A FUZZY BAYESIAN NETWORK APPROACH FOR RISK ANALYSIS OF HAZARDOUS CARGO SHIPS

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ABSTRACT

The increasing global transportation raises some concerns over the handling of hazardous cargo vessels during berthing operations. This paper uses a Fuzzy Bayesian Network for the identification of various influencing factors, the inference, and analysis of these factors. The results show that dangerous cargo ships require more attention to resolve the risk probability. Human and environmental factors are the most prominent factors. On the other hand, training of ship personnel, wind force, water velocity, channel width, dock layout, and port location are other important factors to be taken into consideration. To conduct risk management for hazardous cargo vessels, port authorities need to focus on the invulnerable berthing of hazardous cargo vessels. The proposed model has prominent practical viability for governments, liner companies, and port authorities.

Keywords: Risk Analysis, Bayesian Network, Linguistic Variables, Fuzzy Set Theory, Berthing Operation.
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1. Introduction

Shipping is becoming a bigger part of global trade, which depends on how well the maritime transport system and the seaport system work on the other hand, the increasing number of larger vessels brings more accidents and results in devastating consequences for human health and the environment (Murdoch et al., 2012). Most of the time, the presence of dangerous materials, which can leak out, explode, or catch fire, increases the chance of a terrible accident. Therefore, safety at sea is the most essential issue in the maritime industry. There are some international rules and applications by the ISPD (the International Ship and Port Facility Security Code), SOLAS (Safety of Life at Sea), IMO (International Maritime Organization), and the ISM Code (the International Safety Management Code).

The risk of accidents based on the existence of dangerous materials can result in devastating effects and consequences for human health and the environment when transported for commercial purposes (Inanloo and Tansel, 2015). These hazardous materials contain various petrochemical products that must be transported with enormous care (Akyuz and Celik, 2015).

The most recent incidents during the transport of hazardous materials include fire and explosion basically (Huang and Zhang, 2015). These accidents can be attributed to various factors that have diverted public attention to research on risk assessment and accident prevention (Zhao et al., 2012). Human error is considered an important factor in the maritime hazardous cargo risk assessment, which could be related to various characteristics of the carrying ships and the features of both the port facilities and the environment. This study develops insight into how the sustainability and development of ports, in general, can be improved by analyzing the risk factors affecting the transport of hazardous materials using Fuzzy integrated Bayes Networks. Hence, the outcomes of this study can support the decision-making authorities in terms of adapted processes and sustained costs. To prevent any damage during the berthing operation, precise and gentle control is required. In any uncontrolled situation, several consequences such as a ship run aground, hitting the berth and colliding with other vessels can arise with alarming frequency, including loss of life, environmental pollution, and property damage (Murdoch et al., 2012) (John, et al., 2015). Evaluating the potential risks shows that a large number of accidents occur due to human error (Akyuz, 2016). Furthermore, most of the accidents have occurred because of fires or explosions in terms of hazardous cargo resulting in economic failure, loss of life, and injury.

This article uses the Fuzzy Bayes Networks to analyze the risks of dangerous cargo ships docking operations. In the berthing operations for a hazardous cargo vessel, the risk factors have been explained clearly using Bayesian Network and Fuzzy Set Theory with linguistic variables. The accident risk probabilities under various conditions were achieved through Expert Judgment and Binary Logistics regression. The contributing risk factors and sub-risk factors were determined, respectively, and their probabilities were calculated. It can be said that it is very important in terms of practical applications. Finally, the results and inferences have been given in detail.

2. Literature Review

In the literature, there are a number of ways to figure out how dangerous something is by using probability calculations and graphs, trees, flow charts, etc. to simulate them. It is important to understand the many effects of transporting hazardous materials and the role that the assessment and comparison of these risky play (Reniers et al., 2010). Overall, the risk of hazardous materials in maritime transportation has been measured in different ways and in different areas. With the help of event trees by Ronza et al. (2003), accident data from ports can be used to figure out what happened and in what order. A risk matrix (Cunningham, 2012) is a good way to show that accidents at the port terminal not only cause serious losses of life and property but also put the public's support for port operations at risk. According to Trbojevic and Carr (2000), putting up hazards control barriers and incorporating them into a safety management system can help manage or avoid the risks brought about by dangerous materials at the port. Kite-Powell et al. (1999) found that Bayesian networks can be used to find a link between the terminal environment and the reasons why a commercial ship ran aground. While approaching a terminal, LNG carriers are more susceptible to risks. Aside from the risks of transportation, it seems like a good target for terrorists and intentional damage can cause a release and a big fire that can spread up to 1500 meters (Bubbico et al., 2009). Also, recent studies on shipping suggest that the emission from the ship propulsion system and their environmental risk assessment are very necessary (Blasco et al., 2014). FST is also being used to evaluate the cargo ship risks along with the DEMATEL technique (Mentes et al., 2015).

