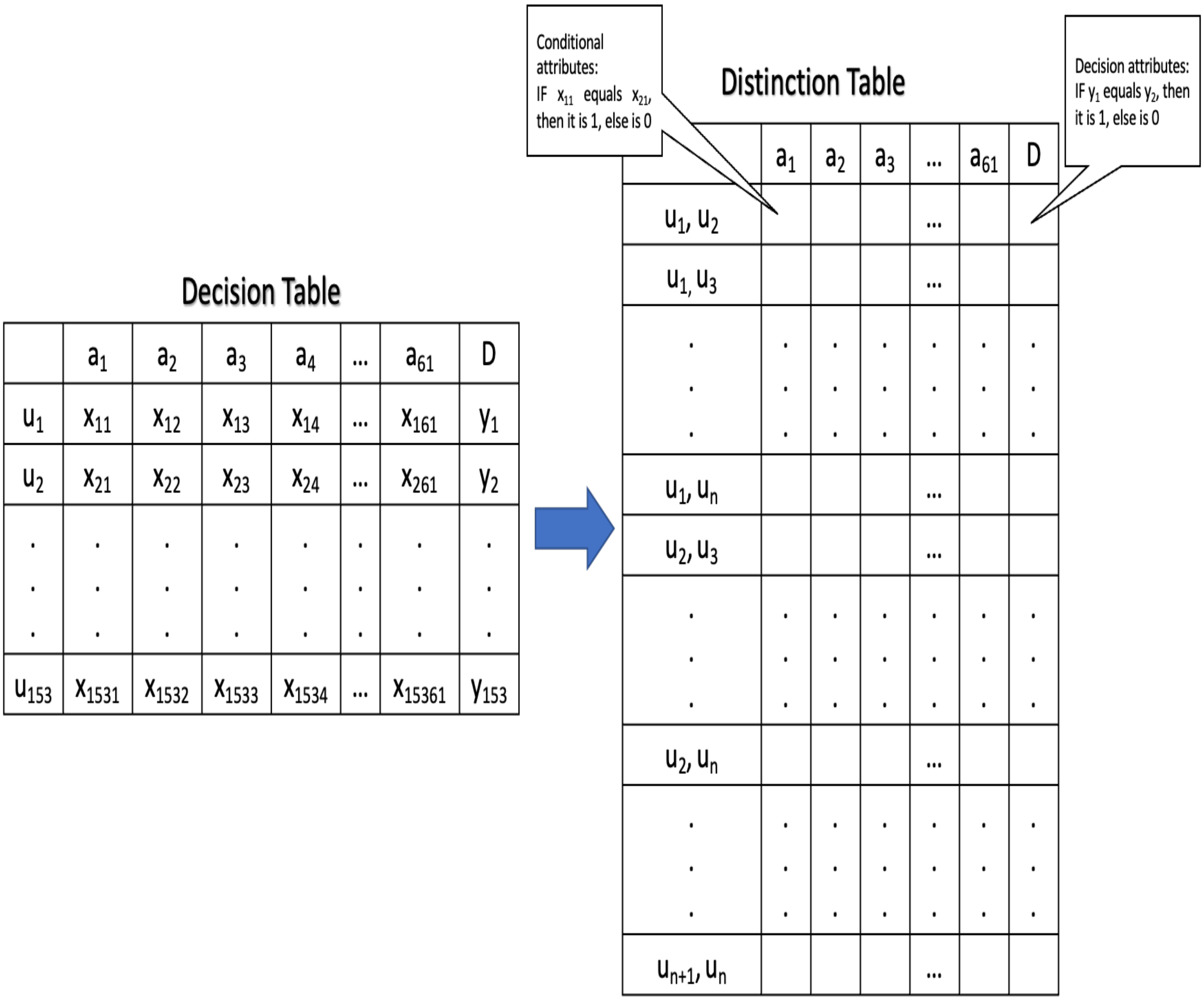


Figure 3.5 Distinction table

The initialization procedure is shown in Algorithm 1 as follows:

```
Algorithm 1 The initialization flow of RSGA
Input: A decision information system $S = \{U, C, V_a, f\}$.
Output: Set the gene of the flag position of the initial population to 1
1)  Produce the first chromosome $t = 1$.
2)  Randomly generate a chromosome.
3)  Compute significance degree – $S_{a_j}(B)$ – in Equation (3.12).
4)  Compute weight indicator – $\bar{S}(B)$ – in Equation (3.14).
5)  Ranking the data $X$.
6)  Generate a new decision table (distinction table).
7)  Judging Hamming distance by computed dependency degree for each pair $I$.
8)  Copy the chromosome to the initial population.
9)  If population size is satisfied, then go to next step. Otherwise, repeated step 2 – 8.
10) End process.
```

Fitness function design

This study's encoding length is the number of conditional attributes in the decision table. For instance, if the conditional attribute set is $\{a_1, a_2, a_3, a_4, a_5, ..., a_{61}\}$, the encoding length is 61. Furthermore, if the reduced binary code is 10001…1, the reduction in the decision table is $\{a_1, a_5, ..., a_{61}\}$. In other words, the conditional attribute room C may be mapped into an individual room, when each bit corresponds to a conditional attribute. Therefore, the latest method in this algorithm may be processed as described in Sub-subsections 3.3.3.1 and 3.3.3.2.

An individual's fitness relies on two aspects: the number of attributes and the ability to classify them. Both dimensions related to the decision-making attribute set is represented in Equation (3.16) and showing as evaluation for fitness function as follows:

$$Fitness\ (R) = p_1 * S_a(R) + p_2 \left(1 - \frac{|R|}{|C|}\right) + p_3 * \bar{S}(R) \tag{3.23}$$

The function consists of three parts. The first part represents the classification ability. A reduction occurs when $S_{a_j}(R) = 1$. The second part shows the reduction rate. For example, the fewer attributes in the attribute subset R indicate that R is a minimum reduction with a high reduction rate. The third part is the weight indicator, which increases the efficiency of the algorithm. The three elements are dynamically adjusted during algorithm evolution.

In this study, the adaptive factors are the adjustment parameters used to ensure correct reduction results with minimum reduction. Figure 3.3 explains the steps for creating a rough set-based genetic algorithm. Moreover, a smaller value of p_1 indicates a high possibility that the chromosome is a reduction set, and its fitness value is greater. As the value of p_2 decreases, the conditional risk attribute set declines, while the fitness value of the reduction increases. Finally, as p_3 increases, the attribute contained in the reduction set becomes more relevant, and the fitness value of the reduction increases. Hence, the adaptive function of this study is defined as:

$$\begin{cases} p_1 = -5, p_2 = -2, p_3 = 1, \gamma_a(D) < \gamma_R(D) \\ p_1 = -6, p_2 = -3, p_3 = 1, \gamma_a(D) = \gamma_R(D) \end{cases} \quad (3.24)$$

Finally, the RSGA generated some sets of reduction attribute with higher dependency degree and without losing their knowledge representative. The intersection conditional seaport risk attributes in reduction sets are defined as core attribute and become central tendency of the SSCR model.

Selection

During the selection operation, the fitness proportional operator and elite strategy are employed, and the roulette mechanism is implemented. Once the fitness score is determined for each string in the population using Equation (3.23), the relative fitness score can be computed as follows: $g_n = \frac{F(x_i)}{\sum_{i=1}^{n} F(x_i)}, i = 1,2, \dots, n$. The relative fitness score serves as a probability distribution for randomly selecting strings to undergo crossover. While the roulette wheel method exhibits a natural selection characteristic, it presents two issues. First, degeneration may occur, wherein the best string might not be chosen. Second, it can be inefficient, especially when strings with different scores are unevenly distributed. For instance, if the best-scoring string comprises more than 90% of the entire roulette wheel, other strings have minimal chances of selection. To address these concerns, we employed the Elitism Selection method. This strategy involves directly copying individuals with the highest fitness value into the next generation, avoiding genetic manipulation. This approach helps the algorithm converge towards the global optimal solution.

RSGA operators

The crossover and mutation operators proposed by Luo et al. (2007) are implemented in this RSGA. For crossover, two strings are selected, and at a specific position, recombination occurs, giving rise to two new offspring strings. Whether these offspring are included in the next generation depends on their fitness scores, as explained in the selection section. Since the objective is to identify the minimum reduct in a decision table, the crossover operation results in new strings with '1' and '0' distributed across different positions. The '1's are of interest as they correspond to attributes included in the potential reduct being sought. The identity of individual strings becomes less relevant at this stage, and the fitness function assesses whether the new string meets the required criteria. In the mutation operation, random mutation points are selected, and a single-point mutation is applied to generate a new individual by inverting the mutation point. The termination criterion for the RSGA process is set to conclude after the 200th iteration of the population. However, it is not guaranteed that the optimal solution will be obtained when the Genetic Algorithm (GA) terminates. It is understood that GA is employed to derive a suboptimal solution for the NP-hard problem, as finding a polynomial algorithm solution for NP-hard problems is not feasible.

3.3.3.3 Evaluation matrix of central tendency

The results of the RSGA belong to the attribute reduction set. To find the central tendency in the attribute reduction set, we manually use the discernibility matrix of the rough set. Concerning the element classification in the universe, a reduction set enables the same classification of elements of the universe as the entire attribute set. For example, let *R* be a subset of *A*; hence, the connecting notion between the core-set attribute and the reduction set attribute is defined by:

$$Core(R) = \cap Red(R) \tag{3.25}$$

Equation (3.25) indicates that the core attribute that becomes the center of the tendency, is the intersection of all the reduction sets. Thus, the core is the most relevant subset of attributes because none of its elements may be removed without affecting the attribute classification power.

3.3.3.4 Evaluation seaport-fulcrum supply chain risk criteria from core attributes

The group of core attribute sets in the new decision table is deployed to calculate the degree of importance. Let S be the information system table of the following tuple: $S = \{U, CA, \omega_i, V_{ij}\}$, where CA is the core attribute *j-th*, ω_i is the weight of *j-th* attribute (core attribute), and V_{ij} is the value of decision-makers *i-th* corresponding to SSCR attribute. We calculate ω_i according to the significance degree of core attribute to find the importance degree. The importance degree is used to calculate weight and it is denoted as follows:

$$\Lambda_j = \frac{S_j}{U} \tag{3.26}$$

$$\omega_j = \frac{\Lambda_j}{\sum_{j=1}^{24} \Lambda_j} \tag{3.27}$$

To estimate which the conditional seaport risk attributes have the highest implication for the SSCR factors, the threat score of SSCR factors is calculated based on the average value of the respondent evaluation for each conditional seaport risk attributes and weight in Equation (3.27), as shown in the following equations:

$$\bar{V}_j = \frac{1}{U} \sum_{i=1}^{n} V_{ij} \tag{3.28}$$

$$\sigma_j = \omega_j \times \bar{V}_j \tag{3.29}$$

The SSCR attribute score in Equation (3.29) also indicates the prioritization which among the conditional seaport risk attribute have highest potential to disrupt supply chain continuity. Overall, the multiple attribute decision-making based rough set for the Sub-subsections 3.3.3.1 until 3.3.3.3 above is shown in Algorithm 2.

Algorithm 2 Multiple attribute decision-making based rough set

```
Input: A decision information system $S = \{U, C, V_a, f\}$.
Output: The core attribute of $S$ and its risk score.
1)  Setting up the stopping criteria (50 times of running criteria).
2)  Defining the data input space (decision tables) and boundary = (lower, upper) value, considering the Pawlak approach.
3)  Addressing genetic algorithm for running algorithm.
4)  Compute positive region $POS_C(D)$ of $S$ and $POS_B(D)$ of $U'$.
5)  Compute dependency degree $\gamma(B, D)$ and $\gamma(C, D)$.
6)  Compute significance attribute in Equation (3.16).
7)  Defining fitness function and compute the Equation (3.23).
8)  Set up the threshold of the fitness function.
9)  Obtain reduction set attribute and its significance degree.
10) Checking the stopping criteria. If "No" repeat steps 2 – 9 until fulfill the stopping criteria.
11) Generating central tendency matrix using Equation (3.25).
12) Obtaining core attributes $Core(B)$ and their importance degree.
13) Generating new decision table $S = \{U, CA, \omega_i, V_{ij}\}$.
14) Compute the weight of core attributes corresponding the significance degree.
15) Compute the risk score in Equation (3.29).
16) Compute the SSCR factors according to the core attributes.
17) Obtain the solution and its risk score.
```

3.3.3.5 Data mining: association rule learning

Association analysis is based on the concept of RST and contains three main measures – strength, certainty, and coverage – as detailed below. Strength indicates how frequently the antecedent C and consequent D both occur across the data set. In other words, it represents the probability that conditional and decisional risk factors occur simultaneously as shown below.

$$strength_x\,(C; D) = \frac{Supp_x(C,D)}{|U|} \tag{3.30}$$

Certainty represents the conditional probability that deficiency itemset *D* occurs under the condition that deficiency itemset *C* occurs, which means the frequency of occurrence is found in the data set as defined below.

$$cer_x(C; D) = \frac{|C(x) \cap D(x)|}{|C(x)|} = \frac{Supp_x(C,D)}{|C(x)|} \tag{3.31}$$

Coverage is defined as the ratio of the conditional probability of occurrence of the antecedent *C* and that of the consequent *D* to the probability of occurrence of the antecedent *C* as expressed below.

$$cov_x(C; D) = \frac{|C(x) \cap D(x)|}{|D(x)|} = \frac{Supp_x(C,D)}{|D(x)|} \tag{3.32}$$

3.4 Results and discussion

3.4.1 Pilot test of questionnaire survey

We test 61 conditional seaport risk attributes and a decisional factor (the relative importance). A total of 153 data units (20% estimated response rate) were collected from SSC stakeholders, which is in line with the planned collection target of 150 data units. The respondents comprised 10.5% seaport managers, 42.5% seaport operators, and 47.0% seaport users. The gender composition of the sample was 69.3% male and 30.7% female. More than half of the respondents (56.9%) had over 10 years of experience, followed by those with 5–10 years of experience (39.2%). This study's procedure began with examining the potential of supply chain disruption as a threat dimension and then generated conditional risk factors rated on a five-level ordinal scale, which indicated the risk implications for supply chain continuity.

Table 3.5 shows the results of the reliability test. According to the Cronbach's alpha, we find the dataset reliable as an input for the rough set-based genetics algorithm. After the pilot test of the primary datasets of the questionnaire survey, we run the RGSA to obtain the core attributes as the central tendency of SSCR. Subsequently, we conduct the reliability test to check the aggregation of seaport risk profiles, corresponding to the orthogonal design.

Table 3.5 Result of reliability test for self-explicated data set

Case Processing Summary		Number of responses	Percentage
Cases	Valid	153	100%
	Excluded [a]	0	0.0
	Total	153	100%
Reliability results for self-explicated data set			
Reliability Statistics [b]			Percentage
Cronbach's alpha		0.882	88.2%
Number of features		62	100%
[a] Listwise deletion based on all variables in the procedure			
[b] Cronbach's alpha level of reliability		0.0–0.20	Less reliable
		> 0.20–0.40	Rather reliable
		> 0.40–0.60	Quite reliable
		> 0.60–0.80	Reliable
		> 0.80–1.00	Very reliable

Based on Cronbach's alpha in the Table 3.5, the dataset was determined to be reliable, with 88.2 percent as an input for the RSGA. Next, a decisional factor was developed to assess this term and determine the impact of seaport disruption on SSCR. The algorithm generates a reduction attribute set that helps obtain a core attribute set. The core attribute set is crucial for understanding the center of the seaport-focal supply chain risk tendency. Besides that, the statistical descriptive is generated to support the reliability test in Table 3.5. The statistical descriptive shown in Appendix E is shown various information such as mean, mode, skewness, and so on referring to the conditional seaport risk attributes (a_j).

3.4.2 Multi-factors set of threat dimension evaluation

Indexing the set is a crucial construction related to the reasonability and accuracy of the comprehensive evaluation. This step is needed to determine the weight of the parameters, and sometimes leads to a multiple attribute decision problem. This study introduces into the algorithm a weight indicator based on the significance degree of the reduction set attribute in Equation (3.14). Furthermore, the reduction attribute set is set up from 200 iterations of the rough set-based genetic algorithm, as shown in Figure 3.6 as the quality of reduction. In Figure 3.6, the criteria that were met imply that the fitness function calculation in Equation (3.23) fulfills the iteration set up in the algorithm, while the percentage stall indicates that the calculation falls into the local optimal solution. Hence, this study only finds the central tendency among the reduction sets with 100% criteria met and 0% stall. The similar reduction sets during the reduction set algorithm in Table 3.6 was compressed into single set. In line with these conditions, the evaluation matrix is introduced to obtain the Boolean function in Table 3.7.

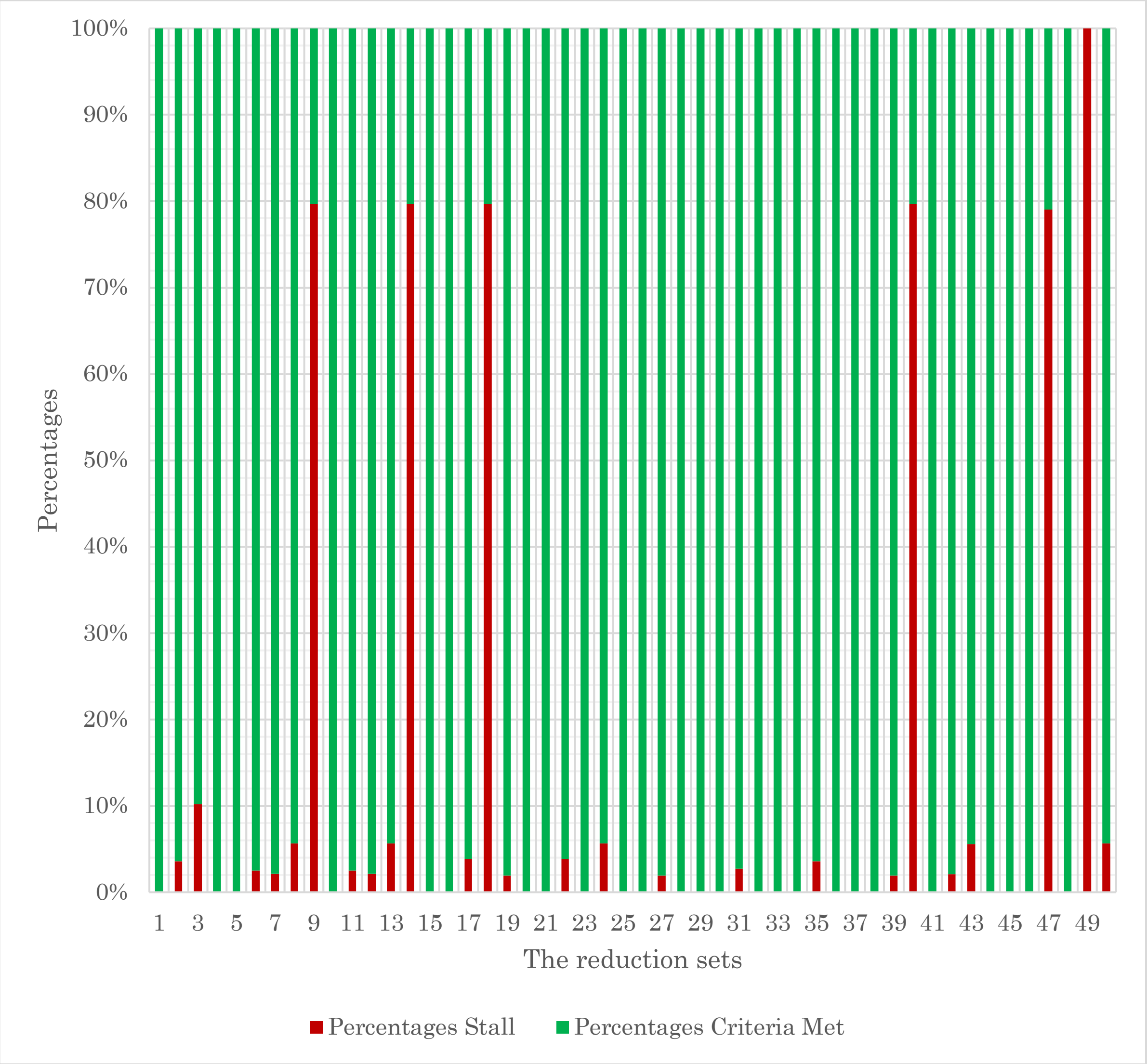


Figure 3.6 The quality of reduction.

According to Figure 3.6, the set of reduction attributes is sourced from the running algorithm as many as 50 times and it is shown in Table 3.6.

Table 3.6 The reduction attribute set from the result of the RSGA.

No.	Reduction attribute sets	No.	Reduction attribute sets
1	$a_5, a_{13}, a_{15}, a_{33}, a_{48}, a_{57}$	26	$a_4, a_{20}, a_{42}, a_{48}, a_{49}, a_{56}$
2	$a_{27}, a_{39}, a_{52}, a_{58}, a_{60}, a_{61}$	27	$a_{20}, a_{28}, a_{35}, a_{52}, a_{54}, a_{60}$
3	$a_3, a_{10}, a_{41}, a_{44}, a_{51}, a_{58}$	28	$a_{15}, a_{26}, a_{46}, a_{49}, a_{53}, a_{59}$
4	$a_6, a_{14}, a_{17}, a_{37}, a_{39}, a_{59}$	29	$a_4, a_5, a_{27}, a_{39}, a_{54}, a_{56}$
5	$a_{20}, a_{25}, a_{36}, a_{47}, a_{48}, a_{57}$	30	$a_1, a_9, a_{13}, a_{20}, a_{21}, a_{46}, a_{48}$
6	$a_{29}, a_{34}, a_{56}, a_{59}, a_{60}$	31	$a_5, a_{16}, a_{17}, a_{24}, a_{45}, a_{51}$
7	$a_8, a_{24}, a_{25}, a_{28}, a_{52}, a_{61}$	32	$a_4, a_{24}, a_{39}, a_{42}, a_{54}, a_{61}$
8	$a_5, a_{14}, a_{32}, a_{35}, a_{51}, a_{53}$	33	$a_{10}, a_{19}, a_{20}, a_{34}, a_{47}, a_{57}$
9	$a_3, a_{12}, a_{26}, a_{31}, a_{40}, a_{46}, a_{55}$	34	$a_{35}, a_{36}, a_{49}, a_{51}, a_{58}, a_{60}$
10	$a_{19}, a_{20}, a_{26}, a_{28}, a_{57}, a_{61}$	35	$a_{17}, a_{40}, a_{41}, a_{46}, a_{52}, a_{59}$
11	$a_{29}, a_{34}, a_{56}, a_{59}, a_{60}$	36	$a_{15}, a_{17}, a_{36}, a_{37}, a_{49}, a_{51}$
12	$a_8, a_{24}, a_{25}, a_{28}, a_{52}, a_{61}$	37	$a_8, a_{20}, a_{37}, a_{51}, a_{57}$
13	$a_5, a_{14}, a_{32}, a_{35}, a_{51}, a_{53}$	38	$a_5, a_{13}, a_{46}, a_{48}, a_{51}, a_{57}$
14	$a_3, a_{12}, a_{26}, a_{31}, a_{40}, a_{46}, a_{55}$	39	$a_{15}, a_{16}, a_{20}, a_{49}, a_{56}, a_{57}$
15	$a_{19}, a_{20}, a_{26}, a_{28}, a_{57}, a_{61}$	40	$a_2, a_5, a_9, a_{11}, a_{28}, a_{56}, a_{59}$
16	$a_6, a_{17}, a_{25}, a_{44}, a_{46}, a_{48}$	41	$a_8, a_{12}, a_{15}, a_{28}, a_{40}, a_{57}$
17	$a_5, a_7, a_{14}, a_{51}, a_{54}, a_{59}$	42	$a_7, a_9, a_{18}, a_{29}, a_{44}, a_{54}$
18	$a_4, a_{15}, a_{22}, a_{33}, a_{44}, a_{50}, a_{57}$	43	$a_{16}, a_{18}, a_{27}, a_{41}, a_{54}, a_{58}$
19	$a_8, a_{32}, a_{40}, a_{41}, a_{55}, a_{57}$	44	$a_9, a_{19}, a_{29}, a_{38}, a_{61}$
20	$a_6, a_{17}, a_{25}, a_{44}, a_{46}, a_{48}$	45	$a_{21}, a_{29}, a_{37}, a_{55}, a_{60}, a_{61}$
21	$a_{19}, a_{24}, a_{28}, a_{55}, a_{61}$	46	$a_{15}, a_{25}, a_{27}, a_{47}, a_{48}, a_{51}$
22	$a_5, a_7, a_{14}, a_{51}, a_{54}, a_{59}$	47	$a_9, a_{13}, a_{24}, a_{27}, a_{39}, a_{58}, a_{59}$
23	$a_{14}, a_{23}, a_{42}, a_{47}, a_{54}, a_{58}$	48	$a_5, a_{10}, a_{11}, a_{22}, a_{51}, a_{58}$
24	$a_4, a_{13}, a_{24}, a_{29}, a_{54}, a_{61}$	49	$a_4, a_{21}, a_{28}, a_{31}, a_{56}, a_{58}, a_{61}$
25	$a_8, a_{20}, a_{42}, a_{45}, a_{59}, a_{61}$	50	$a_4, a_{20}, a_{35}, a_{55}, a_{60}$

From the discernibility matrix in Table 3.7, we generate Boolean function named as discernibility function as follows:

$$f(A) = \{a_5a_{58}a_{48}\} + \{a_6a_{14}a_{37}a_{39}\} + \{a_{47}a_{48}a_{57}\} + \{a_{20}a_{61}a_{57}\} + \{a_{48}\} + \{a_{28}a_{61}\} + \{a_{41}a_{47}a_{54}a_{58}\} + \{a_4a_{20}a_{48}\} + \{a_4a_5a_{27}\} + \{a_{61}\} + \{a_8a_{51} + a_{51}a_{57}\} + \{a_{51}\} \tag{3.33}$$

where “+” denotes the Boolean sum and the Boolean multiplication is omitted in the formula.

According to Equation (3.33), we find 24 core attributes set or central tendency of conditional seaport risk attributes in Indonesia context in Table 3.7. The central tendency is defined as the highest potential conditional seaport-risk factors to the supply chain disruption, which mean that the potential candidates is generated from the intersection of attribute reduction sets.

Table 3.7 The evaluation matrix of reduction attribute sets.

Reduction attribute sets	**Set 1**	**Set 4**	**Set 5**	**Set 10**	**Set 16**	**Set 21**	**Set 23**	**Set 26**	**Set 29**	**Set 32**	**Set 37**	**Set 41**	**Set 45**	**Set 46**	**Set 48**
Set 1		-	a_{48}, a_{57}	a_{57}	a_{48}	-	-	a_{48}	a_{48}	-	a_{57}	a_{15}, a_{57}	-	a_{48}	a_5
Set 4	-		-	-	a_6, a_{17}	-	a_{14}	-	a_{39}	a_{39}	a_{37}	-	a_{37}	-	-
Set 5	a_{48}, a_{57}	-		a_{20}, a_{57}	a_{25}, a_{48}	-	a_{47}	a_{20}, a_{48}	-	-	a_{20}, a_{57}	a_{57}	-	a_{25}, a_{47}, a_{48}	-
Set 10	a_{57}	-	a_{20}, a_{57}		-	a_{19}, a_{28}, a_{61}	-	a_{20}	-	a_{61}	a_{20}, a_{57}	a_{28}, a_{57}	a_{61}	-	-
Set 16	a_{48}	a_6, a_{17}	a_{25}, a_{48}	-		-	-	a_{48}	-	-	-	-	-	a_{48}	-
Set 21	-	-	-	a_{19}, a_{28}, a_{61}	-		-	-	-	a_{24}, a_{61}	-	a_{28}	a_{55}, a_{61}	-	-
Set 23	-	a_{14}	a_{47}	-	-	-		a_{40}	a_{54}	a_{40}, a_{54}	-	-	-	a_{47}	a_{58}
Set 26	a_{48}	-	a_{20}, a_{48}	a_{20}	a_{48}	-	a_{40}		a_4, a_{56}	a_4, a_{40},	a_{20}	-	-	a_{48}	-
Set 29	a_{48}	a_{39}	-	-	-	-	a_{54}	a_4, a_{56}		a_4, a_{39}, a_{54}	-	-	-	a_{27}	a_5
Set 32	-	a_{39}	-	a_{61}	-	a_{24}, a_{61}	a_{40}, a_{54}	a_4, a_{40},	a_4, a_{39}, a_{54}		-	-	a_{61}	-	-
Set 37	a_{57}	a_{37}	a_{20}, a_{57}	a_{20}, a_{57}	-	-	-	a_{20}	-	-		a_8, a_{57}	-	a_{51}	a_{51}
Set 41	a_{15}, a_{57}	-	a_{57}	a_{28}, a_{57}	-	a_{28}	-	-	-	-	a_8, a_{57}		-	-	-
Set 45	-	a_{37}	-	a_{61}	-	a_{55}, a_{61}	-	-	-	a_{61}	-	-		-	-
Set 46	a_{48}	-	a_{25}, a_{47}, a_{48}	-	a_{48}	-	a_{47}	a_{48}	a_{27}	-	a_{51}	-	-		a_{51}
Set 48	a_5	-	-	-	-	-	a_{58}	-	a_5	-	a_{51}	-	-	a_{51}	

3.4.2.1 Reduction performance analysis

To analyze the convergence performance of the algorithm, we record the alterations in the optimal individual and average fitness values, in the iterative process for each reduction attribute set. The convergence speed is stable after ten generations from running the algorithm 50 times, indicated in Figures 3.7 and 3.8, respectively. Because of the elitist strategy, the convergence speed of the RSGA accelerates the evolution mechanism. This strategy copies the individuals with the highest fitness value directly into the next generation, without manipulation in the reduction set. As an impact, the algorithm converges with the global optimal solution.

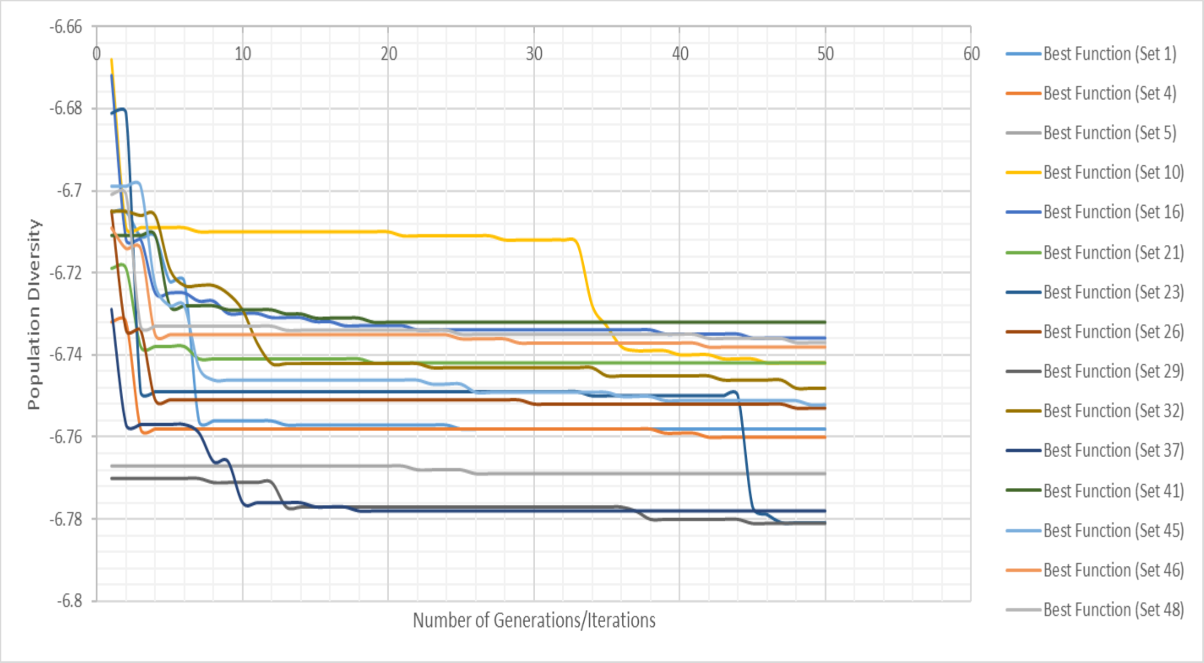


Figure 3.7 Optimal adaptation process.

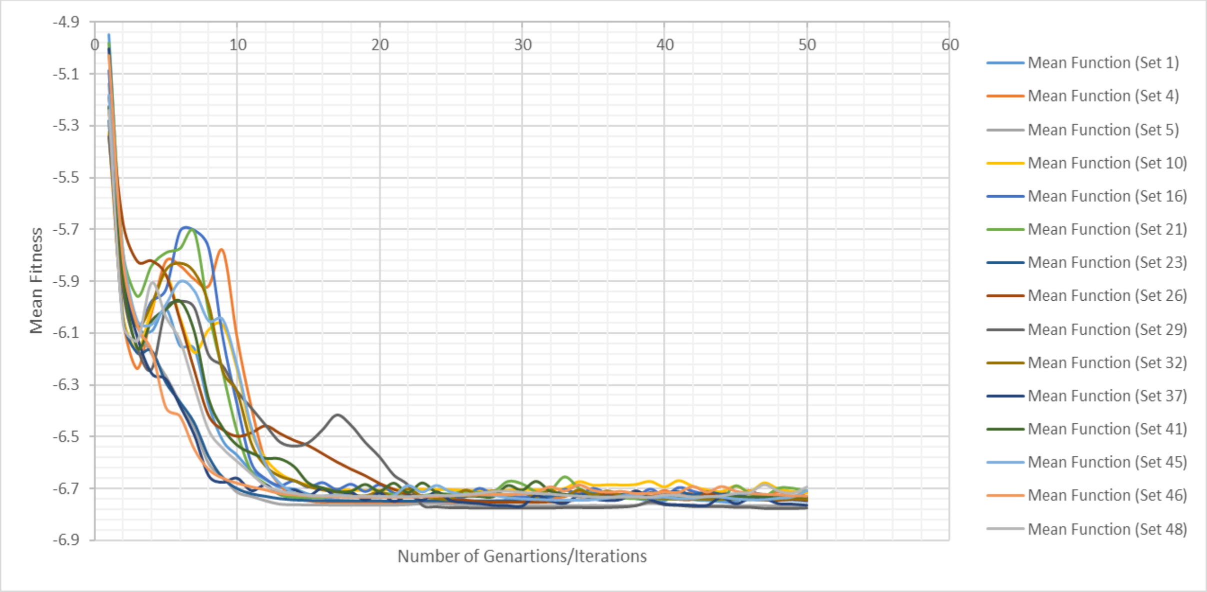


Figure 3.8 Alteration process of the average fitness.

3.4.2.2 Evaluation of attribute ranking and potential threats

Each attribute in Table 3.8 indicates the central tendency of the Indonesian SSCR. These central tendencies are classified on the basis of dimensional threats. For management analysis purposes, we employ Equations (3.26) – (3.29) to calculate the risk score for each dimensional threat. In addition, the scores of the core attributes reflect the feasibility of the attributes. The higher the attribute score, the lower tendency for the SSC. The ranking of the potential threats to supply chain disruption is depicted in Figure 3.9.

Table 3.8 The score of the SSCR.

No.	**SSCR Factors**	**SSCR Attributes**	**Importance degree (Λ_j)**	**Weight (ω_j)**	**Evaluation average value ($\bar{V}_j$)**	**Score (σ_j)**
1	TF_1	a_4	0.023346624	0.047736	2.578947368	0.123108
2		a_5	0.020687628	0.042299	2.605263158	0.1102
3		a_6	0.014946822	0.030561	2.414473684	0.073789
4		a_8	0.014004304	0.028634	2.756578947	0.078932
Sub Total TF_1 (σ_1)						0.38603
5	TF_2	a_{14}	0.018508113	0.037843	3.355263158	0.126973
6		a_{15}	0.018433014	0.037689	3.269736842	0.123234
Sub Total TF_2 (σ_2)						0.250206
7	TF_3	a_{17}	0.013882089	0.028384	2.763157895	0.07843
8		a_{19}	0.015996707	0.032708	2.769736842	0.090592
9		a_{20}	0.024526239	0.050148	2.677631579	0.134277
10		a_{24}	0.01465752	0.02997	2.611842105	0.078276
11		a_{25}	0.022710218	0.046435	2.611842105	0.12128
Sub Total TF_3 (σ_3)						0.502855
12	TF_4	a_{27}	0.014952197	0.030572	2.526315789	0.077235
13		a_{28}	0.020237615	0.041379	2.585526316	0.106987
Sub Total TF_4 (σ_4)						0.184222
14	TF_5	a_{37}	0.0218223	0.044619	2.493421053	0.111254
Sub Total TF_5 (σ_5)						0.111254
15	TF_6	a_{39}	0.021509275	0.043979	2.671052632	0.117471
16		a_{42}	0.021257085	0.043464	2.5	0.108659
Sub Total TF_6 (σ_6)						0.226129
17	TF_7	a_{73}	0.020942113	0.042819	2.565789474	0.109866
Sub Total TF_7 (σ_7)						0.109866
18	TF_8	a_{81}	0.032443677	0.066336	3.210526316	0.212974
Sub Total TF_8 (σ_8)						0.212974
19	TF_9	a_{91}	0.02028208	0.04147	3.006578947	0.124683
20		a_{94}	0.02273076	0.046477	3.361842105	0.156247
21		a_{95}	0.013661941	0.027934	3.480263158	0.097218
Sub Total TF_9 (σ_9)						0.378148

22	TF_{10}	a_{101}	0.034966431	0.071494	3.388157895	0.242235
23		a_{102}	0.016432017	0.033598	2.986842105	0.100352
24		a_{105}	0.026142138	0.053452	2.835526316	0.151564
Sub Total TF_{10} (σ_{10})						0.49415
Total score: $TF_1 + TF_2 + TF_3 + TF_4 + TF_5 + TF_6 + TF_7 + TF_8 + TF_9 + TF_{10}$ (σ_{TF})						2.855835

We consider the issue of supply chain coordination related to disruptive events under the condition of satisfying self-organized criticality. It is worth mentioning that the probabilities of all potential threats cannot be derived. However, the seaport risk score helps understand the feasibility level of the potential threats to supply chain disruptive events. In Table 3.9, σ_i – threat scores – indicates the number of scores from each dimensional threat, and *σ(impact)* – risk implication – indicates the threat factors implication to supply chain disruption. The result is obtained by subtracting σ_i from the total of σ_i of the core set divided by two. This concept denotes in mathematical formula as follows:

$$\sigma(Impact) = \frac{\sum_{TF=1}^{24}\sigma_{TF} - \sum_{j=1}^{m}\sigma_j}{2} \tag{3.34}$$

Equation (3.34) is presented to understand the relation between threat score and threat impact. The higher score of the threat score *(σ)* indicates a high potential threat. In the line with it, the higher value of threat impact (*σ(impact)*) means that the effect of supply chain disruption is high and vice versa. Together with the indifferent curve, we simply can understand a feasibility for each threat factors as depicted in Figure 3.10.

Table 3.9 The potential threat score of the SSCRD model

The Potential Threats of SSC	$\boldsymbol{\sigma = x}$	$\boldsymbol{\sigma(Impact)}$ **= y**
Planning Process threats - TF_1	0.386029955	1.23490249
Infrastructure threats - TF_2	0.250206441	1.302814247
Seaport Service Process threats - TF_3	0.502855333	1.176489801
Distribution Process threats - TF_4	0.184221518	1.335806709
Relationship Process threats - TF_5	0.111254402	1.372290267
Nuclear-enterprise financial threats - TF_6	0.226129396	1.314852769
Monetary threats - TF_7	0.109865816	1.37298456
Location threats - TF_8	0.212974382	1.321430276
Security threats - TF_9	0.378147674	1.23884363
Environmental threats - TF_{10}	0.494150017	1.180842459

In Figure 3.10, the threat factors show a negative slope. The *y-axis* is set up from the highest risk implication (1) to the lowest risk implication (5), which means that the highest value is the lowest risk implication. On the other hand, the *x-axis* is set up from the lowest threat (0) to the highest threat (1), hence the highest value is the highest threat. Thus, we can see that the relationship process threat (TF_5), and monetary threat (TF_7) have the lowest risk implication yet own the highest threat. While the seaport service process threat (TF_3) and the environmental threat (TF_{10}) have the highest risk implication and threat score respectively. Proportionally, another threat factors such as the planning process (TF_1), infrastructure (TF_2), distribution process (TF_4), nuclear enterprise financial (TF_6), location (TF_8), and security (TF_9) follows the trend which the increasing threat score is increasing risk implication. Therefore, the ten-dimensional threats mean that the seaport risk poses potential threats in various dimensions to disrupt supply chain continuity in Figure 3.10.

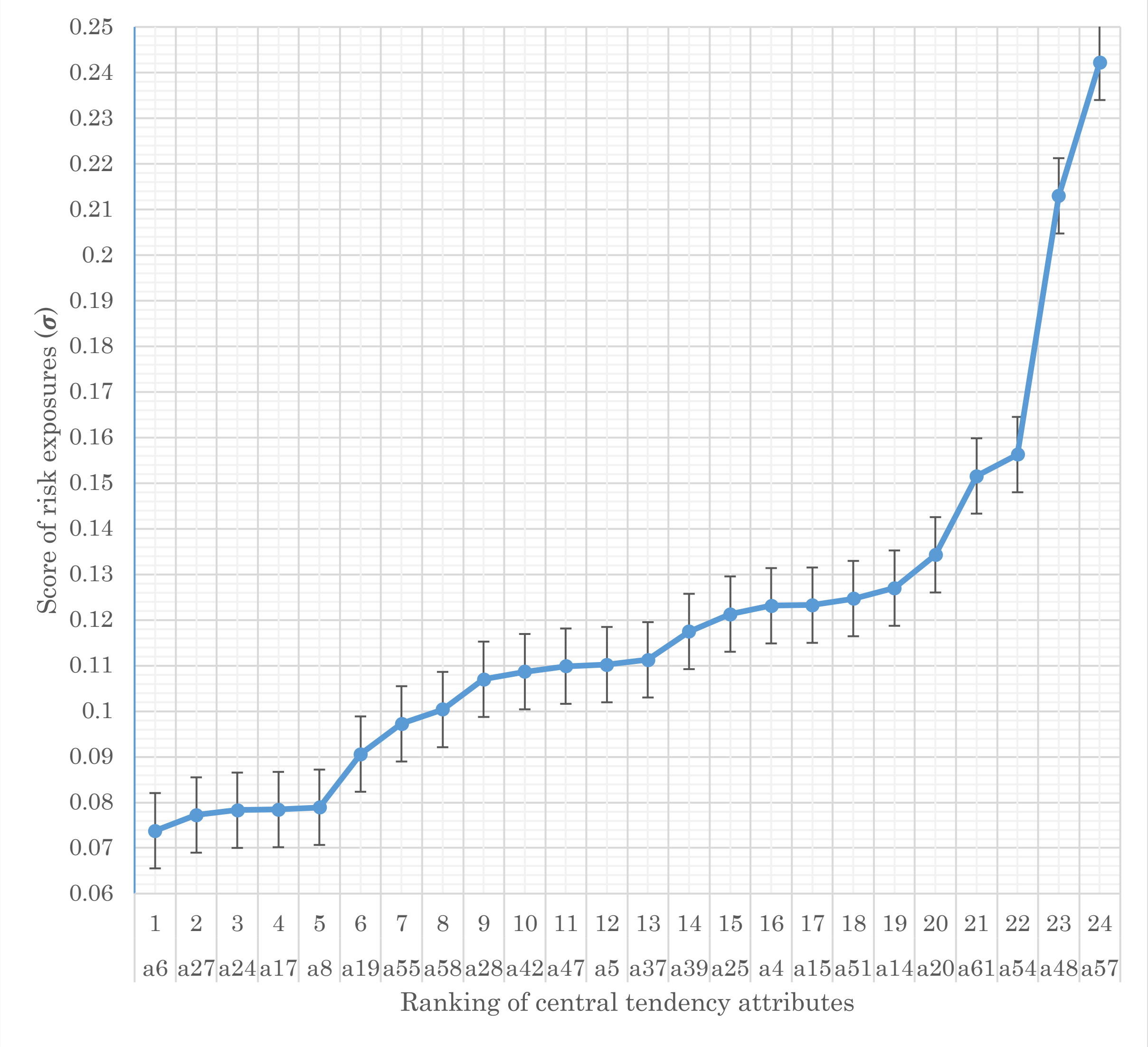


Figure 3.9 The ranking of the SSCR attributes.

