IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received April 8, 2020, accepted April 12, 2020, date of publication April 15, 2020, date of current version April 30, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2988201

Risk Assessment and Decision Support for Sustainable Traffic Safety in Hong Kong Waters

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ABSTRACT Hong Kong's port is one of the busiest in the world. Such heavy traffic is associated with a high accident rate. The present study uses Bayesian Networks to analyze accident risk in Hong Kong waters using 331 accident reports during the period of 1999-2017. The methodology adopted is comprised of an analysis of present literature and expert judgments for the determination of nodes and states. The calculation of probabilities and conditional probability tables (CPT) were done based solely on the real data in accident reports through parameter estimation. The results indicate that the highest portion of accidents was categorized as "other" with a probability of 0.5174. The majority of such accidents took place in port waters. The second highest category was "collision" with a probability of 0.2256. Both of these accident types were associated with the highest fatality rate-one or two people killed. Poor judgment, negligence and insufficient training were found to be the most influential factors with regard to human actions. The highest rate of injuries was associated with passenger ships. The results offer valuable insights into various accident scenarios which involve setting evidence at different states of consequences and accident types to determine the most prominent contributing factors. Sensitivity analysis was also conducted to recognize the most critical variables. This study should prove useful to decision and policy makers seeking to enhance sustainable safety in maritime traffic operations.

INDEX TERMS Accident risk, potential consequences, Bayesian networks, hong kong waters, maritime traffic safety.

I. INTRODUCTION

Maritime transportation has a key role in the advancement of global trade and natural resources. However, the growth in maritime transportation presents challenges to the safety and efficacy required in this sector [1]. Operational safety in marine transportation is subject to various critical factors, like severe operational and environmental conditions along with various factors related to human error and the conditions of ships. A maritime accident is defined here as an unwanted incident leading to equipment and property loss, damage to goods or to ships, environment pollution and above all the loss of life [2].

Maritime transportation accidents in the scholarly literature are considered to be low in frequency but high in impact and damages [3]. Therefore it is of vital importance to understand why and how these accidents occur and devise countermeasures to prevent them [4]. Generally, the foremost intention of risk analysis is to avert accidents. To ascertain higher threat, both the absolute value of risk and the comparative prominence of the most significant causal factors need to be enumerated [5]. Once potential dangers are assessed, strategies and resources for risk management can be developed.

The frequency and magnitude of losses in maritime accidents are related to the type of ship involved. Passenger ships have comparatively lower accident rates, however, they are associated with a higher risk of calamitous consequences in terms of loss of life [6]. Cargo ships are associated with higher accident rates, but the risk of loss of life is lower [7]. Because, passenger vessels account for only 8% of total global commercial ship traffic, most of studies are focused on cargo, fishing and tanker vessels [6]. Although there have been important technological advancements in maritime operations and navigation, there have been many maritime accidents in various areas due to a variety of reasons.

The associate editor coordinating the review of this manuscript and approving it for publication was Kang Li.

With the increasing amount of global maritime traffic, accidents are also increasing and have mostly been attributed to human error, the work environment and various organizational aspects. Although there is no unanimity on the statistical dissemination of accident causation factors, yet technical, mechanical, environmental and human-related aspects are generally understood to be the major factors leading to these incidents [8], [9]. Of all these factors, the human element is considered to be the most important and is attributed to various aspects like fatigue, carelessness and a lack of training and education [1], [10].

The increasing complexity of traffic in maritime waters, in which various factors like human error and environmental factors interaction results in a need for new methods to analyze accidents [11]. There are currently around 100 different methods to analyze maritime accidents and assess associated risks [6]. A review based on the analysis of various definitions and approaches indicates that probabilistic, pragmatic, experimental and accident-database centered approaches are more accurate and successful in understanding maritime traffic [12]. Understanding the mechanism behind the occurrence of accidents and devising preventive measures for shipping accidents is still a prominent issue in the maritime transportation.

Risk is defined as the product of probability of occurrence and the severity of its consequence [5]. The quantitative risk assessment tools have the ability to assess risk in terms of uncertainty and consequences and treat the uncertainty associated with risk in an efficient way [13]. Lack of data and related fuzziness are considered to be the main deterrents in maritime risk assessment [14]. Approaches which group the qualitative and quantitative facets of the information in risk assessment are regarded as the most effective methods. For these reasons, fuzzy logic, Bayesian networks (BN), analytical hierarchy process (AHP), and evidential reasoning (ER) are the most recommended and widely used approaches in maritime accident and risk analysis [1].

Bayesian networks are a combination of graph and probability theory and have the ability to both efficiently capture the most significant causation factor in an accident and to capture the relationship between various causal factors [5]. BN can effectively assess the dynamics involved in the cause-consequence analysis of maritime traffic accidents [1]. Analysis of ship collision data from the Gulf of Finland through BN indicates that the human factor is the most prominent causal element [15], [16]. Bayesian networks facilitate the successful integration of human and organizational factors in the analysis of maritime transportation risk [17]. Bayesian networks have been extensively used in maritime traffic accident analysis and BN has been effective in assessing the factors involved.

However, a majority of these studies have been based on expert judgments, and in many studies the number of nodes along with the number of states per node is kept low with binary states [18]. This practice is adopted to ease the computation and elicitation process. Although these practices are common due to the unavailability of data, they are associated with less accuracy in inferences. Furthermore, these factors can also jeopardize the decision-making process to devise preventive measures and allocate resources. This issue can be solved by the use of real data from past accidents [18]. It will result in more accurate Bayesian inferences and hence more realistic and reliable results for decision making.