Ren et al. (2007) have a study of the risk analysis of an offshore structure by the quantitative analysis of linguistic probabilities in a Bayesian Network. It has been evaluated the human factors affecting the collision risk between a Floating Production, Storage and Offloading (FPSO) unit, and an authorized vessel throughout the berthing process. Zhao et al. (2015) studied Bayesian Network to examine the safety of the LNG carrier system. It was calculated the likelihood of the accident and obtained the maximum chain by diagnostic reasoning in risk assessment. Akyuz (2016) studied a hybrid approach that integrated an Analytical Network Process (ANP) with a

Human Factors Analysis and Classification System (HFAC) to prevent loss of life or injury and enhance safety in maritime transportation. John et al. (2015) used both methods of the fuzzy logic-based approach and Bayesian network in the risk analysis to improve the resilience of a seaport system. Wen-hua et al. (2015) studied the major factors of oil spilling on ports and terminals during mooring and cargo handling. The Bayesian Network approach has been combining with the triangular fuzzy number approach to acquire the conditional probability of each variable. Chang et al. (2013) studied three major risk categories: information flow, physical flow, and payment flow by using both qualitative and quantitative methods.

John et al (2014) studied the safety assessment of seaport operations by using the integrated methods of Evidential Reasoning (ER) and Fuzzy Analytical Hierarchy (FAH). The risk factors were identified by an interview survey as a real case and then the relevant data were conducted by a questionnaire survey. In this study, the level of risks was identified by using a risk map, aiming to facilitate the treatment of uncertainties in seaport operations and optimize systematically the performance effectiveness. Hsu (2015) carried out a study of the risk assessment of ship berthing operation using the integration of a Safety Index (SI) and a Fuzzy Analytic Hierarchy Process (FAHP). This study was validated by investigation of berthing operation at Kaohsiung Port in Taiwan. Yeo et al. (2016) estimated the undesirable probability of an accident with Bayesian Network capability and conducted a dynamic safety analysis. The proposed method was performed on safety analysis for the offloading process of an LNG carrier. Pak et al (2015) conducted a study to evaluate and rank many factors that influence navigational safety in Korean ports. The weather-sea condition, channel condition, volume of traffic inside a port, ship types, and ship size were investigated as main factors by using the Fuzzy Hierarchical Process.

Ports systems consist of a vast variety of interconnected components, and the dynamic nature of these components makes the port operations systems complex. Exploring these systems from the perspectives of their interconnectivity that comprise of the infrastructure physiognomies, operational associations, environmental influences, technical competence, types of failure, and the situation in which the system operates provides a perception of the system intricacy. While reviewing the safety features of a seaport system, a rational tactic is to do itemization into the subsystems containing all the prominent functional components of the system to make decide at all the levels of the system’s design, operations, and maintenance (Khan, R. U. et al., 2021). Therefore, port systems are considered an important entity to make this transport possible and hence play their role in the operations of cities and countries.

Generally, risk is the likelihood of an accident, determining the chances of an incident happening and the severity of aftereffects brought by it. Risk assessment for human, natural, and other associated stimuli is done through the combination of probability theory and statistical techniques as per their tolerability standards. Depending on the degree to which these factors and their analysis rely on numerical indicators, the methods used for their assessment could be classified as qualitative and quantitative methods, and as per situations, these methodologies are made hybrid as semi-quantitative. These hybrid semi-quantitative methods are found to be more accurate, broader, and successful as the qualitative method serves as the basis for all assessments. But quantitative methods are preferred as a result of their ability to cover both the probability and consequence of risks. Hence, quantitative methods are considered more useful as they can be consistently used to provide detailed statistical datasets, enhancing the ability to understand the magnitude and implication of risks.

Bayesian networks that incorporate the quantitative approach of risk assessment and provide viable results are a combination of graph theory and probability theory. The discrete properties of a BN include its ability to undertake the inference inversely, integrate new annotations to the network, handling incomplete and missing data, and provide a graphic illustration of the original cause and effect association (Ren et al., 2009). Bayesian methods have been used in various fields of transportation. In the marine transport and port systems, BNs is being used to evaluate the vessels evacuation in an accidental hazard situation by Eleye-Datubo et al. (2006), incorporation of human and organizational issues in the risk analysis by Trucco et al. (2008), and evaluation of the offshore safety by the integration of BN and the "Swiss Cheese" model by Ren et al. (2008). Apart from these BNs, they have been extensively used along with the uncertainty factors in various modeling approaches for the maritime traffic safety analysis (Hänninen et al., 2014) (Hänninen and Kujala, 2014) (Montewka et al., 2014). Increasing the size of vessels put the port infrastructure under pressure to facilitate the management of effective risk on the loading and unloading of these large vessels. The accident in the port operations system poses a threat not only to goods but also to the environment and human life. The port operational interruption factors may be attributed to vessel accidents and groundings, port machinery and equipment failures, spillage of hazardous materials, and petrochemicals (John et al., 2014). Human error and technical faults hold the major of the responsibility attributed to maritime accidents. Human capabilities in the analysis of maritime accidents have been evaluated previously (O'Neil, 2003) (Akyuz and Celik, 2015) (Hetherington et al., 2006) (Celik et al., 2009).

