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Abstract

Seaport operations are characterised by high levels of uncertainty, as a result their risk evaluation is a very challenging task. Much of the available data associated with the system's operations is uncertain and ambiguous, requiring a flexible yet robust approach of handling both quantitative and qualitative data as well as a means of updating existing information as new data becomes available. Conventional risk modelling approaches are considered to be inadequate due to the lack of flexibility and inappropriate structure for addressing the system's risks. This paper proposes a novel fuzzy risk assessment approach to facilitating the treatment of uncertainties in seaport operations and to optimize its performance effectiveness in a systematic manner. The methodology consists of a fuzzy analytical hierarchy process, an evidential reasoning (ER) approach, fuzzy set theory and expected utility. The fuzzy analytical hierarchy process is used to analyse the complex structure of seaport operations and determine the weights of risk factors while ER is used to synthesise them. The methodology provides a robust mathematical framework for collaborative modelling of the system and allows for a step by step analysis of the system in a systematic manner. It is envisaged that the proposed approach could provide managers and infrastructure analysts a flexible tool to enhance the resilience of the system in a systematic manner.

Keywords: Seaport operations; evidential reasoning approach; fuzzy set theory; fuzzy analytical hierarchy process

1. Introduction

Critical Maritime Infrastructure (CMI) systems, which are defined as ports, waterways, vessels and their intermodal connections are the basis of world economic development. CMI are susceptible to diverse risks in their field of operations as a result of the interaction and interdependence among their components and subsystems. Additionally, the multiplicity of stakeholders in the system and the complex operational scenarios contributes to creating high levels of uncertainty. CMI typically operates in a dynamic environment in which the boundaries of safety are pushed, leading to the disruption of operations.

Serious accidents and cascading events, such as the 9/11 terrorist attacks in 2001, the lock-out of the American West Coast Port in 2002, the Fukushima nuclear disaster in 2011, and the recent piracy related activities off the Gulf of Guinea are clear examples of systemic failures and disruptions of CMI systems. As these systems become highly integrated and play a vital role in advancing the global economy, accidents gradually develop over time through a conjunction of several small failures [1, 2]. Consequently, it is imperative to address the diverse risks of such accidents or disruptions proactively, particularly as new hazards and threats are constantly evolving due to the dynamic nature of the maritime environment.

When critical systems such as maritime infrastructure do not have the robustness to recover in the face of disruption, they present themselves as attractive targets to terrorism related attacks. Given that a large proportion of the world's trade is transported by sea, the global economy is heavily dependent on the effective operation of these systems; disruptions at any point within their operation could potentially result in catastrophic and disastrous consequences.

Building resilience in maritime operations requires creating capabilities and a sustained engagement from the stakeholders involved in their operations. Additionally, academics and industrialists acknowledge that safety and security efforts that are aimed at mitigating risks will always reach a point of diminishing returns. In order to optimise the defence capability of the system, it is essential to constantly revise and update its risk model in such a manner that it would adapt, cope and recover to a desired level of functionality when facing adverse operational constraints. An emphasis on robustness in the system's operations provides a flexible and collaborative model for maritime systems to adopt.

The risk assessment of a CMI system is a complex task due to the integration of technical, organisational, operational and security issues into its daily operations. Conventional techniques such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Failure Mode, Effects and Criticality Analysis (FMECA) and Bow-Tie (BT) have been widely used in reliability analysis of critical systems and have contributed immensely to the literature of risk analysis. However, most of the aforementioned approaches have prescribed setbacks which affect their application for quantitative risk analysis and management due to their inability to account for uncertainties associated with the system operation.

Moreover, large numbers of optional maritime safety and security control measures have been proposed by various regulations to optimise the operational efficiency of the system in such a manner that it will exhibit resilience to disruptions [3, 4, 5, 6]. The use of conventional risk assessment approaches to deal with newly arising hazards and threats (e.g. potential terrorist attack) to maritime infrastructure reveals two major challenges they face in an uncertain environment. Yang [7] expressed the challenges faced by these systems as the lack of capability to process diverse data suitable for input into a risk inference mechanism and the lack of capability to analyse the interactive dependence between risk factors.

One realistic way to analyse unavailable data is to employ subjective assessment using the combination of fuzzy logic, Dempster and Shafer (D-S) theory and Evidential Reasoning (ER). Compared to the traditional fuzzy inference mechanism (i.e. max-min fuzzy operations), an ER approach has the superiority of avoiding the loss of useful information in their inference processes; hence, it can be suitable for modelling complex systems.

The occurrence of natural disasters and the disruptions caused by man-made attacks on CMI systems are imprecise. It is therefore challenging to protect the systems from such perceived scenarios and understand their complex operational processes. The purpose of analysing the system in the face of severe disruptions is to promote security and reduce its susceptibility to hazards. It is important to emphasise that resilient systems are able to recover by delivering their designed expected value and minimising losses in a systematic fashion. Moreover, insufficiency of quantitative risk assessment of maritime related literature together with the vision to establish a secure and resilient CMI system has resulted in an urgent need for an integrated risk assessment methodology capable of tackling the uncertainties associated with the systems operation.

The aim of this paper is to propose an integrated fuzzy risk analysis model for assessment of seaport operations. This has been organised as follows. Section 2 reviews the existing literature on CMI systems, and presents and discusses the diverse range of risk factors associated with seaport operations. Section 3 explains the methodology of the study. Section 4 provides a case study to demonstrate the applicability of the proposed methodology. Sections 5 and 6 present a discussion of results and the conclusion.

2. Literature Review

CMI systems are faced with high operational constraints due to the dynamic interactions among their interrelated components. The level of interdependences and complexity of the system's operations can be acknowledged through its description by the US Department of Homeland Security "as all areas and things of, on, under, relating to, adjacent to, or bordering on a sea, ocean, or other navigable waterway, including all maritime related activities, infrastructure, people, cargo, vessels and other conveyances" [8]. Analysing the systems in terms of their interdependences which include infrastructure characteristics, operational relationships, environmental impacts, technical efficiency, failure types and state of operation provides insight into their complexity, enabling collaborative modelling to be undertaken.

Modern seaports, which are an integral component of CMI systems, focus their operations on continuous handling of flows and efficient transport. Meersman [9], as shown in Figure 1, revealed that these systems progressed from performing cargo handling, stacking and distribution functions to being a complex transportation hub in logistic chains. A vessel operator controls a fleet of vessels with a set of characteristics; the land side can be understood as a system of ports operating at local, national and regional levels. It is worth mentioning that individual ports have several terminals, serving different types of loading technologies and cargoes. Comprehensive analysis of maritime infrastructures has revealed that they consist of ports, terminals, intermodal connects, navigable waterways and vessels.