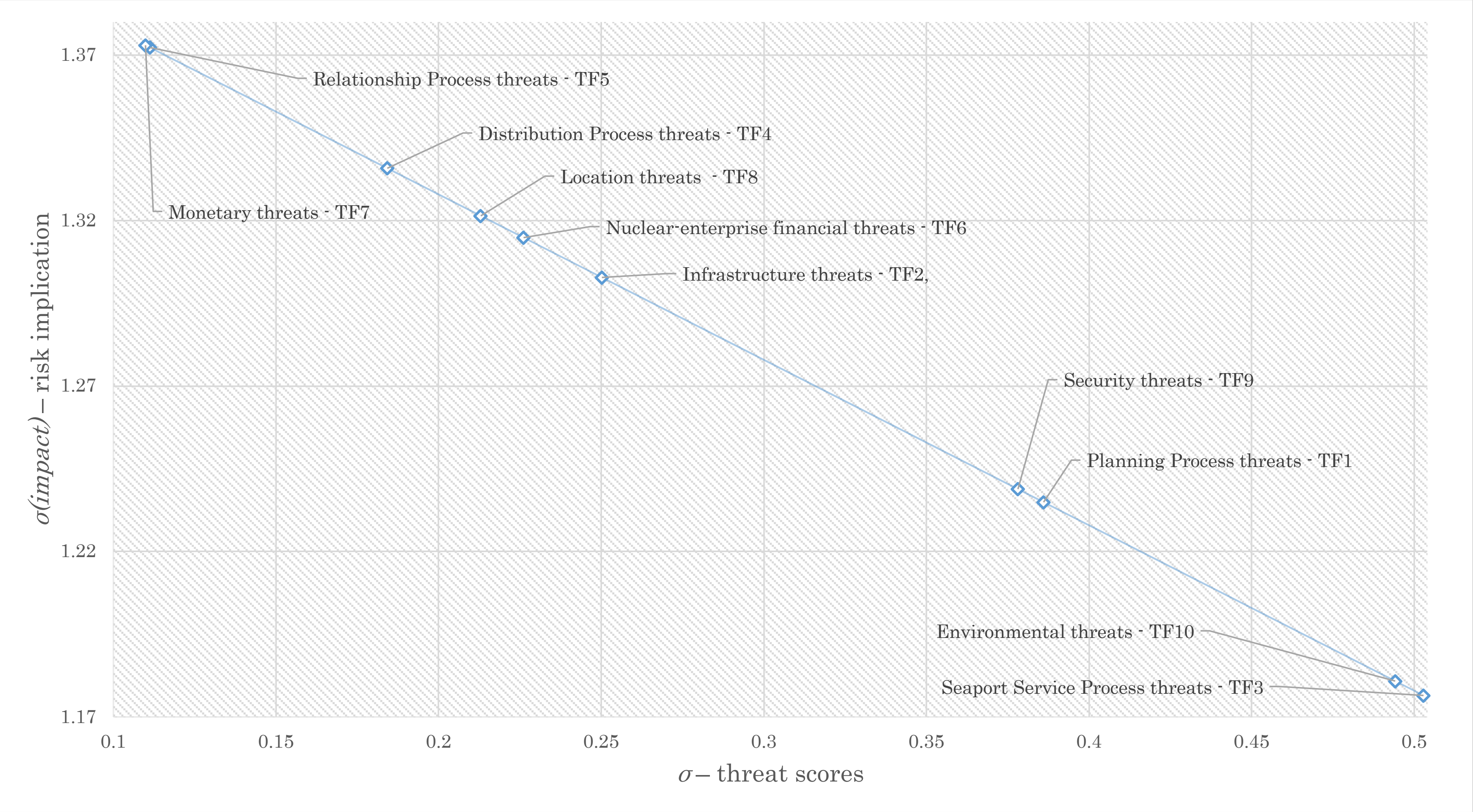


Figure 3.10 The potential threats to the seaport-fulcrum supply chain.

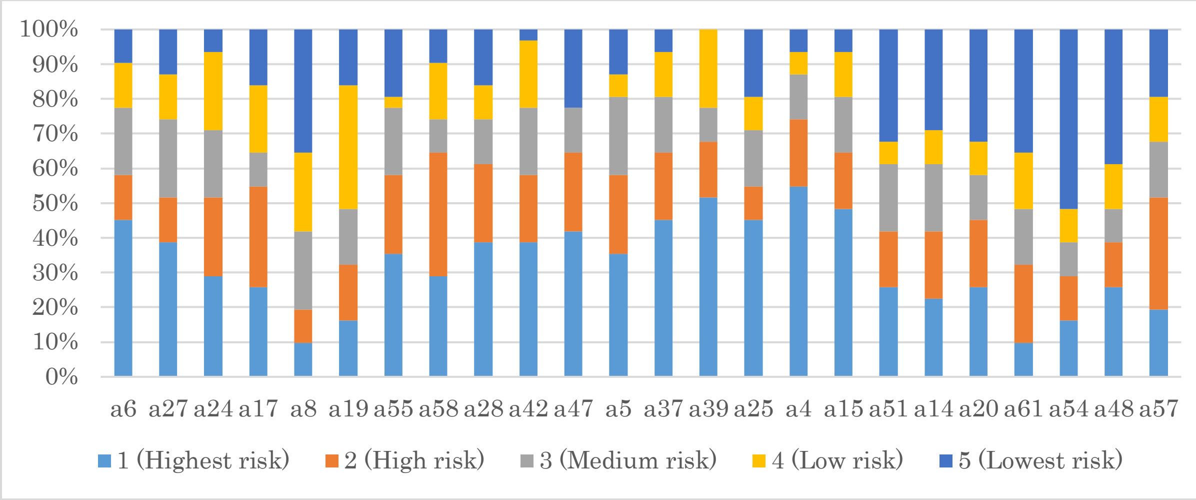
3.4.2.3 Relationship between the decision class and risk level

In the analysis, five decision classes are based on the RST approach employed to understand SSCR attributes level. The decision attributes *D* in Subsection (3.2.2) have five decision class such as, decision class 1 (highest implication with percentage scores between 80 – 100%) and following until decision class 5 (lowest implication to disrupt supply chain continuity with percentage scores between 0 – 20%). The risk level according to Figure 3.11 is then obtained based on the score assigned by the seaport supply chains' stakeholder. There are two kind evaluation that the decision-makers should be assigned. Firstly, they must evaluate the SSCR attributes with five different risk level as shown in Appendix A. Secondly, they should give their relative score (decision attribute) in percentage toward the implication SSCR attributes. The connections between decision class 1 and risk level according to Equations (3.30) – (3.32) are depicted in Figure 3.11.

The frequency among 153 SSC stakeholders on seaport risk levels is depicted in Figure 3.11. Moreover, the central tendency of seaport risks is segmented according to their risk level and shown by three indicator measurements. At the highest risk level, a level of over 40 percent in the strength indicator and coverage indicator, such as less timeliness of port customs clearance, low growth development, less efficient costs in feeder links, less motivation of member interest distribution mechanisms, low revenue, shortage of IT and advanced technology, and lack of ship risk planning, is likely to signify the highest disruption in this supply chain context.

Strength

Certainty



Coverage

Figure 3.11 Decision class 1 (the highest implication of risk to disrupt supply chain continuity).

3.4.3 Discussion

The lack of storage risk planning is ranked highest among 24 central tendencies of SSCRD in Figure 3.9. For example, Siswanto, Kurniawati, Latiffianti, Rusdiansyah, and Sarker (2018) highlighted the problem of storage planning particularly in the fertilizer product supply chain, clearly implicating an inventory routing problem. Initially, the fertilizer company chartered a vessel for some time horizon under the capacity constraint. The demurrage in the loading port implicated a decline of the ship's utility and increased the ship's operational cost. The former clearly affected congestion in the waterways, whereas the latter affected low growth for the factory.

This main risk of the dimensional planning process threat is related to seaport infrastructure and management (Loh and Thai, 2015a). Despite the significant effort required to develop seaport infrastructure, the result will improve its performance with high space utilization. The utilization rate of these areas should be tracked to ensure that new area plans are carried out on time. Furthermore, the risk of a port confronting a dimensional threat of the planning process threat increases if it is either a regional gateway owing to less timely customs clearance, or a transshipment hub port due to less cost efficiency in feeder links and short travel times to the other hub ports. In this example, the hub port may encounter disturbed working schedules if vessels' arrivals are delayed owing to inclement weather, inventory routing, and security problems at earlier ports. A hub port also has a busy waterway since it feeds a network of vessels, some of which may choose to obtain supplementary services, such as water supply and bunkering, while docked in seaport waters, while others might experience vessel bunching.

On the other hand, low punctuality of delivery goods, which was ranked second in the central tendency of the supply chain, results from various risk factors that have significant implications in the supply chain distribution process. Dewi and Purnamasari (2021) revealed that low punctuality of delivery goods is caused by inefficient maritime security inspections at sea as part of seaport customs clearance operations. Consequently, the shipping industry suffers operational delays and increased exposure to liabilities under their contract of carriage. Furthermore, stoppages for maritime security checks at sea generate delays, which raise shipping expenses. If a ship is delayed due to a marine security inspection, the delayed ship will need to speed up to meet the same arrival schedule at its next port and will burn more fuel than expected leading to greenhouse emissions. If its arrival schedule at the destination port changes because of the delay, it may have to pay to reschedule services, including pilotage, class inspections, and planned maintenance.

Generally, the seaport-service is a main duty in seaport operations. This study found that the port capacity shortage, waterways congestion, and hinterland transfer congestion are among the top ten central tendencies that pose threats to the seaport service process. Together with the monetary and location threats, the shipping industry may consider this issue as a port-choice problem. Indonesia, as an archipelago country, faces a difficult challenge in achieving maritime logistics system efficiency. The higher logistics costs account for around 20 – 30% of Indonesia's GDP because of the archipelagic characteristics particularly in eastern Indonesia (Amin et al., 2021). This research shows that a market imbalance in terms of container and cargo throughput exists in the Indonesian maritime supply chain.

The availability of the manufacturing industry and medium enterprises also contributes to the market imparity. Meanwhile, irregular ship schedules, high sea transportation costs, and lack of transportation modes are some issues faced by the maritime supply chain in eastern Indonesia as a result of market imbalance.

Seaport location is also important in the global supply chain since many shipping lines try to maintain a small number of ports of call with maximum market coverage, especially if they are as close to the growth market as possible (Kavirathna et al., 2018). Short sailing time to other hub ports is considered a central tendency of location threat in the Indonesian SSC operation. Such a phenomenon, known as short sea shipping, provides cost competitiveness in the modal shift from road haulage for the seaport-users. However, this also brings a negative ripple effect to the shipping industry and seaport management. The former might draw excessive competition in the shipping market to the SSC society. Excessive competition, for example, may result in the extinction of shipping lines with weak financial conditions, while surviving shipping businesses will use their monopolistic status to hike rates. This will soon have an adverse effect on the shipper and society. Meanwhile, the latter induces congestion within the terminal since the number of container throughputs in the stacking yard increases. Moreover, the more frequent presence of vessels in hub ports due to short sailing times increases greenhouse emissions.

The aforementioned potential threats directly or indirectly impacted the financial condition of the SSC members. Revenue and growth development are also central tendencies in particular cases. Both are primary tendencies of financial risk precautions for each member of the SSC threat. Hence, decreasing financial loss, preventing capital chain breakdown, and avoiding nuclear-enterprise financial risk are compulsory attempts to establish risk retention and risk prevention along the supply chain entities (Jiang et al., 2018).

3.5 Conclusion

In this study, the SSCR was analyzed using the RSGA and data from a questionnaire survey. The proposed method can support study of the combination problem among seaport risk factors as well as between many seaport risk factors and supply chain threats from the perspectives of seaport-manager, seaport-operator, and seaport-user evaluations, which can provide insights into risk management at the seaport. The score aids stakeholders in reacting correctly based on the seaport risks and threats.

We found in Appendix E that every utility in the higher potential threat and risk always reduces expected utility, which means that the utility in higher threat and risk can be useless. According to the study findings, 24 seaport risks in Indonesia pose potential threats to supply chain continuity. In terms of feasibility, the seaport service process (TF_3), relationship process (TF_5), monetary (TF_7), and environmental (TF_{10}) are beyond stakeholder comprehension. The shortage of port capacity, congestion in waterways, and congestion in hinterland transport are among top-ten priorities in the central tendency of the Indonesia SSCRD and induced threat to the seaport service process. Less motivation of member interest distribution mechanism also poses a threat to the relationship process among supply chain entities, whereas less efficient costs in the feeder link is considered a monetary threat. The occurrence of pandemics/epidemics (COVID-19), which is another top-ten priority of the central tendency list, is considered an environmental threat.

Several aspects of the Indonesian SSC operation are in danger of interruption. First, seaport risk factors from various dimensional threat categories, such as planning process (TF_1), infrastructure (TF_2), distribution process (TF_4), nuclear enterprise financial (TF_6), location (TF_8), and security (TF_9), influenced other categories previously, making threats vaguer and more unpredictable. For example, in a specific time frame, there was no planning process or dependable planning procedure. As a result, the unpredictability of the ports service process-related hazard increased. Second, the lack of cooperation among supply chain entities in carrying out their tasks, caused by the lack of incentive of the member sharing interest distribution mechanism, has increased. Furthermore, the container throughput imbalance caused by inefficiency of costs in feeder connections, notably in Indonesia's eastern region, becomes a monetary danger that should be addressed. Finally, the occurrence of COVID-19 has considerably disrupted the supply chain operation at the seaport.

Ultimately, a supply chain emergency management system, as well as a contingency plan and emergency protection mechanism for force majeure events such as seaport risk, should be developed to decrease risk and prevent unanticipated occurrences. The seaport management is also strongly urged to work closely with its stakeholders and the government to ensure that future plans keep up with new trends and are related to consumer requests, as well as national trade and investment goals. Relevant information, such as client vessel size orders, shipping market assessments, and challenges encountered by seaport users, should be communicated with the seaport-operator through the seaport-manager, since these have an influence on the adequacy of future plans. In addition, a supply chain management mechanism for the seaport enterprise core should be established; strategic cooperators should be engaged to improve the ability of upstream and downstream supply chain enterprises to deal with unexpected incidents and prevent supply chain breakdown as a result of these factors.

On the other hand, insufficiencies still exist that should be examined in future research. For example, the importance rating of each potential threat dimension is not clearly explained. Moreover, the risk of seaport disruption to a supply chain's operation is determined by many factors when operating in a complex socio-technical environment. Sensitivity analysis from a pair-wise function is thus needed to determine to what extent the seaport-focal supply chain risk model can be analyzed.

CHAPTER 4: Threat utility function in the seaport-fulcrum supply chain risk factors

4.1 Introduction

The several seaport risks factors and their resulting impact on supply chain continuity have increased the importance given to seaport operations. Traditional seaport business is very labor-intensive and shares an interdependent relationship with other supply chain entities. The process by which this relationship is established poses a dimensional threat to the seaport supply chain, and hence plays a crucial role in seaport disruption events. This relationship process is associated with manpower in term of soft skills and is affected by governmental policies. For instance, inefficient maritime security inspections at sea increase the shippers' exposure to liabilities under the contract of carriage and lead to operational delays, which, in turn, lower the promptness of goods (Komalasari and Purnamasari, 2021; Reagan, 2015). Similarly, miscommunication prevent the effective execution of instructions (Horck, 2008), and labor shortages delay cargo handling (Reagan, 2015). Moreover, a conflict of interest between parties hinders decision-making processes and disintegrates the supply chains (Robinson, 2007). These SSCRD events are related to the relationship process threat dimension.

The literature shows that seaports play a key role in supply chain continuity, given the increasing integration of ports into supply chains. Hence, a disruptive event originating at the seaports can hurt other interdependent businesses and alter the range as well as complexities of seaport service operations with other supply chain entities. An understanding of the seaport risk factors having a relationship with supply chain threats is necessary to elucidate on the characteristics of supply chain concerns, particularly the presence of numerous seaports dangers. Hence, an interdependency analysis should cover the extent to which the seaport risk-related threat factors affect the service level. By evaluating experts' responses objectively, this study proposes a risk model to investigate the association between the many conditional seaport risk attributes and their threats to supply chain continuity.

A hybrid approach was used in this study to manage the large number of conditional seaport risk attributes. This combined the self-explained technique and the complete profile method. The hybrid approach had two stages. In Stage I, the participant provided data on the desirability and relevance of the attributes, similar to the self-explained technique. In Stage II, instead of evaluating all profiles as in the complete profile method, a limited set of profiles was presented to the participant for assessment. These restricted profiles were selected from a master design based on an orthogonal main effects plan or another experimental design. The part-worth functions were estimated at the subgroup level using this hybrid technique.

The data collected in a typical hybrid conjoint study, which includes self-reported desirability and importance ratings alongside evaluations of a subset of profiles from a master design, must be considered. The traditional hybrid conjoint model, as discussed in Chapter 2, combines this data to estimate part-worth utilities at a subgroup level. When applying hybrid models, four key questions arise: 1) How can the threat utility function be estimated from multiple conditional seaport risk factors? 2) How should the multiple data sources in a hybrid design be combined to estimate part-worth at the individual level? 3)

Should the individual's profile data be used to update both self-explicated desirabilities (advantage) and importances (significant), or just the importances? 4) When estimating part-worth for an individual, how can other individuals' responses to the same profiles be leveraged?

4.1.1 Research framework

The last decade has highlighted the importance of understanding the potential threats of seaport operations to supply chain continuity. These threats have implications in several dimensions and giving rise to other threats, which weaken supply chain resilience. In this context, it must be noted that seaports are vulnerable to severe hazards that lead to a wide range of risks, including operational, environmental, security, technological, and organizational risks (John, 2014; Amr, 2009). Deficient seaport operations result in supply chain disruption and negatively impact organizational profitability and reliability. It is critical to identify the causes of disruption originating from seaport operations in order to reduce the impact of disruptions, given the increasing integration of seaports into supply chains (Repetto et al., 2017). Conventionally, a risk matrix is adopted to manage these supply chain risks. This risk matrix is classified into independent categories such as physical, financial, information, relationship, and innovation threats (Rao and Goldsby, 2009; Cavinato, 2004; Spekman and Davis, 2004). However, Ackermann et al. (2014) argued that risk assessment/evaluation and risk treatment following the conventional risk identification techniques fail to account for complex dynamics across risks and risk sources, and hence yield sub-optimal solutions.

This chapter comprehensively considers the MCDM with the utility theory as a risk management approach to understand the complex dynamics under risk criteria. One of the main challenges with applying utility theory in MCDM contexts lies in its assumption of single-attribute utility functions and the aggregation of preferences across different attributes or criteria. This assumption overlooks the complexities involved when decision-makers need to evaluate and compare alternatives based on multiple, often conflicting, criteria. There are four main issues with utility theory in the context of MCDM, such as:

First, single-attribute utility functions: utility theory typically assumes that decision-makers can assign a utility value to each alternative based on its performance on a single attribute (Wu and Liao, 2019). However, in real-world decision-making scenarios, alternatives are evaluated based on multiple criteria simultaneously, each with its own set of utility functions. Aggregating these utility functions to derive an overall utility for each alternative becomes challenging due to potential interactions and trade-offs among the criteria.

Second, Independence of Irrelevant Alternatives (IIA): utility theory often assumes the IIA property, which means that the introduction or removal of an alternative should not affect the relative ranking of the remaining alternatives (Kahraman and Çebı˙, 2019). However, in MCDM, this assumption may not hold true, as the preferences for alternatives can be influenced by the presence or absence of other alternatives due to interdependencies among the criteria.

Third, cardinal vs. ordinal utility: utility theory traditionally deals with cardinal utility, where absolute values of utility can be assigned to outcomes. In MCDM, however, it is often more practical to work with ordinal utility, where alternatives are ranked based on their relative desirability without assigning precise numerical utility values (Wu and Liao, 2019). This makes the aggregation of preferences across multiple criteria more challenging.

Fourth, difficulty in aggregating preferences: combining individual preferences across multiple criteria into an overall preference order is not straightforward. Different aggregation methods may lead to different results, and there is often no universally accepted way to aggregate preferences that satisfies all decision-makers' preferences and requirements (Ko, 2015). The direct aggregation of experts' opinions into collective opinions can provide a distorted picture of the diverse perceptions of experts. In this regard, it must be noted that a large number of conditional seaport risk features make aggregation more uncertain or unsolvable.

To tackle fourth issues above, this study simplified the large number of conditional seaport risk by using RSGA in Chapter 3 and aggregate the utility function from risk profile and expert responses by using Conjoint Analysis (CA). In the computational process, this study effectively retains decision-makers' original opinions on seaport risk criteria and the combination of experts' evaluation. Specifically, it uses CA after the RSGA in Chapter 3 to understand the utilization of the SSCRD. Figure 4.1 illustrates the entire procedures.

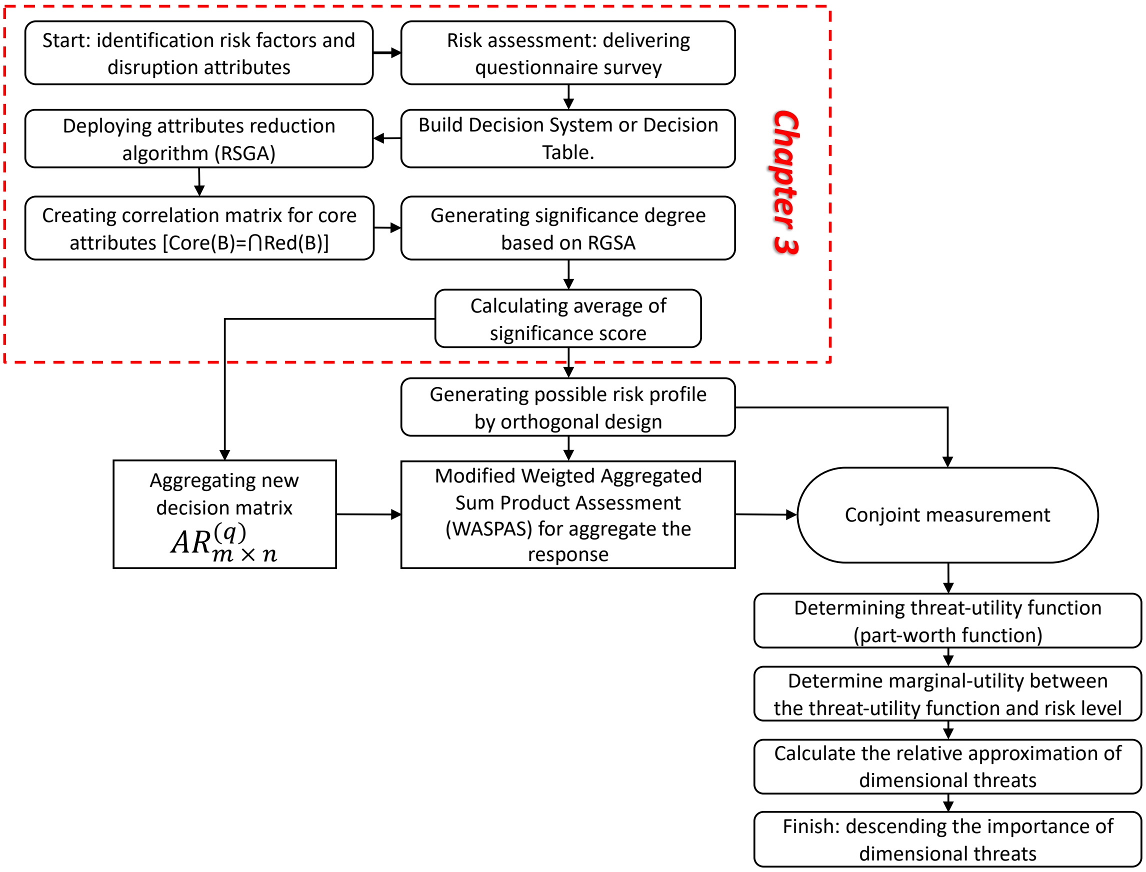


Figure 4.1 Flowchart of the threat utility framework

4.1.2 Objectives

Several interdependent decisions are involved in the formulation of a management seaport risk strategy for a value-added of supply chain operation. These include not only decisions about potential threat of supply chain characteristic but also its importance, implication, and feasibility (vulnerability) to chosen sets of supply chain entities. To avoid the decision from uncertainty, a semi-quantitative approach was introduced. We were using conjoint approach because the supply chain data in particular conditional seaport risk attributes are totally confidential in the case study context. Thus, the main objective of this chapter is to develop some trade-offs among the conditional seaport risk attributes considered individually by the seaport-fulcrum supply chain (SSC) entities and reveal the impact risk factors on a decision-maker satisfaction into a utility function.

Furthermore, we also set up several sub-objectives to tackle some limitation in a conventional MCDM method as follows:

1. To reveal how the SSC stakeholders would choose among (and react to) various deficiency conditional seaport risk profiles or criterions towards supply chain threat factors.
2. To study the SSC stakeholder behavior, such as perceptions, preferences, and choice, into utility function.

4.2 Methodology

Various methods have been used to collect evaluative or preference data from participants in a conjoint study. These methods are often linked to the procedures for creating stimulus sets or profiles. Respondents can assess profiles in multiple ways, such as direct assessment, comparison to others, and individual evaluation. The scales used can be categorical, ordinal, or interval-scaled.

In this study, a hybrid conjoint method was adopted for data collection, with the questionnaire format provided in Appendix A. Risk profiles were generated using an incomplete block design approach (see Sub-subsection 4.2.2.2), and responses were aggregated through performance evaluations using the Weighted Aggregated Sum Product Assessment (WASPAS) method by Zavadskas et al. (2014). The individualized hybrid conjoint design combines conventional conjoint analysis and the WASPAS approach to aggregate partial utility functions and the utility function for the supply chain from two distinct datasets. MATLAB 2022 was used for risk aggregation, and the individualized hybrid conjoint design was generated using R-studio.

4.2.1 Individualized hybrid conjoint design problem

The individualized hybrid conjoint method considered each decision-maker evaluation in conventional hybrid approach. Based on that, there are two data sets that sourced from self-explicated approach and estimation on the subset risk profiles corresponding to WASPAS. In Figure 4.1, the object targeted of SSC entities was asked to evaluate the conditional seaport risk attributes on scale 1 to 5. The explanation of this risk value is provided in Appendix B. The stakeholders are then asked to allocate 0 - 100 points towards whole the conditional seaport risk attributes so as to reflect their relative importance. The RSGA in Chapter 3 was introduced to picture the similarity among of conditional seaport risk toward relative importance (decision attribute). This similarity is computerized to find the highest dependency degree in this self-explicated data set. The RSGA is useful to solve some drawbacks in self-explicated approach such as attribute redundancy, nonlinearity in the part-worth function for a quantitative attribute, and biases regarding relative importance (decision variable) of conditional seaport risk attributes.

In a term of attribute redundancy and biases, the double counting in the self-explicated can be solved by introduced the equivalent class (similarity) according to the indiscernibility relation of RST. The same evaluation by each stakeholder is classified into a set. This approach can also reduce the biases in the self-explicated data set. After the self-explicated data set was generated from RSGA (see Chapter 3), the orthogonal design is used to estimate the subset risk profile for generating part-worth function and the SSC utility function.

The characteristics of the carrier SSCRD conduction referring to Shu et al. (2017) is considered with assumptions as follows:

a. Objective existence: the supply chain uncertainty is influenced by internal resource constraints and the external environment affecting supply chain entities, as well as direct and indirect correlations among these organizations.
b. Random: risk is considered a random variable, and the analysis of risk is guided by probability theory and mathematical statistics.
c. Carrying: the term "carrying" refers to various elements in the supply chain that can interact and contribute to disruption risks. For example, risk factors such as the subjects, objects, and contents involved in risk conduction can exist independently of each other.
d. Conduction: carriers transmit information and content related to supply chain disruption risk. Their carrying function is the premise and condition for this process.
e. Path dependency: The system route evolves under the influence of risk events, forming a habitual pattern that is difficult to replace.

These assumptions starting from the input information value of decision-maker, denoted $x_1, x_2, \ldots, x_n$. Node k in the hidden stage is Type k sub-risk; and the output value in the hidden stage is risk value Y_k of Type k. The correlation weight between input and hidden stages is W_{ij}, and the correlation weight between hidden and output stages is V_{ij}. θ_j and Φ_i indicate the value of each node in the hidden and output stages, respectively. The input information value is entered from the input stage, and after it is transformed by the node function in the input and hidden stages, it is changed to output signal O_i.

The disruption risk value without coupling effects (correlation/interdependency) is calculated, and the node output in the hidden stage is:

$$Y_i = f\left(\sum_{i=1}^{n} W_{ij} x_i - \theta_j\right) \tag{4.1}$$

Where W_{ij} is correlation weight and W is node valve. As Type k disruption risk exceeds the carrying limit, the output value related to many risk subsystems is exported and the overall disruption risk in enterprises is formed. Once the overall disruption risk exceeds the carrying limit of enterprises, risk conduction is exported and released from output nodes till it reaches the next node. The output node is:

$$O_i = f\left(\sum_{i=1}^{n} V_{ij} Y_i - \Phi_j\right) \tag{4.2}$$

The input information in each node comes from disruption risk information within node enterprises and the output information in the preceding node enterprise. The output information O_i in each Node A_i transmits to the next Node A_{i+1}. This model assumption is depicted as follows:

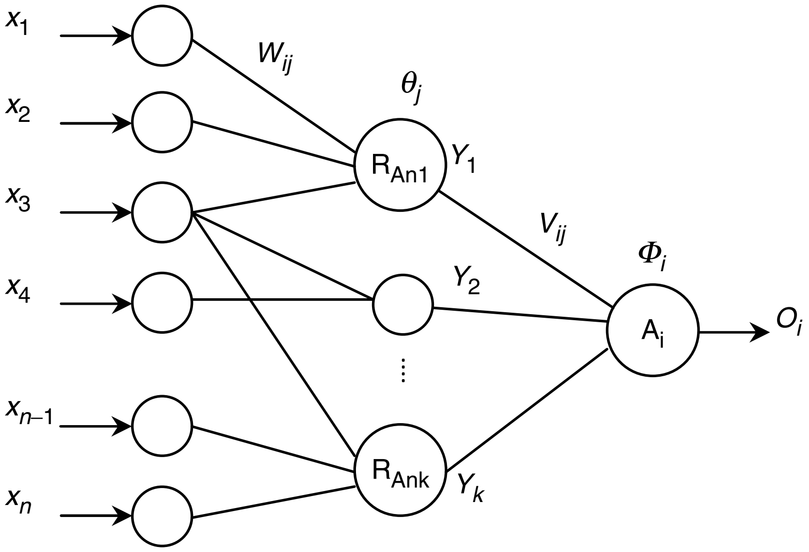


Figure 4.2 An illustration of supply chain disruption risk node nerve network by a decision-maker.

4.2.2 The framework of the threat utility-based hybrid conjoint design

The CA is addressed in MCDM due to its ability to handle decision problem involving multiple criteria or attributes. Basically, CA is designed to assess how individuals make trade-offs between different attributes or criteria when making decisions. In MCDM, decision problems often involve evaluating alternatives based on multiple criteria, and conjoint analysis provides a structured approach to elicit preferences and priorities among these criteria. CA also allows decision-makers to model preferences and utilities for different levels of attributes or criteria. This is particularly useful in MCDM, where decision-makers need to understand the relative importance of each criterion and the trade-offs involved in selecting one alternative over another. Lastly, CA provides a method for estimating the utility or value associated with each level of an attribute. This utility estimation can be used to rank alternatives, assess the impact of changes in criteria levels, and conduct sensitivity analysis in MCDM. However, the CA cannot be used when the number of attributes is increase. Thus, we use hybrid conjoint analysis (conjoint analysis with RSGA) to solve the complexity problem in attribute as mentioned in Chapter 3.

After the central tendency of conditional seaport risk was obtained in Chapter 3, we started to estimate SSCR factors profile. Together with the self-explicated data set, the alternative data set is used to generate threat-utility function and part-worth function of conditional seaport risk attributes. A list some preliminary notation for this framework as follow:

E : Decision-makers/ experts
TF : SSCR factors (threat factors)
C : SSCR attributes (conditional seaport risk attributes)
i : Index for threat factors, $i = 1, 2, ..., m$
j : Index for conditional seaport risk attributes, $j = 1, 2, ..., n$

q : Index for number of decision-makers, $q = 1, 2, \ldots, l$
J : Seaport risk profiles aggregated from the q-th expert, $J = 1, 2, \ldots, k$
V : Risk value from original data set
η : Risk value from successive interval method
μ : Normalization attributes
Q : Weight of observation
λ : Initial criteria accuracy
DR : Design range of risk profile
D_n : $J - 1$ = number of dummy variables for the j-th attribute
D_{mn} : The dummy variable for the m-th threat factors of the n-th risk attribute
D_{mnJ} : Value of the dummy variable, D_{mn} for the risk profile
$U_a(m)$: Utility function for the m-th threat factors for q-th expert

4.2.2.1 Description of threat utility problems

There is a need to address the limitations of the threat utility of SSCRD. Some of the limitations are solving the MCDM problem with multiple expert distortion, the interdependency among several seaports risk factors, and deriving a ranking of alternatives (Wu and Liao, 2019). The first problem can be solved by generating a trade-off by integrating the subordinate ranking sets. However, the difficulty is to integrate the ordinal information from the decision table without losing the decision-maker contexts. The second problem lies in obtaining the tendency attributes by reducing the superfluous features without losing the classification ability of the approach. The third problem is concerned with how to select the optimal alternative that has the biggest probability to achieve the threat utility of all the given criteria. To solve the three aforementioned issues, this study adopts the hybrid-conjoint approach.

Threat utility function is based on two essential concepts: "range of criteria" and "system range". The former refer to the permissible range of a criterion, as assessed by seaport specialists according to their judgement. While the "system range" refers to the genuine attributes (SSCR attributes) of conceivable design system, which corresponds to the performance of an alternative (decision-maker). In the given context, using the RGSA, we evaluate and select the conditional seaport risk attributes by referring to a range of criteria in Appendix B. Subsequently, we present the SSCR factors as criteria, which contain several conditional seaport risk attributes (SSCR attributes) as level of criteria. Second, we generate a risk profile using an orthogonal scheme. We evaluate the risk profiles as independent variables by aggregating the threat variables. Hence, the evaluation of the "range of criteria", that is aggregated by orthogonal array, and RGSA help in solving the first MCDM problem. The aggregation of an alternative also helps in addressing the second and the third issues and in understanding the performance of the "system range" as input parameters of the SSCRD model.

Thus, we create a new decision table for the "system range" comprising a finite set of threat factor (criteria), $TF = \{TF_1, TF_2, \ldots, TF_m\}$, and conditional seaport risk attributes (level), $C = \{c_1, c_2, \ldots, c_n\}$, with a weight vector $w = \{w_1, w_2, w_m\}^T$. We invite a group of experts $E = \{e_1, e_2, \ldots, e_q\}$ to assess these criteria according to level of attribute. Each expert (alternative), e_q, needs to determine the functional requirement (system range) of each criterion. Subsequently, we propose an aggregation for expert evaluations on the alternative denoted as $AR = \{ar_1, ar_2, ..., ar_J\}$. The “range of criteria” has the same expression type as the “system range” corresponding to everyone. Hence, if an expert evaluates the “range of criteria” of a criterion as a numerical number (linguistic term risk level), then the “system range” of the alternative on this criterion will be also expressed in the numerical form. The new aggregation of the individual decision matrix, $AR^{(q)}_{m \times n}$, can be established as follows:

$$AR^{(e_q)}_{mn} = \begin{bmatrix} \frac{V_{11}-\eta_{11}}{\mu_{11}} & \frac{V_{12}-\eta_{12}}{\mu_{12}} & \frac{V_{1j}-\eta_{1j}}{\mu_{1j}} \\ \frac{\mathrm{V}-\eta_{21}}{\mu_{21}} & \frac{V_{22}-\eta_{22}}{\mu_{22}} & \frac{V_{2j}-\eta_{2j}}{\mu_{2j}} \\ \vdots & \ddots & \vdots \\ \frac{V_{i1}-\eta_{i1}}{\mu_{i1}} & \frac{V_{i2}-\eta_{i2}}{\mu_{i2}} & \frac{V_{ij}-\eta_{ij}}{\mu_{ij}} \end{bmatrix} \tag{4.3}$$

The results of RSGA that come along with the core attributes represent the significance degree for each core attribute. We assume that the ratio between the significance value and the total observation represent the average of importance degree in Equation (3.26). Then, we propose the weight in Equation (3.27) to aggregate performance of individual expert evaluations in Equation (4.6). Furthermore, the risk value η_{ij} in original data set is altered from ordinal to successive interval method (Mosier 1940; Edwards and Thurstone 1952) with aims to conduct statistical regression for threat utility function. We also select moderate μ_{ij} normalization to ensure that the attribute levels of different attributes are on a comparable scale for statistical analysis and interpretation.

4.2.2.2 Orthogonal design for range of criteria (risk profile)

In this study, we adopt a hybrid-conjoint approach in which the given risk combination of core attributes is computed using an expert aggregation based on a set of orthogonal designs. Subsequently, we use the utility function to understand the utility in relation to the risk level. The main concept in this orthogonal design is to create a set of orthogonal profiles, subdivide them, and assign them to each subject in a subgroup of people (Rao, 2014). Each conditional seaport risk profile receives the same amounts of replications because of the overall administration. Let J = number of risk profile in the orthogonal design, Γ = replications for each profile, τ = number of profiles administered to any one expert, ρ = number of blocks of profile (each block is administered to one expert in the study). Then, in the balanced incomplete block designs, the following conditions hold. First, each profile appears at most once in a block. Second, each profile appears exactly Γ times in administration. Finally, each pair of profile occurs exactly l times together. In such a way, the following conditions hold among the parameters of design:

$$J * \Gamma = \rho * \tau \; and \; l(J-1) = \Gamma(\tau - 1) \tag{4.4}$$

Consider conjoint research with three attributes, each at three levels. Assuming an orthogonal design, 9 complete profiles are created for this example. Furthermore, the research will be conducted through interviews, with each expert receiving four of the nine profiles. There exists a balanced incomplete design for this situation. Here, J = 9 and τ = 4. The basic design interview for 18 blocks, each block representing an expert and can be replicated across sets of 18 experts in the sample. Each profile (out of nine) is replicated $\Gamma = 8$ times, and each pair appears $l = 3$ times. Related with this chapter, the risk profile design is aggregate from self-explicated data set where each replicative block (alternative) related conditional seaport risk level indicates the higher possibility of SSCR factors (attributes).

4.2.2.3 Reliability and validity system range

This section solves the problems of how to determine the aggregate performance of individual expert evaluations and how to combine the collective information content determined by the RSGA method with the collective information to drive the ranking sets of experts' observations. After deploying the profile of conditional seaport risk attributes, we compute the experts' responses according to Equation (4.3) with the following equation.

$$DR = \sum_{J=1}^{\mathrm{k}} ar_j^{(q)} = \sum \frac{\eta_{ij}^q - Q_l}{\mu_{ij}^q} \tag{4.5}$$

Furthermore, the WASPAS initialized by Zavadskas et al. (2014) is modified to determine the relative importance of observation for aggregating experts' responses, which is mathematically defined as follow:

$$Q_l = \lambda \sum_{j=1}^{n} ar_j^{(q)} \omega_j + (1 - \lambda) \prod_{j=1}^{n} \left(ar_j^{(q)}\right)^{\omega_j}, \ \lambda = 0, \ldots, 1 \tag{4.6}$$

4.2.2.4 Utility representations form

This study makes two considerations to obtain the threat function of a risk combination (profile), such as effective profile, and aggregation risk levels of a profile (reponse). The first consideration is explained in the orthogonal design. The second consideration presents a discretization of the linguistic term set (V_a), which is a set of possible linguistic terms of the linguistic variables. Subsequently, we denote the continuous-valued linguistic term as $Z = [z_{0.1}, z_1]$, where $z_{0.1}$ and z_1 represent the lowest and highest risks, respectively (Xingli and Liao, 2020). In this study, the threat utility follows the assumption that the sum of satisfaction is achieved by reducing the risk level. In other words, the experts always follow the principle of the minimum cost. Thus, the marginal utility can be presented in the following Equation (4.7) as the ratio between the utility and the level of risk factors for each risk factor.

$$MU_Q(m) = \frac{\Delta U_q}{\Delta Z} \tag{4.7}$$

Furthermore, V_a is nominally scaled. Assume that A_{mn} has L_n levels. Let $D_{mLn\text{-}1}$ be the dummy variables for the m-th attribute. Then, the utility function is:

$$U(m) = \beta_0 + \sum \beta_{ij} D_{iL_j - 1} \tag{4.8}$$

To filter the effect of the noise factors affecting the result of the conjoint measurement, let us suppose a new information system in which the response Y (e.g., a threat factors level) aggregated by q respondents to risk profiles composed of m threat attributes can be modelled by a multiple linear regression:

$$\bar{Y} = \bar{\bar{A}} \cdot \bar{\beta} + \bar{\varepsilon} \tag{4.9}$$

where

$$\bar{Y} = \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_l \end{bmatrix}, \bar{\bar{A}} = \begin{bmatrix} 1 & a_{11} & a_{12} & \cdots & a_{1m} \\ 1 & a_{21} & a_{22} & \cdots & a_{2m} \\ & \vdots & \vdots & & \vdots \\ 1 & a_{q1} & a_{q2} & \cdots & a_{qm} \end{bmatrix}, \bar{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix}, \bar{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_l \end{bmatrix} \tag{4.10}$$

a_{qm} is the value of the i-th attribute ($i = 1, 2, \ldots, m$) in the profile aggregated from the l-th expert evaluation, $\bar{\beta}$ is a vector of risk parameters, and $\bar{\varepsilon}$ is a vector of random variables modelling the measurement error.