In addition to these works, there are also various forms of geological, atmospheric, and hydrological parameters of the natural environment for better understanding and handling of risks (Chauvin et al., 2013) (Kröger, 2008). These natural risks are held as the most loss-causing, recurring, and severe disruptions in seaport operations as they disturb the ship's movements through increasing tides and velocity, visibility, increased wind speed, and floods (Lam and Su, 2015). Analyzing the offloading risks of LNG vessels through the dynamic failure modeling based on Bayesian networks indicates that collision can be the most commonly occurring accident at berths leading to calamitous consequences (Yeo et al., 2016). However, literature specifically related to risk assessment of berthing and departure of hazardous cargo ships under the effect of various contributing factors is scarce. Hence, it is of prodigious importance to carry out such studies and evaluate the most prominent and contributing factors to risks in dealing with hazardous cargo at ports.

2.1 Berthing Operation for Hazardous Cargo Ships

For a dangerous cargo ship to dock or berth, it must do a lot of maneuvering that requires a lot of people working together. Since oil and other hazardous materials are potentially inflammable and explosive by nature, an accident will result in fatalities and loss of property, and environmental pollution. After identifying the potential hazards due to the design of the vessel, process, equipment, manpower, materials, port environment, and facilities, it is of extreme vitality to improve the safety of hazardous cargo berthing operations (Hsu, 2015). The most important points of the berthing operation are slow speed, controlled approach, planning, teamwork, and checking equipment. Additionally, the professional skills of all ship personnel as well as knowledge about maneuvers and human mental situations have an essential effect on operations; a positive team approach increases efficiency and communication (Murdoch et al., 2012). In berthing operation, the pilot manages the ship handling and the maneuvering characteristics. Therefore, the pilot's professional skills should be sufficient to manage the operation. On the other hand, poor communication may result in misunderstanding and consequently result in safety problems in berthing operations because of different languages and different cultures.

All equipment must be checked to prevent any malfunction. Before approaching the berth, the main engine, thrusters, steering gears must be fully operational. Before arriving, the main engines should be tested, and remote controls should be checked. Also, all bridge equipment such as engine movement recorders, VDRs, radars, course recorders, echo sounders, and all remote read-outs should be controlled. Some tankers carrying oil and gas must be escorted by tugs in the harbor during berthing operation. Tugs escort the vessel when berthing alongside and departing by pulling and towing the vessel. Using tugs is needed when wind, tide, and current or the ship's handling characteristics cause difficult berthing conditions (Hsu, 2015), (Murdoch, Clarke, & Dand, 2012). While working with tugs, using bow thruster, when under-keel clearance is low, sailing in a narrow channel and when the ship close to another ship, the ship should avoid high forward speed for maneuvering. But at low speed, wind and current have a great effect on maneuvering. Also, the draft and trim information should be clear because they also affect maneuvering. Other important operations are dock operation, facilities and line handling operations. The port management policy has developed rules to manage the port operation of the growing ship density to ensure safety at the port during berthing operations. Complying with these rules may have a great effect on ensuring safety. The weather also creates risk for the berthing operation. Except for the visibility of navigation bridges, wind speeds, currents influence risk. In cold weather, the ship must be prepared for its equipment, such as mooring winches, cargo hose lifting gear, gangway hoists, water lines, and a firefighting system against freeze-up (Det Norske Veritas Inc., 2016).

Hazardous cargo has potential for spills, leaks, explosion, discharge, emission, and fire, and they have the risk to air, soil, sediment, groundwater, water, and habitats within the local port area and the wider environment. There are several reasons, including the presence of explosive, flammable, corrosive, noxious, poisonous, radioactive, and irritative substances, in commodities that emit poisonous vapor, pressurized gases, or bio-medical materials. The regulations for transportation of dangerous cargo have been determined by the International Maritime Organization (IMO). All organizations and port authorities should comply with the IMO regulations for storage, handling, loading, and discharge. IMO classifies the substance into nine groups: explosives, gases, flammable liquids, flammable solids, oxidizing substance and organic peroxides, toxic and infectious substance, radioactive material, corrosive substance, miscellaneous dangerous substance. IMO has a regulation for the shipping of hazardous cargo. As required by SOLAS (Safety of Life at Sea), all shipping of hazardous cargo must comply with the IMO's International Maritime Dangerous Goods (IMDG) code.