In maritime operations, seaports serves as the business hub and provide critical infrastructure functions such as port, roads and rails, and safety and security functions, which involve customs, investments, developments and marketing [10]. Detailed analysis of CMI operational processes and their component parts suggests that seaport infrastructure systems include not only the infrastructure (e.g. assets that are capable of an intended service delivery, such as access channels, turning basins, quay walls, jetties, navigational aids, break waters, pilots, tugs, stacking areas), the superstructure (e.g. computer and logistics systems and ICT, handling equipment, warehouses, *etc*.), but also the operating procedures, management practices and complex interactions with the society to facilitate trade and the transfer of goods and services for economic development [11].

Maritime-related activities are operated at seaports which are located within densely populated and industrial locations that accommodate chemicals and weapons in their storage facilities [12]. The flexibility in the flows of vessels and large amounts of bulk cargoes within these areas has created a huge amount of concern about their integrity because of the numerous opportunities for them to be tampered with for terrorism-related acts or sabotage. Additionally, their operations can be marred by several organisational and environmental risks that range from natural to man-made disasters with disruption likelihood that can potentially result in a large amount of direct and indirect financial losses [13, 14]. External risks that disrupt seaport operations include hurricanes, tornadoes, tsunamis, flood and chemical spills.

When studying the safety aspects of a seaport, a logical approach is to break down the system into functional entities comprising sub-systems and components. Safety modelling of these functional entities can be carried out to fit such a logical structure, then the interrelationships can be examined and a system safety model can be formulated for risk-based decision making in all phases of the system's life, from its conception and design to its operation, maintenance and decommissioning.

The risks associated with seaport operations are complex. This is evidenced by the fact that different risk categories discussed in literature affect the multiplicity of stakeholders involved in their operations. Complexities in the systems may further arise when they interrelate with other risk characteristics such as uncertainty and dependence. This can be explained through the classification of risk as presented in Table 1 [12, 15, 16, 17]. Each risk event as presented in Table 1 is investigated based on its associated causes. These causes are chosen because they are regarded as the most significant ones associated with major disruption of seaport processes. The selection of such disruption risks and causes is conducted based on extensive discussions with experts and a robust literature review.

<Figure 1: Sea-Land Interface of Maritime Transportation Systems>

<Table 1: Causes of Seaport Disruption>

2.1. Operational Risk Factors

The evolution of large carrier vessels for maritime operations has necessitated the need to optimise terminal infrastructures to systematise the management of risk in loading and unloading operations in ports and maximise the possibility of controlling accident risks effectively. Ports cannot afford disruptions caused by unexpected risks. Due to the complexity of the systems, disruption and damage may well be inflicted not only on property but also to human life and the environment once an accident occurs during a system's operations. The operational risk factors that cause disruption of maritime activities are due to port equipment/machinery failures, ships/vessels accident/grounding, and cargo spillage [18]. These are attributed to movement of oil tankers, large and small boats, loading and unloading of oil and other cargoes, ferry services, cargo forwarding operations, human errors and management [10, 19].

2.2. Security Risk Factors

Securing maritime business against disruption due to security incidents presents an enormous task to the globalised world. Since the 9/11 attacks, security experts have shown serious concerns over the efficiency and robustness of CMI system security, with regard to its possible exploitation by terrorists to wreak havoc on the system either through sinking of a large vessel in a port channel or attacking a port's physical infrastructure facilities [20, 21].

Experience has shown that decision makers have invested significant resources on sophisticated security measures in order to ensure smooth flows of trade, yet face a severe challenge in the effectiveness of these security measures [22]. It is worth mentioning that the effective performance of security systems or measures can be built based on the evaluation and aggregation of the security risks associated with seaport operations, such as sabotage, terrorism attacks, surveillance system failure and arson [23].

2.3. Technical Risk Factors

While technical solutions will continue to play an important role in facilitating smooth operations of maritime systems, the need for a systemic understanding and analysis of CMI systems has led to the categorisation of the seaport system as marine constructions, port maintenance, port operations and logistics. Because ports are open facilities with multiple means of access by both land and sea routes, they involve multiple modes and each is managed by a different entity within the system. Due to the importance of maritime operations in global trade and logistics, lack of equipment, navigational aid, IT systems and dredging maintenance have been identified as significant issues in causing severe disruption of seaport operations with long-term financial consequences [16].

2.4. Organisational Risk Factors

Events such as labour unrest, dispute with regulatory bodies, breakdown in organisational communications leading to berth congestion, incompatible management goals leading to gate congestion and poor management procedures leading to storage area congestions are major factors mentioned in literature which lead to the disruption of seaport operations [18, 24]. There is a widespread agreement among safety researchers that the key means of tackling the human element contribution to disruptions will be via the incorporation of resilience into the operations of the system [18].

2.5. Natural Risk Factors

The dynamics of the natural environment affect the entirety of seaports. Its influences are capable of disrupting maritime business and therefore make such business vulnerable to hazards. The most important hazards due to natural factors are hydrological, atmospheric and geologic hazards [25]. The impacts of these hazards have consistently added more cost to management of seaports in the form of annual maintenance, reconstruction and preparedness. Heavy rainfall, flooding and snow are important examples of hydrologic hazards; tsunamis and earthquake are categorised as geological or seismic hazards; hurricanes and cyclones are classed as atmospheric hazards.

3. Methodology

Quantitative risk assessment models are predominantly used over the years to estimate uncertainties in seaport operations. However, in situations where there is lack of data, it is necessary to incorporate expert judgements into a risk assessment process. Past experience on existing CMI systems have shown that major hazards have the potential to cause disruptions of operations with long term consequences. In order to model the complex structure of the system and facilitate a flexible implementation approach, different decision making techniques such as fuzzy set theory, a fuzzy analytical hierarchy process and an evidential reasoning approach are used. Fuzzy set theory has been widely used in different fields of application including system safety, risk assessment and reliability engineering; this is due to the fact that fuzzy logic might provide the flexibility needed to represent the vague information resulting from the lack of data or knowledge [26].