Let us introduce the Equation (4.3) as the risk multiplicative coefficient in the matrix $\bar{\bar{A}}$ mathematically as:

$$\bar{\bar{A}}_{new} = \begin{bmatrix} 1 & ar_1^{(1)} a_{11} & ar_2^{(1)} a_{12} & \cdots & ar_j^{(1)} a_{1m} \\ 1 & ar_1^{(2)} a_{21} & ar_2^{(2)} a_{22} & & ar_j^{(2)} a_{2m} \\ & \vdots & & \ddots & \vdots \\ 1 & ar_j^{(q)} a_{q1} & ar_j^{(q)} a_{q2} & \cdots & ar_j^{(q)} a_{qm} \end{bmatrix} \tag{4.11}$$

Concerning the results, they affected the model in the Equation (4.11). In the case in which $w_{qj} = w_i$ ($\forall q = 1, 2, \ldots, l\ \forall i = 1, 2, \ldots, n$)—the multiplicative coefficients are different for each attribute but common for all the respondents—$\bar{\beta}_{new}$ is related to $\bar{\beta}$:

$$\bar{\beta}_{new} = \left[\beta_0, \frac{\beta_1}{ar_1^{(1)}}, \ldots, \frac{\beta_j}{ar_j^{(q)}} \right]^T \tag{4.12}$$

Equation (4.11) is a purely formal passage. It provides a possibility of introducing the relative weight of importance according to Equation (4.6) in the model. In fact, we observe the model parameters increase proportionally to the relative weight importance ω_i given by the respondents to the m-th attribute. Thus, by introducing the multiplicative coefficient, we obtain the following formula:

$$\bar{\beta}_{new} = w \circ \bar{\beta}, \tag{4.13}$$

where $w \in Q_l$, $w = \{w_1, w_2, w_n\}^T$, and the symbol 'o' denotes the Hadamard product between vectors W and $\bar{\beta}$—$\bar{\beta}_{new}$ is obtained by multiplying element-by-element the vectors W and $\bar{\beta}$. Ultimately, the framework of the threat utility-based hybrid rough set design is depicted in the Figure 4.1.

4.2.3 Individualized hybrid conjoint model

An individualized conjoint model is generated from two data sets, such as the self-explicated data set and an estimation of the conditional seaport risk profile data set. The self-explicated data set is from the stakeholder evaluation of each attribute on a scale 1 to 5 (see Appendix B). The risk profile or alternative is referred from the estimation procedures in Sub-subsection 4.2.2.3. In this conjoint model, the relative importance of stakeholders in the profile was changed according to the estimation steps. The goal of this estimation is to get the relative importance score more objective rather than the subjective evaluation. The real application of CA is always faced with the subjective evaluation with inconsistency from the decision-makers.

For example, considering the situation *"if-then"* analysis from two decision rules, rule one is not contain inconsistency and the other have it as follows. *Rule#1*: if Shortage of facilities or equipment is low and Port capacity is the below standard, then Inflicting losses on state finance impacted to uneconomical, inefficiency, and ineffectiveness supply chain is low. *Rule#2*: if Shortage of facilities or equipment is the lowest and Port capacity is below standard then Inflicting losses on state finance impacted to uneconomical, inefficiency, and ineffectiveness supply chain is high.

The inconsistency of rule two is sourced from a conflicting conditional seaport risk attributes and its decision class, such as the two value of the conditional seaport risk attributes is low, but the decision class value is high. This type of inconsistency is always leading the biases in data set and reduce the accuracy. Thus, the data from the estimation of risk profile referring Sub-subsection 4.2.2.2 is considered to free from inconsistency, hence, the relative importance score of alternatives is more objective.

Therefore, the individualized hybrid conjoint model start from some notation as follows:

E : number of individuals (experts) in the study; denoted by subscript $e = 1,2,\ldots, q$.

i : number of threat factors (attribute), $i = 1, 2, \ldots, m$

j : number of conditional seaport risk attributes (level), $j = 1, 2, \ldots, n$.

J : number of conditioonal seaport risk profiles aggregated from the q-th expert, $J = 1, 2, \ldots, J_q$.

L_m : number of levels for the m-th attribute.

$u_{ml}^{(q)}$: part-worth for the l-th level of the m-th attribute for q-th individual.

$v_m^{(q)}$: derived importance of the m-th attribute for q-th individual.

$f_{ml}^{(q)}$: derived benefit (desirability) for the l-th level of the m-th attribute for the q-th individual.

$w_m^{(q)}$: self-explicated importance for the m-th attribute for q-th individual reffering Equation (4.6).

$d_m^{(q)}$: self-explicated benefit (desirability) for the m-th attribute for the q-th individual.

DR : number of design risk profile (alternative).

$h_{ml}^{(DR)}$: indicator variable taking the value 1 if the m-th attribute in the DR-th profile takes level 1.

$s_J^{(q)}$: estimation score from the q-th individual to the J-th profile.

With this notation, we rewrite the self-explicated part of the hybrid conjoint model can be written as :

$$U_{DR}^{(q)} = \sum_{n=1}^{j} w_n^{(q)} \sum_{l=1}^{L_n} d_n^{(q)} l_{DRnl}^{(q)} \tag{4.14}$$

We define the dummy variables $D_{mn} = J - 1$ for the ten threat variables as follows:

$$D_{mnJ} = \begin{cases} 1, if\ h_{ml}^{(DR)} = 1, where\ DR = J_{J_q}^{(q)} \\ 0, otherwise. \end{cases} \tag{4.15}$$

The individual hybrid conjoint model then is:

$$s_{DR}^{(q)} = a + bU_{DR}^{(q)} + \sum_{m=1}^{i} \sum_{l=1}^{L_m} B_{ml} D_{mnJ}^{(q)} + \varepsilon_J^{(q)} \tag{4.16}$$

The parameters *a, b* and B_{ml} are regression parameters referring the Sub-subsection 4.2.2.4. The estimation method in this model is iterative least squares regression and the associated characteristics equations for the individualized conjoint model as follows:

$$y_{ml} = u_{ml} + \varepsilon_{ml} \tag{4.17}$$

where

$$u_{ml} = w_{ml} d_{ml} \tag{4.18}$$

$$(s_{DR} - \mu)/\tau = \sum_{m=1}^{i} \sum_{l=1}^{L_m} u_{ml} D_{mnJ} + \delta_J; \text{ for } J = 1, 2, \ldots, J \tag{4.19}$$

ε_{ml} and δ_J are independent and identically distributed random variables $N(0, \sigma^2)$.

The estimation steps for this model are based on Hagerty and Srinivasan (1991) is provided as follow:

Step 1: Set $\mu = 0$ and $\tau = 1$ and using Equation (4.6) – Q_l + J observation, estimate u_{ml}.

Step 2: Regress s_{DR} on the predicted score using Equation (4.19). The intercept and slope of this regression will yield estimates of μ and τ.

Step 3: Repeat Step 1 with the estimated values of μ and τ in Step 2.

Step 4: Repeat Step 2 and 3 until the change (reduction) in the error sum of squares is no more than a prespecified number of the number of iterations is exceeded.

4.3 Results

We conduct the initial test of primary data (the self-explicated data set and the subset profiles data sets). This helps us to check the reliability of the dataset after collection. We test 61 conditional seaport risk attributes and a decisional factor from 153 responses and showing in Table 3.5. Furthermore, Table 4.1 shows the results of the reliability test of risk profiles. According to the Cronbach's alpha, we find the dataset reliable as an input for the conjoint measurement. After the pilot test of the primary datasets of the questionnaire survey, we run the RGSA to obtain the core attributes as the central tendency of SSCRD. Subsequently, we conduct the reliability test to check the aggregation of seaport risk profiles, corresponding to the orthogonal design. Specifically, we check the reliability of the dataset of 32 risk profile, as presented in Table 4.1 below.

Table 4.1 Result of reliability test for the aggregation of seaport risk alternatives.

Case Processing Summary		Number of responses	Percentage
Cases	Valid	32	100%
	Excluded[a]	0	0.0
	Total	32	100%
Reliability results for the aggregation of seaport risk alternative			
Reliability Statistics[b]			Percentage
Cronbach’s alpha		0.991	99.1%
Cronbach’s alpha based on standardized items		0.992	99.2%
[a] Listwise deletion based on all variables in the procedure			
[b] Cronbach’s alpha level of reliability		0.0–0.20	Less reliable
		> 0.20–0.40	Rather reliable
		> 0.40–0.60	Quite reliable
		> 0.60–0.80	Reliable
		> 0.80–1.00	Very reliable

4.3.1 Evaluation of core attributes for orthogonal design

After receiving the core attribute from the RSGA process, we run the computation corresponding to Equation (4.4) and Equation (4.5) to provide the preference order. The preference order prioritizes the latent factors in the threat utility function (Gou and Xu, 2021). The order also helps us to understand the utility value and the discretization of risk levels. The RSGA highlights 24 seaport risk criteria, each corresponding to ten threat factors, based on Table 3.8. The orthogonal design of the seaport risk criteria helps in estimating the threat utility function. The error term in Equation (4.11) is essentially the same as the random part of the utility function. Appendix F presents the orthogonal design of the seaport risk criteria.

4.3.2 Part-worth utility and its threat utility function

In this study, the theories of threat utility develop in line with two trends—the topological-set and probabilistic trends. The topological-set trend (conditional seaport risk tendency) assumes the non-measurability of the utility. Using RGSA, we obtain the set trend emerging from the expert evaluation. The probability trend can be defined by referring to the available risk profiles, corresponding to the risk tendency set. Furthermore, by introducing Equation (4.3) and Equation (4.6) and by the monotonic arrangement of variants (seaport risk profiles) in a descending way, we determine the direction of the seaport risk criteria (Rao, 2014). Given this, we define the threat utility as the sum of the disruption level by the seaport risk factor that influences the satisfaction of SSC continuity. In the meanwhile, the marginal utility in Equation (4.7) presents the disrupted satisfaction, according to the setup of the risk level. Both quantifications are carried out by the tendency expressed with the part-worth utility function in the following Table 4.2.

Table 4.2 Part-worth utility function for seaport risk model.

No.	**Threat factors**	**Conditional seaport risk attributes**	**Index (C_{ij})**	**Parameter values ($\bar{\beta}$)**	**Expected Mean Squared Error of Prediction (EMSEP)**
1.	Planning process (TF_1)	Lack of ship risk planning	c_{14}	-0.0508	0.071
		Lack of handling process risk planning	c_{15}	0.0457	0.071
		Lack of storage risk planning	c_{16}	0.0542	0.071
		Lack of distribution risk planning	c_{18}	-0.0491	0.071
2.	Infrastructure (TF_2)	Breakdown of vessel traffic management system	c_{25}	0.0322	0.041
		Breakdown of port information system	c_{26}	-0.0322	0.041
3.	Seaport service process (TF_3)	Congestion in the waterway	c_{31}	0.0085	0.077
		Congestion at hinterland transfer	c_{33}	-0.0616	0.077
		Less services calling at port	c_{34}	-0.0265	0.077
		Shortage of port capacity	c_{38}	0.0080	0.099
		Shortage of IT and advanced technology	c_{39}	0.0716	0.099
4.	Distribution process (TF_4)	Low punctuality of delivery goods	c_{42}	0.0292	0.041
		Less timeliness of port customs clearance	c_{43}	-0.0292	0.041
5.	Relationship process (TF_5)	Less motivation of member interest distribution mechanism	c_{54}	0.3713	0.041
6.	Nuclear-enterprise financial (TF_6)	Low revenue	c_{61}	-0.3713	0.041
		Low growth development	c_{64}	0.0240	0.041
7.	Monetary (TF_7)	Less efficient cost in feeder link	c_{73}	-0.0240	0.041
8.	Location (TF_8)	Short sailing time to the other hub ports	c_{81}	0.3309	0.041

9.	Security (TF_9)	International trade-war	c_{91}	-0.3309	0.041
		Smuggling	c_{94}	0.2483	0.041
		Trafficking	c_{95}	-0.2483	0.041
10.	Environmental (TF_{10})	Earthquake frequency	c_{101}	0.0122	0.054
		Pandemics/epidemics occurrence	c_{102}	0.0158	0.064
		Increasing sedimentary level in the seaport	c_{105}	-0.0279	0.064

In the Table 4.2, the part-worth utility function, each seaport risk factor for each threat variable is affected in proportion to the disrupted utility SSC continuity. For example, the disrupted utility of the SSC because of the planning process threat (TF_1) will increase by 1% only if the lack of ship risk planning (c_{14}) and the lack of distribution risk planning (c_{18}) decline by as much as -5%, while the lack of handling process risk planning (c_{15}) and the lack of storage risk planning (c_{16}) increase by 5%. In the other case, the positive "+" sign in the threat utility function indicates that the increase of conditional seaport risk attributes is linear with potential supply chain threat factors, while the negative "-" sign represents decision-makers desirability.

The negative coefficient and positive coefficient are obtained from dummy variables in Equations 4.10 and 4.17. In dummy coding, one category or level of a categorical variable is chosen as the reference or baseline level. This reference level is represented by a dummy variable that takes a value of 0 for that level and 1 for the other levels. When you estimate a part-worth utility function using dummy-coded variables, the sign and magnitude of the coefficients associated with the dummy variables determine the direction and strength of preference relative to the reference level. For example, suppose we are conducting a conjoint study on smartphones, and the attribute "Color" has three levels: Red (reference), Blue, and Green. You use dummy coding to represent these levels. If the coefficient associated with the Blue dummy variable is positive, it suggests that respondents have a higher preference or utility for Blue phones compared to Red (reference). Otherwise, if the coefficient associated with the Green dummy variable is negative, it suggests that respondents have a lower preference or utility for Green phones compared to Red (reference).

In summary, the use of dummy variables in CA enables to capture the effects of different levels of categorical attributes on respondent preferences. The positive and negative signs in the coefficients of these dummy variables indicate the direction and strength of preference for each level relative to the chosen reference level. This allows to quantify how different attribute levels contribute to overall conditional seaport risk preferences. Hence, the symbols relatively reflect the decision-makers desirability from the conditional seaport risk attributes towards potential supply chain threat factors, which the negative sign indicates low threat from the conditional seaport risk attribute. Furthermore, the "N" factor in TF_5, TF_7, and TF_8 means that other SSCR attributes are in proportion to factors c_{54}, c_{73}, and c_{81} causing the SSCRD. This factor occurs because of the dummy coding (Rao, 2014). In Figure 4.3 below illustrates the whole part-worth function on seaport risk criteria factors.

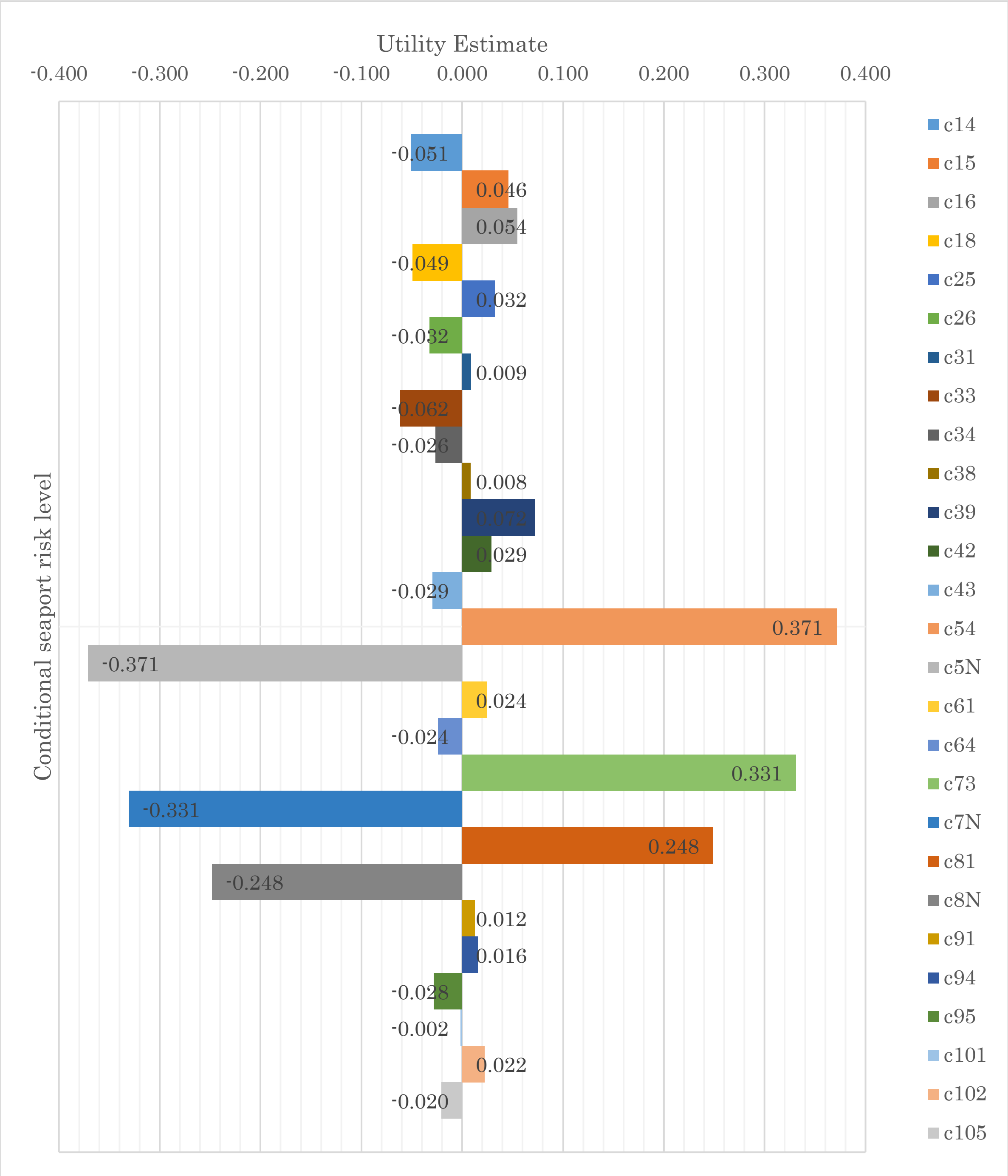


Figure 4.3 Conditional seaport risks ratio

4.3.3 Importance of dimensional threats

In the SSCRD context, the seaport service process should be optimized as a priority in order to reduce the disruption. The factor disrupts utility by as much as 32%, followed by the relationship process threat (TF_5) and planning process threat (TF_1). Hence, these latter two threats assume the second and third priorities, respectively. However, the infrastructure breakdown (TF_2) poses less threat of SSCRD at 9.9%. Figure 4.4 depicts the potential threats. Table 4.2 and Equation (4.14) provide the background risk, and thereby help the seaport manager, operator, and user to determine their resilience path toward these potential threats.

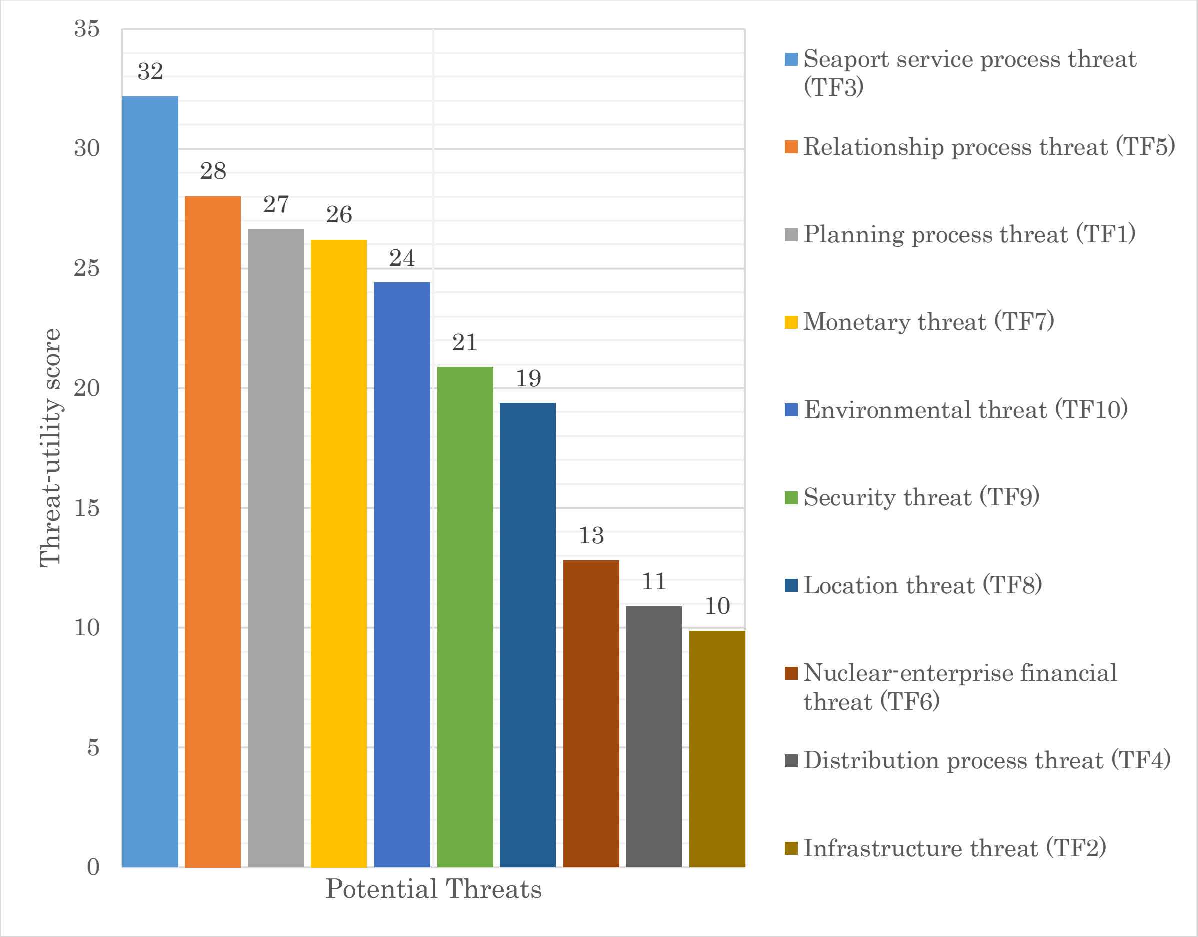


Figure 4.4 Potential threats of the SSCRD in Indonesia

4.3.4 Sensitivity analysis

In the proposed model, we check the performance of the aggregation in Equation (4.6) and Equation (4.10) by setting the accuracy parameter differently (λ). We generate λ from 0 to 1 to check the degree of sensitivity of the estimated threat utility toward the aggregation Equation (4.6). Hence, this sensitivity analysis relies on how to determine the aggregate optimal performance for each criterion (risk profile). In this step, the aggregate optimal performance is calculated as follows:

$$\mu_{qj} = \begin{cases} \frac{V_{qj} - V_{min_{qj}}}{max_{qj} - min_{qj}};\ j\ \in \Omega_{normal} \\ \frac{min_{qj}}{V_{qj}};\ j\ \in \Omega_{min} \end{cases} \tag{4.20}$$

where Ω_{normal} denotes the set of moderate normalization, and Ω_{min} denotes the set of cost criteria.

Both criteria present a robustness parameter of the threat utility. The former refers to the initial condition before the robustness of risk, whereas the latter refers to an attempt to reduce the risk. In this sensitivity analysis, the output relies on the performance of the threat variables' aggregation. Given this, it is important to check the variations in the input variables of that model. The inputs in this MCDM model with hybrid conjoint approach is the aggregation of Equation (4.6). Therefore, the variation in inputs based on the parameter of robustness is provided in Figures 4.5 and 4.6.

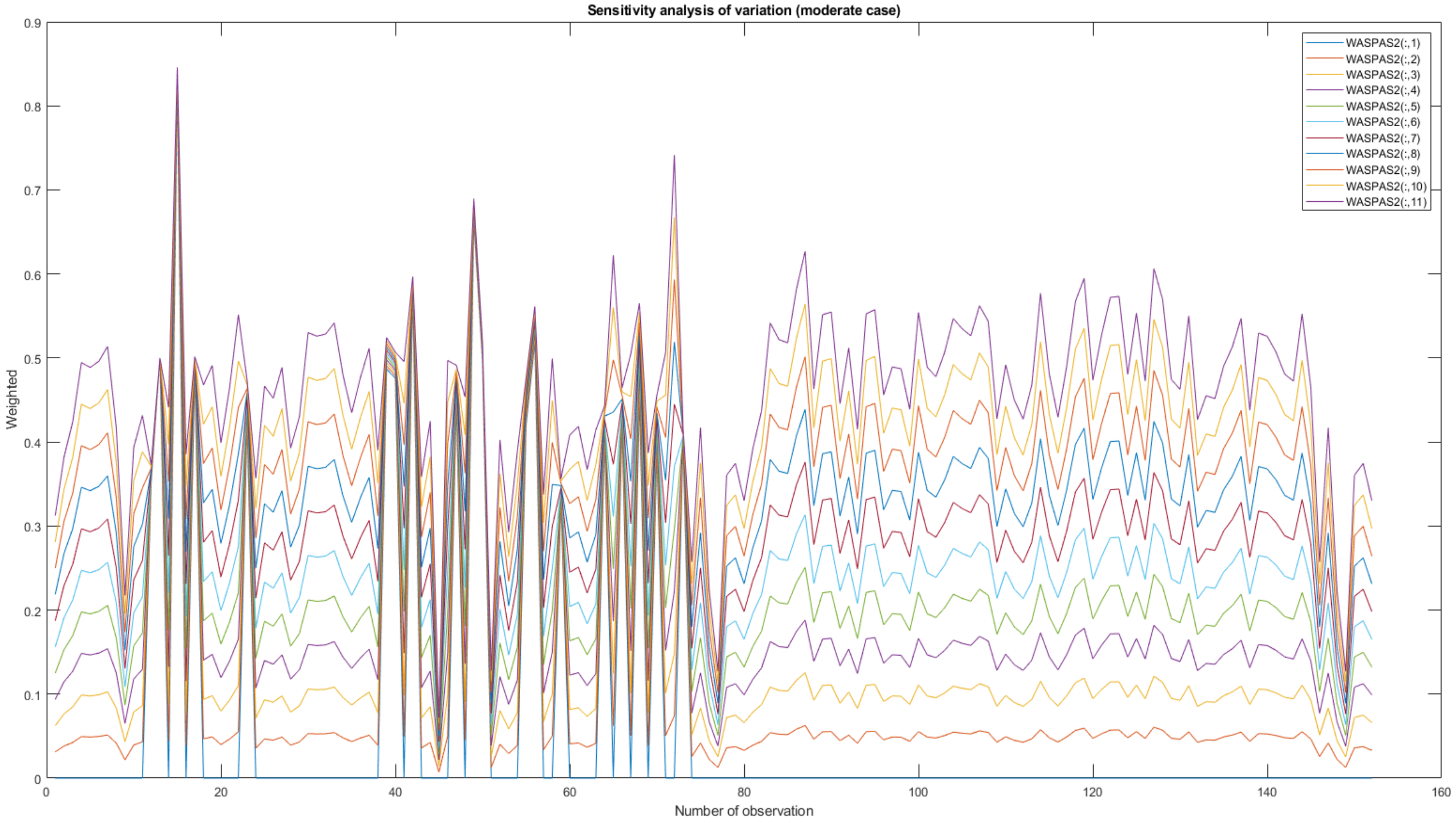


Figure 4.5 Variation in average criteria

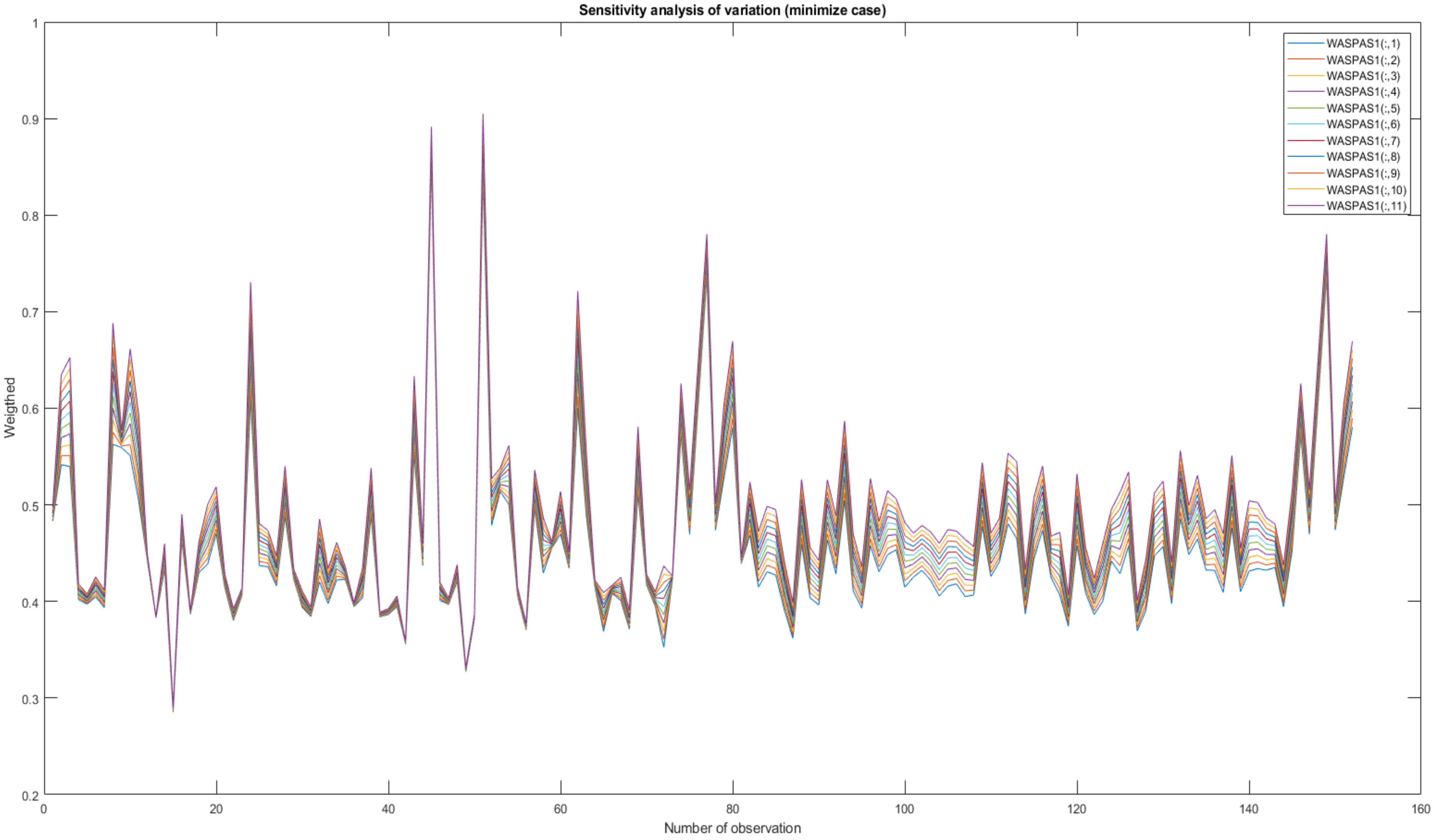


Figure 4.6 Variation in cost criteria

In Figure 4.5, the setup λ is clearly affected by the quality of the input. A higher adjustment in λ indicates the high quality of inputs. However, an increase in λ in Figure 4.6 does not always significantly improve the quality of the inputs. It must be noted that, irrespective of the adjustment level, the adjustment of λ in the input slightly inclines or maintains the output value. If the model reflects the realistic situation, then an increment/decrement in the rate at which any input variable may occur would certainly result in a relative increment/decrement in the rate of the output node. Given this, an inference reasoning of the model is the key to generating the threat-utility knowledge.

4.4 Discussion

Utility, preferences, and stakeholder behavior toward conditional seaport risk attributes in this study are interconnected concept that play a significant role in policy decision-making. In this chapter, the utility and preferences from the potential supply chain threat factor due to conditional seaport risk attributes are elaborated and explained into part-worth utility function (threat utility). Utility in this study refers to the benefit that the stakeholders derive from making a specific decision toward conditional seaport risk attributes. The increasing value of conditional seaport risk attribute is less benefit to the stakeholder and vice versa. Furthermore, the utility is a subjective measurement and varies from expert to expert based on their preferences, needs, and circumstances. The SSC stakeholders' utility is directly related to their preferences. When presented with different risk profile, the stakeholder will choose the alternative that maximize their utility – which means reducing the risk value – based on their preferences. The preferences of the SSC entities are influenced by factors such as personal experience, cultural background, and individual belief.

In risk analysis, the three concepts above are interconnected concepts that play a vital role in understanding how individuals or organizations make decisions in the presence of uncertainty and potential risks. Risk analysis involves identifying, assessing, and quantifying risks to inform decision-making. Utility in risk analysis refers to the subjective value or satisfaction that stakeholders associate with different potential outcomes or scenarios (potential supply chain threat in his study), taking into account their risk attitudes. It represents the stakeholders' preferences for different risk-reward trade-offs. Utility in this study is measured on an ordinal scale, where preferences are ranked but not quantified. In the meanwhile, preference in risk analysis relates to the ranking or ordering of different risky alternatives based on stakeholders' risk attitudes and subjective evaluations. Different stakeholders may have varying risk preferences, such as risk-averse, risk-neutral, or risk-seeking, which influence their decisions regarding the level of risk they are willing to accept. Furthermore, Stakeholder behavior in risk analysis encompasses the actions and decisions taken by individuals, groups, or organizations when dealing with risk and uncertainty. It includes how stakeholders respond to risk analysis results, whether they decide to mitigate, transfer, accept, or avoid certain risks (it is explained in Chapter 6).

Stakeholders' utility functions (individual threat utility function) underlie their risk preferences. Understanding stakeholders' preferences enables risk analysts to identify the relative desirability of different outcomes and evaluate the trade-offs they are willing to make in the face of uncertainty. For instance, risk-averse stakeholders may have diminished marginal utility for higher gains, leading them to favor more certain outcomes with lower risks. Stakeholders' risk preferences directly impact their risk management behavior. Risk-averse stakeholders are more likely to opt for risk mitigation strategies, such as implementing safety measures or diversifying investments, to reduce the potential negative impact of uncertain events. In contrast, risk-seeking stakeholders may be more willing to take on higher risks for the possibility of greater rewards. Stakeholder behavior in risk analysis is influenced by the perceived utility associated with different risk management options. If a risk management strategy is expected to increase stakeholders' overall utility by reducing the likelihood or severity of negative outcomes, they are more likely to adopt and implement that strategy. Furthermore, understanding stakeholders' utility, preferences, and behavior in risk analysis is critical for making informed decisions and developing risk management strategies that align with their objectives and risk tolerances.

In order to determine the impact of each potential threat factor on the satisfaction of SSC continuity, we present the partial utility corresponding to the conjoint measurement in Table 4.2. The threat utility models (partial utility) examine the correlation between two or more seaport risk attributes. The threat utility analysis starts with the 24 conditional seaport risk attributes extracted using the RSGA. The algorithm generates 24 risk factors from 153 evaluations of experts from three stakeholder categories—seaport manager, operator, and user. Based on the results obtained from the proposed model analysis, as shown in Table 4.3, the potential threats to disrupt SSC continuity originate from the 24 seaport risk factors. Referring to Equation (4.10), several seaport risk criteria are independent variables that affect the utility of the threat as dependent variables. This is depicted in Figure 4.3. In the final output, the threat factors are introduced as threat variables to estimate the disruption level of the SSCRD model.

In Table 4.2, it describes the parameters values for empirical equation from the results of the partial utility of each dependent variable, based on the distribution of SSCRD entities. The formula in the function column shows predictions of the seaport risk factors. As a result, the validation model of the final output in Equation (4.21) shows the weighted estimation of experts' judgement in Figures 4.7 and 4.8. We conduct the partial utility using the stepwise method, which allows the model containing significant predictor values to be obtained from the expert model individually in Table 4.3. Furthermore, the iterative least squares approach is used to estimate the regression coefficients. The utility concept and the error term in the iterative least squares method use expected mean squared error of prediction (EMSEP) by Rao (2014). The EMSEP measures the expected squared distance between the parameters of conditional seaport risk attributes predicts for specific value and what the true value is. It is thus a measurement of the quality of a predictor a_{ij}. The EMSEP is different with mean square error (MSE) where the EMSEP is a predictor of parameter and the MSE is an estimator of parameter. An example of an estimator would be taking the average height a sample of people to estimate the average height of a population. An example of a predictor is to average the height of an individual's two parents to guess his specific height. Furthermore, a higher R^2 (maximum value 1.00) indicates that the individual model in overall has high predictive ability. Hence, the SSCRD model is considered good to explain the empirical analysis of the SSC utility in Equation (4.16).

$$Y_{mn} = 1.33 + 26.7U(TF_1) + 9.9U(TF_2) + 32.2U(TF_3) + 10.9U(TF_4) + 28.0U(TF_5) + 12.8U(TF_6) + 26.2U(TF_7) + 19.4U(TF_8) + 20.9U(TF_9) + 24.4U(TF_{10}) \tag{4.21}$$

Table 4.3 Estimated utility of SSCRD factors

SSCR attributes	Estimated Utility						
	Overall	e_1	e_2	e_3	e_4	~	e_{153}
Constant	1.33	0.104	0.162	0.082	0.035	~	0.137
c_{14}	-0.05	0.155	0.242	0.123	0.052	~	0.204
c_{15}	0.05	0.155	0.242	0.123	0.052	~	0.204
c_{16}	0.05	0.155	0.242	0.123	0.052	~	0.204
c_{18}	-0.05	0.155	0.242	0.123	0.052	~	0.204
c_{25}	0.03	0.090	0.140	0.071	0.030	~	0.118
c_{26}	-0.03	0.090	0.140	0.071	0.030	~	0.118
c_{31}	0.01	0.168	0.262	0.133	0.056	~	0.221
c_{33}	-0.06	0.168	0.262	0.133	0.056	~	0.221
c_{34}	-0.03	0.168	0.262	0.133	0.056	~	0.221
c_{38}	0.01	0.218	0.340	0.173	0.073	~	0.287
c_{39}	0.07	0.218	0.340	0.173	0.073	~	0.287
c_{42}	0.03	0.090	0.140	0.071	0.030	~	0.118
c_{43}	-0.03	0.090	0.140	0.071	0.030	~	0.118
c_{54}	0.37	0.090	0.140	0.071	0.030	~	0.118
c_{5N}	-0.37	0.090	0.140	0.071	0.030	~	0.118
c_{61}	0.02	0.090	0.140	0.071	0.030	~	0.118
c_{64}	-0.02	0.090	0.140	0.071	0.030	~	0.118
c_{73}	0.33	0.090	0.140	0.071	0.030	~	0.118
c_{7N}	-0.33	0.090	0.140	0.071	0.030	~	0.118
c_{81}	0.25	0.090	0.140	0.071	0.030	~	0.118
c_{8N}	-0.25	0.090	0.140	0.071	0.030	~	0.118
c_{91}	0.01	0.120	0.186	0.095	0.040	~	0.157
c_{94}	0.02	0.140	0.219	0.111	0.047	~	0.184
c_{95}	-0.03	0.140	0.219	0.111	0.047	~	0.184
c_{101}	0.00	0.120	0.186	0.095	0.040	~	0.157
c_{102}	0.02	0.140	0.219	0.111	0.047	~	0.184
c_{105}	-0.02	0.140	0.219	0.111	0.047	~	0.184
R^2 coefficients	1.00	0.705	0.766	0.899	0.756	~	0.769

To facilitate fair comparison and aggregation of attributes in a conjoint study, we run normalization according to Equation (4.20). Normalization in conjoint analysis aims to ensure that the attribute levels of different attributes are on a comparable scale for statistical analysis and interpretation. Another goal is to observe the performance of the risk profile data set as input. The quality of input influences a model parameter in the threat utility function. This ensures that the relative importance of each attribute and the utility or preference associated with each level within an attribute can be accurately assessed. We compare two normalization cases, such min-max normalization (moderate case) and minimize normalization (cost-criteria case), to see how far the conjoint model sensitivity. In the moderate case, the parameter input of lambda affects the variation of attributes, yet not in the cost-criteria case, as shown in Figures 4.5 and 4.6.

As depicted in Figures 4.7 and 4.8, the moderate case also is more sensitive to the individual hybrid conjoint model in Equation (4.16) rather than a cost-criteria case. In Figure 4.7, the min-max normalization (moderate case) shows the biases due to differences in the magnitude of attributes. When the parameter lambda is zero, the data is distributed into two different kinds. However, when we set up the higher lambda, the distribution tends to be normal. On the contrary, the minimize (cost-criteria) normalization in Figure 4.8 shows less sensitivity to the estimation risk profile that the distribution remains the same for whatever we set up the lambda parameter. It means that the biases due to the differences in the attribute magnitude might arise and reduce the accuracy of the individual hybrid conjoint model. Thus, we select the min-max normalization to generate the conjoint model as shown in Table 4.3.

The Figure 4.4 shows that, in the Indonesian context, the seaport service process (TF_3) is the primary source of SSCRD. In other words, this tendency of SSCRD reduces the threat utility by 32.2% in the 100% utility estimation. This is followed by the relationship process threat (TF_5) and the planning process threat (TF_1) with 28% and 26.6% utility reduction, respectively. The three threats that cause less SSCRD are infrastructure threats (TF_2), distribution process threats (TF_4), and nuclear-enterprise financial threats (TF_2) with 9.9%, 10.9%, and 12.8% utilities, respectively. Moreover, the highest potential threat to SSC continuity originates from waterway congestion, congestion at the hinterland transfer, fewer services calling at port, a lack of port capacity, and a lack of IT and modern technology. The utility of these threats is estimated at about -6% to 7%. It means that these seaport risk factors have the potential to reduce the seaport-fulcrum supply chain operation and reduce its utility to around -6% to 7%. In line with this, Rahmanto (2016) examined some risk factors that directly contribute to congestion within terminals and waterways as well as hinterland transfer, which affects 63.9% of the relative importance of seaport development, implementation, and supply chain operation at Indonesia's seaport.

The second potential threat is the low motivation of distributors. This factors adversely impacts the relationship building process among the entities, at a reduced satisfaction level of 37%. For example, inefficient and inadequate marine security inspection at sea leads to operational delays and increases the liability under the contract of carriage. Overall, it leads to delayed delivery of goods (Komalasari and Purnamasari, 2021). The third potential threat is posed by the planning process. It is key to maintaining the continuity of the SSC operation. The SSCR attributes such as the ship, handling process, storage, and distribution risks' planning provide an estimated satisfaction of around -5% to 5%. This provides implication for planning the resilience in relation to an SSCRD. In fact, Siswanto et al. (2018) highlighted that the storage planning problem induces demurrage in the loading port and leads to a significant decline in the ship utility and an increase in its operational cost. Thus, it is essential to develop an integrated plan to ensure the resilience of the SSC operation.