There are some studies about the safety problems of hazardous cargo. One of the main causes is the inconvenience of storage and segregation. The other causes are human factors. The lack of experienced staff will have very serious consequences. Not knowing any precaution for any dangerous cargo will result in fire, explosion, leakage, spilling, etc. The other human factor is misdeclaration or non-declaration of the cargo by shippers to save money, which is also improbable. In contrast to the shippers who try to save money, not taking any precaution or following the necessary rules will cause more money loss in any dangerous situation. Therefore, that makes risk assessment more important. In this study, the risk factor can be divided into five groups by considering both hazardous cargo vessel and berthing operations: “Human Factor”, “Ship Factor”, “Environmental Factor”, “Operational Factor”, and “Security”.

3. Methodology

Risk is identified as the probability and consequence of uncertain events, and it brings an undesirable outcome such as loss, damage etc. Risk can be formulated as:

$$Risk = Probabaility \times Consequences \tag{1}$$

The scientific part of risk analysis is a risk assessment, which is about figuring out how likely something is to happen and what will happen if it does. One of the key points of risk assessment is a systematic and structured approach. The steps of methodology should be followed, which provide a good risk assessment (Gorris&Yoe, 2014).

Since maritime accident analysis became an important topic, studies have increased. There are several risk analysis methods such as Analytical Network Process by Akyuz (2016), Bayesian Network with Fuzzy Analytical Hierarchy Process by John et al. (2015), Zhao et al. (2015) and Wen-hua et al. (2015), questionnaire survey with mean value method, and stochastics dominance method by Chang et al. (2013), Evidential Reasoning and Fuzzy Analytical Hierarchy Process by John et al. (2014), Safety Index (SI) with a Fuzzy Analytic Hierarchy Process (FAHP) model by Hsu (2015), Formal Safety Assessment (FSA) byWang&Foinikis (2001), Fuzzy Analytical Hierarchy Process by Pak et al. (2015) used in marine accidents.

Risk analysis can be defined as dealing with uncertainty, which can be classified as vagueness, randomness, and ignorance. Randomness is caused by unpredictable events, and probability theory can deal with randomness. Vagueness is caused by ill-defined situations, and Fuzzy can handle the vagueness. Finally, ignorance exists because of the weak correlation between factors and consequences identified by the experts. At this point, Bayesian Network provides enough correlation. Two ways have been asserted to control the risks in marine transportation: to reduce the accident probability and to control the accident extent (Zhao et al., 2015).

3.1 Bayesian Network & Fuzzy Numbers with Linguistic Judgments

Bayesian network is a kind of probabilistic reasoning and uncertainty analysis that has been in recent studies (Yeo et al., 2016) (Zhao & Soares, 2015). In risk analysis, Bayesian Network provides the causal relationships between risk factors and the related occurrence likelihood of each hazardous event (Ren et al., 2009). The Bayesians network model provides prior knowledge with prior probability and conditional probability to show knowledge uncertainty. The changes with new approaches, technologies, and hazardous cargoes create new risks and damages. Therefore, reducing the likelihood of occurrence becomes important.

Public health and safety require the prevention of accidents which makes risk assessment essential. After designating each set of events, a probability measure gives the quantification. But determining the value of the probability is generally impractical. That causes a nebulous probability for the event. Some judgments such as ‘more or less likely’, ‘likely’, ‘possible’, and ‘impossible’ may be used to specify the probability, instead of numerical value. Identifying the probability with linguistic terms as a result of fuzziness, that cannot be said that randomness (Karwowski & Mital, 1986). Evaluation of the risk factor expressed by human experts; these judgments can be transformed into crisp probabilities. Transformation of the linguistic judgments provides cost-saving and BN model modification and maintenance (Ren et al., 2007).

Stefanini et al. (2008) listed two features required to be satisfied to use of fuzzy numbers in applications, which are:

- An easy way to represent and model fuzzy information with enough or possible high flexibility of shapes, without being constrained to strong simplifications, e.g., allowing asymmetries or nonlinearities.

- The relative simplicity and computational efficiency required to perform exact fuzzy calculations or to obtain good or error-controlled approximations of the results.

In modeling the uncertainties, vagueness, uncertainties, fuzzy sets, and numbers are integrative to probability and statistics. The fuzzy sets are coming from the interval analysis which defines the rules error propagations. The mathematical model of a vaguely defined quantitative piece of information is the notion of a fuzzy quantity.

3.2 Theoretical Background

Bayesian Network

Bayes' rule is coming from conditional probability. As Devin Soni said (Soni, 2018), "*Bayes rule provides us with a way to update our beliefs based on the arrival of new, relevant pieces of evidence*."

Bayes' theorem which used the calculate the conditional probability can be represented as follows (Ünal, 2018):

$$P(A|B) = (P(A)P(B|A))/P(B) \qquad (2)$$

Where $P(A|B)$ is the probability of the happening of the A when the B has happened (posterior):

$P(A)$ is the probability of the happening of the A (likelihood):

$P(B|A)$ is the probability of the happening of the B when the A has happened (likelihood):

$P(B)$ is the probability of the happening of the B (marginal).