The proposed framework (Figure 2) is capable of quantifying judgements of experts qualitatively and allows for a step-by-step analysis of the system in a transparent manner and is described as follows:

1. Identify risk factors and present them in a hierarchical structure.
2. Calculate the weight of each criterion in the hierarchy using the Fuzzy Analytical Hierarchy Process (FAHP).
3. Apply fuzzy set theory and belief degree concept to measure the risks of a seaport.
4. Implement the Evidential Reasoning (ER) algorithm to synthesise the risk results.
5. Determine the crisp result of the risk synthesis using expected utility approach.
6. Perform sensitivity analysis.

<Figure 2: Framework for Risk Assessment of Seaport Operations>

3.1. Identify Risk Factors and Present them in a Hierarchical Structure (Step)

Providing a structured and systematic approach for making better decisions about maritime operations requires a thorough understanding of the risks and vulnerabilities of the system. It is essential to display the problem in a hierarchical structure so that decision makers can have a clear picture of the whole problem, especially when there are many criteria to be considered, which in turn may consist of sub-criteria and even sub-sub-criteria.

As presented in Figure 3, the first level represents the goal of the problem. In the second level, there are several criteria, each of which has its contribution to measuring and helping to achieve the goal of the problem. Some of these criteria may be broken down further and the process continues up to the level where decision makers are able to make practical decisions.

Based on the literature review [15, 16, 18, 20, 21, 25], as well as the available information presented in section 2, a generic model with a hierarchical structure is constructed and presented in Figure 3. Due to the complexity of the systems, only those criteria that are of significance in causing disruptions are considered. By doing so, it can help to reduce the scale and diversity of the model for ease of its modelling. Also, because this analysis is based on a short-term projection, rising sea level (RSL) which can only have an input over a long period, is ignored.

<*Figure 3: Generic Model for Disruption of Seaport Operations*>

3.2. Application of Fuzzy Analytical Hierarchy Process (FAHP) (Step 2)

As discussed in section 3.1, and because each criterion contributes differently to the risk of disruption, their weights have to be taken into account in order to represent their relative importance to the overall estimate of disruption. FAHP is employed in this study to obtain the weight of each attribute in the hierarchy and to synthesise the risks from the bottom to the top level of the hierarchy in a systematic fashion. Compared to the conventional AHP method, which uses crisp values in evaluating the relative importance of each attributes, FAHP uses fuzzy ratios for ease of expert knowledge elicitation.

An advantage of FAHP is its flexibility to be integrated with different techniques such as evidential reasoning in risk analysis. Therefore, FAHP leads to the generation of weighting factors to represent the primary risk within each category of the model.

3.2.1. Procedure of FAHP Algorithm

When considering a group of attributes for evaluation, the main objective of the technique is to provide judgements on the relative importance of these attributes and to ensure that the judgements are quantified in such a manner that permits simplified quantitative interpretation [26]. In determining the weight of an attribute, an expert's judgement is in the form of pair-wise comparisons based on an estimation scheme, which lists the intensity of importance using linguistic terms. Furthermore, each linguistic term has a corresponding triangular fuzzy number and can be presented by Equation 1 [27].

$$\tilde{a}_x = (L, M, U) \tag{1}$$

where *L*, *M* and *U* stand for the smallest possible number, the most promising number and the largest possible number that describe a fuzzy event. Table 2 shows the linguistic variables for a criterion and its corresponding triangular fuzzy number (TFN), as modified and adopted from [27], it is used in this study for the purpose of weighting factor estimation.

<Table 2: Weight Estimation Scheme>

3.2.2. Formulating a Fuzzy Pair-wise Comparison Matrix

In a risk assessment group, suppose there are *n* experts or decision makers with equal weights, the elements in a fuzzy pair-wise comparison matrix can be modelled as follows:

$$\tilde{a}_{i,j} = \left(\frac{1}{n}\right) \otimes \left({e^1}_{i,j} \oplus {e^2}_{i,j} \oplus \dots . {e^k}_{i.j} \dots . \oplus {e^m}_{i,j}\right) \tag{2}$$

$$\tilde{a}_{j,i} = \frac{1}{\tilde{a}_{i,j}} \tag{3}$$

where $\tilde{a}_{i,j}$ is the relative importance by comparing events i and j while ${e^k}_{i.j}$ represents the *kth* expert judgement in TFN format. For a $n \times n$ fuzzy pair-wise comparison matrix, $\tilde{A}$ can be obtained as follows:

$$\tilde{A} = \begin{pmatrix} \tilde{a}_{1,1} & \tilde{a}_{1,2} & \dots & \tilde{a}_{1,n} \\ \tilde{a}_{2,1} & \tilde{a}_{2,2} & \dots & \tilde{a}_{2,n} \\ \vdots & \vdots & \tilde{a}_{i,j} & \vdots \\ \tilde{a}_{n,1} & \tilde{a}_{n,2} & \dots & \tilde{a}_{n,n} \end{pmatrix} \tag{4}$$

The weight factors of each element in the hierarchy can be computed using the geometric mean technique [28].

$$\tilde{r}_i = \left(\tilde{a}_{i,1} \otimes \tilde{a}_{i,2} \otimes \dots \otimes \tilde{a}_{i,n}\right)^{1/n} \tag{5}$$

$$\tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \dots \oplus \tilde{r}_n)^{-1} \tag{6}$$

where $\tilde{a}_{i,n}$ is the fuzzy comparison value of the fuzzy pair-wise comparison matrix, $\tilde{r}_i$ is the geometric mean of the i^{th} row in the fuzzy pair-wise comparison matrix, and $\tilde{w}_i$ is the fuzzy weight of the i^{th} criterion of a triangular fuzzy number (TFN) indicated by $\tilde{w}_i = \left(w_i^l, w_i^m, w_i^u\right)$, while $w_i^l, w_i^m \; and \; w_i^u$ are the lower, middle and upper values of the fuzzy weight of the i^{th} criterion respectively.

The geometrical mean obtained from the triangular fuzzy weight using Equation 6 needs to be defuzzified into a crisp weight factor using an approach derived by Tang [29].