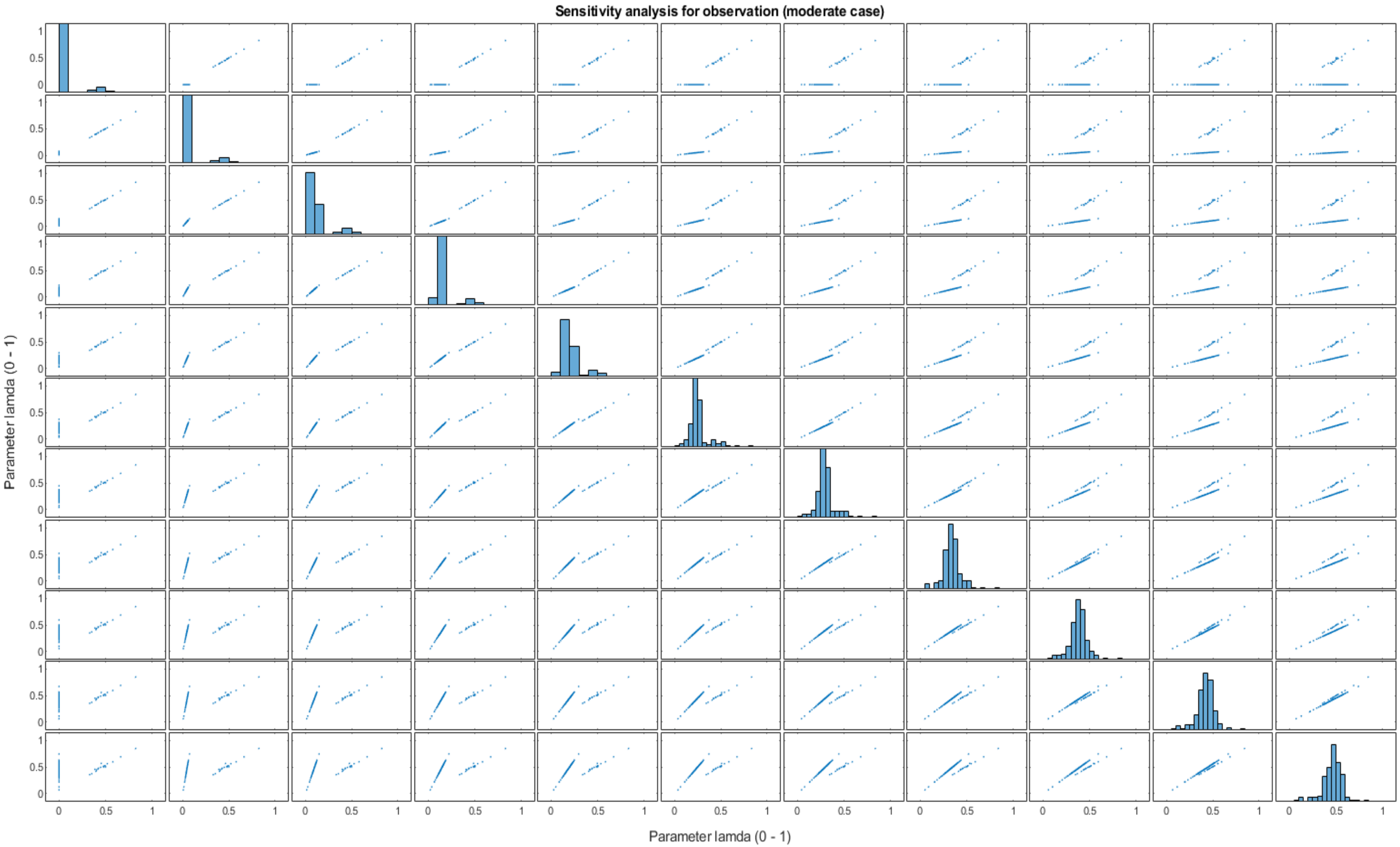


Figure 4.7 Distribution of moderate criteria

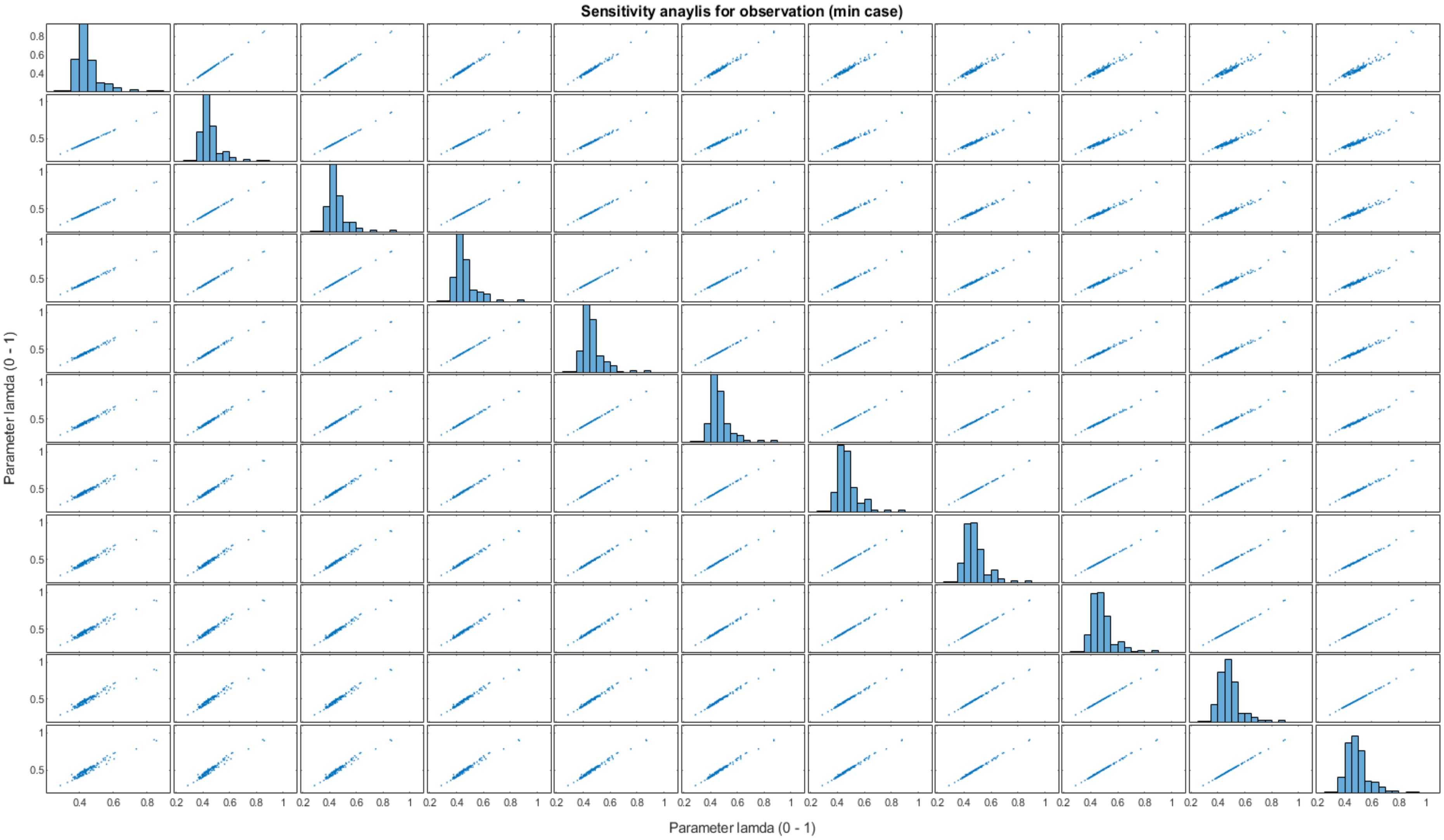


Figure 4.8 Distribution of cost criteria

In terms of the risk level, assuming the risk level *Z*. This level represents an escalation in threat utility from $z_{0.1}$ to the peak seaport risk level z_1 shown in the Figure 4.9. By introducing Equation (4.7), we can understand that some of the 24 conditional seaport risk underwent positive trend, while others experienced a negative trend. The positive trend of risk factors in Figure 4.9 contributes to an increase in the threat utility. It indicates that the conditional seaport risk attributes can be predictable. It also shows an increasing trend in the seaport-fulcrum supply chain operation and development, such as shipping activities and seaport activities, in the Indonesian context. However, it needs attention comprehensively from the seaport-fulcrum supply chain stakeholders.

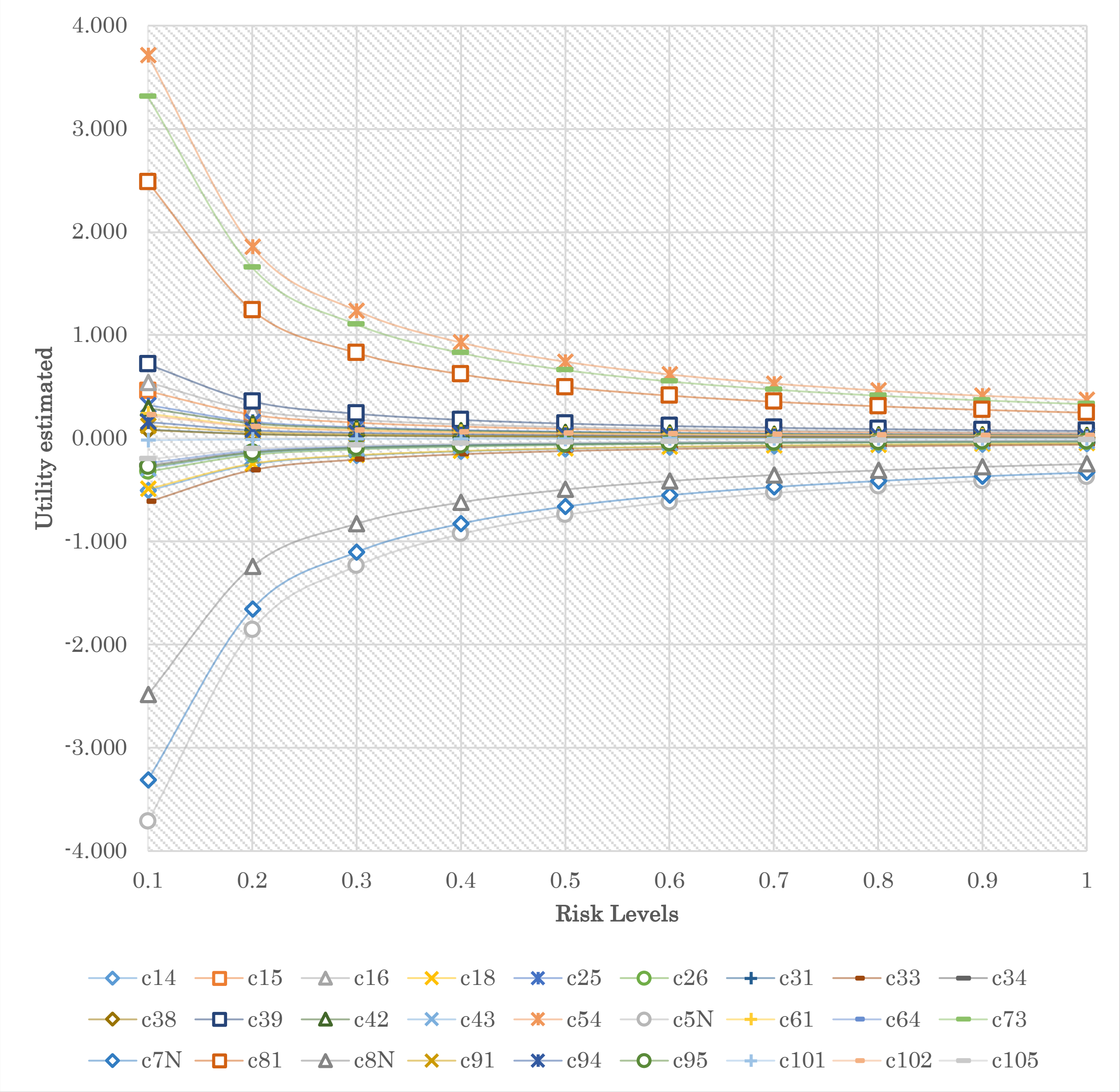


Figure 4.9 Trend of risk level toward seaport risk factors.

In the meanwhile, the negative trend from the others risk factors in Figure 4.9 indicates that the threat utility is declining when the risk level is increasing. Hence, the conditional seaport risk attributes significantly contribute to SSCRD and make the conditional seaport risk attributes more unpredictable.

4.5 Conclusion

In this study, the SSCRD model reveals that the 24 conditional seaport risk attributes are the central tendency risk factors play a key role in in the SSC operations. They impose ten potential threats that decrease the utility of the SSCRD model. In the Indonesian context, the key source of SSCRD is the ports' service procedure (TF_3). In other words, the SSCRD tendency lowers utility (satisfaction) by up to 32.2% in a 100% utility assessment. It is followed by the relationship process threat (TF_5) and the planning process threat (TF_1), with utility estimates of 28% and 26.6%, respectively. Infrastructure risks (TF_2), distribution process threats (TF_4), and nuclear-enterprise finance threats (TF_2) contribute less to SSCRD, with 9.9%, 10.9%, and 12.8% utilities, respectively.

As regards the level of risk, the utility of SSC exists when the SSCR peaks at the highest level. The highest level of SSCR attributes is maintained at the utility level of 1%-37%. The SSC utility of earthquake (a_{57}) is zero for the first time, in the robustness test in Table 4.3. It means that the utility this factor is 0 in its first occurrence. This negative trend points out that entities must simultaneously focus on planning, implementation, and development directed toward enhancing resilience.

This study also provides a new holistic framework to analyze the SSCRDs that disrupt the SSC operation, in relation to satisfaction. In relation to the threat utility, the study highlights the areas where each SSC operation can lead to supply chain disruption related the threat utility (potential threat). Given this, the study identifies a list of threat utility functions as indicators applicable to all the seaports in Indonesia. A limitation of this study is that the risk-level setting does not reflect the real situation of the dataset. Hence, future studies should consider another approach to discretize the real risk level, referring to this dataset. Moreover, the SSC stakeholders have different experiences and thoughts that are geographically diverse. Hence, it is possible to extract varied results from the RGSA. These variations might influence the findings on the threat utility.

CHAPTER 5: Interdependency patterns of potential seaport risk factors in relation to supply chain disruption

5.1 Introduction

In the context of global economic integration, seaports are key components of wider transportation systems, both within and between countries. Otherwise, the competitive position of seaport depends more on their role in the supply chain. Modern seaport organisations have thus become an important node in the globally integrated supply chain. In addition, their role has changed from transport or distribution centres to integrated logistics service centres. As an intersection of the global mobility chain of goods and people, ports have become a critical part of effectively and efficiently assessing and managing seaport-fulcrum supply chain risks (SSCR) (Loh et al. 2017), protecting people and the environment, and maintaining quality and performance. For instance, issues such as the giant ship blocking the Suez Canal due to high winds in 2021, and the pandemic-related ship backlog in Southern California resulted in severe shipment delays and significant financial losses (Notteboom et al. 2021).

Disruptive events at seaports affect various stakeholders and dimensions of the seaport supply chain. Identifying seaport risks involves understanding threats to the supply chain from disruptive events. Correctly identifying these risks contributes to the logistics industry by increasing seaport resilience and ensuring business sustainability. According to Shu et al. (2017), supply chain disruption risk carriers can be classified into two main types: macro-carriers and micro-carriers. Macro-carriers are mainly environmental, demand, and financial risks that cover events, market, and foreign exchange risks. Microcarriers can be divided into overt and covert carriers, and primarily concern internal risks such as with capital, cost, quality, technology, and information. Overt carriers include capital, information, and logistics, while covert carriers pertain to the bullwhip effect (Lee et al. 1997), financial leverage effect and the domino effect, among many others. Therefore, the risk assessment needs to include various elements related to the maritime industry and its supply chain system.

Some disruption-management activities that seaport enterprises conduct considerably influence seaport operators in Indonesian seaports and can be involved in supply chain disruption. According to statistics from the Inspectorate General Ministry of Transportation of the Republic of Indonesia (2014–2018), a total of 9,755 disruption management actions have occurred. Furthermore, cargo distribution imbalances, such as those due to infrastructure availability, shipping patterns, and the supply and demand of maritime transport, including port connectivity, between the western (developed economic region) and eastern (developing economic region) parts of Indonesia create challenges related to supply chain risk disruption, reduce the satisfaction level of seaport operation, and increase high logistics costs and price disparity between the two regions (Chapter 4). Moreover, these shipping costs affect the gross regional domestic product per capita in some developing economies due to the above-mentioned disparity.

Assessing the significance of seaports toward supply chain continuity in the past increases awareness of conditional risks and concerns to maintain its resilience. Therefore, the SSCR model proposed in Chapter 3 is defined as all activities of conditional seaport risk attributes that have the potential to threaten the supply chain continuity. Although various studies (Esteban et al. 2020; Jiang et al. 2018; Dewi and Purnamasari 2021; Loh et al. 2017; Morris 2020; Weng et al. 2020) have attempted to explain such a phenomenon, few studies have been conducted to describe interdependence patterns (degree) among conditional seaport risk attributes and identify the potential risks of these correlations. Therefore, the purpose of this study is to provide a procedure for evaluating the interdependence, implications, and associations among various seaport risk factors for supply chain threats by analysing current practices of Indonesian seaport operations in the developed economic region.

To reduce uncertainty and address the large number of risk factors in the dataset, this study employs the RSGA to examine the patterns between conditional seaport risk attributes. Furthermore, an output of the rough set generates the core attribute set, which is independent of the multiple reduction attribute set, taking into account the calculation of the degree of dependency of the rough set (Pawlak, 1991). The RSGA is then useful to separate the seaport risk factors into two categories - core (independent variables) and non-core (dependent variables) attributes - based on their degree of dependence on the rough set. Furthermore, the separation is assessed using a multivariate analysis of variance (MANOVA) to generate model interactions for both attributes. The purpose of the MANOVA is to test whether the vector of means of the seaport risk variables for observations of two or more groups are from the same sampling distribution. As a result, MANOVA is used to analyse the interaction between certain dependent variables and numerous predictors, and then to determine whether the interactions are significant for a linear combination of variables or for each variable separately. Accordingly, the regression risk model is used as the predictive model for SSCR attributes. Finally, the association rule learning is calculated according to the rough set model to explain the extent to which the degree of interdependence affects the implication degree of implication of the conditional seaport risk attributes. This comparison can provide insight into the potential conditional seaport risk attributes that can disrupt supply chain continuity.

5.2 Interdependency pattern based rough set

In general, an interdependency between two or more entities/factors is a correlation dependency between them. In recent decades, many studies have focused on the risk analysis of interdependencies between the critical infrastructure as a centre and other entities or factors. For example, Mota et al. (2016) investigated the impact of cascading failures in complex infrastructure systems that clearly affect the whole transport system, including its supply chain network. Understanding other risk factors, such as the mutual risk events between natural disasters and emergency risk planning, high logistics costs and price disparities, or other seaport disruptions with economic impacts, is as important as critical infrastructure correlation (shown in Chapter 3). In addition, Adiliya (2019) addressed the issue of high logistics cost and price disparity in Indonesian seaport operations. Amin et al. (2021) found that shipping costs are detrimental to per capita gross regional domestic product in some developing countries due to the above-mentioned disparity. While some of the developed regions in Indonesia are still struggling with dwell time, inefficient maritime security inspections at sea reduce the productivity of ships, leading to fees and contract cancellations, and increasing voyage costs (Dewi and Purnamasari 2021; Zaman et al. 2015; Komarudin et al. 2017). Amin et al. (2021) showed that the lower demand for containers due imbalance of cargo throughput in the developing regions of Indonesia leads to higher sea transport costs and maritime logistics and reduces port performance. Loh et al. (2017) revealed that the mismatch communication among stakeholders may be responsible for port strikes. They further stated that such an event can result in the inability to fulfil orders, breach of contractual obligations, negative impact on manufacturing, retail, and food industries, and delayed, duplicated or lost shipments of supplies, delayed shipments to customers, and inventory build-up.

The literature review above shows that seaports are increasingly integrated into the continuity of the supply chain, and therefore disruptive events originating from seaport can affect these entities. However, many supply chain risk identification and assessment models emphasise seaport infrastructure in terms of interdependency. Therefore, further research is likely to be needed to elucidate the interdependence between conditional seaport risk attributes and supply chain concerns, as well as their potential risks in terms of stakeholder preferences. Limited research has been conducted explaining the above phenomena of interdependence. Therefore, this study fills the research gap by providing an interdependency risk factor analysis of stakeholder preferences regarding risk management in seaport using the case study in Indonesia seaport.

Renowned for its capability in assessing imprecise attributes and facilitating knowledge discovery, RST is also valuable for establishing correlation dependencies among conditional seaport risk attributes. It proves crucial in uncovering the interdependencies between these risk factors. In essence, RST asserts that a set of attributes D is entirely dependent on another set of attribute's C, denoted as $D \Rightarrow C$, if all values of attributes in D are uniquely determined by the values of attributes in C. This functional dependency is further elucidated in Section 3.3.3.1. Through the utilization of Equation (3.9), we categorized the conditional seaport risk attributes into endogenous and exogenous attributes, establishing relationships among them in a predictive model. Consequently, a MANOVA was employed to assess the significance between these variables.

5.3 Model formulation

5.3.1 Interdependency evaluation using MANOVA

After the RSGA, we separated the conditional seaport risk variables into independent and dependent variables. Both were analysed using a MANOVA, and the procedures are shown in Figure 5.1. In this study, MANOVAs were used in two circumstances. First, we wanted to check some associated dependent variables from the seaport risk features in the single test to this collection of variables rather than multiple individual tests. Second, we aimed to investigate how independent factors impact certain response patterns of dependent variables. In this case, we used an equivalent of contrast codes on the dependent variables to test hypotheses regarding how the independent factors differentially predict the dependent variables.

The MANOVA was performed using IBM SPSS. The categorical data from the subjective preferences of seaport stakeholders shown in Table 1 were transformed into continuous data using a successive interval method (Mosier 1940; Edwards and Thurstone 1952). For the MANOVA, we performed a statistical test in a single attempt and checked whether it retained the characteristics of the dependent and the independent variables. If there was insignificance from the first attempt, we changed the original variables to other variables until we obtained significance for all features. In this way, we were able to predict the risk of supply chain disruption for the seaport fulcrum using the multiple regression function generated. The flowchart of the method is presented in Figure 5.1

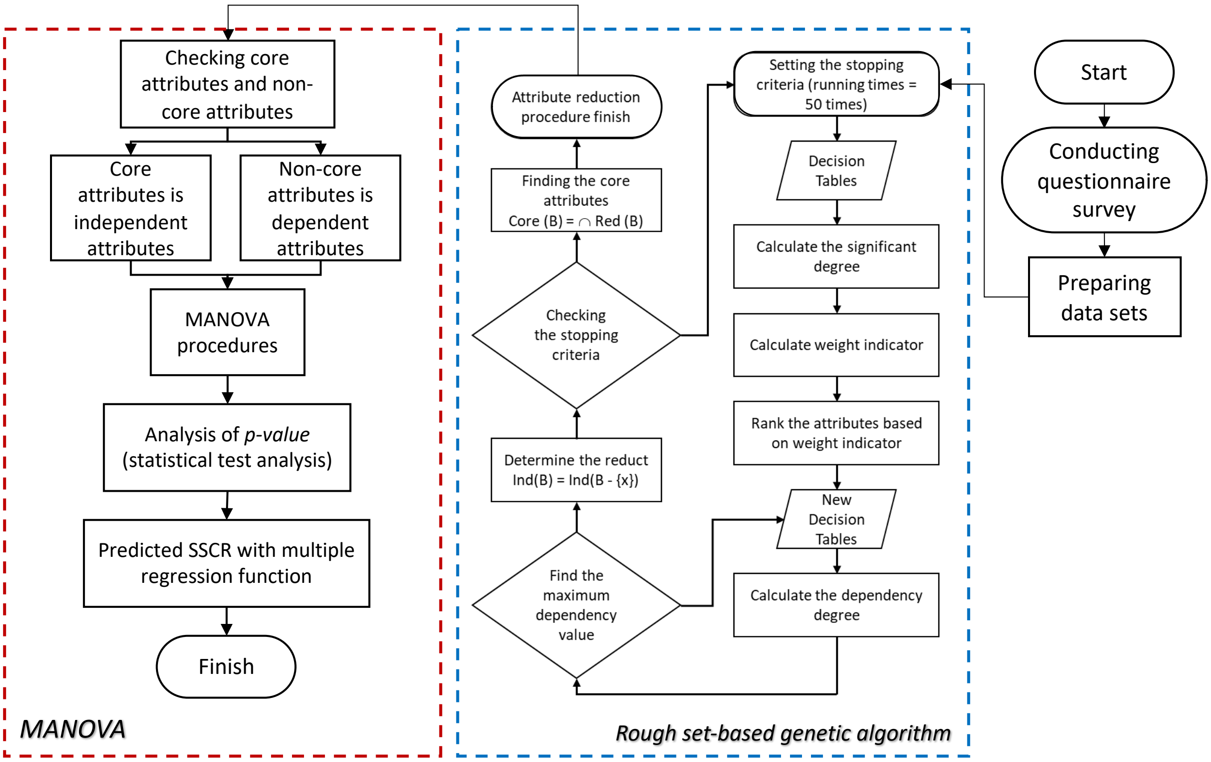


Figure 5.1 Flowchart of the method.

5.3.2 Rule induction for evaluation the potential risk

To analyse the potential risks for SSC disruption, we used rule induction according to Chapter 3 sub-subsection 3.3.3.5 Our basic assumption is that the datasets are presented as decision tables. As mentioned in Sub-subsection 3.3.3.1, the set of all cases is denoted by U, $U = \{1, 2, 3, \dots, 153\}$, and the conditional seaport risk attributes (features) are divided to denote conditional attributes (C_j) and decisional attributes (D_j). For attribute a and case x, $a(x)$ denotes the value of attribute a for case x. Hence, it can be generated as an equivalence relation using the rough set presented in Sub-subsection 3.3.3.1.

The elementary sets of the equivalence relation are based on partition $\{d\}$, which are referred to as concepts. Each concept contains five different risk levels according to Section 3.3.3.5. The set of all equivalence classes $[x]_B$ is a partition of U denoted by B^*. Thus, the definition of rule r is expressed as follows:

$$(c_1, v_1)\&(c_2, v_2)\& \dots \&(c_i, v_5) \rightarrow (d, w) \tag{5.1}$$

where $c_1, c_2, \dots, c_i$ are distinct attributes, d is a decision, $v_1, v_2, \dots, v_5$ are respective attributes values, and w is decision values.

A case (object) *x* is covered by a rule *r* if and only if any attribute value pairs of *r* are satisfied by the corresponding value of *x*. By this definition, we can determine some domains of the conditional seaport risk level (range of value) from both attributes respectively:

$$V_C = \bigcup_{c_i \in C} V_{c_i} \text{ for conditional attributes} \tag{5.2}$$

$$V_D = \bigcup_{d_j \in D} V_{d_j} \text{ for decisional attributes} \tag{5.3}$$

Based on Equations (5.1 – 5.2), we can obtain a foundation to determine a decision protocol. We consider the frequency of risk level in the simplicity of the analysis. Then, we can compute the decision protocol according to the risk level as follows: $V_{c_i}^1 \rightarrow V_{d_j}^1$ for the decision protocol highest risk, $V_{c_i}^2 \rightarrow V_{d_j}^2$ for the decision protocol high risk, $V_{c_i}^3 \rightarrow V_{d_j}^3$ for the decision protocol medium risk, $V_{c_i}^4 \rightarrow V_{d_j}^4$ for the decision protocol low risk, and $V_{c_i}^5 \rightarrow V_{d_j}^5$ for the decision protocol lowest risk.

The above assumptions are useful for computing degrees of interdependency (*coverage factors*) and implication (*certainty factors*). According to Chapter 3 subsection 3.3.3.5, *certainty* represents the conditional probability that deficiency itemset *D* will occur under the condition that deficiency itemset *C* occurs, which means the frequency of occurrence is found in the dataset as defined below. If the certainty is equal to 1, itemset *C* implicates itemset *D*, while if the certainty is between 0–1, an itemset *C* is dependent on the others to implicate itemset *D.* While *coverage* is defined as the ratio of the conditional probability of the occurrence of antecedent *C* and that of consequent *D* to the probability of the occurrence of antecedent *C*, as expressed below. Coverage can be used explain a decision class. Both degrees are denoted as follows:

$$cer_x(C;D) = \frac{|C(x) \cap D(x)|}{|C(x)|} = \frac{Supp_x(V_{c_i}^h \rightarrow V_{d_j}^h)}{|C(x)|} \tag{5.4}$$

$$cov_x(C;D) = \frac{|C(x) \cap D(x)|}{|D(x)|} = \frac{Supp_x(V_{c_i}^h \rightarrow V_{d_j}^h)}{|D(x)|} \tag{5.5}$$

5.4 Numerical illustration and analysis results

5.4.1 Evaluation of interdependency using MANOVA

We used a two-way MANOVA with an interaction parameter and examined the presence of interaction. The RSGA creates predictor features, while the remaining characteristics serve as dependent factors. Hence, we used a null hypothesis to test the significance of both variables as follows:

H0 : The dependent variables from the reduction algorithm have similar matrix correlations (variance–covariance) with the predictor features.

This study uses a significance level (alpha) of 0.05 indicating a 5% risk of concluding that an association exists when there is no actual association. This means if the *p-value* is less than the significance level, it can be concluded that the differences between the means are statistically significant. In the first attempt, we obtained four predictors and two dependent variables that were not statistically significant (*p-value* > 0.05). In the second attempt, the insignificant factors used as independent variables were switched to be dependent variables. However, variable a_{44} (bad defect condition of goods) remained non-significant with a score of 0.202 in the second try. A change is allowed if the significance test is below 5%. Thus, the variable was determined to be ineffective as a classifier and removed from the dataset. In Table 5.1, the orange-coloured shading indicates that a variable is not significant. Table 5.1 additionally presents a comparison of various predictor features and predicted factors. The dependent variables differ substantially from the independent variables, as demonstrated by a *p-value* of 0.05 in the statistical test.

Table 5.1 MANOVA results for between-subject effects

First attempt				**Second attempt**			
Dependent atts.	**Sig. test (*p-value*)**	**Independent atts.**	**Sig. test (*p-value*)**	**Dependent atts.**	**Sig. test (*p-value*)**	**Independent atts.**	**Sig. test (*p-value*)**
a_{1}	0.000	a_{4}	0.012	a_{1}	0.000	a_{4}	0.003
a_{2}	0.000	a_{5}	0.000	a_{2}	0.000	a_{5}	0.000
a_{3}	0.000	a_{6}	0.004	a_{3}	0.000	a_{6}	0.001
a_{7}	0.000	a_{8}	0.010	a_{7}	0.000	a_{8}	0.006
a_{9}	0.000	a_{14}	0.000	a_{9}	0.000	a_{14}	0.000
a_{10}	0.000	a_{15}	0.000	a_{10}	0.000	a_{15}	0.000
a_{11}	0.000	a_{17}	0.185	a_{11}	0.000	a_{19}	0.000
a_{12}	0.000	a_{19}	0.001	a_{12}	0.000	a_{20}	0.035
a_{13}	0.000	a_{20}	0.016	a_{13}	0.000	a_{24}	0.018
a_{16}	0.000	a_{24}	0.027	a_{16}	0.000	a_{25}	0.000
a_{18}	0.000	a_{25}	0.000	a_{17}	0.001	a_{27}	0.009
a_{21}	0.000	a_{27}	0.009	a_{18}	0.000	a_{28}	0.000
a_{22}	0.000	a_{28}	0.000	a_{21}	0.000	a_{37}	0.000
a_{23}	0.000	a_{37}	0.000	a_{22}	0.000	a_{39}	0.000
a_{26}	0.000	a_{39}	0.000	a_{23}	0.000	a_{47}	0.000
a_{29}	0.146	a_{42}	0.051	a_{26}	0.000	a_{51}	0.003
a_{30}	0.001	a_{47}	0.000	a_{30}	0.000	a_{55}	0.000
a_{31}	0.000	a_{48}	0.621	a_{31}	0.000	a_{57}	0.000
a_{32}	0.001	a_{51}	0.008	a_{32}	0.000	a_{58}	0.001
a_{33}	0.000	a_{54}	0.513	a_{33}	0.000	a_{60}	0.004
a_{34}	0.000	a_{55}	0.014	a_{34}	0.000	a_{61}	0.016
a_{35}	0.000	a_{57}	0.000	a_{35}	0.000	**21 variables in total**	
a_{36}	0.000	a_{58}	0.001	a_{36}	0.000		
a_{38}	0.000	a_{61}	0.006	a_{38}	0.000		
a_{40}	0.007	**24 variables in total**		a_{40}	0.000		
a_{41}	0.000			a_{41}	0.000		

a_{43}	0.000		a_{42}	0.000	
a_{44}	0.000		a_{43}	0.000	
a_{45}	0.000		a_{44}	0.000	
a_{46}	0.000		a_{45}	0.000	
a_{49}	0.007		a_{46}	0.000	
a_{50}	0.000		a_{48}	0.040	
a_{52}	0.000		a_{49}	0.004	
a_{53}	0.000		a_{50}	0.000	
a_{56}	0.031		a_{52}	0.000	
a_{59}	0.000		a_{53}	0.000	
a_{60}	0.112		a_{54}	0.000	
37 variables in total			a_{56}	0.007	
			a_{59}	0.000	
			39 variables in total		

5.4.2 Predictive model

Table 5.2 shows how the 39 conditional seaport risk attributes in this investigation depended on 21 predictor features. Hence, the significance levels were used to evaluate the relationship between the variables, and multiple linear regression analysis was used to build the predictive model. Moreover, the empirical equation from the predictive model of the relationships among seaport risk factors based on the distribution of SSC stakeholders is described in Appendix G, in which the first column shows the dependent variables followed by the intercept and the predictor features. The significance features of the predictors on the dependent variables are shown in Figure 5.2.

In Figure 5.2, a less efficient deviation cost significantly (a_{73}) contributes to the other 14 dependent seaport risk factors, followed by a shortage of IT and advanced technology (a_{39}) with 12 offshoots to other seaport risk factors. However, the 21 predictors did not significantly influence short sailing time to the other hub port (a_{81}).

Table 5.2 Predictive model of the conditional seaport risk attributes.

R^2	Adjusted R^2	Predictive model
0.50	0.42	$a_1 = 0.11 + 0.29a_5 + 0.17a_8 - 0.15a_{57} + 0.14a_{58}$
0.38	0.28	$a_2 = 0.25 + 0.22a_4 + 0.19a_6 - 0.20a_{15}$
0.42	0.32	$a_3 = 1.87 + 0.26a_5 - 0.28a_{14} + 0.29a_{15} + 0.18a_{19} + 0.36a_{25} - 0.19a_{37} + 0.24a_{47}$
0.41	0.31	$a_7 = 0.67 + 0.19a_6 + 0.25a_8 + 0.23a_{28}$
0.47	0.39	$a_9 = 0.02 + 0.20a_4 + 0.105a_{58}$
0.31	0.19	$a_{10} = 0.49 + 0.34a_{14} + 0.24a_{51}$
0.38	0.28	$a_{11} = 0.27 + 0.32a_{14} + 0.21a_{25} - 0.21a_{47} + 0.24a_{55}$

0.42	0.33	$a_{12} = 1.15 + 0.31a_{15} - 0.28a_{27} + 0.24a_{47} + 0.22a_{57}$
0.38	0.28	$a_{13} = 0.46 + 0.19a_{14} + 0.21a_{15} - 0.19a_{25} - 0.31a_{27} + 0.20a_{57}$
0.47	0.38	$a_{16} = 1.71 - 0.18a_{4} + 0.17a_{6} + 0.31a_{14} + 0.27a_{15} + 0.23a_{24} - 0.25a_{25} + 0.18a_{47}$
0.28	0.16	$a_{17} = 1.03 - 0.22a_{5} + 0.18a_{8} + 0.23a_{19} - 0.21a_{55}$
0.37	0.27	$a_{18} = 0.31 - 0.23a_{19} + 0.20a_{24} + 0.26a_{25} - 0.24a_{28} + 0.21a_{57}$
0.32	0.21	$a_{21} = 0.52 + 0.35a_{25}$
0.39	0.29	$a_{22} = 0.93 - 0.18a_{4} + 0.22a_{25} + 0.32a_{37} + 0.29a_{47} - 0.21a_{51} - 0.23a_{58}$
0.42	0.33	$a_{23} = 1.47 - 0.26a_{5} + 0.40a_{6} + 0.20a_{15} + 0.21a_{24} - 0.18a_{37} - 0.34a_{55} - 0.21a_{60}$
0.35	0.24	$a_{26} = -0.17 + 0.19a_{8} + 0.26a_{27} + 0.18a_{37} - 0.17a_{58}$
0.31	0.20	$a_{30} = 1.57 + 0.17a_{28} + 0.23a_{39}$
0.34	0.23	$a_{31} = 0.78 + 0.25a_{28} + 0.28a_{39}$
0.32	0.21	$a_{32} = 0.85 + 0.27a_{20} - 0.21a_{55} - 0.16a_{60}$
0.34	0.24	$a_{33} = 0.88 + 0.33a_{37}$
0.44	0.35	$a_{34} = 0.52 + 0.20a_{5} - 0.21a_{14} + 0.22a_{15} + 0.21a_{25} + 0.22a_{28} + 0.22a_{47}$
0.52	0.44	$a_{35} = 0.58 + 0.20a_{8} - 0.28a_{19} + 0.27a_{20} + 0.25a_{37} + 0.18a_{39} + 0.17a_{51} - 0.18a_{55}$
0.34	0.23	$a_{36} = 0.32 + 0.26a_{25} + 0.29a_{47}$
0.46	0.38	$a_{38} = 0.17 + 0.19a_{8} + 0.24a_{37} + 0.25a_{39} + 0.22a_{47}$
0.33	0.22	$a_{40} = 0.52 + 0.21a_{6} + 0.26a_{39} + 0.23a_{47} - 0.28a_{60}$
0.43	0.34	$a_{41} = 0.56 + 0.17a_{8} + 0.30a_{25} - 0.20a_{27} - 0.34a_{28} + 0.21a_{47}$
0.42	0.33	$a_{42} = -0.36 + 0.18a_{4} + 0.20a_{14} - 0.20a_{28} - 0.22a_{39} - 0.16a_{51}$
0.43	0.34	$a_{43} = 0.46 + 0.19a_{19} + 0.32a_{39}$
0.33	0.23	$a_{44} = 0.78 - 0.22a_{24} + 0.19a_{27}$
0.48	0.40	$a_{45} = 0.46 + 0.19a_{5} + 0.22a_{8} + 0.20a_{19} - 0.22a_{24} + 0.17a_{28} + 0.17a_{39} + 0.35a_{47} - 0.17a_{61}$
0.51	0.43	$a_{46} = -0.26 + 0.28a_{15} + 0.16a_{20} + 0.28a_{39} + 0.30a_{47} - 0.15a_{55}$
0.26	0.14	$a_{49} = 1.25 - 0.21a_{4} + 0.22a_{47}$
0.38	0.28	$a_{50} = 1.95 + 0.25a_{5} - 0.21a_{6} + 0.22a_{15} + 0.27a_{25} - 0.26a_{27} + 0.18a_{47} + 0.21a_{60} - 0.30a_{61}$
0.43	0.33	$a_{52} = 0.37 - 0.19a_{4} + 0.17a_{20} + 0.23a_{51} + 0.35a_{55}$
0.40	0.31	$a_{53} = 0.66 + 0.18a_{8} + 0.32a_{55} + 0.28a_{57} - 0.18a_{60} + 0.23a_{61}$
0.43	0.34	$a_{54} = 0.90 + 0.23a_{5} - 0.21a_{6} - 0.16a_{19} + 0.22a_{24} + 0.17a_{28} + 0.44a_{55}$
0.25	0.13	$a_{56} = 1.14 + 0.21a_{6} + 0.20a_{61}$
0.37	0.27	$a_{59} = 1.92 + 0.18a_{4} + 0.24a_{14} + 0.20a_{25}$

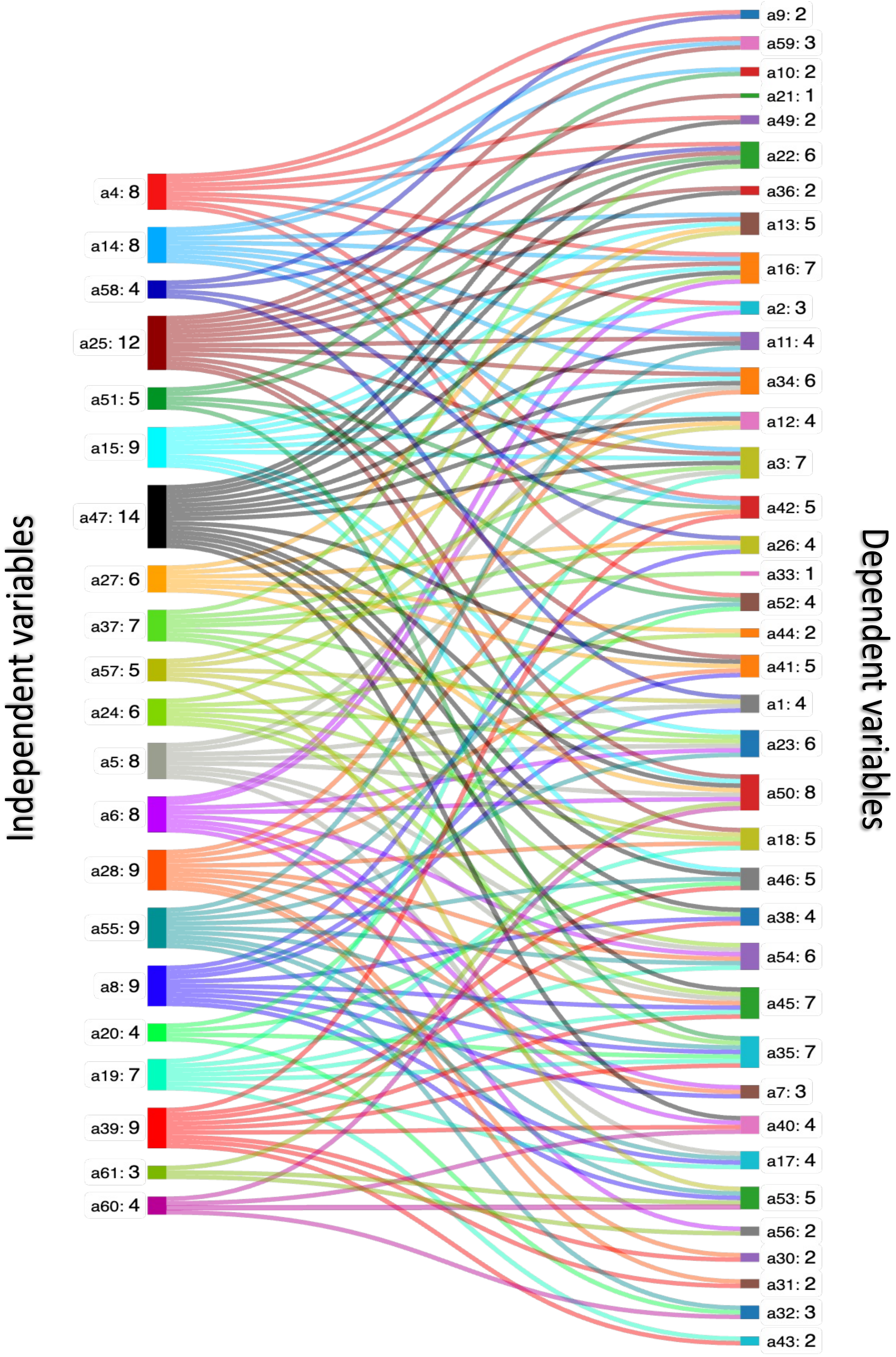


Figure 5.2 The significant relationships among independent variables.

5.4.3 Potential conditional seaport risk

The predictive model in Table 5.2 explains the correlation from the conditional seaport risk attributes towards the supply chain disruption. To conduct a better evaluation, we used association rule mining according to Sub-subsection 3.3.3.5 to find the potential risks in the predictive model. Association rule mining aims to find interesting associations (potential risk) among the features of a large dataset, referring to the parameters in Equations (5.4) – (5.5). The discovery of a potential risk that implies a single concept is referred to as an interdimensional association rule, since it contains a single distinct concept with multiple occurrences in the dataset. Therefore, we generated the decision protocol's highest risk to understand the potential risk of SSC disruption in the dataset.