Let's apply the Bayesian Inference on a random variable X, which is any one of the sets of values. Assume that $V=\{X_1,X_2,\ldots,X_n\}$ is a set of variables with X_i having a countable infinite space. The definition of joint probability distribution required that if the function of $P(X_1=x_1,X_2=x_2,\ldots,X_n=x_n)$ satisfied the following conditions;

For every combination of values of the x_i's

$$P \leq (X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) \leq 1 \qquad (3)$$

$$\sum_{x_1, x_2, \ldots, x_n} P(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = 1 \tag{4}$$

Directed acyclic graphs (DAG) are the basis of the probabilistic models, which are also known as Bayesian networks within cognitive science and artificial intelligence (Condary & Jouffe, 2013). The illustration of the Bayesian network can be specified with directional edges (Figure 1). A Bayesian network can be defined mathematically as a set of edges (Stephen, 2000):

Two important points of DAG can be shown in Figure 1:

- There is not any cyclic
- The edges are directed.

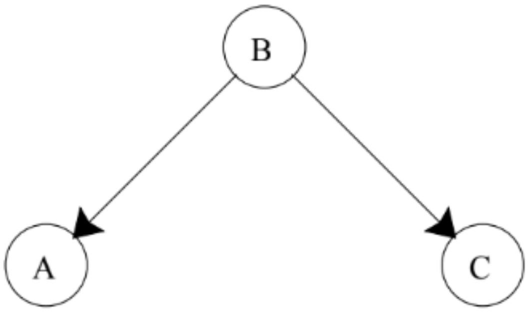

Figure 1. An example of the Bayesian network

The acyclic property provides to not cycle back means when you leave the initial node and go with the edge direction, you cannot back to the initial node again. The conditionally independent nodes in Figure 1 are A and C. The probabilities can be represented as followed (Stephen, 2000):

$$P(A|B,C) = P(A \mid B) \tag{5}$$

$$P(C|B,A) = P(C \mid B) \tag{6}$$

$$P(A,B,C) = P(A|B).P(B).P(C|B) \tag{7}$$

The joint distribution probability can be represented in general form as (Stephen, 2000);

$$P(X) = \prod_{i=1} 〖P(X_i \mid parents(X_i))〗 \tag{8}$$

and, then

$$\begin{aligned}(A,B,C) = P(A|B).P(B).P(C|B) &= \frac{P(B|A)P(A)}{P(B)}.P(B).P(C|B) \\ &= P(B|A).P(A).P(C|B)\end{aligned} \tag{9}$$

A Bayesian network should satisfy the following two conditions:

- The structure of the directed network (DAG)
- Probability distribution

The goal of the Bayesian network is to show in a graph a number of conditionally independent relationships. A Bayesian network with several nodes and edges can be represented. Every node in the network is a forest if each node has either one or no parent. If one node has no parent, it is called a tree (Stephen, 2000). The final form of the Bayesian network has become as followed:

$$P(B \mid A) = (P(A;B;C))/P(A) \;= (P(A \mid B).P(B).P(C \mid B))/P(A) \tag{9}$$

Linguistic Variables and Fuzzy Sets

Assigning the numerical values of the risk factors gives a quantitative value of the risk. The risk score (S_{jk}) is calculated based on likelihood, exposure, and consequences. In general, the numeric values of the risk score are obtained from the judgments of the experts. But, in the given period, there is no unique risk that the hazard will happen. Therefore, risk analysis deals with imprecise and uncertain values based on personal experiences. This means that the experts' judgments are generally verbal expressions. The risk scores were derived based on human judgments and their corresponding quantitative expressions were obtained by the analysts in the system safety area (Karwowski & Mital, 1986). As the likelihood is described vaguely and imprecisely, the probability of events P will also be described with linguistic variables. The linguistic values as very likely, likely, more-or-less likely, and others can notate as P_i and the numerical values are in the interval of $0 \leq P_i \leq 1$ (Karwowski&Mital, 1986). As described by Stefanini et al. (2008), the elements are defined by their membership function $\mu: X \rightarrow T \subseteq [0,1]$. The membership grade of the, $x \in X$ is notated with the value $\mu_u(x) \in [0,1]$. The u is assumed fuzzy set over X. The crisp value is defined as the subset of points of X called as support.

$$supp(u) = \{x \dashv | x \in X, \mu_u\,(x) > 0\} \tag{11}$$

For $\alpha \in [0,1]$, the α -cut of u is:

$$[u_\alpha] = \{x | x \in X, \mu_u\,(x) \geq \alpha\} \tag{12}$$

If $x \in$ supp(u) means that μ_u (x)=0, then:

$$\mu_u\,(x) = supp\{\alpha \mid \alpha \in]0,1]\; for\; which\; x \in [u]_\alpha\} \tag{13}$$

When the supp(u) has considered as a convex set, then the membership function is quasi-concave if α-cut of u are convex sets for all $\alpha \in [0,1]$. Detyniecki and Yager (2001) introduced the representative value, Val(u) of a fuzzy number u as followed:

$$Val(u) = \frac{\int Average(u_\alpha).f(\alpha).d\alpha}{\int f(\alpha).d\alpha} \tag{14}$$

Where f is mapping from [0, 1] to [0, 1]. There are two complementary parametrized functions: an increasing family of function and decreasing family of function.