The defuzzified mean value $DF_{\tilde{w}_i}$ for $\left(w_i^l,\ w_i^m,\ w_i^u\right)$, can be obtained as follows:

$$DF_{\tilde{w}_i} = \frac{\left(w_i^u - w_i^l\right) + \left(w_i^m - w_i^l\right)}{3 + w_i^l} \tag{7}$$

The normalised weight of the i^{th} attribute can be obtained using Equation 8.

$$w_i = \frac{DF_{\tilde{w}_i}}{\sum DF_{\tilde{w}_i}} \tag{8}$$

In order to control and ensure accuracy in the result of the method, consistency ratio for each of the matrices needs to be analysed. The consistency ratio (CR) is used to estimate the consistency of the pair-wise comparisons as follows:

$$CR = CI/RI \tag{9}$$

$$CI = \frac{\lambda_{max} - n}{n-1}$$

$$\lambda_{max} = \frac{\sum_{j=1}^{n} \frac{\sum_{k=1}^{n} w_k\, a_{jk}}{w_j}}{n}$$

where *CI* stands for consistency index, *RI* stands for average random index (Table 3), *n* stands for matrix order, and λ_{max} stands for maximum weight value of the *n-by-n* comparison matrix. When CR is less than 0.10 the comparisons are acceptable, otherwise, they are not acceptable and should be revised in order to obtain a consistent opinion [30].

<Table 3: Value of RI versus Matrix Order> [31]

3.3. Application of Fuzzy Risk Assessment (Step 3)

After identifying risk attributes or hazards associated with the operation of a seaport system based on interviews with domain experts and literature review, the next phase of a risk management process is to assess/evaluate the risks in order to apply measures to prevent or mitigate their effect on the system [55]. Risk levels in seaport operations can be determined using the following parameters:

$$P = L \otimes S \tag{10}$$

where *P* is the risk associated with each hazardous event, *L* represents the occurrence likelihood of the hazard or risk factors, *S* represents the consequence severity of the hazard and $\otimes$ denotes the multiplication relationship between the occurrence likelihood and the consequent severity. The occurrence likelihood illustrates the expected number of occurrences of an undesired event, which can be stated as events per unit time, while the consequence severity depicts the scale of the undesired event that can negatively have an effect on subjects of interest. It can be expressed as number of people affected (injured or killed), damage to property and amount of spill, area affected, and time outage [55]. This definition of risk as presented in Equation 10 has been applied to risk assessment in many applications such as software development [54], environment modelling [48], mechanical system design [40], process plant modelling [41,42,45], water pipe deterioration analysis [43,44] and offshore oil and gas well analysis [52]. In this paper, Equation 10 is used to describe the risk levels associated with each risk factor or hazardous event in seaport operations. This definition indicates that, if L and/or S are represented by fuzzy numbers, P will also be a fuzzy number.

3.3.1. Application of the Belief Degrees in Maritime Risk Assessment

After the determination of the risk level in section 3.3, it is necessary to transform the fuzzy ratings of all parameters into belief structures with the same set of evaluation grades. Given that an analyst often cannot provide exact estimates for assessing risk in many situations, it is preferred to assess risks using linguistic terms rather than numerical values. This paper uses linguistic risk levels to represent the risk profile of each risk parameter.

A belief degree generally represents the strength to which an answer is believed to be true, and it must be equal to or less than 100% or able to be described as the degree of expectation that, given an alternative, will yield an anticipated outcome on a particular criterion. The use of individual belief degrees depends on an analyst's expertise, knowledge of the subject matter and experience regarding the operation of the system. The justification for the use of belief degrees is as a result of the fact that human decision making involves ambiguity, uncertainty and imprecision; individuals make judgements in probabilistic terms with the help of their knowledge.

In risk analysis, one realistic way to analyse a risk with incomplete objective data is to employ a fuzzy *IF-THEN* rule built from human understanding, where premise and conclusions contain the linguistic variables used to describe risk attributes [7]. Fuzzy *IF-THEN* rules with a belief structure can be constructed to model a risk assessment scenario. Based on Li and Liao [47], it is necessary to convert the fuzzy ratings of risk attributes into a belief structure with the same set of evaluation grades when measuring their risk levels. The evaluation of risks by each of the risk parameters can be explained by the following expression:

$$\mathrm{Z} = \left[\mathrm{Z}_{1,}\mathrm{Z}_2, \mathrm{Z}_3, \mathrm{Z}_4, \mathrm{Z}_5\right] = \{\text{Very Low, Low, Medium, High, Very High}\} \tag{11}$$

The estimation of risk level obtainable in Equations 10 and 11 can be converted using the five steps presented in Table 4. The obtained result (i.e. FTN_{LS}) can be converted into fuzzy risk in order to simplify the computational analysis and present the risk's level in a unified space of discourse which can subsequently be used as input data into the IDS software for aggregation and ranking [47,48].

3.3.2. Linguistic Variables for Risk Parameters

Because risk is a fuzzy problem that is uncertain and imprecise, it is usually challenging to quantify it due to the fact that potential hazards or threats occur infrequently and their closed interval range can have an assumed value of 0 and 1. A practical and efficient way to express risk levels in a seaport is to use qualitative descriptors, particularly from the safety analyst or subject matter experts during safety audits.

The likelihood of hazard can be assessed using such terms as Very Low, Low, Medium, High and Very High while the consequence or impact of hazard can be assessed as Negligible, Moderate, Serious, Very Serious and Disastrous, as presented in Table 6.

These subjective variables can further be defined in terms of their membership functions with a curve that defines how each point in the input space can be mapped into a membership value between 1 and 0. Bilgiç and Turksen [50] analysed various methods for determining membership functions. Due to the complexity of engineering systems, it is believed that in some cases the expressions of membership functions are not the dominant factors used for analysis [45]. Different scales of linguistic terms for expert assessment were proposed by Chen and Hwang [51]. However, the most commonly used membership functions are the triangular and trapezoidal [32]; this research uses the five-scale method, adapted and modified from Ngai and Wat [53], to represent the L and S levels of risk, as shown in Figure 4 with uniform distribution of linguistic variables and Table 6 respectively.

<Figure 4: Fuzzy triangular membership function>

As discussed earlier, the risk level is the combination of the occurrence likelihood (L) of a hazard and its consequence severity (S). When the occurrence likelihood (L) of a hazard and its consequence severity (S) are assumed to be independent of each other, their combination is equal to the product of the two. Hence, under the same assumption of independence, the product of the two fuzzy triangular numbers denoted by $\tilde{L} = (a_L, b_L, c_L)$ and $\tilde{S} = (a_S, b_S, c_S)$ can yield the desired risk level of each hazardous event under investigation, as presented in Equation 11:

$$Z = FTN_{LS} = FTN_L \otimes FTN_S = (a_L \otimes a_S, b_L \otimes b_S, c_L \otimes c_S) \quad (12)$$

where FTN represents fuzzy triangular numbers. FTN is used because of its computational simplicity and the ease with which it can be applied during the calculation process.