Attributes of the decision table referring to Sub-subsection 3.3.3.1 are divided into two disjointed groups. Each object (*U*) induces a specific decision rule, which is the level of disruption according to Subsection 5.3.2. Furthermore, if a decision rule uniquely determines a decision in terms of conditional seaport risks, the decision rule is certain; otherwise, the decision rule is uncertain (shown in Chapter 3). In general, certain decision rules describe positive approximations of decisions in terms of conditional seaport risk attributes, whereas uncertain decision rules refer to the boundary regions of decisions. Hence, both definitions lead to two conditional probabilities parameters called the *certainty* coefficient and the *coverage* coefficient.

The certainty and coverage are compared in the scatter plot in Figure 5.3 to provide insight into the implication degree and interdependency degree, referring the decision protocol in the Subsection 5.3.2. The distribution of the conditional seaport risk attributes is provided in Appendix H. Looking at the distribution of seaport risk features, we plotted the position of each feature (marker) that refers to the centroid with hexagonal binning to create a scatter plot between the implication and interdependency degrees using IBM SPSS software. Thus, we obtained the results for potential risks, as shown in Figure 5.3.

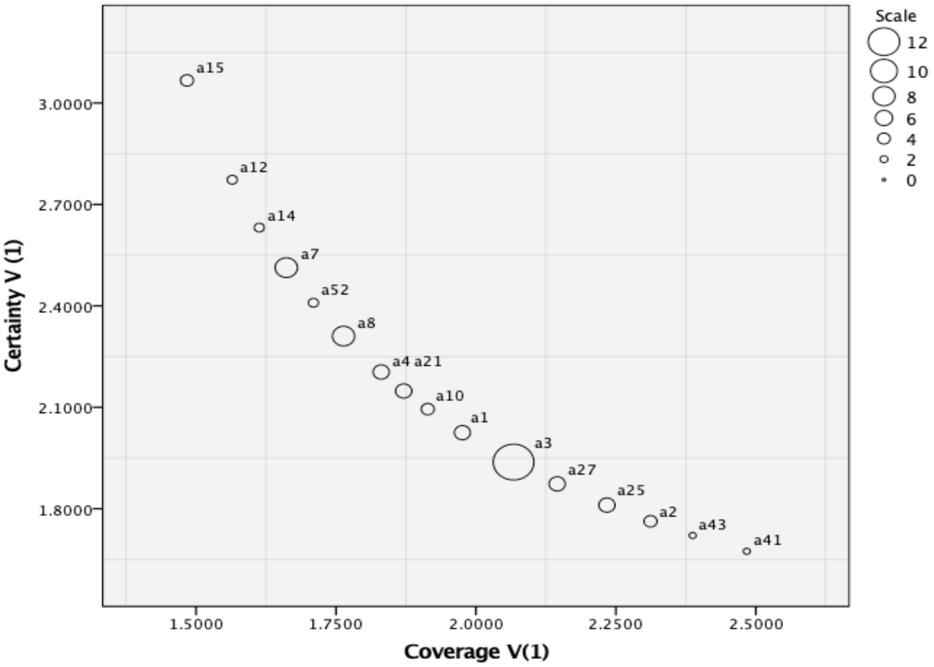


Figure 5.3 The highest potential risk of the SSCR.

In Figure 5.3, the certainty coefficient expresses the conditional probability of seaport risk factors that an object belongs to the decision class specified by the decision rule, given that it satisfies the condition of the decision protocols in Subsection 5.3.2. Thus, the higher the certainty coefficient, the greater the implication of the conditional seaport risk attributes for the specific decision class. Meanwhile, the coverage coefficient provides the conditional probability of consequence *(D)* for a given decision, which means that the more conditional seaport risk attributes *(C)* are associated with the decision protocols, the more interdependency occurred in the dataset. Thus, both parameters satisfy Bayes' theorem. Moreover, 15 features are considered to pose the highest potential risk to SSC continuity. The scale in the legend indicates the correlation referring to the interdependency and implication degrees. Breakdown of port information system (a_{15}) had the highest certainty but the lowest coverage degree, whereas low-efficiency operation (a_{41}) had the lowest certainty but the highest coverage degree. In the middle was lack of supply chain strategic risk planning (a_3), which had the highest correlation among the seaport risk features, referring to the decision protocol as the highest risk level.

5.5 Discussions

The interdependency pattern of this study was identified based on seaport risk features selection with RSGA and an assessment of their variance with a MANOVA. The potential risk was then obtained from each decision protocol of the risk level. Regarding the highest risk in the decision protocol, 15 features are considered to have the highest potential risk level, such as the lack of seaport-enterprise strategic risk (a_1); lack of berth risk planning (a_2), lack of supply chain strategic risk planning (a_3), lack of ship risk planning (a_4), lack of transfer risk planning (a_7), lack of distribution risk planning (a_8), port equipment breakdown (a_{10}), occupational accidents (a_{12}), breakdown of vessel traffic management systems (a_{14}), breakdown of port information systems (a_{15}), number of ship visits (a_{21}), shortage of IT and advanced technology (a_{25}), low punctuality of goods delivery (a_{27}), low-efficiency operations (a_{41}), less cash flow (a_{43}), and war or terrorist attacks (a_{52}). Therefore, the six potential threats are planning process threats (TF_1), infrastructure threats (TF_2), seaport service process threats (TF_3), distribution process threats (TF_4), nuclear-enterprise financial threats (TF_6), and security threats (TF_9), based on their potential risk in rule induction analysis.

Referring to the decision protocol highest risk ($V_{c_i}^1 \rightarrow V_{d_j}^1$), the predictive model generated four responses, including lack of seaport-enterprise strategic risk (a_1), lack of berth risk planning (a_2), lack of supply chain strategic risk planning (a_3), and lack of transfer risk planning (a_7), which are related to potential threats in planning process (TF_1). Meanwhile, the lack of ship risk planning (a_4) and lack of distribution risk planning (a_8) are independent variables in Figure 5.2 that can explain eight and nine dependent features, respectively. These relationships are depicted in the multiple regression model in Table 5.1. Our results show that the growing seaport-enterprise strategic risk (a_1) significantly increases by 29% for handling process risk (a_5), 17% for distribution risk (a_8), -15% for earthquake frequency (a_{57}), and 14% for pandemic/epidemic incidence (a_{58}). This is in line with Triantoro's (2020) explanation of the problem of distribution risk that can introduce more uncertainty in the strategic planning of supply chain entities. The main issue is related to the cost of moving trucking containers from the warehouse to the seaport. For example, the average trucking cost in Surabaya is around two million rupiah for an average distance of 68 km, which is half of the total cost spent from warehouse to seaport before being loaded onto a vessel (Subiyanto et al. 2015). This situation also occurs in Makassar, where the trucking charges reach close to two-thirds of the cost spent from warehouse to seaport.

Regarding the potential risk related to infrastructure threats (TF_2), port equipment breakdown (a_{10}) and occupational accidents (a_{12}) are the response variables, whereas the breakdown of vessel traffic management systems (a_{14}) and breakdown of port information systems (a_{15}) are predictor variables. Those factors are considered to pose potential threats that could disrupt supply chain continuity in Indonesia. Regarding the response variables, we found that earthquake and typhoon frequency impact the seaport component and occupational accidents. Similarly, Conca (2020) found that the loss of performance of seaport equipment due to an earthquake during a simulation could be significantly attributed to either direct damage or interdependencies (i.e. the domino effect). Furthermore, Notteboom et al. (2021) has shown that typhoon frequency is positively associated with all seaport risks, including jeopardization of seaport infrastructure. For example, the giant ship blocking the Suez Canal due to strong winds, disturbing the vessel traffic management system in 2021, led to severe shipment delays and substantial financial losses. In the Indonesian context, a climate event could clearly induce other risks to Indonesia SSC operations, such as risk related to seaport operations, shipping voyages, and shipping operations. The force majeure factor causes nine ship accidents per year that mainly affect vessel traffic management systems and IT and advanced technology and it relates with finding in Chapter 4.

Considering the congestion in seaport service process threat (TF_3), two factors have the highest potential risk for this supply chain issue: number of ship visits (a_{21}) and shortage of IT and advanced technology (a_{25}). Both factors clearly have a linear relationship, in which a one-unit decrease affects the technology shortage (a_{25}) by 35%. However, low punctuality of delivery goods (a_{27}) poses the highest risk that is significantly related to the distribution process threat (TF_4). As shown in Figure 5.2, the low punctuality of delivery goods (a_{27}) causes a cascade to six conditional seaport risk attributes. Such seaport risk factors occurred in Indonesia due to several issues. First, too many agencies are involved in maritime security with no clear division of responsibilities. Second, although most maritime security inspections should be conducted at port, merchant ships are commonly stopped at sea for inspection by maritime security agencies (Dewi et al. 2020). Hence, time loss due to the inspection at sea detrimentally affects ship operations in several ways, including by reducing the ship's productivity. Furthermore, we determined that the low punctuality of delivery goods (a_{27}) made claims and contract cancellation more uncertain, inducing higher costs for running ships.

In the potential highest risk related to nuclear-enterprise financial threats (TF_6), we found that low-efficiency operation (a_{41}) and less cash flow (a_{43}) result from five and two predictors of seaport risk factors, respectively, in Table 5.1. Both factors have significant implications for the transhipment process (shown in Chapter 4). Fahmiasari and Parikesit (2017) previously compared several routes according to journey costs for container shipping in Indonesia, such as the 'Nusantara Pendulum' and

‘Sea Toll-way’ and found the Sea Toll-way is 8% more efficient than the initial routes. However, both deviation and port costs have low competitiveness in North Maluku Province (Amin et al. 2021). This study’s results agree with the recent findings that most of the market shares in Indonesia’s container plan are more profitable in western rather than eastern Indonesia. Based on Table 5.1, both costs are significantly affected by the revenue of the seaport organisation.

5.6 Conclusion

This study used RSGA to identify features and MANOVA to assess correlations among conditional seaport risk attributes and their dimensional threats, based on questionnaires distributed to supply chain players in Indonesia. To evaluate the highest potential risk, a decision protocol using rough set rule induction was employed. The results showed that 39 conditional seaport risks are dependent variables predicted by 21 other conditional seaport risk attributes as independent variables. The 15 features with the highest potential risk levels were identified. This study provides an analysis of seaport operational deficiencies that can affect supply chain continuity in Indonesia using RSGA and MANOVA. The predictive models identify areas where port operations can disrupt the supply chain, offering a clear list of applicable indicators.

Moreover, regarding practical implications, the identification of seaport risk factors for supply chain threats aids supply chain industries, such as logistics and shipping, by enhancing operational resilience and ensuring business sustainability. The results can support the study of combined problems among conditional seaport risk attributes, and between many conditional seaport risk attributes, from the perspectives of seaport managers, seaport operators, and seaport users, providing insight into seaport risk management. Furthermore, the predictive model allows seaport managers to monitor the impact of seaport risk on seaport operational activities.

Lastly, seaport managers can use the list of indicators to regularly monitor activities and minimize supply chain disruptions. They should pay close attention to relational threat factors by collaborating with seaport users and authorities, especially where terminal designs cannot be easily revised. The monetary threat dimension, such as the disparity between western and eastern Indonesia, should be considered in more depth as it significantly impacts cargo throughput. The prediction and analysis of conditional seaport risk probabilities are conducted dynamically based on information shared between port authorities and shipping lines. This study incorporates different types of conditional seaport risks as key factors in the seaport risk resilience model.

This study also has some limitations, such as risk aversion analysis by SSC stakeholders, aggregated risk levels, and the representation of risk levels. The first problem might occur because of the uneven representation of respondents. Risk aversion analysis can only be performed if the data equally represent the SSC stakeholders. Different seaport locations and types of seaport activity could also produce diverse results related to risk aversion. The second and third issue are related to the possibility the RSGA could produce inconsistencies during the computation. Thus, future research can use a mathematical approach (e.g. fuzzy-rough set model) to more accurately express seaport risk levels.

CHAPTER 6: The risk appetite model to optimize acceptable risk and minimize revenue loss toward the utility estimation.

6.1 Introduction

In today's dynamic and competitive business landscape, organizations are constantly striving to strike a delicate balance between managing risk and maximizing revenue. The risk appetite model has emerged as a crucial tool in this endeavor, enabling businesses to optimize acceptable risk levels and minimize potential revenue losses (Kirkwood, 2004). This study presents a utility-based approach to risk appetite management, providing a framework for organizations to enhance their decision-making processes and achieve sustainable growth.

The importance of considering risk aversion in decision analysis has been highlighted in the literature (Kirkwood, 2004). While the ability to capture risk preference may not be a concern in all business decisions, ignoring risk aversion can lead to significant errors in some cases. Furthermore, the concept of risk appetite has been widely discussed, with various definitions and perspectives proposed (Aven, 2012). As mentioned in Chapter 2, the tolerance level for risk is influenced by the decision maker's risk appetite, which is classified into three types: risk-neutral, risk-averse, and risk-seeking. In supply chain management, risk-averse individuals tolerate only slight deterioration in the target values of an efficiency- or effectiveness-oriented goal, provided that an effectiveness- or efficiency-based goal is maintained or improved (Mauro et al., 2020)(Chen et al., 2007). On the other hand, risk-seeking decision-makers accept a higher degree of value deterioration in one goal in exchange for maintaining or enhancing an opposing goal. Risk-neutral supply chain managers do not show a preference for either objective type (Mauro et al., 2020)(Hung & Ryu, 2008).

Existing supply chain risk management frameworks have paid limited attention to the risk appetite of decision-makers (Griffis & Whipple, 2012)(Sobel & Turcic, 2008)(Wu et al., 2010)(Mauro et al., 2020). To the best of the authors' knowledge, developing a SCRM framework that accounts for the decision-maker's risk appetite in the context of interdependent risks within a network setting has not been explored in the literature. However, a recent concept in risk management research proposes integrating utility indifference curves into the risk matrix, which divides the matrix into five distinct zones: Negligible, Acceptable, Controllable, Critical, and Unacceptable (Ruan et al., 2015)(Pascarella et al., 2021)(Garvey, 2019).

However, it is unclear whether the utility indifference curves-based risk matrix concept, which was designed for evaluating independent risks, can be effectively applied to address interdependent risks (Ruan et al., 2015). While some recent studies have explored probabilistic supply chain risks to assess and manage interdependencies, the selection of optimal risk mitigation strategies has received limited attention in both the broader risk management literature and specifically within supply chain risk management (Griffis & Whipple, 2012)(Aqlan & Lam, 2015)(Ang et al., 2016)(Hou & Zhao, 2020). The primary challenge lies in advancing these studies to incorporate the risk appetite of decision-makers. Consequently, the central research question guiding this study is: How can a SCRM process be developed to integrate the systemic interaction between risks and the risk appetite of a decision-maker?

6.2 Problem description

In a scenario where a network of interdependent seaport risks is encountered instead of a set of independent risks, risks display positive or negative correlations with each other. A mitigation strategy may be linked to multiple risks, or multiple strategies may impact a single risk. Existing frameworks are unable to assess and manage such interconnected networks of risks. To address interdependent risks, marginalizing probability values by assigning conditional probabilities to the risks becomes necessary. The criticality of interdependent risks is not effectively articulated by current risk matrix-based tools. Furthermore, established criteria for performing cost-benefit analyses within the risk network and potential strategies are lacking, particularly in relation to the decision makers' risk appetite and the performance of individual risks on the risk matrix.

In the realm of risk treatment, simple mathematical operations are found to be inadequate. Each potential strategy or combination of strategies must be intricately connected to the risk network, leading to the re-evaluation of marginal probability values and the subsequent mapping of resulting risks onto a new dataset. This process thus becomes iterative rather than sequential. While EUT is widely used in decision-making under uncertainty, applying it to a network with even 5 risks and 5 strategies with binary states requires the elicitation of a large number of values (1024 values for 2^{5+5} combinations) from decision makers regarding the utility of different risk and strategy combinations. Additionally, practitioners often rely on risk matrix-based tools to prioritize risks, as indicated in the literature (Ruan et al., 2015, Subsection 2.3.3). Therefore, a method is proposed in Chapter 4 that modifies the utility indifference curves-based threat-utility approach and utilizes cost-benefit analysis to prioritize supply chain risk mitigation strategies, all while considering the risk appetite of decision makers.

6.3 Mathematical model formulation

Rather than addressing seaport risks in isolation, we introduce a novel concept by establishing the conditional seaport risk network. This process commences with delineating the context, defining the boundaries of seaport risks related to the supply chain/network, and identifying the stakeholders engaged in the risk management process, spanning Chapters 3 through 5.

Since much of the literature currently in publication uses conventional instruments and methods to identify risk categories, the identification of the risk network is a critical step that necessitates a change in strategy. The creation of causal risk networks or pathways has received little attention (Garvey et al., 2015). It goes beyond only identifying hazards and their sources to include potential techniques for risk reduction inside the network. Depending on the use of certain risk mitigation measures, the analysis of the risk network entails determining conditional probability values and loss values associated with hazards (see Chapter 3).

New risk measures that are simply computed, able to capture the network-wide effect of hazards, and take risk appetite into account are needed to be explored throughout the risk network's review stage. In addition to determining how risks affect the network as a whole, it's important to show how each risk affects it and make sure that all risks have been reduced to the necessary extent.

6.3.1 Assumptions

As the aim of our research is to introduce a risk management process for interdependent risks, the focus is placed on techniques for establishing the risk appetite of a decision maker. The procedure proposed by Ruan et al. (2015) can be employed for the implementation of the proposed process. Additionally, the probability and loss values are derived from the estimation according to Equation (4.16). Thus, the model is based on the following assumption:

- The SSCR, corresponding sources and potential mitigation strategies are given from Chapter 3 and Chapter 4. These can be modelled as a directed acyclic graph according to RST.
- All conditional seaport risk variables and risk mitigation strategies from the potential threat are represented by binary states.
- The probability risk values of the conditional seaport and associated losses can be elicited from the stakeholders and the resulting network represents a close approximation to the actual perceived risks and interdependency between different risks. This data is given from Chapter 4.

Thus, the SSCR network for this Chapter is identified by the five-tuple (5-tuples) $S = \{U, A, V_a, f, S\}$, that consisting of

- U is a finite set of decision-makers evaluation, $A = \{a_1, a_2, \ldots, a_n\}$ is a finite set of attributes (seaport risk), V_a is the value set of attribute a, where $V = 1, 2, \ldots, 5$ indicates the highest to the lowest evaluation, $V = \cup_{a \in A} V_a$, and
- A link is defined as a total function of $f: U \times A \rightarrow V$ such that $f(x,a) \in V_a$ for each $a \in A$, and $x \in U$ is called the information function. A string vector describes each object x of U. Thus, the description of x is expressed in terms of the evaluation of the attributes from A. It represents the available information about x, as shown in Equation (3.5) and Equation (3.6).
- S is a set of utility function. $S(x)$ with respect x of U.

6.3.2 Nomenclature

Referring the assumption in the Subsection 6.3.1, the notations used in the risk appetite model are shown in Table 6.1 as follows:

Table 6.1 The nomenclature of Chapter 6.

Sets and indices	
U	Set of observations, indexed by $x \in U$.
TF	Set of the threat related to revenue loss, indexed by $a_{ij} \in TF$ for all attributes
C	Set of conditional seaport risk attributes, indexed by $a_{ij} \in C_j$
V_a	Set of risk magnitude $\{1, 2, 3, \ldots, h\}$ indexed by $f(x,a) \in V_a$.
e	Set of decision-makers (stakeholders).
i	Index of possible threats, $i = 1, 2, \ldots, n$
j	Index of conditional seaport risk attributes, $j = 1, 2, \ldots, m$.
l	Index of decision-makers (stakeholders), $l = 1, 2, \ldots, q$.

Parameters	
α	The minimum required discrepancy level according to c_{ij}.
F	The sampling fraction (the ratio of sample size to the total number of stakeholders).
d_{ikj}	Discrepancy between threat *i-th* and *k-th* due to conditional seaport risk *j-th.*
Variables	
a_{ij}	The potential risk score of risk aptitude from conditional seaport risk *i-th* towards potential threats *j-th*.
$P_{qj\|s}$	The predicted probability of revenue loss of the *j-th* conditional seaport risk attributes by the *q-th* decision-maker in the sample under the scenario *s-th*.
$S(a_{ijq})$	Utility score of the *q-th* experts associated with *i-th* condtional seaport risk attributes for *j-th* potential threats.
Z	Potensial loss due to conditional seport risk factors

6.3.3 Formulation

The risk appetite risk model formulation is started with the problem from Ruszczyński (2013). Considering we have the set of conditional seaport risk attributes in relation with the supply chain threat and the set of the stakeholder, the risk appetite model is a static optimization model, in which the "revenue" $Z(x, a_{ij})$ is given and depend on decision variables x in space $\chi = R^n$, as well as on an elementary conditional seaport risk event a_{ij} in some probability space (C, D, S).

According to that, Let $A = \{A_1, A_2, ..., A_n\}$ be a given set of potential threat of the seaport-fulcrum supply chain (SSC) stakeholders $E = \{e_1, e_2, ..., e_q\}$ and the set of the condition seaport risk variables $C = \{C_1, C_2, ..., C_m\}$. The identification a minimal subset of the conditional seaport risk attributes $C_a \subset C$ referring to the experts (decision-makers) is important because it implies minimizing the potential lost of the potential threat. Moreover, all potential threat can be perfectly distinguished from each other according to the levels of conditional seaport risk attributes in C_a.

The main problem is to minimize the potential loss of revenue. The $Z(x, a_{ij})$ with respect to $x \in U$ and $x \in E$ is a feasible set. Due to the characteristic of $Z(x)$ is random, the risk appetite model deal also has random constraint. Hence, the objective in this model is expected value and the risk aversion is represented by a system of constraint. In addition, the stochastic parameters are represented in integer, thus, a mix integer linear programming is used to minimized potential loss of revenue from the minimum set under some rules.

The risk appetite model is presented as follows:

$$Min\ Z = \frac{1}{F}\sum_{e\in q}\sum_{i\in n}\sum_{j\in m} S(a_{ijq}) \cdot P_{qj|s} \cdot a_{ij} \tag{6.4}$$

subject to,

$$\sum_{i\in n}\sum_{j\in m} d_{ikj}a_{ij} \geq \alpha;\ \forall i,k \in \{1,\ 2,\ \dots,n\},\ i \neq k \tag{6.5}$$

$$where,\ d_{ikj} = \begin{cases} 1\ if\ c_{ij} \neq c_{kj} \\ 0\ if\ c_{ij} = c_{kj} \end{cases};\ \forall i \tag{6.6}$$

$$1 \leq \sum d_{ikj} \leq 5 \tag{6.7}$$

$$C_{\alpha} > 0 \tag{6.8}$$

The Equation (6.4) is objective function to minimize total loss from the threat-utility and estimation of predicted cost referring the SSC stakeholders. By minimizing Z, we try to reduce the impact of potential threats by possibly adjusting factors like the probability $P_{qj|s}$ and the severity $S(a_{ijq})$. The inclusion of the sampling fraction F scales this loss calculation based on the sample size, making the result representative of the full population or scenario. The entities of this supply chain model are divided into port-authority as q_1 – including seaport operator – and seaport users as q_2.

There are four constraints subject to the objective function. Firstly, constraints in Equation (6.5) and Equation (6.6) are measurement of the discrepancy between potential threat A_i and A_k in terms of the conditional seaport risk attributes. This can be interpreted as a minimum required level of distinctiveness between each pair of threats. In other words, for the risk assessment to be considered valid, the threats need to be sufficiently different in their risk profile as defined by the attributes. For decision-makers (from set e), this objective function could represent a requirement to ensure that each threat factor i is sufficiently distinct from each other threat factor k in terms of conditional seaport risk attributes. This distinctiveness is essential for prioritizing or categorizing threat responses effectively. If two threats were too similar (i.e., their discrepancy falls below α), it could imply a need to adjust the criteria for assessing threats.

Secondly, constraint in Equation (6.7) enforces a controlled range of discrepancy between pairs of threat factors, ensuring that there is a minimum amount of difference (at least 1) between any two threat factors and there is also an upper limit (no more than 5) to prevent extreme values that might skew the analysis. Furthermore, the constraint ensures that the total discrepancy between any two threat factors i and k across all relevant attributes falls within a balanced range. This balanced range prevents the threat factors from being too similar (lower bound) or too divergent (upper bound), likely supporting a more standardized or manageable assessment framework for decision-makers.

Lastly, constraint in Equation (6.8) is a level of discrepancy level we set up. This constraint has relation with Equation (6.5). In this case, it coincides with the number of conditional seaport risk attributes in C_0 that take different levels for the threat factors related to revenue loss TF_i and TF_k, and α is the corresponding minimum number, for any pair (TF_i, TF_k) of threat factor, that are required to have an acceptable subset C_{α}. This means that $\alpha - 1$ conditional risk attributes can be missing and we still can differentiate any pair of threat factor (TF_i, TF_k).

The estimation of threat-utility function (part-worth function) can be used to answer various “what if” questions, such as how will the revenue loss change for an existing policy of SSC stakeholders if its competing entities change its policy? What will be the change in market share? and Which conditional seaport risk attributes have big implications for the change? Hence, the aim of this model is to predict the conditional probability of seaport risk factors leading to the loss of revenue and getting acceptable risk from each conditional seaport risk attributes.

Therefore, the predicting revenue loss defined as the probability of choice of a seaport risk factors under some rules for each decision-makers in the sample. This probability based on the predicted utility computed according to the conjoint model in Chapter 4. There are two rules that used as constraint in this model according to Rao (2014) as follows:

$$\begin{cases} 1, \ if \ s_j \ is \ max(s_1, \dots, s_j) \\ 0, \ otherwise \end{cases} ; \ Sporadic \ rule \ case \tag{6.9}$$

$$\frac{s_j^{\alpha}}{\sum_{j \in m} s_j^{\alpha}} \ ; repetitive \ rule \ case \tag{6.10}$$

The constraint in Equation (6.9) is used to check non-routine risk or sporadic risk, while Equation (6.10) is used to check repetitive risk. Therefore, the additional constraint in Equation (6.9) and Equation (6.10) are used differently with an aim to check the acceptable risk of conditional seaport risk attributes under the risk characteristic. The sporadic and repetitive rule cases in Equations (6.9) and (6.10) are depicted the heterogeneous risk event. The characteristic of sporadic risk events is the conditional seaport risk attributes occurring at irregular intervals or only in a few places; scattered or isolated. While, the repetitive risk event is the conditional seaport risk attributes occurring repeatedly, especially when tiresome and lacking in variety. The model formulation in this chapter is built on Matlab 2022.

6.4 Solving method

6.4.1 Determining the utility value of risk attributes

The expected utility is given from the threat-utility function in Chapter 4. Within the context of decision making under uncertainty, risk can be related to a utility function that reflects the preferences of a decision maker with regard to various possible consequences of a decision. EUT posits that a decision-makers preference over an outcome x can be represented by a utility function $s(x)$, and if there are $i = 1, \dots, n$ potential threat of supply chain which occurs with probability p_i and which the outcome is x_i then the decision-maker (experts) cares about their expected utility $\sum_{i=1}^{n} p_i s(x_i)$.

When presented with a range of options, a decision maker will opt for the alternative that provides the maximum expected utility. The configuration of the utility function reflects the risk attitude of the decision maker: it is concave for a risk-averse individual, convex for a risk-seeking individual, and linear for a risk-neutral individual. Risk-averse decision makers would consistently prefer a certain option over a risky one with an equivalent expected value; conversely, risk-seeking individuals would reject a certain option in favor of a risky one with the same expected value. In essence, risk-averse individuals require compensation for undertaking risk.

6.4.2 Selection instance (potential revenue loss) problem

The basic idea is to estimate the threat-utility function of conditional risk factors that are considered by an individual and use certain rules to translate these utilities into threat probabilities. Rules (scenarios) of the predicted probabilities ($P_{qj|s}$) for each dimensional threat under some scenarios as mentioned in Equation (6.9) and (6.10). The selection instance problem is depicted in Table 6.2.

Table 6.2 Conditional seaport risk attributes associated with potential threat factors in Equation (6.4)

Experts	Potential threat	Conditional seaport risk attributes									Expected utility
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	
q_1	TF_1	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	$S(a_{ijq1})$
	TF_2	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}	a_{28}	a_{29}	
	TF_3	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	a_{36}	a_{37}	a_{38}	a_{39}	
	a_{ij} ; $C_a > 0$										
	TF_{10}	a_{101}	a_{102}	a_{103}	a_{104}	a_{105}	a_{106}	a_{107}	a_{108}	a_{109}	
q_2	TF_1	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	a_{16}	a_{17}	a_{18}	a_{19}	$S(a_{ijq2})$
	TF_2	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	a_{26}	a_{27}	a_{28}	a_{29}	
	TF_3	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	a_{36}	a_{37}	a_{38}	a_{39}	
	a_{ij} ; $C_a > 0$										
	TF_{10}	a_{101}	a_{102}	a_{103}	a_{104}	a_{105}	a_{106}	a_{107}	a_{108}	a_{109}	

6.4.3 Minimizing potential loss of the expected utility

The problem of "minimizing" in Equation (6.4) is based on Ruszczyński (2013). The risk appetite model adopt the random outcome *Z(x)* is related to another random outcome in constraints. Hence, the optimizing risk appetite model is based on the expected utility functionals as follows:

$$\min_{x\in E} E[Z(a_{ij})] \tag{6.11}$$

Considering model in Equation (6.11) with the usual stochastic order $\preccurlyeq_{(1)}$ and with the increasing convex order $\preccurlyeq_{(icx)}$. We focus on the latter because it is most convenient for modelling risk-averse preferences. Models with first order constraints are nonconvex, in general and frequently involve combinatorial considerations (Dentcheva and Ruszczynski, 2004; Luedtke, 2008; Noyan et al., 2006; Noyan and Ruszczynski, 2008). Hence, the problem in Equation (6.11) considering our model can be rewrite as follows:

$$\min_{x\in E} P_{qj|s}(S(a_{ij})) \tag{6.12}$$

subject to,

$$S(a_{ij})) \preccurlyeq_{(icv)} Y, x \epsilon E \tag{6.13}$$

in which the random function *S(.)* is convex (a.s.), and the set *X* is convex and closed.

This model (6.12) is a "cost/revenue loss" version of the model (6.11) with second order stochastic dominance constraints of Dentcheva and Ruszczyński (2004). Under suitable regularity conditions, Ruszczyński (2013) can prove that $\hat{x}$ is an optimal solution of this problem, if and only if a convex nondecreasing utility function $\hat{u}(.)$ exists, such that $\hat{x}$ is also a solution of the following expected utility problem:

$$\min_{x\in E} E\left[Z(a_{ij}) + \hat{s}\left(Z(a_{ij})\right) - \hat{s}(Y)\right] \tag{6.14}$$

The function above plays the role of a Lagrangian, with the utility function $\hat{u}(.)$ playing the role of the Lagrange multiplier. Corresponding duality relations can be developed as well. The EUT of and the dual utility theory (Ruszczyński, 2013), provide dual objects for stochastic order constraints. For problems with first order constraints, local optimality conditions can be derived, with the use of the Largangian functions (6.14), but with utility functions *s(.)* and rank-dependent utility functions *u(.)*, which are not necessarily convex.

6.5 Numerical illustration and analysis results

While the EUT offers a standardized normative framework for decision-making under uncertainty, its practical application is limited, primarily due to challenges in assigning utility values to all conceivable outcomes (Aven and Kristensen, 2005). In scenarios where a network comprises N risks, each with binary outcomes, the need to elicit 2^N utility values poses a considerable challenge, given the potentially extensive number of values. To address this issue, we propose a novel approach for assessing interconnected risks within a network using RST and a hybrid CA. Additionally, we employ Mixed-Integer Linear Programming (MILP) to minimize potential revenue loss in alignment with the principles of EUT. Moreover, numerical illustration aims at demonstrating the utility and relevance of the risk appetite model and solution methodology above in real context of Indonesian SSCRD. Details of the interconnected risk and EUT can be referred from Chapter 3 Subsection 3.2.2 and Chapter 4 Subsection 4.2.2 respectively.

As a brief information, the data in this study is categorical data wich each category are represented in Appendix B. To understand the bahaviour from each stakeholder, such port-authority and seaport-user, we can see the distribution or frequency from the conditional seaport risk attributes toward the observation groups, e.g. port-authority and seaport-user. The skewness of the observation groups is presented in Appendix Q. Overall the skewness for seaport-user is a balanced distribution which is indicated by the positive and negative deviations around zero (-0.5 and 0.5). It means that positive and negative deviations from the mean are equally likely and of similar magnitude. Whereas, there are higher positive and negative skew for port-authority. The positive skewness of conditional seaport risk attributes, such as lack of seaport-enterprise strategic risk, lack of berth risk planning, lack of supply chain strategic risk planning, lack of ship risk planning, lack of handling process risk planning, lack of storage risk planning, lack of transfer risk planning, deficiency of berth allocation risk planning, congestion within terminals, and shortage of facilities or equipment, indicated that these conditional seaport risk attributes are categorized as higher risk – where the mode of these factors are around two (see Appendix O). Moreover, the negative skewness for porth-authority, such as occupational accidents, collisions in the waterway, stowaway, smuggling, trafficking, and exchange rate, indicated that these conditional seaport risk attributes are lower risk.

Hence, this means that the seaport operations are less likely to experience significantly negative outcomes related the potential supply chain threat. Considering for the risk management, the focus may be on protecting against downside risks while seeking to averse on the potential for positive outliers. Additionally, the statistical descriptive from both stakeholders in Appendice O and P is explained as a brief information of the conditional seaport risk attributes. However, it needs to consider the implication conditional seaport risk attributes to supply chain threat factor by considering expected utility from the stakeholders.

There are ten-dimensional threats related average revenue loss in percent depicted in Table 6.3 were identified to diagnose the probability of potential revenue loss. Instead of following top-down approach, we developed the correlation network utilizes a bottom-up approach. The correlation network was developed and explained in Chapter 3 and the expected utility value (EUV) is generated from Chapter 4. The EUV of each decision-maker is shown in Figures 6.1 and 6.2. Some decision-makers were asked to fill out the questionnaire survey regarding the conditional seaport risk and ten-dimensional threat, while 17 (11%) experts as director in Table 3.3 was face to face interview to determine the conditional seaport risk attributes associated potential threat of supply chain disruption. Additionally, whole decision-makers were asked to estimate potential revenue loss associated threat factors. The average of this estimation is shown in Table 6.3 as follows:

Table 6.3 Potential supply chain threat and associated revenue loss

Supply chain threat	*Indices*	Average potential revenue loss (percentage)
Planning Process threats	TF_1	83
Infrastructure threats	TF_2	93
Seaport Service Process threats	TF_3	96
Distribution Process threats	TF_4	87
Relationship Process threats	TF_5	63
Nuclear-enterprise financial threats	TF_6	95
Monetary threats	TF_7	91
Location threats	TF_8	82
Security threats	TF_9	79
Environmental threats	TF_{10}	88

Furthermore, Table 6.3 together with the expected utility value from Chapter 4 becomes input in MILP. The expected utility value is divided into two categories such as, port-authority (PA) and seaport-users (SU). Both are depicted in Figure 6.1 and Figure 6.2 respectively. The model (6.4) was computed for each possible combination of potential revenue loss and the expected utility value was evaluated for each instance. Figures 6.1 and 6.2 plots the cost and expected utility combination for each conditional seaport risk attributes. If decision maker was targeting a particular cost of minimize revenue loss, they should choose the conditional seaport risk attributes that gives the highest expected utility for that cost. Thus, using MILP we got maximum potential revenue loss according to their expected utility value in Table 6.4. As references, we enclosed the information about risk level frequency according to port-authority (PA) and seaport-user (SU) in Appendices I and J respectively.

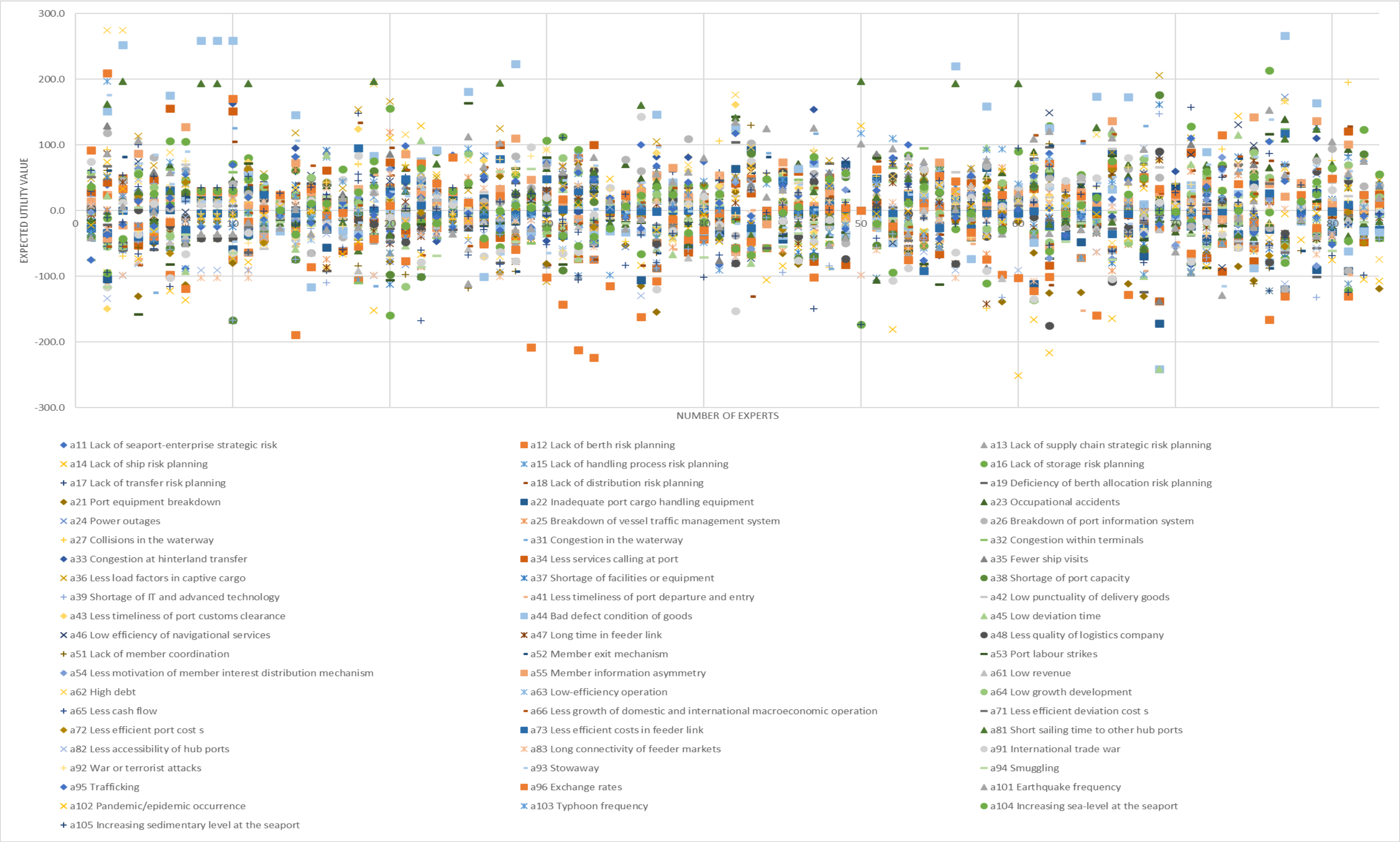


Figure 6.1 Expected utility value of port-authority

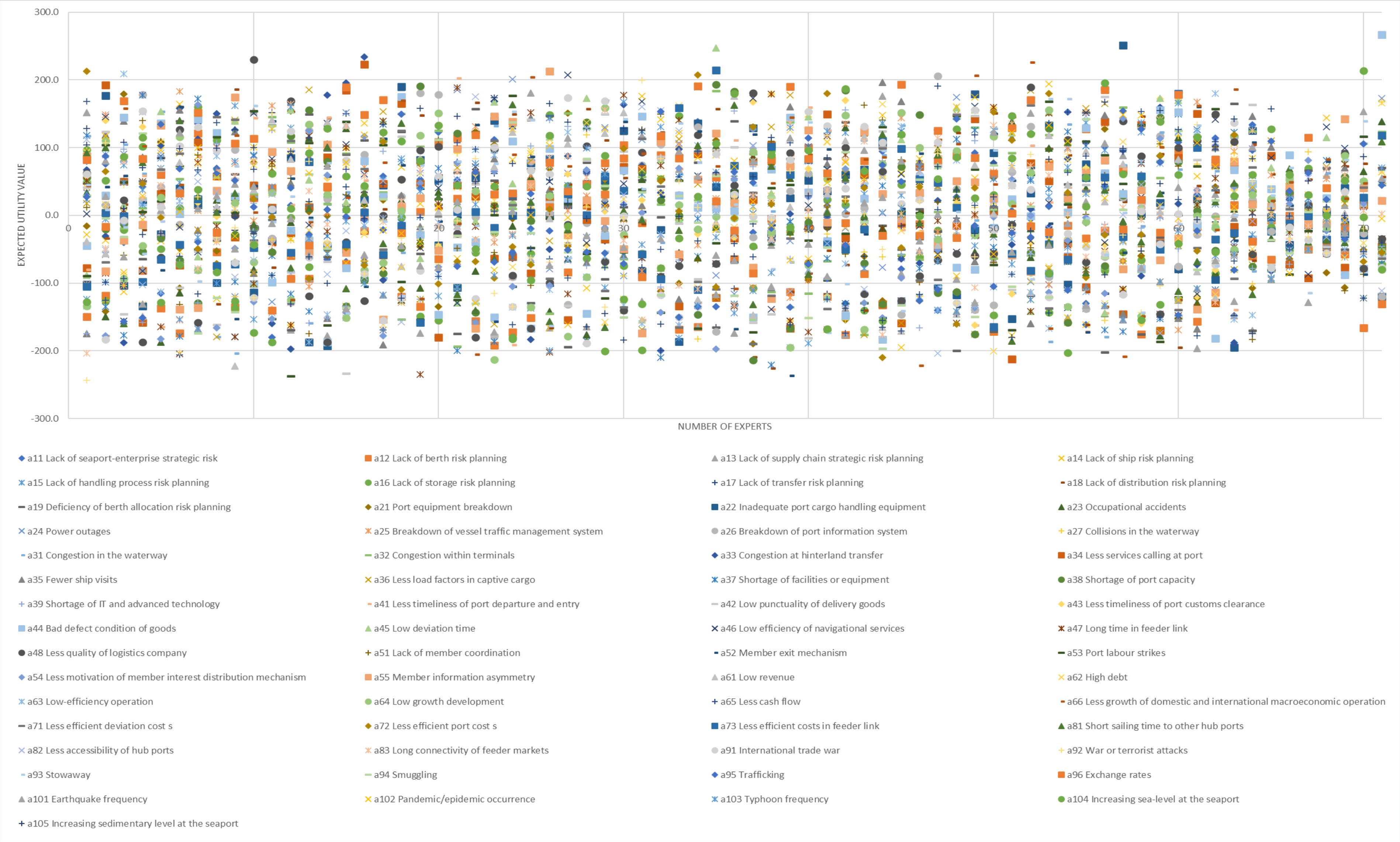


Figure 6.2 Expected utility value of seaport-user

Table 6.4 Potential revenue loss referring different scenario

	Rule 1		Rule 2	
	Port-authority (PA)	Seaport users (SU)	Port-authority (PA)	Seaport users (SU)
Percentage of potential revenue loss	-8.67	-7.12	-0.19	-0.17