The increasing family:

$$F: \alpha \rightarrow f(\alpha) = \alpha^q \ with \ q \geq 0 \tag{15}$$

The decreasing family:

$$F: \alpha \rightarrow f(\alpha)(1-\alpha)^q \ with \ q \geq 0 \tag{16}$$

If the q=0, f becomes constant, which means it equals1.

If the q= ∞, f becomes a direct function.

q=0:

$$Val(u(a,b,c,d)) = \frac{\left(\frac{b+c}{2}\right) + \left(\frac{a+d}{2}\right)}{2} \tag{17}$$

q=∞:

$$Val(u(a,b,c,d)) = \left(\frac{b+c}{2}\right) \tag{17}$$

To make the judgments of experts more rational, they can adjust subjective parameter values by using different ‘q’ values in the f-weighted valuation function (Ren et al., 2007). In this study, two ‘q’ values have been used, and analyses have been completed for both.

4. Risk Analysis of Hazardous Cargo Ships

Following the structure of the risk analysis below is an important point for obtaining a realistic analysis. Therefore, the steps explained in the Methodology sections will be applied as a guideline for analysis. The test case is a risk analysis of the hazardous cargo vessel during the berthing operations. Fuzzy and linguistic judgment will be conducted with Bayesian Network for risk analysis. The proposed risk analysis in this study consists of the transformation of linguistic judgments into crisp values, creating a Fuzzy Set and Bayesian Inference. After determining and defining the problem, the risk analysis process can be divided into six steps as follows: Figure 2 shows the steps of the proposed method.

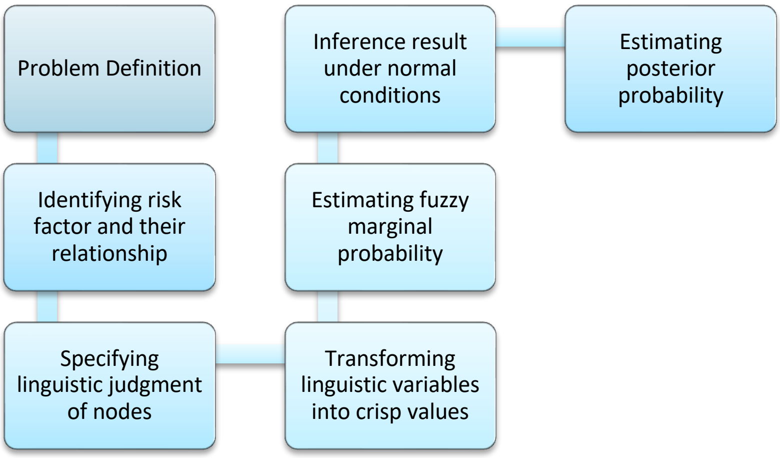

Figure 2. Flow diagram of the test case

Step.1: Identifying risk factors and their relationship.
Step.2: Specifying linguistic judgment of nodes.
Step.3: Transforming linguistic variables into crisp values.
Step.4: Estimating Fuzzy marginal probability.
Step.5: Inference result under normal conditions.
Step.6: Estimating Posterior Probability.

Step 1: Identifying risk factors and their relationship.

The first rule for berthing operation is slow and controlled speed and the second is bridge teamwork and preparation. Therefore, operational and human factors are handled in the test case. The operational factor is divided into three factors which are tugboat operation, dock operation, and port management policy. The human factor has two sub-factors: the pilot factor and the crew factor. All language and communication skills, operation knowledge, vessel knowledge are assessed under business skill for both pilot and crew factor. Also, mental skill is evaluated for both crew and pilot factor. Fuzzy and linguistic judgment was conducted with Bayesian Network for risk analysis. The risk factors that have been evaluated in the test case (see, Table 1).

Table 1. The evaluated risk factors in the test case.

Main Factor	Sub Factor	
Human Factor	Pilot Factor	Business skill
		Mental state
	Crew Factor	Business skill
		Mental state
Operational Factor	Tugboat Operation	
	Dock Operation	
	Port Management Policy	

The purpose of the test case is to evaluate the posterior probability of business skill of pilot factor (X1) when the hazardous cargo vessel risk (U1) is 100% (Figure 3)