As presented in Table 6, if a risk based on experts' judgement has an occurrence likelihood (L) of (0.25, 0.5, 0.75) (Medium) and consequence severity (S) of (0.5, 0.75, 1) (Very Serious), the corresponding risk P (i.e. the multiplication of L and S) will be FTN_{LS} (0.125, 0.375, 0.75). The obtained risk result FTN_{LS} is mapped over FTN_P (i.e. 5 grades defined over the universe of discourse of risk (VL, L, M, H and VH)) as shown in Figure 5. Based on Figure 5, the point where the newly mapped FTN_{LS} intersects each linguistic term of FTN_P are circled, and maximum values are used at points where FTN_{LS} and a linguistic term of FTN_P intersect at more than one points, and the corresponding results are presented in Table 5. Z_P (i.e. the intersecting points) is normalised to obtained Z. These steps are demonstrated in Figure 5 and Tables 4 and 5 respectively [49].

<Table 4: Five Steps of Converting FTN_{LS} into Fuzzy Risk Z>

<Figure 5: Example of converting fuzzy ratings to five non-normalized grades>

<Table 5: Example of converting fuzzy FTN_{LS} into fuzzy risk>

<Table 6: Qualitative Descriptors for Triangular Fuzzy Numbers>

<Table 7: Definition of linguistic variables used for risk evaluation and risk levels based on TFNs>

Based on Table 7, the standard categories of risk levels can be evaluated using Equation 11, as follows:

$$\begin{aligned}
&P_{Very\ Low} = L_{Very\ Low} \otimes S_{Negligible} \\
&P_{Low} = L_{Low} \otimes S_{Moderate} \\
&P_{Medium} = L_{Medium} \otimes S_{Serious} \qquad (13) \\
&P_{High} = L_{High} \otimes S_{Very\ Serious} \\
&P_{Very\ High} = L_{Very\ High} \otimes S_{Disastrous}
\end{aligned}$$

where P denotes fuzzy risk variable; L and S stand for occurrence likelihood and consequence severity respectively. Table 7 presents the definitions of risk levels based on TFNs. K is the risk level number used for the analysis and can be obtained using Equation 14.

$$K = \frac{1}{2}(a_1 + a_2 + a_3) \qquad (14)$$

3.4. Aggregating Assessment via Evidential Reasoning Algorithm (Step 4)

The theory of evidence was first generated by Dempster [33] and further developed by Shafer [34]. It is often referred to as Dempster-Shafer theory of evidence or D-S theory. The D-S theory was originally used for information aggregation in expert systems as an approximate reasoning tool [35]. Subsequently, it has been used in decision making under uncertainty [36]. Due to the ever-changing environment and the multiple criteria decision making problems having a degree of uncertainty, the ER algorithm was developed. The ER approach can be elucidated as follows [37]:

Let "*R*" represent the set of the four risk expressions and be synthesised by two subsets R_1 and R_2 from two different assessors. Then, for example, R, R_1 and R_2 can separately be expressed by:

R = { β^1 "*Low*", β^2 "*Medium*", β^3 "*Fairly High*", β^4 "*High*"}

R_1 = { β_1^1 "*Low*", β_1^2 "*Medium*", β_1^3 "*Fairly High*", β_1^4 "*High*"}

R_2 = { β_2^1 "*Low*", β_2^2 "*Medium*", β_2^3 "*Fairly High*", β_2^4 "*High*"}

where "*Low*", "*Medium*", "*Fairly High*" and "*High*" (the risk expression) are associated with their corresponding degrees of belief. Suppose the normalised relative weights of two assessors in the risk evaluation process are given as ω_1 and ω_2 ($\omega_1 + \omega_2 = 1$). ω_1 and ω_2 can be estimated by using an AHP technique. Suppose M_1^m and M_2^m (*m* = *1*, *2*, *3* or *4*) are individual degrees to which the subsets R_1 and R_2 support the hypothesis that the risk evaluation is confirmed to the four risk expressions. Then, M_1^m and M_2^m are obtained as follows:

$$\begin{aligned} M_1^m &= \omega_1 \times \beta_1^m \\ M_2^m &= \omega_2 \times \beta_2^m \end{aligned} \qquad (15)$$

where $m = 1, 2, 3, 4$.

Suppose H_1 and H_2 are the individual remaining belief values unassigned for M_1^m and M_2^m (*m* = *1*, *2*, *3*, *4*). Then, H_1 and H_2 are expressed as follows [37]:

$$\begin{aligned} H_1 &= \overline{H}_1 + \tilde{H}_1 \\ H_2 &= \overline{H}_2 + \tilde{H}_2 \end{aligned} \qquad (16)$$

where $\overline{H}_n$ (*n* = *1* or *2*) representing the degree to which the other assessor can play a role in the assessment, and $\tilde{H}_n$ (*n* = *1* or *2*) is caused by the possible incompleteness in the subsets R_1 and R_2. $\overline{H}_n$ (*n* = *1* or *2*) and $\tilde{H}_n$ (*n* = *1* or *2*) are described as follows:

$$\overline{H}_1 = 1-\omega_1 = \omega_2$$
$$\overline{H}_2 = 1-\omega_2 = \omega_1$$
$$\tilde{H}_1 = \omega_1(1-\sum_{m=1}^{4}\beta_1^m) \tag{17}$$
$$\tilde{H}_2 = \omega_2(1-\sum_{m=1}^{4}\beta_2^m)$$

Suppose $\beta^{m'}$ ($m = 1, 2, 3$ or 4) represents the non-normalised degree to which the risk evaluation is confirmed to each of the four risk expressions as a result of the synthesis of the judgments produced by assessors 1 and 2. Suppose H_U' represents the non-normalised remaining belief unassigned after the commitment of belief to the four risk expressions because of the synthesis of the judgments produced by assessors 1 and 2. The ER algorithm is stated as follows [37]:

$$\beta^{m'} = K(M_1^m M_2^m + M_1^m H_2 + M_2^m H_1)$$

$$\overline{H}_U' = K(\overline{H}_1\overline{H}_2)$$

$$\tilde{H}_U' = K(\tilde{H}_1\tilde{H}_2 + \tilde{H}_1\overline{H}_2 + \tilde{H}_2\overline{H}_1)$$

$$K = [1-\sum_{T=1}^{4}\sum_{\substack{R=1\\R\neq T}}^{4} M_1^T M_2^R]^{-1} \tag{18}$$

After the above aggregation, the combined degrees of belief are generated by assigning $\overline{H}_U'$ back to the four risk expressions using the following normalization process [37]:

$$\beta^m = \beta^{m'}/1-\overline{H}_U' \quad (m = 1, 2, 3, 4)$$

$$H_U = \tilde{H}_U'/1-\overline{H}_U' \tag{19}$$

where H_U is the unassigned degree of belief representing the extent of incompleteness in the overall assessment. The above gives the process of combining two subsets. If three subsets are required to be combined, the result obtained from the combination of any two subsets can be further synthesized with the third one using the above algorithm. In a similar way, the judgements of multiple assessors or the risk evaluations of lower level criteria in the chain systems (i.e. components or subsystems) can also be combined.