In Table 6.4, there are two different scenarios showing that the potential loss from two different perspective such as, sporadic risk event and repetitive risk event. The negative sign in both rules indicates the sign for revenue loss. Furthermore, the result shows that the port-authority is more reluctant to experience with revenue loss rather than seaport user. The potential revenue loss is affected by different conditional seaport risk attributes. This is clearly depicted in Figure 6.3 and Figure 6.4:

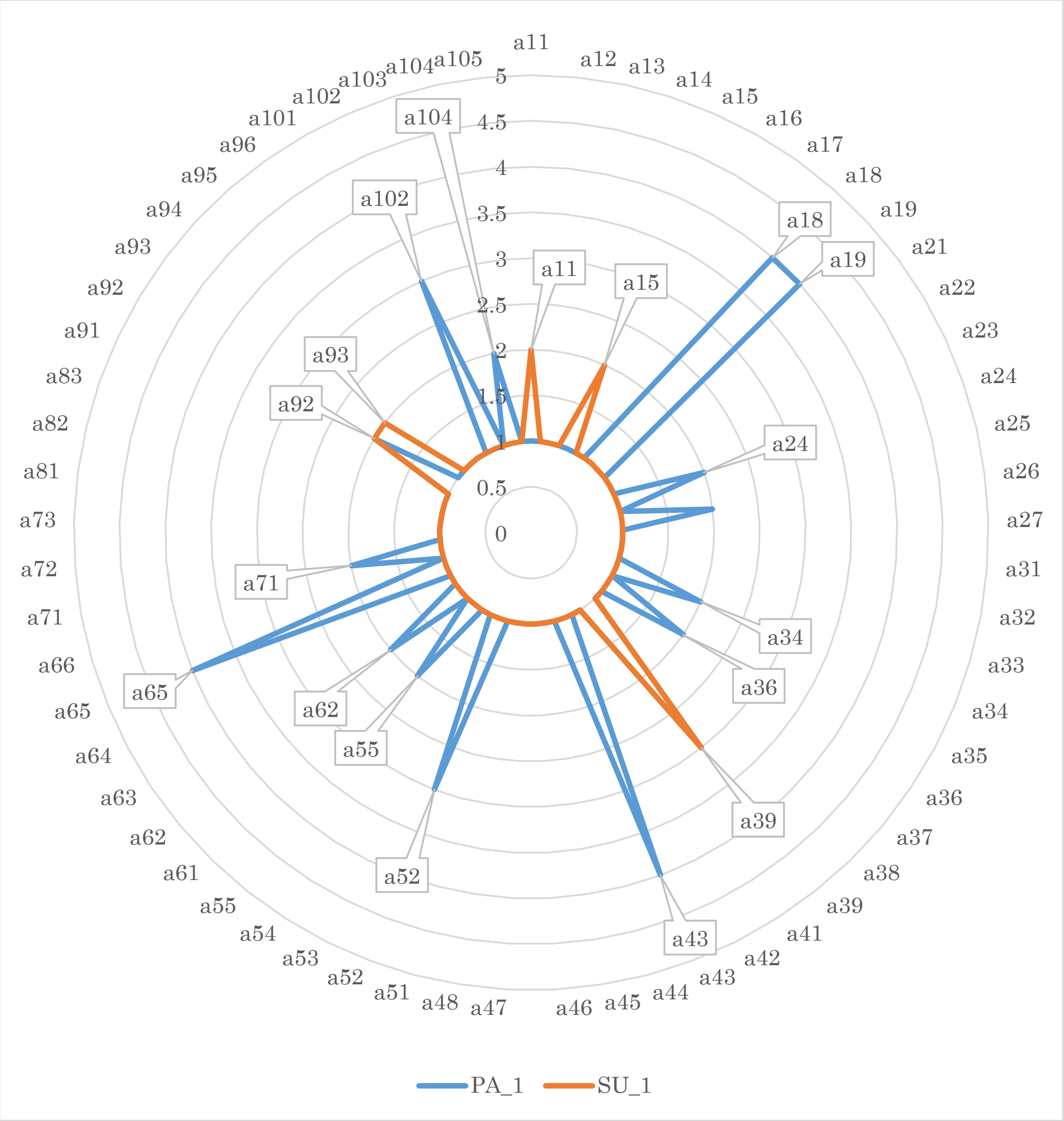


Figure 6.3 Acceptable risk of risk appetite model for sporadic case

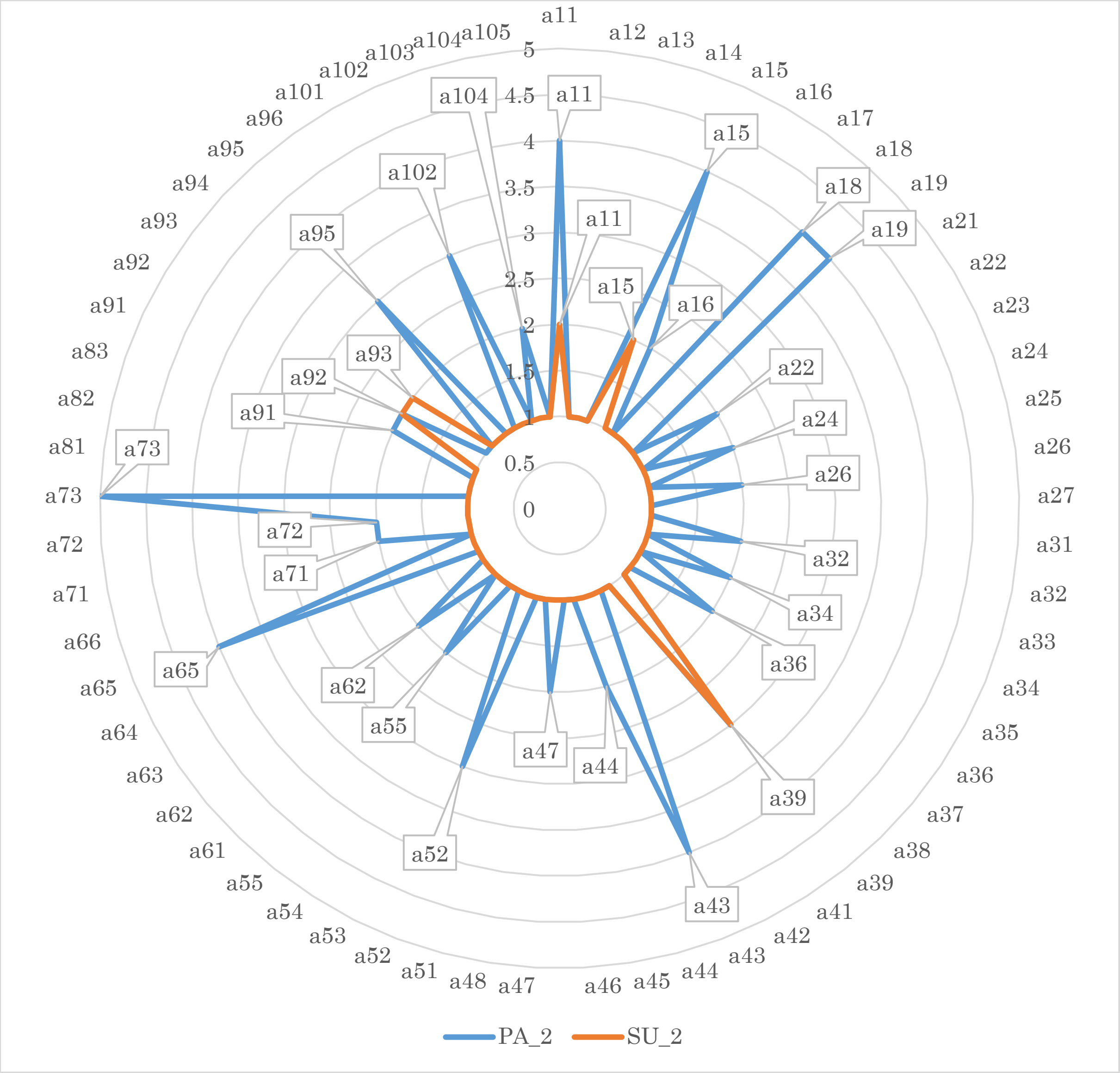


Figure 6.4 Acceptable risk of risk appetite model for repetitive case

If we assume the percentage of highest risk is between 0 – 20%, then every decreasing the degree of risk accepted is reduced 20% from the utility value. Lack of distribution risk planning (a_{18}), deficiency of berth allocation risk planning (a_{19}), less timeliness of port customs clearance (a_{43}), and less cash flow (a_{65}) are considered as the high risk to be acceptable risk until risk level 4 by port authorities (Seaport-management and seaport-operator) either in sporadic risk case and repetitive risk case. They indicate that the degree of risk accepted by the port-authority should not exceed 40% from 100% of their utility value. Meanwhile, whatever risk case for seaport-users, shortage of IT and advanced technology (a_{39}) should not exceed 60% of their utility value. Moreover, the highest unacceptable risk is less efficient cost in feeder link (a_{73}) for port-authority in repetitive case, which should be below 20%.

This analysis is resulted from MILP where the expected utility value (parameter) of decision-makers is translated into integer. This programming process is shown in Figure 6.5 until Figure 6.8. Furthermore, the bar in left hand side each figure indicates risk level. Furthermore, the result related risk level from each decision-maker is shown in Appendices K, L, M and N.

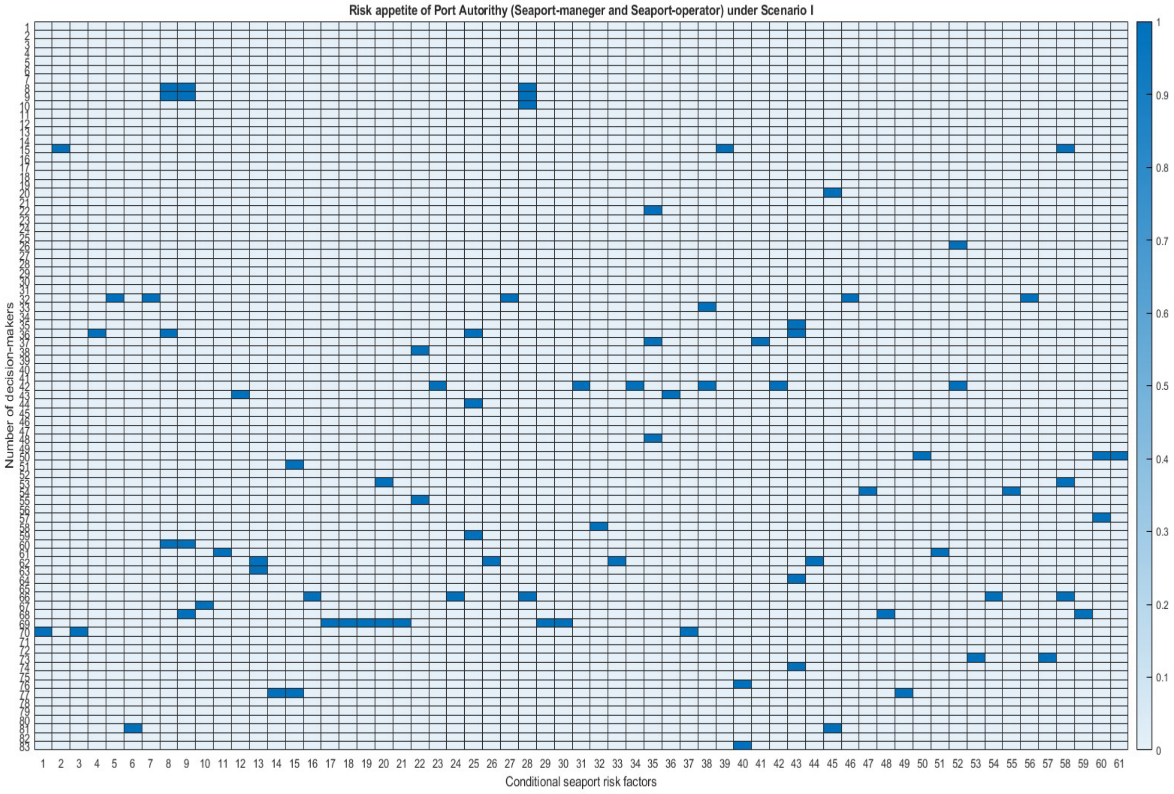


Figure 6.5 The results of MILP for port-authority under rule 1

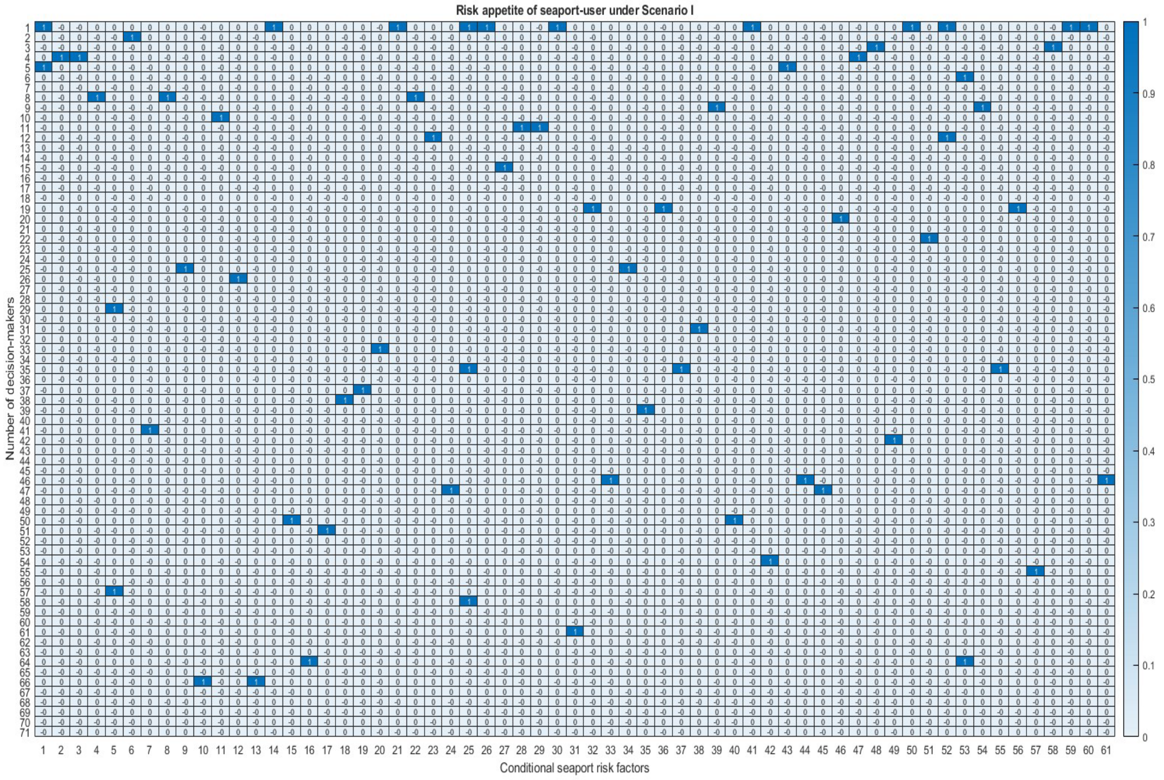


Figure 6.6 The results of MILP for seaport-user under rule 1

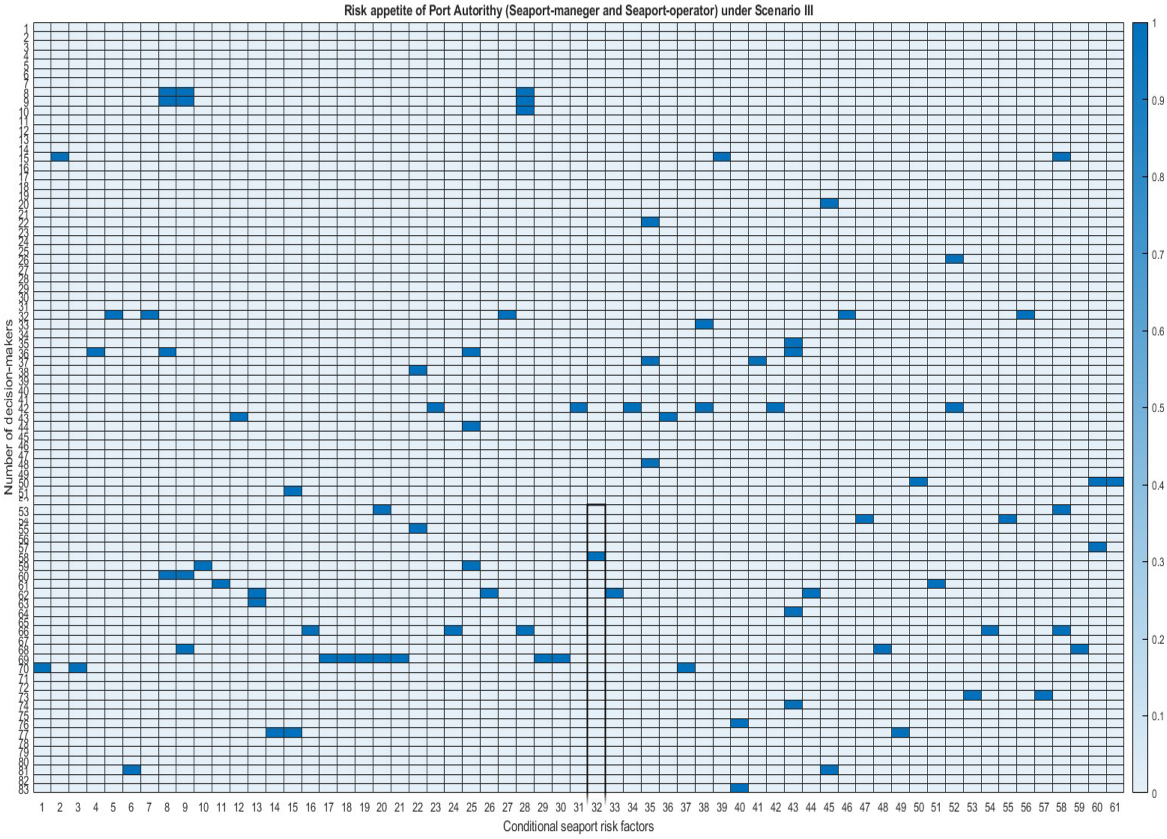


Figure 6.7 The results of MILP for port-authority under rule 2

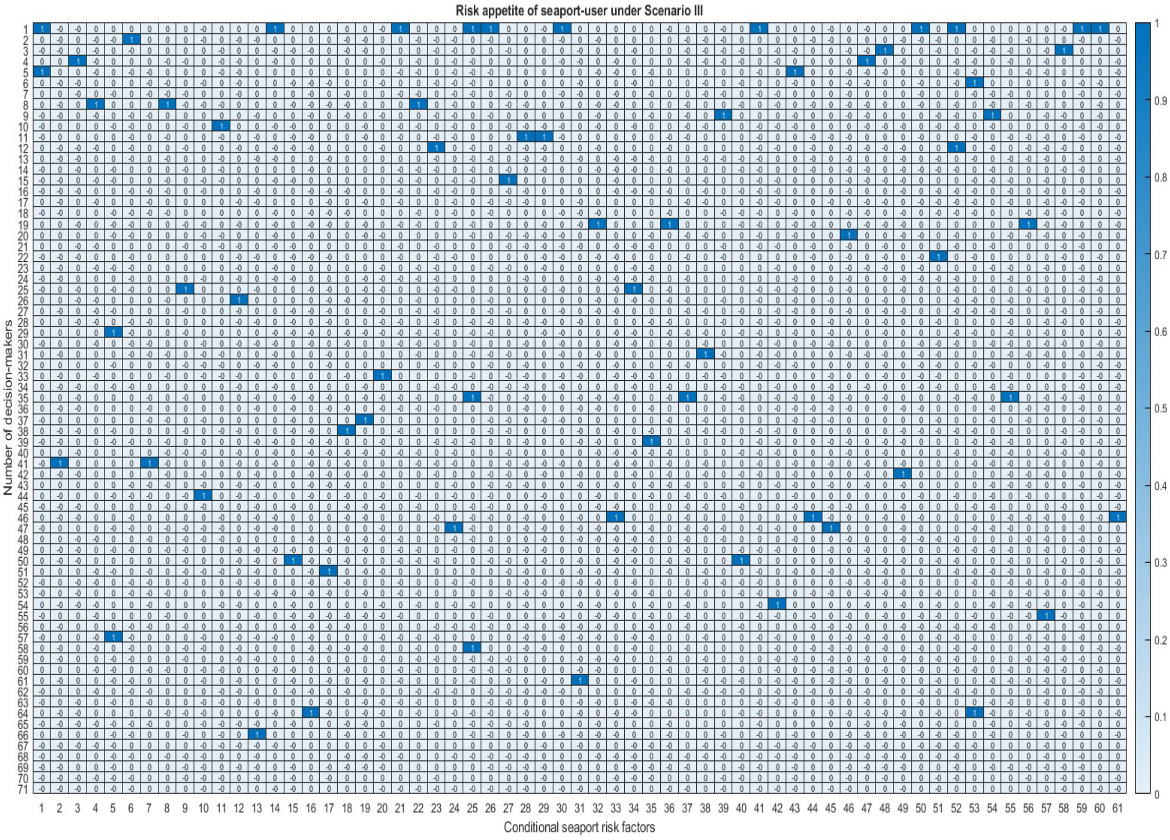


Figure 6.8 The results of MILP for seaport-user under rule 2

6.6 Discussions

In this chapter, it has correlation with Chapter 4 and together in this dissertation it presents the analysis about the utility, preferences, and stakeholders' behavior towards conditional seaport risk attributes related with potential supply chain threat factors. Stakeholder behavior is guided by preferences. Different stakeholders may have conflicting preferences or interests in a given situation. Their choices and actions will be influenced by what they perceive as maximizing their utility. For instance, in a business context, stakeholders might have different preferences regarding company policies or investment decisions, leading to diverse behavior. Furthermore, stakeholders' behavior can be influenced by the utility they expect to gain from a particular action or decision. If a stakeholder anticipates a high level of utility from a specific outcome, they are more likely to support or pursue it. On the other hand, if an action is expected to reduce their utility, they might oppose it.

In the context of risk management, the relationship between utility, preference, and stakeholder behavior becomes crucial for understanding how individuals and organizations make decisions when faced with risks. Utility in this study refers to the perceived value or benefit that stakeholders associate with the potential outcomes of a decision in the presence of risks. In this context, utility is not just about maximizing benefit but also about minimizing potential negative consequences. On the other hand, different stakeholders may have varying risk preferences, and their utility functions can differ based on their risk tolerance. Hence, preferences relate to the ordering of different risky alternatives based on stakeholders' advantages and disadvantages concerning the potential outcomes (potential supply chain threat) and associated conditional seaport risks. Furthermore, stakeholders may have different risk preferences, ranging from risk-averse (preferring more certain outcomes) to risk-neutral or risk-seeking (accepting more uncertainty for potentially higher rewards). As an impact, stakeholder behavior is influenced by their perceived utility and risk preferences. Stakeholders may decide to avoid, accept, transfer, or mitigate risks based on their utility assessments and risk tolerance.

Stakeholders' utility and risk preferences influence their risk attitude or risk appetite and decision-making. Risk-averse stakeholders, for example, are more likely to place a higher value on avoiding losses than seeking gains. On the other hand, risk-seeking stakeholders might be willing to accept higher risks for the possibility of higher returns. Stakeholders' risk preferences play a significant role in determining their risk management strategies. Stakeholders' utility assessments of potential supply chain threat with associated conditional seaport risks can drive their behavior in risk management. If a stakeholder perceives a particular risk as having severe consequences and low utility, they are more likely to take action to mitigate or avoid that risk. Conversely, if a risk is perceived as less critical or the potential rewards are high, stakeholders may be more willing to accept the risk.

In order to build risk mitigation strategies, this chapter present a model to depict the potential revenue loss in Table 6.4 as starting point and follow by understanding the acceptable risk according to the time of risk that the SSC entities should be anticipated. Moreover, the characteristic of risk-occurrence related time is presented, e.g. sporadic risk and repetitive risk case. Sporadic risk refers to a type of risk that occurs irregularly and unpredictably. It is characterized by being infrequent, occurring at irregular intervals, and lacking a clear pattern or trend. Sporadic risks are often unexpected and can be challenging to anticipate or plan for, making them difficult to manage effectively. Whereas repetitive risk, also known as recurring risk or continuous risk, refers to a type of risk that occurs repeatedly and consistently over time. Unlike sporadic risks that happen irregularly and unpredictably, repetitive risks display a clear and identifiable pattern or trend, making them more predictable and manageable.

In Table 6.4, the SSC stakeholders – such as port-authority and seaport-user – encounter a potential revenue loss of as much as 8.67% and 7.12% respectively in the sporadic case. Additionally, both stakeholders have similar potential revenue loss in the repetitive case which is 0.2%. This means that the port-authority can work as closely as possible with seaport-user under repetitive risk events (where the conditional seaport risk attribute consistently existed over time), while the corporation between both entities is difficult in sporadic risk events. By collaborating with each other, the SSC stakeholder can share their risk and together improve their productivity towards effective and efficient supply chain continuity. However, the corporation is less beneficial when facing the sporadic risk event from the conditional seaport risk attributes. Hence, each stakeholder has to put extra effort to control which the conditional seaport risk attributes give the higher score to the business operations (supply chain continuity).

Controlling the conditional seaport risk attributes to reduce the potential supply chain threat is meaningless. Because the risk in every business process is inevitable. Hence, the possible way is to allocate some resources and increase their performance to the conditional seaport risk attributes that give higher implications to the business process and let some conditional seaport risk attributes exist. This study proposed an analysis to calculate the acceptable risk (risk tolerance) that can help the decision maker from the SSC stakeholders to control the risk. In sporadic risk case, the port-authority can tolerate the lack of distribution risk planning (a_{18}), deficiency of berth allocation risk planning (a_{19}), less timeliness of port customs clearance (a_{43}), and less cash flow (a_{65}) until risk level 4. While the pandemics/epidemics occurrence (a_{102}) is only up risk level 3. Furthermore, the rest of the conditional seaport risk cannot be allowed to exceed risk levels 2 and 1 as presented in Figure 6.3. On the other hand, the higher acceptable risk of the seaport-user is only shortage of IT and advanced technology (a_{39}) which is until risk level 3, and the other risk should not over risk levels two and one. In repetitive risk case, the port-authority also can accept the lack of distribution risk planning (a_{18}), deficiency of berth allocation risk planning (a_{19}), less timeliness of port customs clearance (a_{43}), and less cash flow (a_{65}) until risk level 4 as well as less efficient cost in feeder link (a_{73}) until risk level 5. In the meanwhile, the acceptable risk (risk tolerance) of seaport-user is totally similar with the sporadic risk case. Accordingly, the port-authority in Figures 6.3 and 6.4 is more risk-seeking rather than the seaport-user which is risk-averse. Risk-averse stakeholders (seaport-user) may opt for conservative risk management approaches, such as buying insurance or implementing stringent safety measures to follow the changing policy. In contrast, risk-seeking stakeholders might take on higher risks and invest in projects with potentially higher returns.

6.7 Conclusion

Although there are many quantitative tools available for SCRM, there is a notable lack of a complete framework that covers all phases of the risk management process and takes into consideration the interdependent effects of common risk triggers and the risk preferences of decision-makers. Current frameworks tend to concentrate on maximizing a single goal or performance metric, often ignoring the intricate trade-offs between revenue loss and related goals, including supply chain risk management. Another essential component that is missing is the empirical assessment of these frameworks to determine their advantages and disadvantages in terms of practical application, especially with regard to tools that take interdependencies into account. An integrated SCRM approach has been developed and used in a case study inside the Indonesian SSC setting in order to solve these gaps. To operationalize the suggested method, a variety of techniques have been modified and combined, such as multi-criteria decision analysis, conditional seaport risk characteristics, and decision-making under uncertainty.

To sum up this chapter, we found that port-authority, including seaport-operator, have more tendency to commit the conditional seaport risks rather than the seaport-user either sporadic case or repetitive case. It is indicated that seaport-users rely on the policy from port-authority. Furthermore, the potential revenue loss in sporadic risk event case is more severe when occurred, where the port-authority is impacted most significant with percentage 8.67% while seaport operator is 7.12%. In the sporadic case, the unacceptable risk for port-authority is from the lack of distribution risk planning (a_{18}), the deficiency of berth allocation risk planning (a_{19}), the less timeliness of port customs clearance (a_{43}), and the less cash flow (a_{65}) with category high risk. Whereas the seaport-user is only considered the shortage of port capacity (a_{38}) with category medium risk. Meanwhile, in the repetitive case, the unacceptable risk for port-authority is the less efficient costs in feeder link (a_{73}) with category highest risk that give revenue loss as many as 0.19%. The shortage of port capacity (a_{38}) with category medium risk in addition is considered by seaport-user for 0.17% of the revenue loss. Therefore, seaport-users in general are the risk-averse decision makers referring both cases. While the port-authority (including seaport-operators) are the risk-seeking decision makers.

CHAPTER 7: Conclusions

7.1 Seaport-fulcrum supply chain risk management in perspective

A novelty of this dissertation addressed a new framework in SCRM applicated to the seaport. It is named the seaport-fulcrum supply chain risk (SSCR) model. The model consists of ten potential threats of the supply chain disruption and each potential threat source from 61 conditional seaport risk attributes, such this clearly depicted in Figure 1.3 and Table 3.4 respectively. For better understanding, a block diagram is presented in Figure 7.1 which manifests the methodological contribution of this dissertation to the established risk management process.

The SSCRD model in Figure 7.1 analyzes three factors: potential threats, risk conduction, and risk appetite. This comprehensive approach helps SSC stakeholders identify, assess, and mitigate risks in seaport operations. The potential threat component focuses on operational risks that can disrupt supply chains. The risk conduction component examines how seaport risks can propagate and amplify disruptions through the supply chain. The risk appetite component evaluates the port stakeholders' ability to manage these risks, considering factors like financial resources, organizational resilience, and external support. Understanding the port's capacity to withstand and recover from disruptions is crucial for developing effective risk mitigation strategies.

The RSGA in Chapter 3 was first used to find the causal relation between conditional seaport risk attributes and the potential threat to the supply chain. The higher dependency degree in the correlation network is then classified as core attributes. Moreover, the core attributes owned higher dependency degree among the conditional seaport risk attributes were used to determine the expected utility function, namely the threat-utility function. Threat-utility function in Chapter 4 indicated a potential threat to the supply chain due to the core attribute set of conditional seaport risk attributes in the Indonesian context.

In a feasibility study, we believe that the seaport risk variable can induce other conditional seaport risk attributes. Thus, we investigated the phenomena using MANOVA and RST in Chapter 5. RSGA was used to determine whether conditional seaport risk attribute sets are dependent or not. After that, we introduced the null hypothesis to check the significance between independent attributes and dependent attributes. The null hypothesis is also used to understand the relationship between endogenous and exogenous among the conditional seaport risk attributes.

Lastly, the potential revenue loss from the estimation of the decision-maker was computed by MILP to understand the implication of conditional seaport risk attributes in Chapter 6. This process consisted of two input data such as expected utility value and average of revenue loss-related supply chain threats factors. The expected utility captures the advantage and the significance of conditional seaport risk attributes, while the estimation of revenue loss is defined as relative importance. By selecting some conditional seaport risk, we highlight the higher implication related to revenue loss and minimizing revenue loss in percentage. The different percentage among the SSC entities in relation to revenue loss helps us to understand the behavior of the stakeholder and also which conditional seaport risk attributes significantly contributed. This is called the risk appetite model.

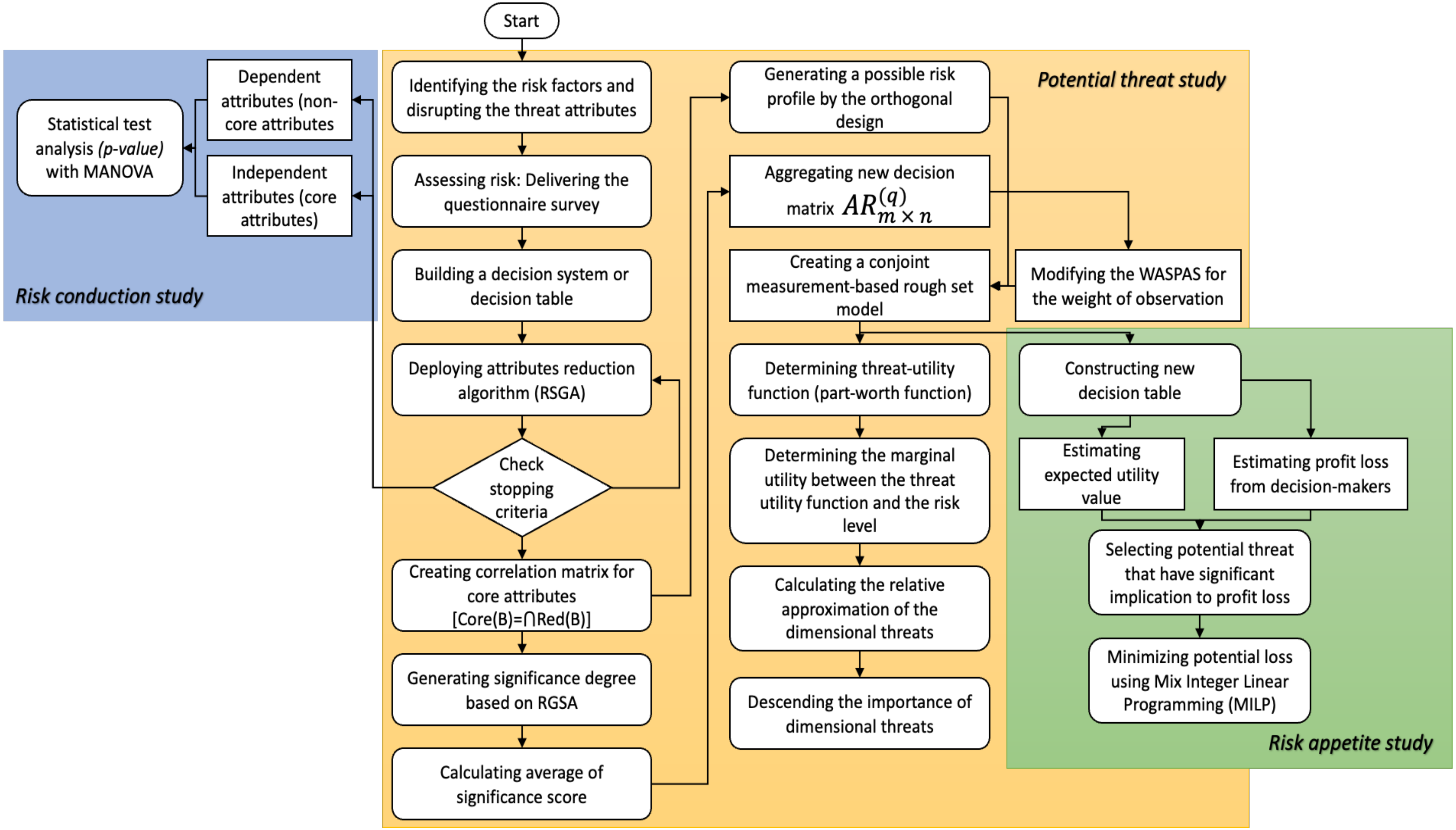


Figure 7.1 Seaport-fulcrum supply chain risk management framework considering interdependency

7.2 Summary and conclusion

In the recent decades, the field of SCRM has been burgeoning attention from both academics and practitioners. However, review of the extant of the literature particularly in SCRM framework reveals a general lack of studies focusing on seaport's integration on the supply chain network. These trends collectively result in larger vessel sizes and capacities, port traffic growth, cargo growth and expose the ports to greater vulnerabilities. Exploring the implications of seaport's adoption of new roles and objectives in supply chains would assist in the identification of SSCRD threats and define the context of the management model for the SSCRD threats such that the actions in the framework remain relevant to its peripheral setting.

In doing so we studied different dimensions of supply chain threats from determining seaport risk events and supply chain stakeholder preferences. Furthermore, some models and methodolodies are developed for determining three performance measures of the SSCRD as mentioned in Section 7.1. The methodologies were developed to enable the evaluation of qualitative and quantitative attributes, and decision-making approaches which play a vital role in enabling comprehensive analysis of multiple aspects of the conditional seaport risk problem related to the supply chain threats. Hence, this dissertation presented new framework in SCRM considering interdependency and risk appetite. The following sections summarize what has been achieved through each chapter in retrospect to the objective of this study.

Chapter three – One of the key decisions to evaluate the supply chain threat related seaport risk is to determine and decide what potential supply chain threat factors and which conditional seaport risk attributes affected to the threat factors. The SSC operations often have more than one objective and related with many stakeholder interests. Thus, we decide to examine three kind of entities such as seaport-manager, seaport-operator, and seaport-user. Seaport-manager is a seaport enterprise or state-owned enterprise, while seaport-operator is a stakeholder who handled the operational process in the seaport like containers and non-containerized cargoes such as vehicles, liquid, and dry bulk. Seaport-user is a stakeholder who are those entities that have a proximate working relationship with port operators and those with direct interest in the cargo transported through ports. Therefore, cargo owners, freight forwarders, ship owners and ship management companies were included in the target population. The cargo owners who were approached comprise mainly sea-freight forwarders and/or logistics companies since they are usually representatives of cargo owners. From the decision-makers evaluation, we computed and analyze multi-criteria decision making/analysis considering the interdenpendency between the supply chain threat factors (threat variables) with their risk event (conditional seaport risk as observable attributes) by calculating the dependency degree using rough set-based genetic algorithm. According to the study findings, 24 seaport risks in Indonesia pose potential threats to supply chain continuity. The lack of storage risk planning is ranked highest among 24 central tendencies of SSCRD in Figure 3.9. The twenty-four seaport risks, furthermore, is used to estimate the utility of the supply chain threat in chapter fours.

Chapter four – The estimation of potential supply chain threats considering the interdependence conditional seaport risk is not a trivial task. After solving the combinatorial interdependency problem of conditional seaport risk attributes, the calculation should be deal with the uncertainty and inconsistency on the decision-makers evaluation. In order to solve both issues, this study used hybrid conjoint measurement to capture the decision-makers preferences and classify the significant of potential supply chain threat related the advantage of conditional seaport risk attributes. In hybrid CA, two parameters were used to understand decision-maker preference and behavior such as desirabilities (advantage) and importances (significant). The former is useful to categorize which conditional seaport risk that possess the advantage for the decision makers, while the later is useful to seize the supply chain threats. In the significant context, the seaport service process should be optimized as a priority in order to reduce the disruption. The factor disrupts utility by as much as 32%, followed by the relationship process threat (TF_5) and planning process threat (TF_1). Hence, these latter two threats assume the second and third priorities, respectively. However, the infrastructure breakdown (TF_2) poses less threat of SSCRD at 9.9%. Figure 4.4 depicts the potential threats. In the advantage context, the positive trend of risk factors in Figure 4.9 contributes to an increase in the threat utility. It indicates that the conditional seaport risk attributes can be predictable. It also shows an increasing trend in the SSC operation and development, such as shipping activities and seaport activities, in the Indonesian context. In the meanwhile, the negative trend from the others risk factors in Figure 4.9 indicates that the threat utility is declining when the risk level is increasing. Hence, the conditional seaport risk attributes significantly contribute to SSCRD and make the conditional seaport risk attributes more unpredictable. As regards the advantage related to the level of risk, the highest level of SSCR attributes is maintained at the utility level of 1%-37%. Unless the SSC utility of earthquake (c_{101}) is zero for the first time, in the robustness test in Table 4.3. It means that the utility this factor is 0 in its first occurrence. This negative trend points out that SSC entities must simultaneously focus on planning, implementation, and development directed toward enhancing seaport-fulcrum supply chain resilience.

Chapter five – This chapter introduces the feasibility study considering the concept of interdependency among the conditional seaport risk attributes and evaluate them according to the rough set parameter, such as *certainty* and *coverage.* The *certainty* represents the conditional probability (conditional seaport risk attributes) that deficiency itemset *D* (relative importance of supply chain risk factors) will occur under the condition that deficiency itemset *C* occurs, which means the frequency of occurrence is found in the dataset as defined below. If the certainty is equal to 1, itemset *C* implicates itemset *D*, while if the certainty is between 0–1, an itemset *C* is dependent on the others to implicate itemset *D.* While *coverage* is defined as the ratio of the conditional probability of the occurrence of antecedent *C* and that of consequent *D* to the probability of the occurrence of antecedent *C*. The interdependency was started by divided the conditional seaport risk attributes into two attributes – independent and dependent variables. Moreover, the MANOVA was used to check whether the dependent variables from the reduction algorithm have similar matrix correlations (variance–covariance) with the predictor features. Such an interdependency approach is also useful to understand the endogenous and exogenous from the conditional seaport risk attributes. As results, there are 16 features are considered to pose the highest potential risk to SSC continuity in Figure 5.3. The scale in the legend indicates the correlation referring to the interdependency and implication degrees. Breakdown of port information system (a_{15}) had the highest certainty but the lowest coverage degree, whereas low-efficiency operation (a_{41}) had the lowest certainty but the highest coverage degree. In the middle was lack of supply chain strategic risk planning (a_3), which had the highest correlation among the seaport risk features, referring to the decision protocol as the highest risk level. In a term of feasibility to the supply chain threat, the threats from the planning process (TF_1), infrastructure (TF_2), distribution process (TF_4), nuclear enterprise financial (TF_6), location (TF_8), and security (TF_9) are clear in terms of risk probability, while the threats from the seaport service process (TF_3), relationship process (TF_5), monetary (TF_7), and environmental (TF_{10}) are beyond stakeholder comprehension. Hence, the ten-dimensional threats mean that the seaport risk poses potential threats in various dimensions to disrupt supply chain continuity in Figure 3.10.

Chapter six – This chapter explaining about risk appetite model to understand which conditional seaport risk attributes implicate to risk tolerance of SSC stakeholders. Risk appetite of the SSC stakeholders drives the tolerance level with respect to the acceptance of risks. However, no existing study has investigated designing a risk management framework within a network setting of interacting risks (the supply chain threat related conditional seaport risk attributes) driven by the risk appetite of decision-maker particularly in the seaport. Integration of utility indifference curves within this risk appetite model is from the Chapter 4. According to the Figure 7.1, the input of this model comes from the expected utility value and estimation of potential revenue loss by the decision-makers. The expected utility in Chapter 4 successfully tackled the interdependency between the threat variable of potential threat factors and the observe variable of conditional seaport risk attributes. Using MILP, we selected the risk factors that have minimum tolerance level with regards to the risk acceptance. The minimum acceptance risk level helped to minimize the revenue loss; hence, we got a comprehensive understanding which conditional seaport risk that useful to minimize revenue loss and how far the revenue loss can be minimized. By this, we also computed the minimizing revenue loss problem considering two rules or scenarios, such as sporadic risk case and repetitive risk case. As a result, the potential revenue loss for the port-authority is 8.67% and followed by 7.12% of seaport-user in the sporadic case. Whereas 19% and 17% of the potential revenue loss from port-authority and seaport-user respectively is impacted from the repetitive risk case. In figure 6.3 and 6.4, if we assume the percentage of highest risk is between 0 – 20%, then every decreasing the degree of risk accepted is reduced 20% from the utility value. So, the lack of distribution risk planning (c_{18}) deficiency of berth allocation risk planning (c_{19}), less timeliness of port customs clearance (c_{43}), and less cash flow (c_{65}) is considered as the high risk to be unacceptable risk by port authorities (Seaport-management and seaport-operator) either in sporadic risk case and repetitive risk case. They indicate that the degree of risk accepted by the port-authority should not exceed 40% from 100% of their utility value. Meanwhile, whatever risk case for seaport-users, shortage of IT and advanced technology (a_{39}) should not exceed 60% of their utility value. Moreover, the highest unacceptable risk is less efficient cost in feeder link (a_{73}) for port-authority in repetitive case, which should be below 20%.