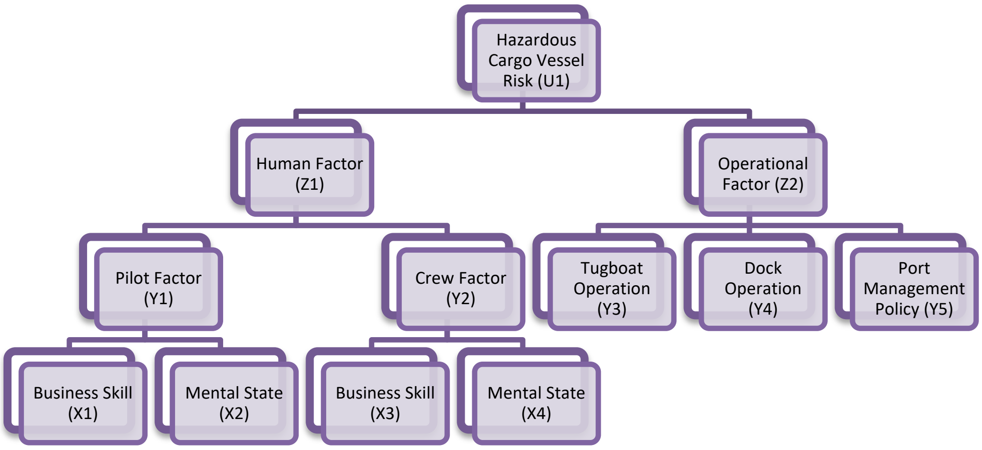

Figure 1. The structure of risk factors.

Step 2: Specifying linguistic judgment of nodes.

The linguistic judgment depends on the experts' experience. The risk level is determined verbally by the experts. The labels start with the event is occurred, which has been labeled as "Certain". The situation of an event that does not occur is labeled as "Impossible". Between "Impossible" and "Certain", there are 7 different linguistic labels. The Fuzzy membership functions vary between 0-1. The "Impossible" is accepted as 0 and the certain is accepted as 1.0. The interval linguistic labels and their membership functions are used (see, Table 2).

Table 2. Linguistic labels and their meanings.

Linguistic Label	Meaning	Fuzzy Membership Function
Impossible	Never occur	(0, 0, 0)
Nearly Impossible	The likelihood probability of occurrence is nearly impossible	(0.001, 0.002, 0.005) (0.040, 0.050, 0.080)
Very Unlikely	The likelihood probability of occurrence is very unlikely	(0.190, 0.200,0.230) (0.220, 0.250, 0.260) (0.240, 0.250, 0.280)
Unlikely	The likelihood probability of occurrence is unlikely	(0.340, 0.350, 0.380) (0.390, 0.400, 0.430)
Even Chance	The likelihood probability of occurrence is even chance	(0.490, 0.500, 0.510)
Likely	The likelihood probability of occurrence is likely	(0.570, 0.600, 0.610) (0.620, 0.650, 0.660)
Very Likely	The likelihood probability of occurrence is very likely	(0.720, 0.750, 0.760) (0.740, 0.750, 0.780) (0.770, 0.800, 0.810)
Nearly Certain	The likelihood probability of occurrence is nearly certain	(0.920, 0.950, 0.960) (0.995,0.998,0.999)
Certain	Definitely occur	(1, 1, 1)

All prior probability calculations are completed according to the linguistic label of factor and corresponding Fuzzy Membership function. The linguistic label for the likelihood probability of Business Skill of Pilot (X1) is “Very Unlikely”, Mental Skill of Pilot (X2) is “Even Chance”, Business Skill of Crew (X3) is “Unlikely”, Mental Skill of Crew (X4) is “Very Unlikely”, Tugboat Operation (Y3) is “Even Chance”, Dock Operation (Y4) is “Unlikely”, and Port Management Policy (Y5) is “Likely”. The corresponding fuzzy membership functions are given (see, Table 3, Table 4, Table 5, Table 6, Table 7, Table 8, and Table 9).

Table 3. The Fuzzy occurrence probability of business skill of a pilot.

Business Skill of Pilot (X1)	
P(X1=1)	P(X1=0)
0.24	0.72
0.25	0.75
0.28	0.76

Table 4. The Fuzzy occurrence probability of mental state of a pilot.

Mental State of Pilot (X2)	
P(X2=1)	P(X2=0)
0.49	0.49
0.50	0.50
0.51	0.51

Table 5. The Fuzzy occurrence probability of business skill of crew

Business Skill of Crew (X3)	
P(X3=1)	P(X3=0)
0.34	0.62
0.35	0.65
0.38	0.66

Table 6. The Fuzzy occurrence probability of mental state of crew.

Mental State of Crew (X4)	
P(X4=1)	P(X4=0)
0.24	0.72
0.25	0.75
0.28	0.76

Table 7. The Fuzzy occurrence probability of tugboat operations.

Tugboat Operations (Y3)	
P(Y3=1)	P(Y3=0)
0.49	0.49
0.50	0.50
0.51	0.51

Table 8. The Fuzzy occurrence probability of dock operations.

Dock Operations (Y4)	
P(Y4=1)	P(Y4=0)
0.34	0.62
0.35	0.65

0.38	0.66

Table 9. The Fuzzy occurrence probability of Port Management Policy.