3.5. Obtaining a Crisp Value for Disruption Estimate (Step 5)

The concept of expected utility is utilised to generate numerical values equivalent to the distributed assessment of the top-level criterion or goal of each alternative for ranking in order to obtain the probable risk level of disruption for decision making. In light of the above, let the utility value of an evaluation grade H_n be denoted as $u(H_n)$ and $u(H_{n+1}) > u(H_n)$ if H_{n+1} is preferred to H_n [38]. It is worth mentioning that $u(H_n)$ represents utility values of each linguistic term and can be determined using the decision makers' preference. If there is no preference information available, it could be presumed that the utilities of the evaluation grades are equidistantly distributed in a normalised utility space. The utilities of evaluation grades that are equidistantly distributed in a normalised utility space are calculated as follows:

$$u(H_n) = \frac{V_n - V_{min}}{V_{max} - V_{min}} \tag{20}$$

where V_n is the ranking value of the linguistic term that has been considered *(H_n)*, V_{max} is the ranking value of the most preferred linguistic term *(H_N)*, and V_{min} is the ranking value of the least preferred linguistic term (H_1). The utility of the top level or general criterion *S(E)* is denoted by *u(S(E))*. If $\beta_H \neq 0$ (i.e. the assessment is incomplete, $\beta_H = 1 - \sum_{n=1}^{N} \beta_n$) there is a belief interval $[\beta_n, (\beta_n + \beta_H)]$, which provides the likelihood that *S(E)* is assessed to H_n. Without loss of generality, suppose the least preferred linguistic term having the lowest utility is denoted by $u(H_1)$ and the most preferred linguistic term having the highest utility is denoted by $u(H_N)$. Then the minimum, maximum and average utilities of *S(E)* are defined as follows [38]:

$$\begin{aligned} u_{min}(S(E)) &= \sum_{n=2}^{N} \beta_n u(H_n) + (\beta_1 + \beta_H) u(H_1) \\ u_{max}(S(E)) &= \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_N + \beta_H) u(H_N) \\ u_{average}(S(E)) &= \frac{u_{min}(S(E)) + u_{max}(S(E))}{2} \end{aligned} \tag{21}$$

Obviously if all the assessments are complete, then $\beta_H = 0$ and the maximum, minimum and average utilities of *S(E)* will be the same. Therefore, *u(S(E))* can be calculated as follows:

$$u(S(E)) = \sum_{n=1}^{N} \beta_n u(H_n) \tag{22}$$

The above utilities are only used for characterising an assessment and not for criteria aggregation.

3.6. Validation of the Model Using Sensitivity Analysis (Step 6)

Uncertainties are inherently present in different influencing factors. Since the proposed methodology provides a numerical estimation of disruption risk without identifying the most important input event, sensitivity analysis (SA) is a systematic approach that can provide managerial insight in evaluating quantitative information in order to identify the weakest points or areas of a system in order to improve its designs [39].

This study employed the SA approach to test how sensitive the model output is to a minor change in the input data. The relative change may be the variation of the parameters of the model or changes in the degrees of belief assigned to the linguistic variables used to describe the parameters of the model. If the methodology is sound and its inference reasoning is logical, then the sensitivity analysis must at least pursue the following three axioms [7]:

Axiom 1: Slight increment/decrement of degree of beliefs (DoBs) associated with a risk oriented linguistic variables of the lowest criteria will certainly result in the decrement/increment of the safety preference degree of the model output.

Axiom 2: If the degrees of belief associated with the highest preference linguistic variable of a lowest level criterion are decreased by p and q (i.e. simultaneously, the degrees of belief associated with its lowest preference linguistic variable are increased by p and q $(1 > q > p)$), and accordingly the utility value of the model's output is assessed as U_p and U_q respectively, then U_p should be greater than U_q.

Axiom 3: If x and y $(y < x)$ criteria from all the lowest level criteria are selected and the degree of belief associated with the highest preference linguistic variables of such x and y criteria is decreased by the same amount (i.e. simultaneously, the degrees of belief associated with the lowest preference linguistic variables of such x and y criteria are increased accordingly by the same amount), the utility value of the model's output will be assessed as U_x and U_y; in this case, U_x should be greater than U_y.

4. Test Case

This test case is used to illustrate how the methodology can be implemented to assess the impact of risk scenarios on the smooth operation of a seaport system. Based on the generic model in Figure 3 and the available information in section 2, decision makers can assess the key systems' elements, and identify areas that need attention.

4.1. Identify risk factors associated with seaport operations (Step 1)

This phase of the analysis involves the identification of risk factors associated with seaport disruption through a robust literature search and brainstorming session conducted with selected experts whose backgrounds are presented in section 4.3. The identified risk factors are presented in Table 1.

4.2. Develop a generic risk model for seaport operations

At this stage, the identified risk factors in Table 1 are represented in a hierarchical structure and presented in Figure 3. Based on the generic model (Figure 3) and the available information in section 2, a specific model is constructed to demonstrate the applicability of the methodology. Following a review of Wang *et al.* in [40], linguistic terms used for safety expression were in the range of four to seven for effective information processing. Therefore, this research adopts four to five linguistic terms in representing the assessment of disruptions based on the domain expert's opinion.

<Figure 6: A Specific Model for Disruption of a Seaport Operation>

4.3. Model the Hierarchy to Obtain the Weights using FAHP (Step 2)

FAHP is used to obtain the various weights of the parameters of the model. To conduct the assessment let $R51$, $R52$ and $R53$ represent geologic, hydrologic and atmospheric factors respectively. Three experts with the following backgrounds evaluated the relative importance of each of the risk items for their associated upper level criterion (i.e. natural risk factors, Figure 6):

- A senior operations manager who has been involved with port operational services for over 20 years.
- A senior marine and safety engineer who has been involved in maritime and port operational management for over 20 years.
- A chief superintendent of maritime transportation systems who has been involved with maritime operations for over 20 years.