In general, the supply chain operation should not be focused on the manufacturing perspective. The integration of the seaport should be considered in the supply chain network. Thus, the SSC operations should focus on optimizing cost, profit, and capacity. In fact, the discrepancy can be observed in real-life operations where minimizing revenue loss becomes a significant objective when the risk event occurred. In this dissertation, we have developed three model to understand the interdependency phenomena, such as supply chain threat with conditional seaport risk, conditional seaport risk with conditional seaport risk, conditional seaport risk with profit loss referring the risk-appetite of decision-makers. Chapter 3 and 4 has developed combinatorial optimization problem to reveal the central tendency of conditional seaport risk and which supply chain threat are significant in Indonesia context. Similarly, in Chapter 5 endogenous and exogenous relation is presented to understand the interdependency among the conditional seaport risk attributes. While the implication from supply chain threat and conditional seaport risk attributes toward the potential profit loss were calculated using risk appetite model.

7.3 The findings related archipelagic country

The management of supply chain risks in archipelagic countries, where seaports serve as critical hubs, is a complex and multifaceted challenge. These countries, characterized by dispersed islands and waterways, require a comprehensive approach to addressing the diverse risks that can disrupt the flow of goods and services. In these island-based economies, seaports are the primary gateways for trade, serving as the fulcrum upon which the entire supply chain pivots. In this section, we compare some results from Chapter 3 until Chapter 6 according to Figure 7.1 to emphasize the SSCR in Indonesia as an archipelagic country. As mentioned in Chapter 1, the SSCR comprises into three studies, such as potential threat, feasibility, and implication. Hence, these studies explain as follows:

7.3.1 Potential seaport-fulcrum supply chain threat factors and they risk attribute

Potential seaport-fulcrum supply chain threat factors and their conditional risk attributes explain in the utility function that examined in Chapter 4. The study was started to assign and analysis the preferences of seaport-fulcrum supply chain stakeholders from the negative scenarios in Chapter 3. Their preferences reflect the priorities and values that stakeholders assign to different aspects of the SSC threat factors, such as planning process, infrastructure, seaport service process, distribution process, relationship process, nuclear-enterprise financial, monetary, location, security, and environmental. These preferences influence how risks are perceived and managed within the seaport-fulcrum supply chain system.

In the seaport-fulcrum supply chain, various stakeholders (such as seaport operators, shipping companies, logistics firms, customs, regulators, and suppliers) have different preferences. For instance, a shipping company might prioritize speed and reliability in the seaport service process. Furthermore, a regulator might prioritize security and compliance with international standards. While, a logistics firm might prioritize cost-efficiency and timeliness in distribution process. Hence, the risk management strategies in place must balance these diverse preferences. For example, ensuring operational efficiency while managing the risks associated with potential delays or security issues. A decision that maximizes utility for one stakeholder might reduce utility for another, necessitating trade-offs or compromises.

After that, the utility function was deployed to capture the stakeholders' attitude toward the potential threat factors and the conditional seaport risk attributes. Utility, in this context, represents how stakeholders perceive and value different outcomes related to potential threat factors of seaport operations and supply chain risks. Utility theory, especially under uncertainty, is used to assess how much value (or utility) stakeholders derive from different decisions or strategies. In this seaport-fulcrum supply chain risk analysis, part-worth utilities function is used to evaluate different risk management strategies and trade-offs. The positive and negative signs help guide stakeholders in identifying which risk factors or mitigation strategies should be prioritized and which should be reconsidered or avoided.

Therefore, it captures the potential threat factors of seaport-fulcrum supply chain and their conditional seaport risk attributes in the Chapter 4. The potential threat to the supply chain disruption is shown in the utility function as follows: $Y_{mn} = 1.33 + 26.7U(A_1) + 9.9U(A_2) + 32.2U(A_3) + 10.9U(A_4) + 28.0U(A_5) + 12.8U(A_6) + 26.2U(A_7) + 19.4U(A_8) + 20.9U(A_9) + 24.4U(A_{10})$

In the Indonesian context, the seaport service process (TF_3) is the primary source of SSCRD. In other words, this tendency of SSCRD reduces the utility (satisfaction) by 32.2% in the 100% utility estimation. This is followed by the relationship process threat (TF_5) and the planning process threat (TF_1) with 28% and 26.6% utility reduction, respectively. The three threats that cause less SSCRD are infrastructure threats (TF_2), distribution process threats (TF_4), and nuclear-enterprise financial threats (TF_2) with 9.9%, 10.9%, and 12.8% utilities, respectively.

The most significant of service process threat (TF_3) is from several conditional seaport risk attributes such as, congestion in the waterway (a_{17}), congestion at hinterland transfer (a_{19}), less services calling at port (a_{20}), shortage of port capacity (a_{24}), and shortage of IT and advanced technology (a_{25}). This correlation is depicted into part-worth utility function $U(TF_3) = 0.009a_{17} - 0.062a_{19} - 0.026a_{20} + 0.008a_{24} + 0.072a_{25}$.

In the part-worth utility function, the decision-makers will prefer and likely prioritize that have positive parth-worth utility values, such as congestion in the waterway (a_{17}), shortage of port capacity (a_{24}), and shortage of IT and advanced technology (a_{25}). For example, reducing congestion in the waterways while increasing port capacity and the advancement technology will impact to the seaport's service efficientcy and increase supply chain activities. On the other hand, the strategies with negative part-worth utility value might be avoided or re-evaluated. For instance, the congestion at hinterland transfer and less services calling at port that slows the operations might be rejected unless the safety improvement (high-cost compliance measure) justifies the disruption. Hence, the potential seaport-fulcrum supply chain threat factors and they risk attribute is shown in Figures 4.4 and 4.9.

Moreover, the threat scores and risk exposure score are proposed to assess the degree of potential threats factors and their conditional seaport risk attributes. Risk exposure in this study refers to potential negative impact stakeholders may face due to conditional seaport risk. Furthemore, the highest risk exposure score for conditional seaport risk attributes indicates the lowest risk implication and the lowest risk exposure score indicates the highest risk implication. In the meanwhile, the highest threat score indicates the lowest risk implication. These can be seen in Figures 3.9 and 3.10.

7.3.2 Conduction of conditional seaport risk attributes

The examination of seaport risk attributes within a conditional framework is a crucial aspect of modern maritime logistics and transportation management. Table 5.2 reveals the dependencies between the 39 conditional seaport risk attributes and 21 predictor features explored in this investigation. Significance levels were used to assess the relationships between the variables, and multiple linear regression analysis was employed to develop the predictive model. Additionally, the predictive model's empirical equation describing the relationships among seaport risk factors, based on the distribution of SSC stakeholders, is detailed in Appendix G. This equation lists the dependent variables, followed by the intercept and predictor features. Furthermore, the significance of the predictors on the dependent variables is illustrated in Figure 5.2.

According to Figure 5.2, a less efficient deviation cost (a_{73}) significantly contributes to 14 other dependent seaport risk factors. Additionally, a shortage of IT and advanced technology (a_{39}) is linked to 12 other seaport risk factors. However, the 21 predictors did not significantly impact the short sailing time to other hub ports (a_{81}). Furthermore, the predictive model in Table 5.2 demonstrates the correlation between conditional seaport risk attributes and supply chain disruption.

To further evaluate the findings, we applied association rule mining as described in Sub-subsection 3.3.3.5 to identify potential relationships among the conditional seaport risk attributes within the predictive model. Association rule mining is a technique used to uncover interesting associations between features in a large dataset, considering the parameters outlined in the referenced equations. The identification of a potential risk that represents a single concept is known as an interdimensional association rule, as it encompasses a single distinct concept with multiple occurrences in the data. Consequently, we generated the decision protocol's highest risk level to gain insights into the potential risks of supply chain disruption in the dataset.

The attributes in the decision table, as described in Sub-subsection 3.3.3.1, are divided into two distinct groups. Each object (*U*) generates a specific decision rule, which corresponds to the level of disruption as outlined in Subsection 5.3.2. If a decision rule uniquely determines a decision in terms of conditional seaport risks, it is considered a certain decision rule; otherwise, it is an uncertain decision rule. In general, certain decision rules represent positive approximations of decisions regarding conditional seaport risk attributes, while uncertain decision rules pertain to the boundary regions of decisions. These definitions lead to two conditional probability parameters: the certainty coefficient and the coverage coefficient.

The scatter plot in Figure 5.3 compares the certainty and coverage coefficients to provide insight into the conduction degree, referring to the decision protocol discussed in Subsection 5.3.2. The distribution of the conditional seaport risk attributes is provided in Appendix H. Examining the distribution of seaport risk features, we utilized IBM SPSS software to plot the position of each feature relative to the centroid using hexagonal binning, creating a scatter plot that depicts the implication and interdependency degrees. This process enabled us to obtain the results for the conduction risks, as presented in Figure 5.3.

The analysis identified 15 seaport risk attributes that pose the highest potential risk to supply chain continuity, with varying degrees of implication, interdependency, and conduction. The breakdown of the port information system (a_{26}) had the highest implication but the lowest interdependency to supply chain disruption, while low-efficiency operations (a_{63}) had the lowest implication but the highest interdependency. The lack of supply chain strategic risk planning (a_{13}) exhibited the highest conduction degree among the seaport risk features, representing the highest risk level according to the decision protocol.

7.3.3 Risk appetite of seaport-fulcrum supply chain stakeholders

One critical factor in this process is understanding the risk appetite of different stakeholders within the seaport-fulcrum supply chain. Stakeholders, such as port authorities, shipping companies, and logistics providers, may have varying tolerance levels for risk, which can influence their approach to risk management and the resilience of the overall supply chain. For instance, port authorities may be more risk-averse, prioritizing the physical security and operational continuity of port infrastructure, while shipping companies may be more willing to accept certain operational risks in pursuit of greater efficiency and cost-effectiveness.

Understanding these nuanced risk preferences is crucial for developing effective risk management strategies that can balance the interests and concerns of all stakeholders. By adopting a holistic, stakeholder-centric approach to risk assessment and mitigation, seaport operators can better identify and address the multifaceted threats facing their operations, ensuring the long-term resilience and sustainability of the broader supply chain.

In this study, a risk appetite model is considered to demonstrate how far the port authority can set up risk tolerance towards various types of conditional seaport risk attributes and risk events. Regarding the characteristic risk events, the analysis found that the maximum potential revenue loss from sporadic risk events is 8.67%, while for repetitive risk events, it is 0.19%. Additionally, several risk tolerances for conditional seaport risk attributes were identified based on both types of risk events, as depicted in Figures 6.3 and 6.4. This measurement can assist decision-makers, especially the PA, in adjusting their policies and capacities to deal with diverse risk factors and the timing of their occurrence. By understanding the risk appetite of different stakeholders, the PA can develop more effective risk management strategies that balance the interests and concerns of all parties, ensuring the long-term resilience and sustainability of the broader supply chain.

Similar with the port authority, the study found that the maximum potential revenue loss from sporadic risk events for the supply chain stakeholders is 7.12%, while for repetitive risk events, it is 0.17%. Furthermore, the analysis revealed that whatever the risk case in Figures 6.3 and 6.4 for the SU, the shortage of IT and advanced technology (a_{39}) should not exceed 60% of their utility value. This conditional seaport risk attribute is identified as the most impactful from any case of the risk event. This indicates that the IT and advanced technology in the seaport operations have the greatest implication for the SU. Hence, the SU must work as closely as possible with the PA to address this critical risk factor and ensure the long-term resilience and sustainability of the broader supply chain.

7.4 Practical implication

Based on the insight gained in the course of this dissertation, this section discusses what implications the research findings have for the decision-makers for improving the SSC operations.

1) In real-world scenarios, the operations of extensive SSCs often involve multiple stakeholders, entities, and decision-makers. Nonetheless, neglecting to align with the identified decision-makers could result in adverse consequences. Therefore, involving multiple entities in the initial stages of decision-making enables coordination by consolidating a collective outcome from the judgments of various decision-makers. This approach fosters a sense of ownership in the SSC and its functions, a crucial element for optimizing the efficient utilization of established hubs and promoting collaborative efforts.
2) The adoption of the group decision-making technique also allows for the reduction of disparities caused by a lack of knowledge or information asymmetry. When a group makes a choice, more precise knowledge about possible threats and their conditional seaport risk elements may be acquired while decreasing duplicated information and operation. The practical significance of incorporating decision-makers early in the information-scarce reaction phase.
3) The seaport management is also strongly urged to work closely with its stakeholders and the government to ensure that future plans keep up with new trends and are related to consumer requests, as well as national trade and investment goals. Relevant information, such as client vessel size orders, shipping market assessments, and challenges encountered by seaport users, should be communicated with the seaport-operator through the seaport-manager, since these have an influence on the adequacy of future plans. In addition, a supply chain management mechanism for the seaport enterprise core should be established; strategic cooperators should be engaged to improve the ability of upstream and downstream supply chain enterprises to deal with unexpected incidents and prevent supply chain breakdown as a result of these factors.
4) In relation to the threat utility, the dissertation highlights the areas where each SSC operation can lead to supply chain disruption related the threat utility (potential threat) and which conditional seaport risk attributes are involved. Given this, the study identifies a list of threat utility functions as indicators applicable to all the seaports in Indonesia. Furthermore, the threat utility parameter and function can help the decision-maker to make decision-policy that suitable to the specific supply chain threat and control the conditional seaport risk related to the specific threat.
5) In managerial implication, seaport managers can use this list of indicators to regularly monitor activities and minimize supply chain disruptions. Seaport managers are encouraged to pay particular attention to the relational threat factors by working closely with seaport users and the authorities, especially where existing terminal designs cannot be easily revised. The monetary

threat dimension should be considered in greater depth, as the disparity between western and eastern Indonesia is clearly a significant problem for cargo throughput. In addition, the prediction and interdependency diagnosis of the conditional seaport risk probabilities are carried out in a dynamic manner based on the information available in practical operations between port authorities and shipping lines. Thus, the results of this study pioneer the inclusion of different types of conditional seaport risks as key factors in the seaport risk resilience model.

6) The trade-off between estimation revenue loss with expected utility from each decision-maker provides an insight into the SSC actors in action and how far they should react towards the risk tolerance of the conditional seaport risk attributes in order to get advantages and reduce the revenue loss too. Furthermore, the sporadic risk event case and repetitive event case help each decision-maker to formulate their resilience policy to maintain their resources and reduce revenue loss referring to the risk event toward conditional seaport risk attributes. Under the lack of information on SCRM, the decision-makers can consider sporadic risk cases to tighten up their policy.

7.5 Future direction

The focus of future research aims to overcome the constraints identified during the execution of this study. While the ideas, methodological advancements, and discoveries presented in this dissertation contribute to the existing literature, especially in the realm of SCRM, the insights gained throughout the study suggest several specific areas for potential future investigations.

1) **Resilience-based interdependency risk**: To mitigate seaport risks, a supply chain emergency management system, contingency plan, and protection mechanism should be developed. Seaport management should work closely with stakeholders and the government to ensure future plans align with new trends, consumer demands, and national trade and investment goals. Relevant information, such as vessel size orders, shipping market assessments, and user challenges, should be communicated to the seaport operator to inform adequate future planning. Additionally, a supply chain management mechanism should be established, and strategic partners engaged, to improve the ability of supply chain enterprises to address unexpected incidents and prevent breakdowns.
2) **Level of risk**: A limitation of this study is that the risk-level setting does not reflect the real situation of the dataset. Hence, future studies should consider another approach to discretize the real risk level, referring to this dataset. Moreover, the seaport-fulcrum supply chain stakeholders have different experiences and thoughts that are geographically diverse. Hence, it is possible to extract varied results from the RGSA. These variations might influence the findings on the threat utility.
3) **The significance of decision-makers:** Practical decision-making often engages multiple decision-makers, each with distinct levels of importance dictated by their hierarchy or expertise. A potential extension involves creating a methodology to assess the relative importance of decision-makers and integrating it into the model.

4) **Level of uncertainty**: A risk aversion analysis by SSC stakeholders, aggregated risk levels, and the representation of risk levels. The first problem might occur because of the uneven representation of respondents. Risk aversion analysis can only be performed if the data equally represent the SSC stakeholders. Different seaport locations and types of seaport activity could also produce diverse results related to risk aversion. The second and third issue are related to the possibility the RSGA could produce inconsistencies during the computation. Thus, future research can use a mathematical approach (e.g. fuzzy-rough set model) to more accurately express seaport risk levels.

Furthermore, the limitation that need to be tackled for future study as follows:

a. Limitation in data set
   - The questionnaire survey was conducted because the supply chain risk data related seaport is confidential. Many seaport users such as shipping company, freight forwarder, and liners does not want to share the data willingly. It was believed that they do not want to open their data because the competition existed among the seaport users in Indonesia.
   - In the sampling data (Chapter 3), the measurement of each conditional seaport risk attributes uses the categorical (discrete) value. Thus, the results and interpretation might be different when using continuous value.
   - The object of this study is only limited for three entities such as: seaport managements, seaport operators, and seaport users. Hence, the data set can be expanded to another supply chain entities.

b. Limitation in approach
   - In the Chapter 3, the operator to determine the importance degree in the reduction set step is oversimplified, because it was based on the average of observation. Hence, the operator can be altered with fuzzy operator to reduce computational time and increase the accuracy as well.
   - In the Chapter 4, the result should be confirmed by the seaport-fulcrum entities to check reliability of the result. Furthermore, the comparison referring the performance measurement, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Relative Absolute Error (RAE), need to be considered to select better results.
   - In the Chapter 5, despite the null hypothesis was presented to check whether the dependent variables from the reduction algorithm of rough set model have similar matrix correlations (variance–covariance) with the predictor features, the conditional seaport risk, however, is sometimes refer the seaport characteristics and stakeholder behavior. Hence, the hypothesis assumption can be extended to find the better comparison.
   - In the Chapter 6, the model is based on the utility estimation of stakeholder preferences in conjoint measurement to minimize the potential revenue loss for each stakeholder. However, the result might be different if the risk budget estimation and capacity (seaport and vessel) constraint are considered in the calculation.

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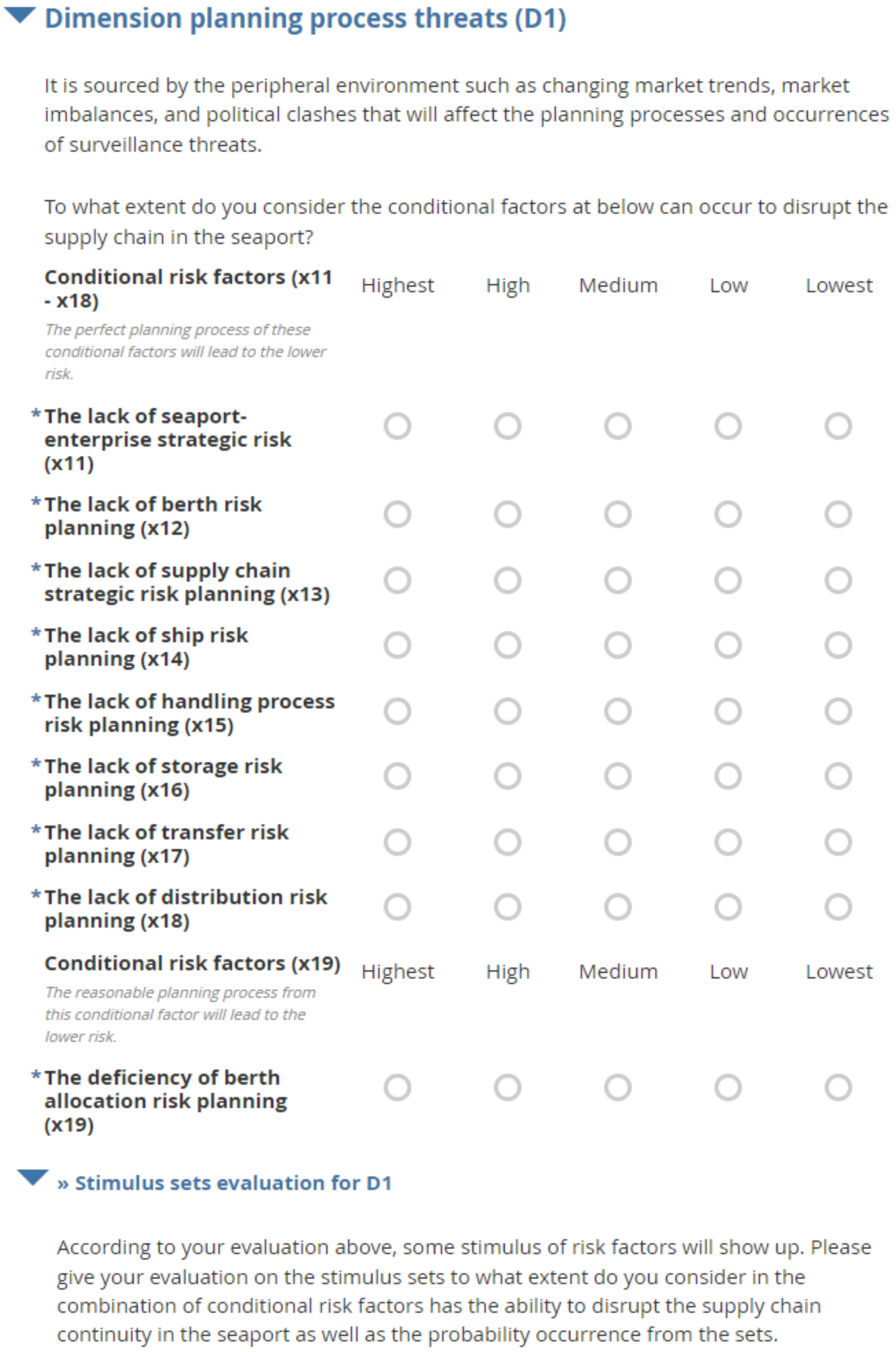
Appendices

Appendix A: A section of the questionnaire.



Dimension planning process threats (D1)

It is sourced by the peripheral environment such as changing market trends, market imbalances, and political clashes that will affect the planning processes and occurrences of surveillance threats.

To what extent do you consider the conditional factors at below can occur to disrupt the supply chain in the seaport?

Conditional risk factors (x11 - x18) *The perfect planning process of these conditional factors will lead to the lower risk.*	Highest	High	Medium	Low	Lowest
***The lack of seaport-enterprise strategic risk (x11)**	○	○	○	○	○
***The lack of berth risk planning (x12)**	○	○	○	○	○
***The lack of supply chain strategic risk planning (x13)**	○	○	○	○	○
***The lack of ship risk planning (x14)**	○	○	○	○	○
***The lack of handling process risk planning (x15)**	○	○	○	○	○
***The lack of storage risk planning (x16)**	○	○	○	○	○
***The lack of transfer risk planning (x17)**	○	○	○	○	○
***The lack of distribution risk planning (x18)**	○	○	○	○	○

Conditional risk factors (x19) *The reasonable planning process from this conditional factor will lead to the lower risk.*	Highest	High	Medium	Low	Lowest
***The deficiency of berth allocation risk planning (x19)**	○	○	○	○	○

» Stimulus sets evaluation for D1

According to your evaluation above, some stimulus of risk factors will show up. Please give your evaluation on the stimulus sets to what extent do you consider in the combination of conditional risk factors has the ability to disrupt the supply chain continuity in the seaport as well as the probability occurrence from the sets.

Appendix B: Seaport-fulcrum supply chain risks value & interpretation

Risk value (scale) of attributes					**The SSCR factors and attributes**	
1	**2**	**3**	**4**	**5**	**Threat Dimensions**	**Set of conditional seaport risk attributes**
Very often/Highest/High standard	Often/High/Around upper standard	Normal/Medium/Medium standard	Seldom/Low/Around lower standard	Rarely/Lowest/Below standard	Planning process threats (TF_1)	a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9
					Seaport Service Process threats (TF_3)	a_{17}, a_{18}, a_{19}, a_{20}, a_{21}, a_{22}, a_{23}, a_{24}, a_{25}
					Monetary threats (TF_7)	a_{45}, a_{46}, a_{47}
					Security threats (TF_9)	a_{51}, a_{52}, a_{53}, a_{54}, a_{55}, a_{56}
					Environmental threats (TF_{10})	a_{57}, a_{58}, a_{59}, a_{60}, a_{61}
15 times occurred in a quarter with over 15 persons death	15 times occurred in a quarter with less than 15 persons death	15 times occurred in a semester with less than 15 persons injured	Average 15 times occurred in a year with over 15 persons injured	Below 15 times occurred in a year with less than 15 persons injured	Infrastructure threats (TF_2)	a_{10}, a_{11}, a_{12}, a_{13}, a_{14}, a_{15}, a_{16}

No response/No standard	Long bottleneck/Unresponsive/Below standard	Short bottleneck/Low response/Around lower standard	Normal/ Responsive/ Good standard	Just in time/ High response/ High standard	Distribution Process threats (TF_4)	a_{26}, a_{27}, a_{28}, a_{29}, a_{30}, a_{31}, a_{32}, a_{33}
More than 50 cases in a month/ Over 21 cases in a month with more than 1% loses in state finance	Below 50 cases in a month / Below 21 cases in a month with less than 1% loses in state finance	More than 170 cases in a year/ Over 248 cases in a year with more than 14% loses in state finance	Below 170 cases in a year/ Below 248 cases in a year with less than 14% loses in state finance	Zero cases in a year/ Zero cases in a year with zero percent loses in state finance	Relationship Process threats (TF_5)	a_{34}, a_{35}, a_{36}, a_{37}, a_{38}
					Nuclear-enterprise financial threats (TF_6)	a_{39}, a_{40}, a_{41}, a_{42}, a_{43}, a_{44}
High frequency and short distance	High frequency and long distance	Normal	Low frequency and short distances	Low frequency and long distances	Location threats (TF_8)	a_{48}, a_{49}, a_{50}

Appendix C: The Theorem and Proof of Equation (3.12)

Theorem 1. Suppose $a_j \in \beta$, where β denotes the attribute reduction set. Then, *Max (B (D)),* which follows the condition attribute a_j belonging to the condition set of attributes *B* (where $B \subseteq A$), is *D*-superfluous if it has no effect on the lower approximation of *D*. Otherwise, attribute a_j is *D*-indispensable in A.

Proof 1. As defined in Sub-subsection 3.3.3.1, for $\forall a \in C$, the $S_B(D) = \gamma_C(D) - \gamma_{B-\{a_j\}}(D)$; if $k = 1$, *D* depends entirely on *C,* the $S_B(D)$ becomes larger, and the $\gamma_{B-a_j}(D)$ decreases, as mathematically defined by Equation (3.9). Furthermore, the smaller $\left|POS_{(B-a_j)}(D)\right|$, the greater the dependency of decision attribute *D* on attribute *a,* and the larger $\gamma(C, D)$, as mathematically shown in $S_C(D) = \frac{\left|POS_{(C-a_j)}(D)\right|}{|U|}$, where $|U|$ is a fixed value. Owing to the addition of attributes in the order of significance, a reduction may be obtained, so that *Max* $(I_B (D))$ $\forall a_j \in \beta$. The set of *D-indispensable* attributes in *A* is called *the D-core* of *A*. However, the minimal subsets of conditional attributes that discern all equivalence classes of the relation Ind(*D*), discernible by the entire set of attributes, are called *D-reducts*. In other words, if each conditional attribute in the decision table is independent of D, then the conditional attribute set *C* is independent of *D*; otherwise, *C* is dependent on *D.*

Appendix D: The Proof of Equation (3.13)

Proof 2. Let the conditional attribute set be *C* and *B* be a subset of *C*. As shown in Equation (3.12), for a_j element *B*, each attribute in *B* is independent of *D*, and $\bar{S}(B)$ becomes larger. Otherwise, $\gamma_{B-a_j}(D)$ becomes smaller than in Equation (3.12). Thus, *B* is more likely to be reduced. Specifically, when $POS_B(D) = POS_C(D)$, *B* is the reduction in *C* according to the definition in Equations (3.9) and (3.11).

Appendix E: Statistical descriptive of self-explicated data set

SSCR attributes (a_{ij})	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Sum	Count	Confidence Level (95.0%)
a_1	2.569	0.105	2.000	2.000	1.297	1.681	-0.763	0.608	393.000	153.000	0.207
a_2	2.444	0.105	2.000	2.000	1.302	1.696	-0.525	0.739	374.000	153.000	0.208
a_3	2.536	0.100	2.000	2.000	1.236	1.527	-0.555	0.584	388.000	153.000	0.197
a_4	2.575	0.093	2.000	2.000	1.151	1.325	-0.555	0.496	394.000	153.000	0.184
a_5	2.595	0.106	2.000	2.000	1.310	1.716	-0.859	0.502	397.000	153.000	0.209
a_6	2.412	0.092	2.000	2.000	1.133	1.283	-0.212	0.648	369.000	153.000	0.181
a_7	2.680	0.096	2.000	2.000	1.185	1.403	-0.600	0.525	410.000	153.000	0.189
a_8	2.752	0.099	3.000	2.000	1.226	1.504	-0.830	0.335	421.000	153.000	0.196
a_9	2.484	0.098	2.000	2.000	1.215	1.475	-0.318	0.764	380.000	153.000	0.194
a_{10}	3.078	0.113	3.000	4.000	1.403	1.967	-1.275	-0.098	471.000	153.000	0.224
a_{11}	3.131	0.104	3.000	4.000	1.286	1.654	-1.103	-0.229	479.000	153.000	0.205
a_{12}	3.386	0.112	3.000	5.000	1.382	1.910	-1.183	-0.297	518.000	153.000	0.221
a_{13}	3.346	0.110	4.000	4.000	1.364	1.859	-1.112	-0.366	512.000	153.000	0.218
a_{14}	3.366	0.110	4.000	5.000	1.361	1.852	-1.102	-0.340	515.000	153.000	0.217
a_{15}	3.281	0.106	3.000	4.000	1.305	1.703	-1.154	-0.194	502.000	153.000	0.208
a_{16}	3.353	0.113	3.000	5.000	1.402	1.967	-1.315	-0.216	513.000	153.000	0.224
a_{17}	2.765	0.108	3.000	2.000	1.337	1.786	-0.981	0.356	423.000	153.000	0.213
a_{18}	2.627	0.104	2.000	2.000	1.287	1.656	-0.898	0.407	402.000	153.000	0.206
a_{19}	2.771	0.097	3.000	3.000	1.200	1.441	-0.821	0.174	424.000	153.000	0.192
a_{20}	2.680	0.099	3.000	3.000	1.228	1.509	-0.796	0.311	410.000	153.000	0.196
a_{21}	2.634	0.098	2.000	2.000	1.207	1.457	-0.727	0.442	403.000	153.000	0.193
a_{22}	2.621	0.091	2.000	2.000	1.124	1.263	-0.475	0.426	401.000	153.000	0.180
a_{23}	2.601	0.105	2.000	2.000	1.299	1.689	-0.828	0.522	398.000	153.000	0.208

a_{24}	2.614	0.102	2.000	2.000	1.257	1.581	-0.860	0.422	400.000	153.000	0.201
a_{25}	2.608	0.110	2.000	2.000	1.363	1.858	-0.974	0.488	399.000	153.000	0.218
a_{26}	2.366	0.094	2.000	2.000	1.163	1.352	-0.641	0.521	362.000	153.000	0.186
a_{27}	2.536	0.101	2.000	2.000	1.246	1.553	-0.674	0.527	388.000	153.000	0.199
a_{28}	2.588	0.098	2.000	2.000	1.211	1.467	-0.647	0.432	396.000	153.000	0.193
a_{29}	3.163	0.107	3.000	4.000	1.320	1.743	-1.060	-0.219	484.000	153.000	0.211
a_{30}	2.745	0.100	3.000	3.000	1.233	1.520	-0.809	0.285	420.000	153.000	0.197
a_{31}	2.575	0.095	2.000	2.000	1.174	1.378	-0.423	0.510	394.000	153.000	0.187
a_{32}	2.601	0.098	3.000	3.000	1.216	1.478	-0.793	0.272	398.000	153.000	0.194
a_{33}	2.529	0.095	2.000	2.000	1.170	1.369	-0.644	0.415	387.000	153.000	0.187
a_{34}	2.562	0.104	2.000	2.000	1.292	1.669	-0.656	0.566	392.000	153.000	0.206
a_{35}	2.680	0.107	2.000	2.000	1.326	1.759	-0.891	0.454	410.000	153.000	0.212
a_{36}	2.667	0.112	2.000	2.000	1.386	1.921	-1.107	0.392	408.000	153.000	0.221
a_{37}	2.490	0.104	2.000	2.000	1.283	1.646	-0.772	0.552	381.000	153.000	0.205
a_{38}	2.621	0.094	3.000	2.000	1.164	1.355	-0.527	0.425	401.000	153.000	0.186
a_{39}	2.667	0.111	2.000	1.000	1.372	1.882	-1.074	0.358	408.000	153.000	0.219
a_{40}	2.797	0.098	3.000	3.000	1.216	1.478	-0.980	0.040	428.000	153.000	0.194
a_{41}	2.373	0.100	2.000	1.000	1.240	1.538	-0.571	0.622	363.000	153.000	0.198
a_{42}	2.503	0.096	2.000	2.000	1.193	1.423	-0.636	0.475	383.000	153.000	0.191
a_{43}	2.595	0.103	3.000	3.000	1.280	1.637	-0.989	0.225	397.000	153.000	0.204
a_{44}	2.693	0.094	3.000	3.000	1.160	1.346	-0.738	0.239	412.000	153.000	0.185
a_{45}	2.569	0.101	2.000	2.000	1.245	1.550	-0.722	0.474	393.000	153.000	0.199
a_{46}	2.523	0.099	2.000	2.000	1.220	1.488	-0.794	0.387	386.000	153.000	0.195
a_{47}	2.562	0.095	3.000	3.000	1.180	1.393	-0.572	0.373	392.000	153.000	0.188
a_{48}	3.209	0.106	3.000	3.000	1.316	1.732	-1.012	-0.130	491.000	153.000	0.210
a_{49}	2.621	0.101	2.000	2.000	1.246	1.553	-0.871	0.382	401.000	153.000	0.199
a_{50}	2.673	0.099	2.000	2.000	1.224	1.498	-0.743	0.409	409.000	153.000	0.195

a_{51}	3.007	0.104	3.000	3.000	1.290	1.664	-0.982	-0.031	460.000	153.000	0.206
a_{52}	3.190	0.112	3.000	5.000	1.380	1.905	-1.233	-0.134	488.000	153.000	0.220
a_{53}	3.542	0.106	4.000	5.000	1.308	1.710	-0.835	-0.514	542.000	153.000	0.209
a_{54}	3.366	0.115	4.000	5.000	1.422	2.023	-1.151	-0.392	515.000	153.000	0.227
a_{55}	3.490	0.115	4.000	5.000	1.419	2.015	-1.158	-0.413	534.000	153.000	0.227
a_{56}	2.928	0.100	3.000	3.000	1.236	1.528	-0.968	0.096	448.000	153.000	0.197
a_{57}	3.392	0.113	4.000	5.000	1.401	1.964	-1.109	-0.408	519.000	153.000	0.224
a_{58}	2.980	0.107	3.000	2.000	1.325	1.756	-1.159	0.088	456.000	153.000	0.212
a_{59}	3.124	0.110	3.000	3.000	1.364	1.859	-1.162	-0.086	478.000	153.000	0.218
a_{60}	3.261	0.099	3.000	3.000	1.224	1.497	-0.843	-0.230	499.000	153.000	0.195
a_{61}	2.843	0.094	3.000	2.000	1.165	1.357	-0.847	0.133	435.000	153.000	0.186

Appendix F: Orthogonal design of seaport risk combinations (risk profile)

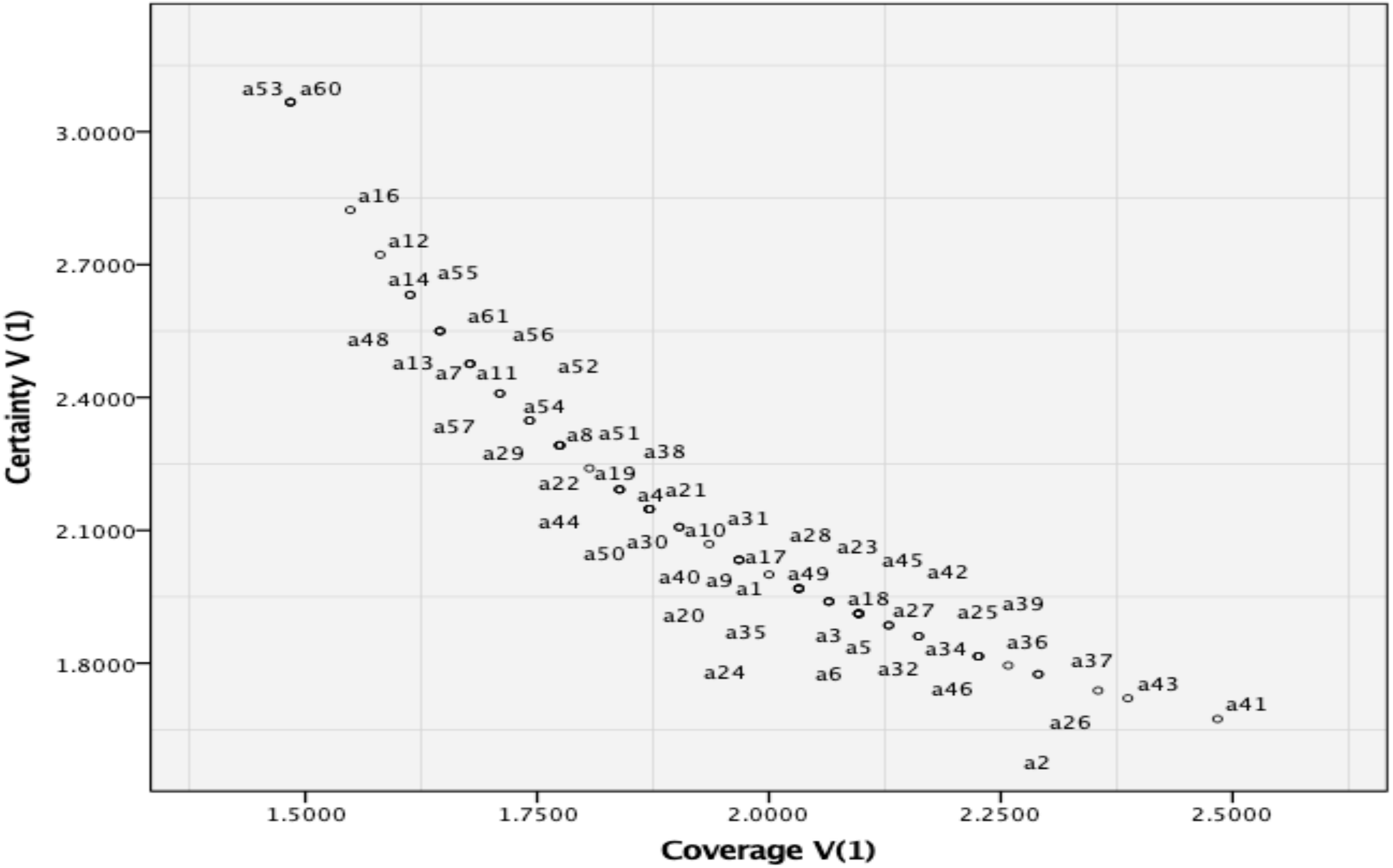
Numbers of risk profiles	Threat factors (SSCR factors)									
	TF_1	TF_2	TF_3	TF_4	TF_5	TF_6	TF_7	TF_8	TF_9	TF_{10}
1.	c_{18}	c_{25}	c_{31}	c_{42}	c_{5N}	c_{61}	c_{7N}	c_{8N}	c_{91}	c_{101}
2.	c_{18}	c_{25}	c_{39}	c_{43}	c_{54}	c_{64}	c_{7N}	c_{8N}	c_{91}	c_{101}
3.	c_{18}	c_{26}	c_{31}	c_{42}	c_{5N}	c_{61}	c_{7N}	c_{81}	c_{94}	c_{101}
4.	c_{14}	c_{25}	c_{31}	c_{42}	c_{54}	c_{61}	c_{73}	c_{81}	c_{91}	c_{101}
5.	c_{18}	c_{26}	c_{33}	c_{43}	c_{54}	c_{61}	c_{73}	c_{8N}	c_{91}	c_{102}
6.	c_{18}	c_{26}	c_{33}	c_{43}	c_{54}	c_{61}	c_{7N}	c_{81}	c_{95}	c_{101}
7.	c_{16}	c_{26}	c_{38}	c_{42}	c_{5N}	c_{61}	c_{73}	c_{81}	c_{91}	c_{101}
8.	c_{14}	c_{26}	c_{31}	c_{42}	c_{54}	c_{61}	c_{73}	c_{8N}	c_{95}	c_{101}
9.	c_{14}	c_{26}	c_{33}	c_{43}	c_{5N}	c_{61}	c_{73}	c_{8N}	c_{94}	c_{101}
10.	c_{15}	c_{26}	c_{34}	c_{43}	c_{5N}	c_{61}	c_{7N}	c_{8N}	c_{91}	c_{101}
11.	c_{16}	c_{25}	c_{31}	c_{43}	c_{54}	c_{61}	c_{7N}	c_{81}	c_{91}	c_{102}
12.	c_{15}	c_{26}	c_{39}	c_{42}	c_{54}	c_{61}	c_{73}	c_{81}	c_{95}	c_{105}
13.	c_{16}	c_{26}	c_{34}	c_{43}	c_{54}	c_{61}	c_{73}	c_{81}	c_{91}	c_{101}
14.	c_{16}	c_{25}	c_{33}	c_{42}	c_{5N}	c_{61}	c_{7N}	c_{81}	c_{91}	c_{105}
15.	c_{14}	c_{26}	c_{34}	c_{42}	c_{54}	c_{61}	c_{7N}	c_{81}	c_{91}	c_{102}
16.	c_{14}	c_{25}	c_{34}	c_{42}	c_{54}	c_{61}	c_{7N}	c_{8N}	c_{94}	c_{105}
17.	c_{16}	c_{26}	c_{31}	c_{43}	c_{54}	c_{61}	c_{7N}	c_{8N}	c_{95}	c_{105}
18.	c_{14}	c_{25}	c_{39}	c_{43}	c_{5N}	c_{61}	c_{73}	c_{81}	c_{91}	c_{101}
19.	c_{15}	c_{25}	c_{33}	c_{42}	c_{54}	c_{61}	c_{73}	c_{8N}	c_{91}	c_{102}
20.	c_{18}	c_{26}	c_{34}	c_{42}	c_{5N}	c_{61}	c_{73}	c_{8N}	c_{91}	c_{105}
21.	c_{16}	c_{25}	c_{33}	c_{42}	c_{5N}	c_{61}	c_{73}	c_{8N}	c_{95}	c_{101}
22.	c_{16}	c_{25}	c_{34}	c_{43}	c_{54}	c_{61}	c_{73}	c_{8N}	c_{94}	c_{101}
23.	c_{15}	c_{25}	c_{33}	c_{42}	c_{54}	c_{61}	c_{7N}	c_{81}	c_{94}	c_{101}
24.	c_{18}	c_{25}	c_{38}	c_{43}	c_{54}	c_{61}	c_{73}	c_{81}	c_{94}	c_{105}
25.	c_{15}	c_{26}	c_{38}	c_{42}	c_{54}	c_{61}	c_{7N}	c_{8N}	c_{91}	c_{101}
26.	c_{18}	c_{25}	c_{34}	c_{42}	c_{5N}	c_{61}	c_{73}	c_{81}	c_{95}	c_{102}
27.	c_{14}	c_{25}	c_{38}	c_{43}	c_{5N}	c_{61}	c_{7N}	c_{8N}	c_{95}	c_{102}
28.	c_{15}	c_{25}	c_{31}	c_{43}	c_{5N}	c_{61}	c_{73}	c_{8N}	c_{91}	c_{105}
29.	c_{16}	c_{26}	c_{39}	c_{42}	c_{5N}	c_{61}	c_{7N}	c_{8N}	c_{94}	c_{102}
30.	c_{14}	c_{26}	c_{33}	c_{43}	c_{5N}	c_{61}	c_{7N}	c_{81}	c_{91}	c_{105}
31.	c_{15}	c_{26}	c_{31}	c_{43}	c_{5N}	c_{61}	c_{73}	c_{81}	c_{94}	c_{102}
32.	c_{15}	c_{25}	c_{34}	c_{43}	c_{5N}	c_{61}	c_{7N}	c_{81}	c_{95}	c_{101}

Appendix G: Predictive model with significance test (t-test) by predictors.