Port Management Policy (Y5)	
P(Y5=1)	P(Y5=0)
0.62	0.34
0.65	0.35
0.66	0.38

Step 3: Transforming linguistic variables into crisp values.
The crisp values have been evaluated by the value function. In this study, both values of q in the f-weighted valuation function are used (q=0 and q=∞) (Table 10).

Table 10. The crisp values for the test case.

	The crisp values	
	q=0	q=∞
P(X1=1)	0.255	0.250
P(X1=0)	0.745	0.750
P(X2=1)	0.500	0.500
P(X2=0)	0.500	0.500
P(X3=1)	0.355	0.350
P(X3=0)	0.645	0.650
P(X4=1)	0.255	0.250
P(X4=0)	0.745	0.750
P(Y3=1)	0.500	0.500
P(Y3=0)	0.500	0.500
P(Y4=1)	0.355	0.350
P(Y4=0)	0.645	0.650
P(Y5=1)	0.645	0.650
P(Y5=0)	0.355	0.350

The next steps can be named Bayesian Inference, which starts with the calculation of marginal probabilities and posterior probability calculation.

Step 4: Estimating Fuzzy marginal probability.
The marginal probabilities of Pilot Factor (Y1), Crew Factor (Y2), Human Factor (Z1), Operational Factor (Z2), and Hazardous Cargo Vessel Risk (U1) were calculated and given (see, Table 11).

Table 11. The marginal properties.

	P(Y1=1)	P(Y1=0)	P(Y2=1)	P(Y2=0)	P(Z1=1)	P(Z1=0)	P(Z2=1)	P(U1=1)	P(U1=0)
q=0	0.2065	0.7935	0.1737	0.8263	0.1228	0.8772	0.5000	0.1668	0.8332
q=∞	0.2000	0.8000	0.1663	0.8338	0.1170	0.8830	0.5000	0.1616	0.8384

Step 5: Inference result under normal conditions
By using the results of marginal probabilities calculated in Step 4, the inference under normal conditions for both q=0 and q= ∞ are given in Table 12 and Table 13.

Table 12. The inferences under normal conditions for q=0.

X1-Business Skill	Y1-Pilot Factor	Z1-Human Factor	U1-Hazardous Cargo Vessel Risk
0.2550			
	0.2065		
X2-Mental Skill			
0.5000			
X3-Business Skill	Y2-Crew Factor	0.1228	
0.3550			
	0.1737		
X4-Mental Skill			
0.2550			
			0.1668
	Y3-Tugboat operation	Z2-Operational Factor	
	0.5000		
	Y4-Dock operation		
	0.3550	0.5000	
	Y5-Port Management Policy		
	0.6450		

Table 13. The inferences under normal conditions for $q = \infty$.

X1-Business Skill	Y1-Pilot Factor	Z1-Human Factor	U1-Hazardous Cargo Vessel Risk
0.2500			
	0.2000		
X2-Mental Skill			
0.5000			
X3-Business Skill	Y2-Crew Factor	0.1149	
0.3500			
	0.1663		
X4-Mental Skill			
0.2500			
			0.1595
	Y3-Tugboat operation	Z2-Operational Factor	
	0.5000		
	Y4-Dock operation		
	0.3500	0.5000	
	Y5-Port Management Policy		
	0.6500		

Step 6: Estimating Posterior Probability.
The final step of the methodology is the calculation of the posterior probability. The probability of business skill of pilot has been assessed when the hazardous cargo vessel risk is 100% (U1=1).

5. Results & Conclusion

This study presents an application of the Fuzzy Bayesian Network Approach of hazardous cargo vessels during berthing operations. The risk factors have been evaluated by the judgments of experts. The linguistic judgments in the methodology are expressed quantitatively with fuzzy membership functions. For the Bayesian inference evaluations, they have been transformed to crisp value with an f-weighted value function. The value of q has been applied with the value function (q=0 and q=∞). Risk analysis can be considered as an assessment of uncertainty. In this case, three terms become important, namely vagueness, randomness, and ignorance. The Fuzzy handles the vagueness with occurs due to the ill-defined situations. Ignorance becomes a problem when experts are unable to make a strong connection between a factor and its consequences. The Bayesian network with a good correlation between factors and consequences eliminates ignorance.

Finally, probability theory can address the randomness resulting from unpredictable events. The human and operational factors have also been assessed. In this study, the mental state and business skills of the pilot and crew are the sub-factors for the human factor. The operational factors have been divided into tugboat operation, dock operation, and port management policy. The result for both q values are very close: for the crisp value, q=0 the posterior probability P(X1=1│U1=1) = 0.260, when the likelihood probability P(X1=1) = 0.255; for the q=∞ the posterior probability P(X1=1│U1=1)=0.290, when the likelihood probability P(X1=1)=0.250. When the posterior probability for both q=0 and q=∞ are compared, the difference is very small. It can be indicated that the f-weighted value function is reasonable in both cases q=0 and q=∞ and the occurrence of business skill for a pilot has increased. The correlation between hazardous cargo vessel risks and the business skill of a pilot is strong.

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