As an example, the three experts made these comparisons of $R51$ with $R53$. The first expert's judgement was between 'equal and weak importance', (1, 2, 3), the second expert estimated the comparisons as 'equal importance', (1, 1, 2) and the third expert evaluated the comparisons as 'equal importance', (1, 1, 2). By using Equations 2 and 3 the combined pair-wise comparison outcomes can be obtained as follows:

$$\tilde{a}_{1,3} = \left(\frac{1}{3}\right) \otimes \left((1,2,3) \oplus (1,1,2) \oplus (1,1,2)\right)$$

$$= \left(\left(\frac{1+1+1}{3}\right), \left(\frac{2+1+1}{3}\right), \left(\frac{3+2+2}{3}\right)\right)$$

$$= (1.00, 1.33, 2.33) \approx (1, 1, 2)$$

$$\tilde{a}_{3,1} = \frac{1}{\tilde{a}_{1,3}} = (0.5, 1, 1)$$

Similarly, when the experts made their judgements, they assigned values to each criterion until all the elements in the pair-wise comparison matrix were obtained. A 3×3 fuzzy pair-wise comparison matrix is constructed as follows:

$$\begin{bmatrix} (1,1,1) & (1,1,2) & (1,1,2) \\ (0.5,1,1) & (1,1,1) & (1,1,2) \\ (0.5,1,1) & (0.5,1,1) & (1,1,1) \end{bmatrix}$$

The consistency ratio was measured by applying Equation 9 and was found to be acceptable. Accordingly, by utilising Equations 5 and 6, the weights of the three risk factors can be calculated.

$$\tilde{r}_1 = ((1,1,1) \otimes (1,1,2) \otimes (1,1,2))^{\frac{1}{3}}$$

$$= \left((1 \times 1 \times 1)^{\frac{1}{3}}, (1 \times 1 \times 1)^{\frac{1}{3}}, (1 \times 2 \times 2)^{\frac{1}{3}}\right)$$

$$= (1,1,1.59),\ \tilde{r}_2 = (0.79,1,1.26),\ \tilde{r}_3 = (0.63,1,1)$$

$$\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 = (2.42, 3.00, 3.85)$$

$$\widetilde{w}_1 = \tilde{r}_1 \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3)^{-1} = \frac{(1,1,1.59)}{(2.42,3.00,3.85)} = \left(\frac{1}{3.85}, \frac{1}{3}, \frac{1.59}{2.42}\right)$$

$\widetilde{w}_1 = (0.26, 0.33, 0.66)$ Similarly, $\widetilde{w}_2 = (0.21, 0.33, 0.52)$ $\widetilde{w}_3 = (0.16, 0.33, 0.41)$

These fuzzy weights obtained are defuzzified into crisp weights by Equation 7 and presented as follows:

$$DF_{\widetilde{w}_1} = \frac{(0.66 - 0.24) + (0.33 - 0.26)}{3 + 0.26} = 0.14$$

In a similar way, $DF_{\widetilde{w}_2} = 0.13$ and $DF_{\widetilde{w}_3} = 0.13$

The normalised weight $\widetilde{w}_1$ can be calculated using Equation 8 as follows:

$$\mathrm{w}_1 = \frac{0.14}{0.14 + 0.13 + 0.13} = 0.35$$

In a similar way, the weights of the other risk items are calculated and presented below:

$$\mathrm{w}_2 = 0.325,\ \mathrm{w}_3 = 0.325$$

The calculated weights of the geological, hydrological and atmospheric factors are presented in Table 5. Following the same procedure of calculations, the weights of the remaining risk factors are calculated and their consistencies ratio checked. The results are presented in Table 6.

<Table 8: Weights of Natural Risk Factors>

<Table 9: Weights of Disruption Risk Factors>

4.4. Application of Fuzzy Risk Assessment for a Seaport Operation (Step 3)

During an interview session, the experts utilised for this assessment, whose backgrounds are presented in section 4.3 used the linguistic variables shown in Table 6 to rate this port by indicating an appropriate grade for the *L* and *S* of the generated 20 risk factors presented in Figure 6. Based on the experts' assessment, the grades of *L* and *S* were confirmed, and the disruption risks obtained from the analysis using Equation 10 are presented in Table 10. The risk of disruption obtained in Table 10 is in the form of TFN_{LS}. However, the intersection results of all the evaluated risks based on the experts' assessment are presented in Table 11; these results are subsequently normalised using the procedure discussed in section 3.3.2 and Table 4, and the resulting risks obtained are presented in Table 12.

<Table 10: Fuzzy risk of disruption>

<Table 11: Intersection result of disruption risk factors>

<Table 12: Normalised fuzzy risks of disruption>

4.5. Aggregating Assessment via Evidential Reasoning Algorithm (Step 4)

Given the weights of the risk factors in Table 7, the aggregation calculations for operational risk factors (R11, R12, R13 and R14) are conducted using Equations 15 to 19 and the result (Very Low 0.3074, Low 0.4566, Medium 0.12223, High 0.0137, Very High 0.0000) is obtained. Using the same technique with which operational risk factors was calculated, the main criteria (security, technical, organisational and natural risk factors) are evaluated and the aggregation results are presented in Table 13.

<Table 13: Aggregation of the main criteria>

Also, by performing similar calculations using Equations 15-19 based on the aggregation results of the main criteria, the assessment risk of disruption is obtained, as presented in Table 13.

4.6. Evaluating the Final Rate of Disruption's Risk (Step 5)

Assessment based on a single value is much easier and is a more realistic tool for a decision maker to rank the risk factors in order to design the system for resilience. Therefore, to obtain a single crisp value for the assessment, the utility value associated with each linguistic term has to be calculated from Equations 20-22. In view of the fact that the fuzzy output set for the goal was characterised by five linguistic terms, the highest preference is given to the "Very High" linguistic term and the lowest preference is given to the "Very Low" linguistic term. The assessment obtained for disruption risk, as shown in Table 14, is presented as follows:

$\text{DR} = \{(Very\ Low, 0.2349), (Low, 0.4610), (Medium, 0.2348)(High, 0.0693), (Very\ High, 0.0000)\}$

where DR stands for disruption risk. Based on Table 14, the disruption risk (D_{DR}) was evaluated as 0.285 or 25.8%. Ultimately, this value represents the experts' assessment of the risk of disruption regarding the operation of the port under investigation and it belongs to the class of significant risk category as shown in Table 7. This value means that the risk must be reduced if practicable. Such a result can be used to help port safety analysts to carry out formal safety assessment of a port, and also initiate safety audit and review of key performance indicators of various port departments for enhanced operation. This approach may provide a viable approach where there is lack of objective or statistical data in such an assessment for the port under investigation.