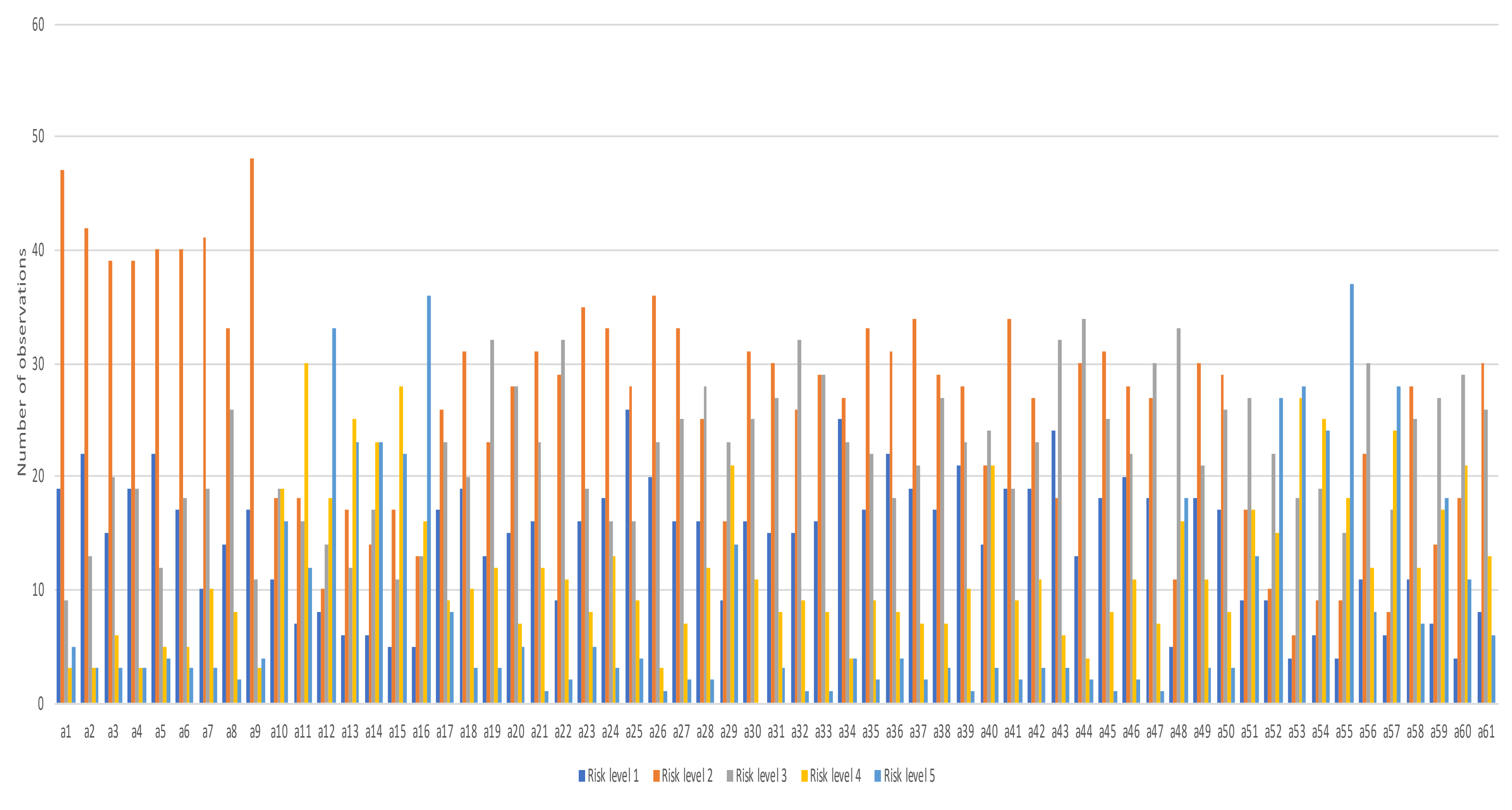
	β_0	a_4	a_5	a_6	a_8	a_{14}	a_{15}	a_{19}	a_{20}	a_{24}	a_{25}	a_{27}	a_{28}	a_{37}	a_{39}	a_{47}	a_{51}	a_{55}	a_{57}	a_{58}	a_{60}	a_{61}
a_1	0,82	0,16	0,00	0,17	0,03	0,84	0,09	0,49	0,27	0,80	0,71	0,09	0,28	0,25	0,84	0,32	0,06	0,16	0,04	0,05	0,55	0,24
a_2	0,64	0,01	0,27	0,04	0,39	0,17	0,03	0,25	0,86	0,25	0,40	0,38	0,66	0,59	0,75	0,37	0,87	0,15	0,31	0,51	0,24	0,24
a_3	0,00	0,41	0,01	0,44	0,13	0,00	0,00	0,02	0,17	0,11	0,00	0,40	0,90	0,02	0,75	0,01	0,24	0,72	0,08	0,14	0,19	0,93
a_7	0,22	0,61	0,20	0,03	0,00	0,10	0,39	0,23	0,54	0,23	0,32	0,59	0,00	0,94	0,33	0,61	0,49	0,29	0,13	0,94	0,09	0,69
a_9	0,97	0,01	0,06	0,06	0,07	0,97	0,37	0,63	0,67	0,77	0,10	0,28	0,06	0,87	0,13	0,45	0,07	0,50	0,06	0,04	0,38	0,13
a_{10}	0,40	0,19	0,58	0,81	0,42	0,00	0,39	0,64	0,13	0,92	1,00	0,43	0,21	0,82	0,16	0,27	0,01	0,90	0,23	0,41	0,70	0,57
a_{11}	0,62	0,35	0,35	0,16	0,26	0,00	0,20	0,28	0,26	0,07	0,02	0,74	0,50	0,67	0,06	0,02	0,16	0,00	0,39	0,94	0,40	0,98
a_{12}	0,03	0,08	0,41	0,80	0,37	0,07	0,00	0,10	0,78	0,30	0,34	0,00	0,35	0,89	0,07	0,01	0,61	0,15	0,01	0,75	0,72	0,34
a_{13}	0,40	0,86	0,94	0,64	0,34	0,03	0,02	0,69	0,46	0,78	0,03	0,00	0,85	0,11	0,55	0,53	0,48	0,12	0,01	0,07	0,33	0,53
a_{16}	0,00	0,02	0,07	0,04	0,70	0,00	0,00	0,43	0,77	0,01	0,00	0,17	0,38	0,71	0,48	0,03	0,34	0,41	0,17	0,17	0,16	0,15
a_{17}	0,08	0,99	0,05	0,19	0,05	0,61	0,71	0,01	0,06	0,20	0,40	0,36	0,73	0,90	0,20	0,89	0,53	0,02	0,09	0,86	0,22	0,62
a_{18}	0,58	0,63	0,74	0,90	0,06	0,22	0,76	0,01	0,90	0,02	0,00	0,33	0,00	0,51	0,64	0,58	0,77	0,31	0,01	0,42	0,67	0,56
…																						
a_{45}	0,36	0,85	0,04	0,09	0,00	0,22	0,11	0,01	0,63	0,01	0,50	0,78	0,03	0,93	0,03	0,00	0,37	0,47	0,24	0,98	0,80	0,02
a_{46}	0,59	0,11	0,52	0,98	0,31	0,42	0,00	0,47	0,03	0,80	0,79	0,76	0,08	0,76	0,00	0,00	0,55	0,03	0,61	0,82	0,06	0,47
a_{48}	0,05	0,16	0,61	0,10	0,14	0,63	0,05	0,19	0,38	0,60	0,29	0,56	0,84	0,59	0,57	0,23	0,10	0,14	0,98	0,13	0,89	0,37
a_{49}	0,04	0,03	0,25	0,35	0,94	0,77	0,74	0,45	0,54	0,93	0,08	0,30	0,16	0,23	0,97	0,03	0,76	0,46	0,13	0,84	0,86	0,36
a_{50}	0,00	0,09	0,01	0,02	0,09	0,09	0,02	0,26	0,62	0,12	0,00	0,00	0,10	0,17	0,08	0,05	0,28	0,29	0,13	0,06	0,01	0,00
a_{52}	0,48	0,03	0,28	0,07	0,16	0,60	0,32	0,13	0,04	0,20	0,58	0,25	0,11	0,16	0,33	0,43	0,00	0,00	0,13	0,98	0,59	0,46
a_{53}	0,22	0,95	0,33	0,11	0,03	0,11	0,60	0,10	0,65	0,10	0,68	0,87	0,24	0,20	0,32	0,51	0,39	0,00	0,00	0,13	0,02	0,00
a_{54}	0,09	0,10	0,02	0,01	0,23	0,56	0,62	0,04	0,18	0,01	0,29	0,49	0,03	0,88	0,73	0,13	0,46	0,00	0,88	0,28	0,62	0,38
a_{56}	0,06	0,37	0,52	0,03	0,24	0,63	0,07	0,15	0,97	0,05	0,90	0,85	0,64	0,43	0,34	0,96	0,06	0,91	0,35	0,08	0,21	0,02
a_{59}	0,00	0,04	0,10	0,55	0,16	0,01	0,08	0,58	0,69	0,77	0,02	0,12	0,28	0,22	0,91	0,28	0,27	0,75	0,29	0,19	0,74	0,57

Noted: green shading indicates the significance of attributes ($p < 0.05$)

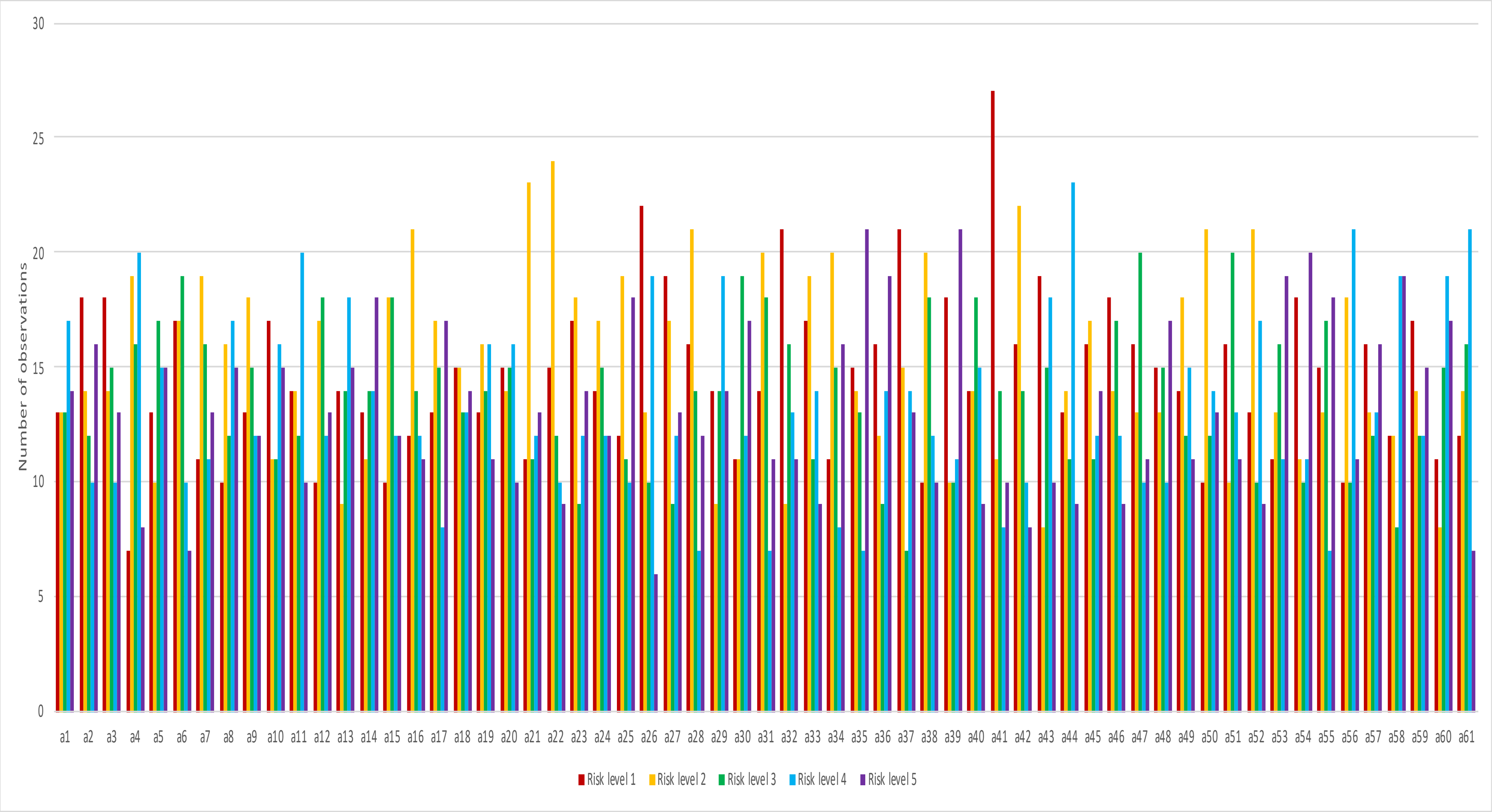
Appendix H: The scatter plot between the highest interdependency and the highest implication of risk factors.



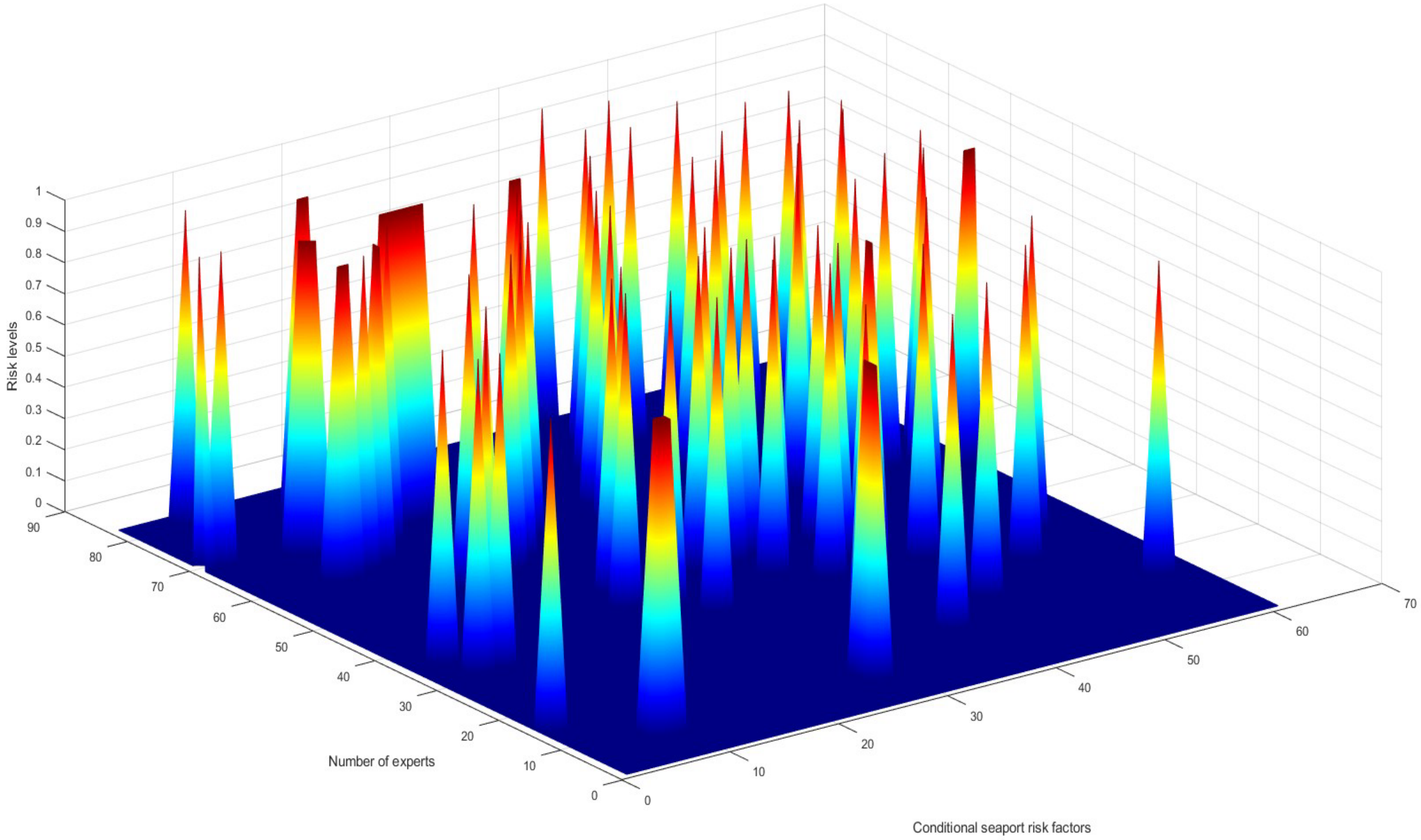
Appendix I: Frequency of risk level of conditional seaport risk attributes (port-authority - PA)



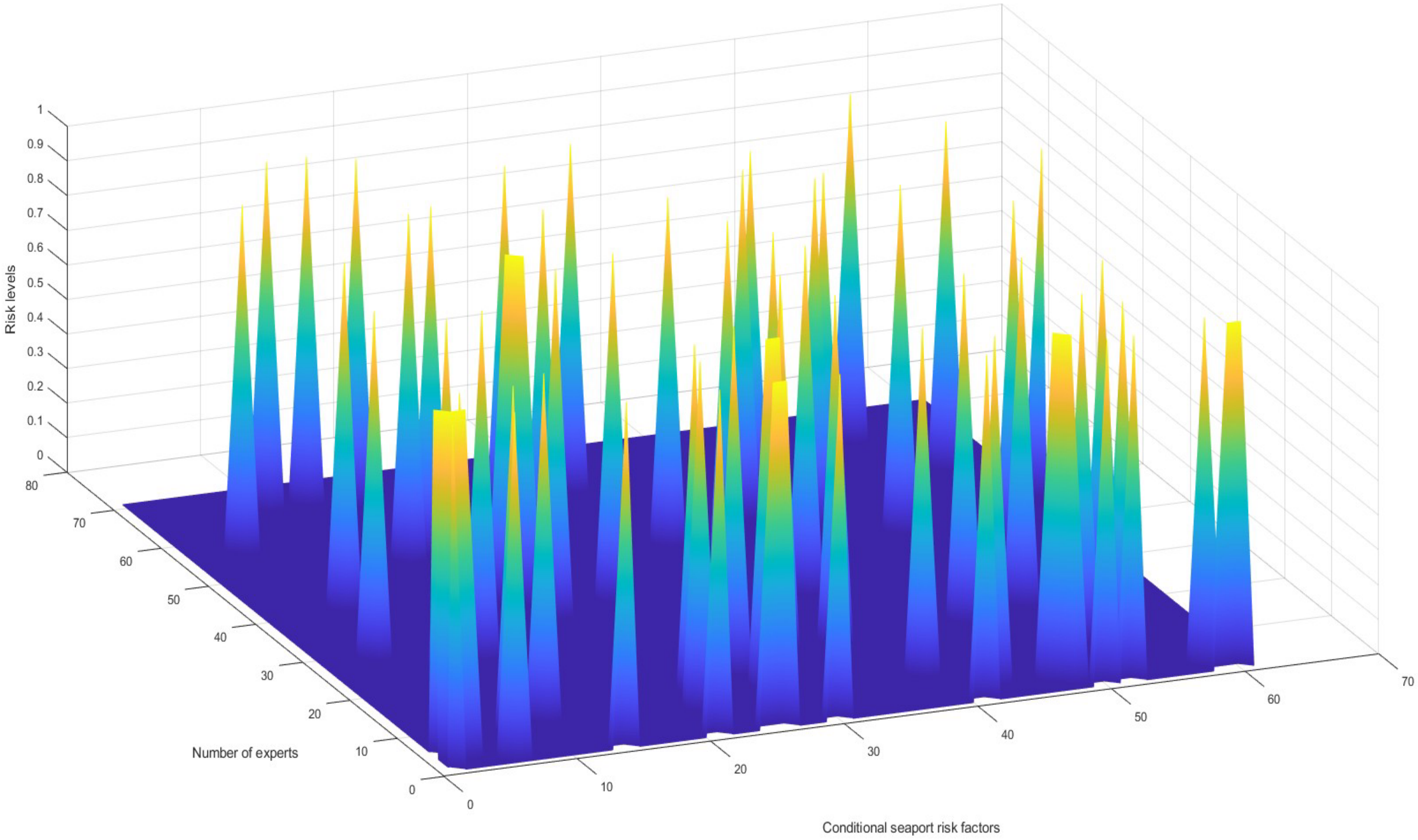
Appendix J: Frequency of risk level of conditional seaport risk attributes (seaport user - SU)



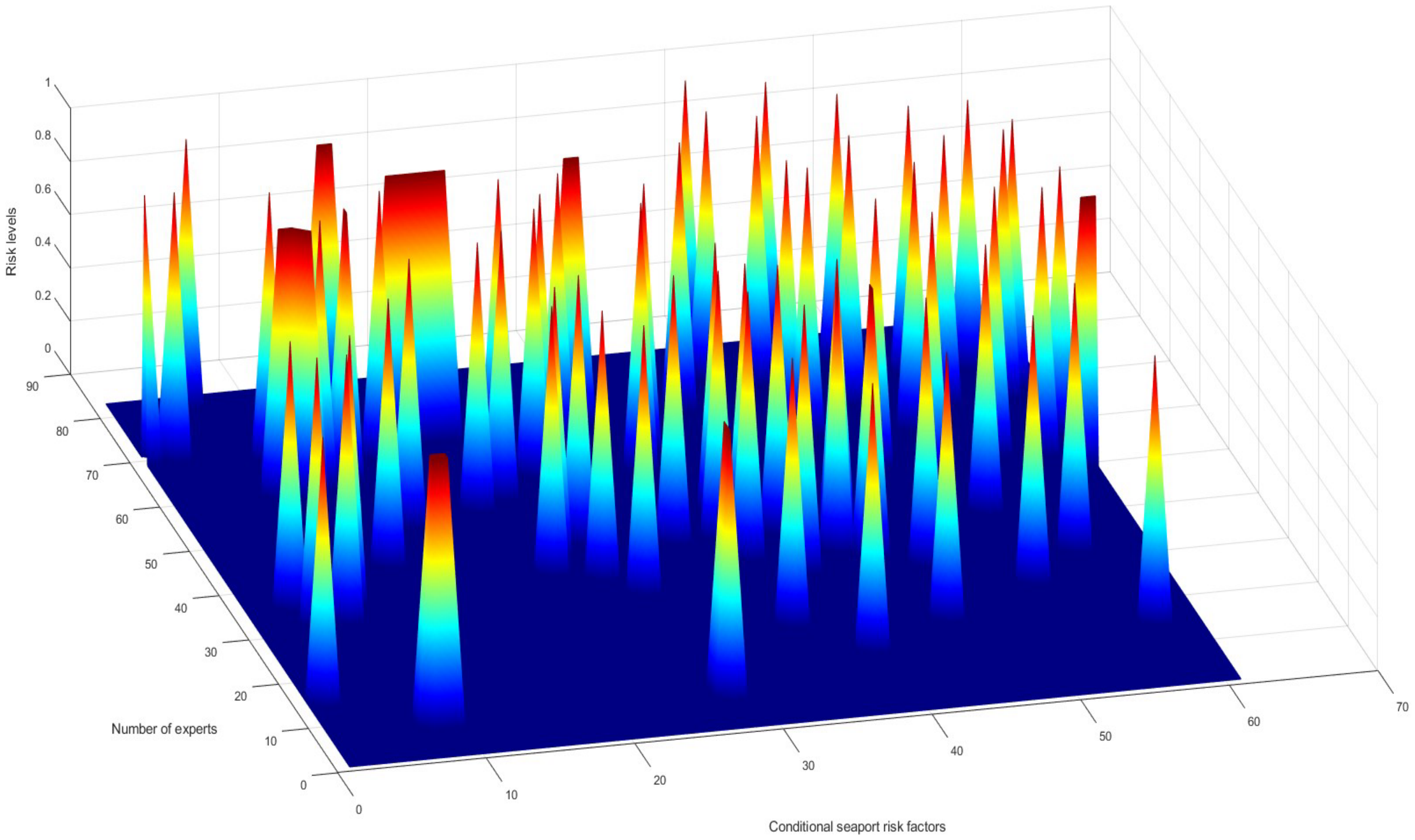
Appendix K: The results of MILP related risk level for port-authority under rule 1



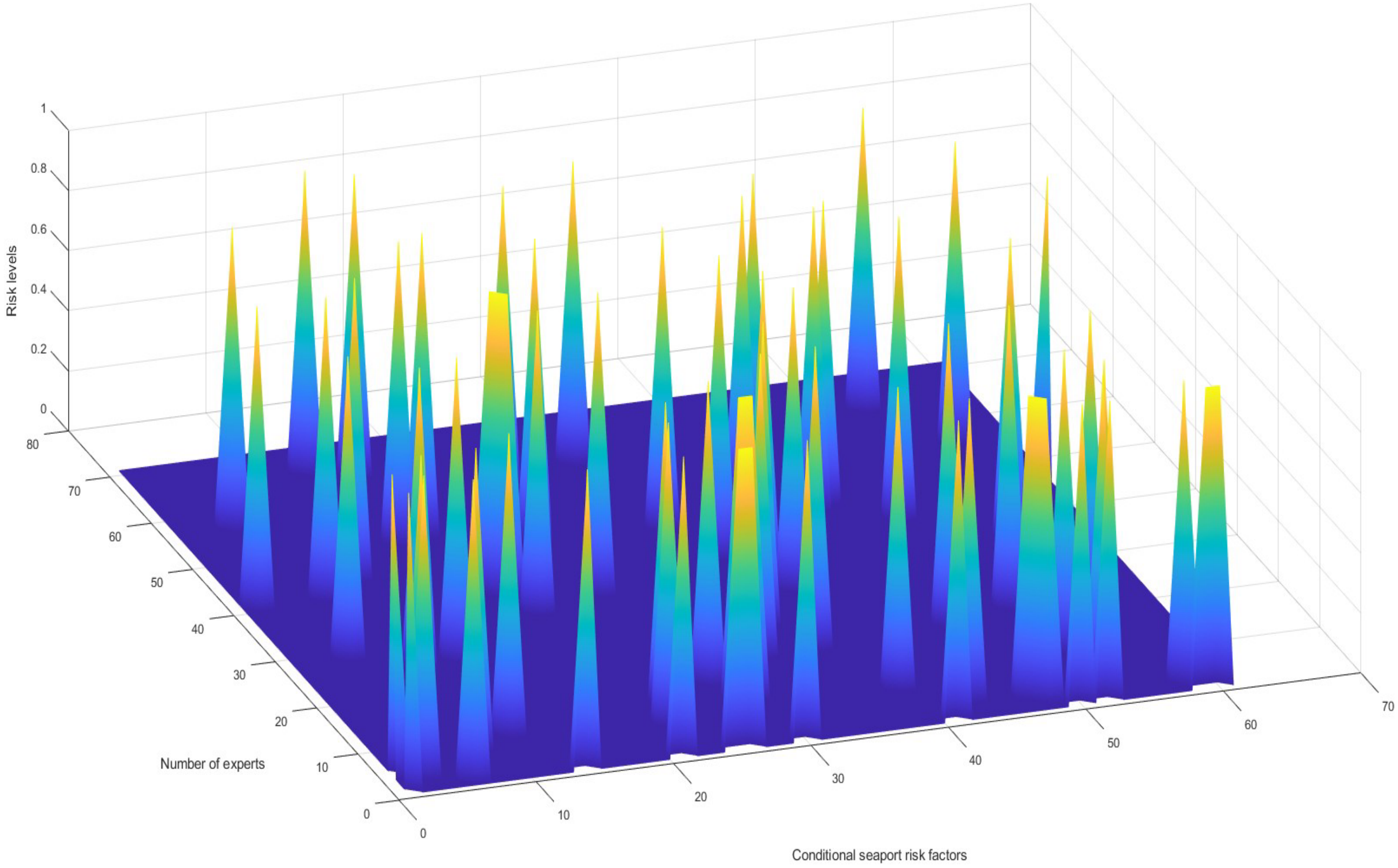
Appendix L: The results of MILP related risk level for seaport-user under rule 1



Appendix M: The results of MILP related risk level for port-authority under rule 2



Appendix N: The results of MILP related risk level for seaport-user under rule 2



Appendix O: Statistic descriptive of port-authority (PA)

Index a_j	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Sum	Count	Confidence Level (95.0%)
a_1	2.133	0.111	2	2	1.009	1.019	2.081	1.405	4	177	83	0.220
a_2	2.072	0.104	2	2	0.947	0.897	1.787	1.177	4	172	83	0.207
a_3	2.313	0.107	2	2	0.974	0.949	0.589	0.787	4	192	83	0.213
a_4	2.181	0.104	2	2	0.952	0.906	1.170	0.931	4	181	83	0.208
a_5	2.145	0.114	2	2	1.037	1.076	1.070	1.113	4	178	83	0.227
a_6	2.241	0.106	2	2	0.970	0.941	0.858	0.890	4	186	83	0.212
a_7	2.458	0.107	2	2	0.979	0.959	0.178	0.720	4	204	83	0.214
a_8	2.410	0.106	2	2	0.963	0.928	-0.055	0.431	4	200	83	0.210
a_9	2.145	0.104	2	2	0.952	0.906	2.271	1.356	4	178	83	0.208
a_{10}	3.133	0.145	3	4	1.323	1.751	-1.133	-0.088	4	260	83	0.289
a_{11}	3.265	0.132	4	4	1.200	1.441	-0.915	-0.314	4	271	83	0.262
a_{12}	3.699	0.149	4	5	1.359	1.847	-0.784	-0.686	4	307	83	0.297
a_{13}	3.506	0.142	4	4	1.291	1.668	-1.033	-0.431	4	291	83	0.282
a_{14}	3.518	0.139	4	4	1.263	1.594	-0.898	-0.433	4	292	83	0.276
a_{15}	3.542	0.137	4	4	1.252	1.568	-0.944	-0.480	4	294	83	0.273
a_{16}	3.783	0.144	4	5	1.316	1.733	-0.861	-0.672	4	314	83	0.287
a_{17}	2.578	0.133	2	2	1.211	1.466	-0.544	0.488	4	214	83	0.264
a_{18}	2.361	0.118	2	2	1.077	1.160	-0.320	0.549	4	196	83	0.235
a_{19}	2.627	0.113	3	3	1.033	1.066	-0.422	0.128	4	218	83	0.225
a_{20}	2.506	0.118	2	3	1.075	1.155	-0.076	0.497	4	208	83	0.235
a_{21}	2.410	0.110	2	2	1.000	1.001	-0.642	0.292	4	200	83	0.218
a_{22}	2.614	0.103	3	3	0.935	0.874	-0.170	0.209	4	217	83	0.204
a_{23}	2.410	0.120	2	2	1.094	1.196	0.031	0.724	4	200	83	0.239
a_{24}	2.398	0.121	2	2	1.104	1.218	-0.505	0.545	4	199	83	0.241

a_{25}	2.241	0.127	2	2	1.154	1.331	-0.263	0.731	4	186	83	0.252
a_{26}	2.145	0.096	2	2	0.871	0.759	0.271	0.505	4	178	83	0.190
a_{27}	2.349	0.106	2	2	0.968	0.937	0.003	0.480	4	195	83	0.211
a_{28}	2.506	0.114	3	3	1.040	1.082	-0.618	0.183	4	208	83	0.227
a_{29}	3.181	0.136	3	3	1.241	1.540	-0.914	-0.157	4	264	83	0.271
a_{30}	2.373	0.104	2	2	0.946	0.895	-0.848	0.154	3	197	83	0.207
a_{31}	2.446	0.111	2	2	1.015	1.031	-0.103	0.438	4	203	83	0.222
a_{32}	2.458	0.105	3	3	0.954	0.910	-0.508	0.080	4	204	83	0.208
a_{33}	2.386	0.104	2	2	0.948	0.898	-0.433	0.206	4	198	83	0.207
a_{34}	2.217	0.119	2	2	1.083	1.172	0.173	0.735	4	184	83	0.236
a_{35}	2.349	0.110	2	2	1.005	1.011	-0.205	0.499	4	195	83	0.220
a_{36}	2.289	0.122	2	2	1.110	1.232	-0.088	0.715	4	190	83	0.242
a_{37}	2.265	0.109	2	2	0.989	0.978	0.048	0.604	4	188	83	0.216
a_{38}	2.398	0.112	2	2	1.023	1.047	-0.088	0.459	4	199	83	0.223
a_{39}	2.301	0.112	2	2	1.021	1.042	-0.670	0.346	4	191	83	0.223
a_{40}	2.735	0.124	3	3	1.127	1.270	-0.952	-0.032	4	227	83	0.246
a_{41}	2.289	0.112	2	2	1.018	1.037	-0.154	0.594	4	190	83	0.222
a_{42}	2.422	0.120	2	2	1.095	1.198	-0.536	0.405	4	201	83	0.239
a_{43}	2.349	0.119	2	3	1.087	1.181	-0.497	0.311	4	195	83	0.237
a_{44}	2.422	0.099	2	3	0.899	0.808	0.327	0.292	4	201	83	0.196
a_{45}	2.313	0.106	2	2	0.962	0.925	-0.410	0.339	4	192	83	0.210
a_{46}	2.361	0.117	2	2	1.066	1.136	-0.581	0.403	4	196	83	0.233
a_{47}	2.349	0.105	2	3	0.956	0.913	-0.488	0.186	4	195	83	0.209
a_{48}	3.373	0.126	3	3	1.145	1.310	-0.614	-0.131	4	280	83	0.250
a_{49}	2.410	0.119	2	2	1.082	1.172	-0.437	0.475	4	200	83	0.236
a_{50}	2.410	0.114	2	2	1.036	1.074	-0.186	0.450	4	200	83	0.226
a_{51}	3.096	0.133	3	3	1.216	1.478	-0.829	-0.022	4	257	83	0.265

a_{52}	3.494	0.148	4	5	1.347	1.814	-0.963	-0.417	4	290	83	0.294
a_{53}	3.831	0.123	4	5	1.124	1.264	0.053	-0.819	4	318	83	0.245
a_{54}	3.627	0.134	4	4	1.217	1.481	-0.496	-0.615	4	301	83	0.266
a_{55}	3.904	0.135	4	5	1.226	1.503	-0.406	-0.830	4	324	83	0.268
a_{56}	2.807	0.125	3	3	1.142	1.304	-0.520	0.239	4	233	83	0.249
a_{57}	3.723	0.135	4	5	1.233	1.520	-0.389	-0.731	4	309	83	0.269
a_{58}	2.711	0.124	3	2	1.132	1.281	-0.500	0.389	4	225	83	0.247
a_{59}	3.301	0.135	3	3	1.227	1.506	-0.852	-0.154	4	274	83	0.268
a_{60}	3.205	0.118	3	3	1.079	1.165	-0.646	-0.004	4	266	83	0.236
a_{61}	2.747	0.117	3	2	1.069	1.143	-0.393	0.404	4	228	83	0.233

Appendix P: Statistic descriptive of seaport-user (SU)

Index a_j	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Sum	Count	Confidence Level (95.0%)
a_1	3.086	0.169	3	4	1.412	1.993	-1.287	-0.124	4	216	70	0.337
a_2	2.886	0.181	3	1	1.518	2.306	-1.436	0.148	4	202	70	0.362
a_3	2.800	0.173	3	1	1.451	2.104	-1.279	0.213	4	196	70	0.346
a_4	3.043	0.143	3	4	1.197	1.433	-0.990	-0.032	4	213	70	0.285
a_5	3.129	0.168	3	3	1.403	1.969	-1.195	-0.170	4	219	70	0.335
a_6	2.614	0.153	3	3	1.277	1.632	-0.867	0.339	4	183	70	0.305
a_7	2.943	0.161	3	2	1.350	1.823	-1.145	0.179	4	206	70	0.322
a_8	3.157	0.165	3	4	1.379	1.902	-1.271	-0.120	4	221	70	0.329
a_9	2.886	0.163	3	2	1.368	1.871	-1.176	0.177	4	202	70	0.326
a_{10}	3.014	0.179	3	1	1.499	2.246	-1.443	-0.078	4	211	70	0.357
a_{11}	2.971	0.164	3	4	1.372	1.883	-1.282	-0.086	4	208	70	0.327
a_{12}	3.014	0.158	3	3	1.324	1.753	-1.098	0.089	4	211	70	0.316
a_{13}	3.157	0.171	3	4	1.431	2.047	-1.244	-0.254	4	221	70	0.341
a_{14}	3.186	0.174	3	5	1.458	2.124	-1.315	-0.188	4	223	70	0.348
a_{15}	2.971	0.156	3	2	1.307	1.709	-1.059	0.134	4	208	70	0.312
a_{16}	2.843	0.160	3	2	1.337	1.787	-1.111	0.259	4	199	70	0.319
a_{17}	2.986	0.173	3	5	1.450	2.101	-1.321	0.143	4	209	70	0.346
a_{18}	2.943	0.173	3	1	1.443	2.084	-1.341	0.073	4	206	70	0.344
a_{19}	2.943	0.163	3	4	1.361	1.852	-1.222	0.035	4	206	70	0.324
a_{20}	2.886	0.163	3	4	1.368	1.871	-1.225	0.037	4	202	70	0.326
a_{21}	2.900	0.164	3	2	1.374	1.888	-1.234	0.254	4	203	70	0.328
a_{22}	2.629	0.158	2	2	1.321	1.744	-0.903	0.490	4	184	70	0.315
a_{23}	2.829	0.177	2.5	2	1.484	2.202	-1.399	0.221	4	198	70	0.354
a_{24}	2.871	0.165	3	2	1.382	1.911	-1.198	0.169	4	201	70	0.330

a_{25}	3.043	0.176	3	2	1.469	2.158	-1.423	0.093	4	213	70	0.350
a_{26}	2.629	0.167	2.5	1	1.395	1.947	-1.409	0.172	4	184	70	0.333
a_{27}	2.757	0.178	2	1	1.488	2.216	-1.382	0.269	4	193	70	0.355
a_{28}	2.686	0.166	2	2	1.389	1.929	-1.014	0.455	4	188	70	0.331
a_{29}	3.143	0.169	3	4	1.417	2.008	-1.225	-0.260	4	220	70	0.338
a_{30}	3.186	0.166	3	3	1.386	1.922	-1.156	-0.142	4	223	70	0.331
a_{31}	2.729	0.159	3	2	1.329	1.766	-0.895	0.404	4	191	70	0.317
a_{32}	2.771	0.174	3	1	1.456	2.121	-1.339	0.122	4	194	70	0.347
a_{33}	2.700	0.164	2	2	1.376	1.894	-1.203	0.289	4	189	70	0.328
a_{34}	2.971	0.168	3	2	1.404	1.970	-1.246	0.214	4	208	70	0.335
a_{35}	3.071	0.185	3	5	1.545	2.386	-1.496	0.023	4	215	70	0.368
a_{36}	3.114	0.185	3	5	1.547	2.393	-1.514	-0.124	4	218	70	0.369
a_{37}	2.757	0.183	2	1	1.527	2.331	-1.484	0.223	4	193	70	0.364
a_{38}	2.886	0.152	3	2	1.269	1.610	-0.957	0.220	4	202	70	0.303
a_{39}	3.100	0.191	3	5	1.598	2.555	-1.572	-0.102	4	217	70	0.381
a_{40}	2.871	0.158	3	3	1.318	1.737	-1.097	0.048	4	201	70	0.314
a_{41}	2.471	0.175	2	1	1.462	2.137	-1.124	0.502	4	173	70	0.349
a_{42}	2.600	0.156	2	2	1.301	1.693	-0.862	0.465	4	182	70	0.310
a_{43}	2.886	0.171	3	1	1.430	2.045	-1.347	-0.069	4	202	70	0.341
a_{44}	3.014	0.161	3	4	1.346	1.811	-1.254	-0.174	4	211	70	0.321
a_{45}	2.871	0.175	3	2	1.464	2.143	-1.369	0.172	4	201	70	0.349
a_{46}	2.714	0.163	3	1	1.364	1.859	-1.133	0.221	4	190	70	0.325
a_{47}	2.814	0.163	3	3	1.365	1.864	-1.087	0.171	4	197	70	0.326
a_{48}	3.014	0.177	3	5	1.479	2.188	-1.370	0.030	4	211	70	0.353
a_{49}	2.871	0.165	3	2	1.382	1.911	-1.263	0.136	4	201	70	0.330
a_{50}	2.986	0.162	3	2	1.357	1.840	-1.249	0.134	4	209	70	0.323
a_{51}	2.900	0.164	3	3	1.374	1.888	-1.149	0.012	4	203	70	0.328

a_{52}	2.829	0.160	3	2	1.340	1.796	-1.237	0.174	4	198	70	0.320
a_{53}	3.200	0.171	3	5	1.431	2.046	-1.290	-0.119	4	224	70	0.341
a_{54}	3.057	0.190	3	5	1.587	2.518	-1.565	-0.052	4	214	70	0.378
a_{55}	3.000	0.177	3	5	1.484	2.203	-1.350	0.082	4	210	70	0.354
a_{56}	3.071	0.159	3	4	1.333	1.777	-1.255	-0.096	4	215	70	0.318
a_{57}	3.000	0.179	3	1	1.494	2.232	-1.427	0.000	4	210	70	0.356
a_{58}	3.300	0.175	4	5	1.468	2.155	-1.319	-0.343	4	231	70	0.350
a_{59}	2.914	0.178	3	1	1.491	2.224	-1.414	0.097	4	204	70	0.356
a_{60}	3.329	0.165	4	4	1.380	1.905	-1.022	-0.414	4	233	70	0.329
a_{61}	2.957	0.152	3	4	1.268	1.607	-1.086	-0.137	4	207	70	0.302

Appendix Q: Comparisons skewness between port-authority and seaport-user