< Table 14: Calculation of Disruption Risk>

4.7. Sensitivity Analysis (Step 6)

Sensitivity analysis is conducted to validate the proposed methodology. This is achieved by utilising the three axioms introduced in section 3.6. The implementation of the axioms will help to identify the most important system elements that contribute to a seaport's disruptions and to improve its robustness to operational uncertainties. To carry out the study the degrees of belief associated with the highest preference linguistic terms of each sub-criterion are decreased by p and simultaneously, the degrees of belief associated with the lowest preference linguistic terms of the corresponding sub-criterion are increased by p; accordingly, the results are obtained. It is noteworthy to mention that when decreasing the belief degree of the highest preference linguistic term β_α of a criterion by p, simultaneously the belief degree of its lowest preference linguistic term has to be increased by p. However if β_α is less than p, then the remaining belief degree (i.e. $p-\beta_\alpha$) can be taken from the belief degree of the next linguistic term. This process continues until p is consumed.

The utility values obtained after performing the experiment (i.e. decreasing the degrees of belief associated with the highest preference linguistic terms (by 10%, 20% and 30% respectively) of each sub-criterion) are tabulated in Table 15 and the graph displaying the sensitivity of the result is presented in Figure 7. It is worth mentioning that all the results obtained are in harmony with Axioms 1 and 2 respectively.

According to Axiom 3, if the model is logical and reflects the reality, then the preference degrees of the risk attributes at the lower level of the hierarchy associated with y factors (evidence) will always be smaller than the one from "$x-y$" ($y \in x$) factors (sub-evidence). This can be examined by comparing the preference degrees of the risk attributes for analysis in a transparent manner. For example, if the input data associated with the highest preference linguistic values of all the lower level criteria are decreased by 30%, the utility value (i.e. disruption risk) is evaluated as 0.158. However, by selecting 15 (i.e. port equipment/machinery failures, vessel collision/grounding, cargo spillage, human errors, sabotage, terrorism attacks, surveillance system failures, arson, labour unrest, berth congestion, gate congestion, geologic, hydrologic, atmospheric and lack of equipment maintenance) out of 20 lower level criteria of the analysis and decreasing the input data by the same amount of 30%, the utility value obtained is 0.257. Given that 0.158 is less than 0.257, it can be claimed that the investigation of the model is validated to be sound and aligned with Axiom 3.

<Figure 7: Sensitivity Analysis of the Model Output to the Variation of Each Sub-Criterion>

<Table 15: Decrement/Increment of the Model's Input Data>

5. Results and Discussion

As presented in Table 14, the obtained assessment (goal) has the highest belief degree of 46.1% linked to the Low linguistic term and lowest belief degree of 6.93% associated with High linguistic term. This result shows the risk of disruption associated with the port under investigation. It is noteworthy to mention that all these values are obtained from the synthesis of experts' judgements.

The risk of disruption to a seaport's operation is determined by many factors when operating in a complex socio-technical environment. It is evident from the analysis that a minor change results in a corresponding change of the model's output.

Based on the result obtained from the model analysis, as shown in Table 14, the risk of disruption due to the occurrence of the models' parameters for the port under investigation was evaluated as 0.285 or 28.5%. However, this value is not fixed as it may vary given the dynamic conditions and the operational uncertainty to which the port is subjected over a particular period of time and at a given location. Based on Figure 7, it is clear that the model is more sensitive to terrorism attacks (rank 1), sabotage (rank 2), human related errors (rank 3) and lack of equipment maintenance (rank 4) than to the other attributes. The result of the sensitivity test has further proved the importance of security risk factors in the maritime industry. Literature reviews [18, 12] have shown that the major infrastructure systems that seaports accommodate, such as container terminals, petroleum tank farms, oil refineries, petrochemical facilities, bridges, and passenger terminals are targets for terrorism attacks, with potentially disastrous and long-term consequences.

The results also reveal that human related errors are a significant factor leading to the disruption of maritime operations with high and long-term economic loss to the operator. Figure 7 allows the analysts to say that the lack of equipment maintenance and the failures of port equipment/machineries during operations further compound the pressures to which these ports are subjected in a dynamic operational environment. The model's results highlighted the influence of each attribute in contributing to disruptions of seaport operations. The model equally provides an understanding of the system's performance. Such knowledge is invaluable for the safety analysts and decision makers to develop necessary organisational strategies or measures that will enhance the operational efficiency of individual port processes and make them robust to unforeseen scenarios.

6. Conclusion

This paper proposes a novel methodology using fuzzy set theory, a fuzzy analytical hierarchy process and evidential reasoning approach for determining the disruption risk of a seaport's operations using diverse and imprecise data which are either quantitative or qualitative in nature, in order to optimize the operational efficiency of the system in a systematic manner. Different from the conventional risk assessment methodologies which cannot address uncertainty in complex systems operations, the framework is characterized with flexible presentation and unification of input and output data.

Moreover, in the risk-based modelling approach, input data can be expressed by fuzzy values with a belief degree structure. This approach presents a favourable means with flexibility where precise data, random numbers and subjective judgements can be modelled in a unified manner. By using the FAHP and ER approaches, uncertainties and vagueness from the subjective estimates and the experiences of the multiple decision makers can be represented and addressed effectively. The ER approach provides a procedure for aggregation which can preserve the original features of multiple attributes under high and imprecise situations.

The methodology has the following advantages compared to other risk analysis techniques currently applied in the maritime domain:

- The methodology provides managerial insights to analysts in a rational, reliable and transparent manner for collaborative modelling of complex systems with a group of experts under situations of high operational constraints.
- The methodology provides researchers with an effective tool to make full use of the information generated at the lowest level in design to evaluate the safety of the whole system for resilience improvement of its operations.
- The methodology has been versatile, robust yet flexible in application, and can be useful in safety analysis and synthesis in many industrial environments.
- It is easily programmable and could be used as a computerised kit for advanced risk assessment of maritime infrastructure systems under high uncertainties.

It is envisaged that the proposed approach could provide risk managers and infrastructure analysts with a flexible tool for use in understanding the importance of developing organisational strategy in order to increase the resilience of the system to unforeseen operational uncertainties in a transparent manner.

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