Hong Kong port is one of the busiest and safest ports in the world [19]. The Hong Kong port and its associated waters handle a huge amount of maritime traffic and traffic has been increasing every year as trade in the region grows. This study seeks to analyze past accidents in Hong Kong waters, both within the port environment and in open waters. The causation factors selection and causal relationship development was done in concurrence to the existing literature and finalized by expert judgment. The data of 331 accidents from the period 1999 to 2017 will be used in a BN environment to identify the most prominent accident causation factors among human error, conditions in the environment and the prevailing ship and traffic conditions. Furthermore, this study will analyze the fatalities and injuries resulting from various accidents from the perspective of the ships involved along with the type and location of the accident. This study will have immense practical value for governments, ports and other decision making bodies to improve sustainability in maritime traffic safety.

II. LITERATURE REVIEW

Bayesian networks are an amalgamation of graph and probability theory and are considered to be a useful tool in analyzing the interconnectivity and vagueness associated with the variables involved in a model [20]. BNs are directed acyclic graphs and an amalgamation of qualitative and quantitative methodologies generating significant results in risk analysis. The qualitative portion of the network represents its structure, giving a graphical depiction of the causal relation between the variables providing facts on the movement of evidence, inference or information through the developed model [18]. The quantitative portion is associated with the conditional probabilities among the variables and concerned states of the model as per their causal order or connectivity.

BNs are widely recognized to be a robust tool for causal inference. BNs not only can identify the most prominent contributory factor but they also can determine the nature of the relationship between various factors involved [5]. The salient features associated with BNs are their ability to accommodate inverse or reciprocal inferences, amalgamate new information or evidence and utilize semantic probabilistic ability to deal with missing or partial data [21]. Furthermore, BNs have the ability to demonstrate genuine visual and graphical causal relationships between the variables involved.

Apart from the ability of BNs to impart information on the prominence and connectivity of various factors, they have an edge over other visual models due to the BN's basis in mathematical knowledge [2]. Although, it is not a novel technique, BNs do not have a long history of use in in the field of transportation [22]. However, in the past decade BNs have been progressively employed in transportation risk assessment, accident and safety analysis.

In concurrence to some devastating mooring failures, a risk assessment for the threats associated with the offshore floating structures have been conducted using Bayesian networks [23]. Similarly, in another study, BN environment was utilized to conduct risk assessment for marine structures under severe climate conditions [24]. BN environment was employed to assess the effect of human fatigue over the passage of time on the safety of maritime operations [25]. Likewise, to assess the risks concomitant to the grounding of ships in shallow waters, a BN inference environment was used to facilitate the concerned authorities with safety measures [26]. To focus on the growing concerns of maritime traffic safety in arctic waters, a BN model was used to evaluate the collision, grounding and foundering accidents on the northern sea route [27]. Risk assessment for the marine and port operations through various tools is a less explored domain when it comes to the maritime transportation [28].

BNs have been used to understand various dimensions of maritime transportation, like the occurrence of grounding and collisions between ships, and the factors that contribute to these accidents [14], [15], [29]. This method has also been used to analyze oil spills from tanker collisions [12], [30]. BNs have been employed in the analysis of the ships' safety in various navigational situations, particularly in winter conditions [31]. A study investigating the effects of human fatigue on grounding accidents indicates that fatigued operators of large ships increase the probability of running aground by 23% in long distance transportation [32]. The role of humans and related factors has also been studied in different scenarios and from different perspectives [32], [33]. In devising cost-efficient safety management approaches for the analysis of collision between vessels, BNs have been used in conjunction with the evidential reasoning approach [34]. A study focused on port operations [35] indicates that the accidents in port processes can be attributed to various reasons including organizational, technical and environmental factors.

Furthermore, the application of BNs to the operations of military ocean patrol vessels from a security perspective resulted in recommendations for the improvement of the design of these vessels to augment their resilience and endurance [36]. Another study that focused on economic decisions in the shipping sectors of Indian and African regions employed the BN model to evaluate the likelihood of a ship being hijacked [37]. Similarly, various studies [38], [39] have used BNs to model the effective methods of evacuation in emergency situations. The dynamic failure analysis model, which is based on the BN model, has indicated that collisions are the most probable type of accident in the offloading of liquefied natural gas tankers arriving at a port terminal [40]. The diversity of themes covered in these studies indicates the popularity of BNs in analyzing maritime transportation and safety.

In spite of such popularity and acceptance, BNs face a general criticism that for these models to be effective, a huge amount of data is required in the form of erstwhile probabilities. This volume and type of data are considered difficult to obtain, and in some instances impossible to access [5]. Moreover, the number of variables and respective states also have to be controlled, which otherwise will increase the dimensions of the conditional probability table (CPT) resulting in enhanced intricacy and difficulty in computation. Attributed to hindrances in the accessibility of empirical data, most of the studies have focused on the development of CPTs through expert judgment and elicitation [5]. However, in the case of large-scale BNs with numerous nodes and states [41], the calculation of CPT is rendered impossible by the time required, impracticality and incongruousness.

Nevertheless, these limitations have been addressed by various studies offering different options. Large-scale likelihood in various accidents can be conformed to prior probabilities through the use of binary logistic regression [5], however, this method still requires a large data set. Another approach that has been adopted is Noisy-OR, which simplifies the elicitation of CPTs into individual CPDs (Conditional probability distributions) of the binary nature between the cause-consequence and parent-child [42]. Developed in 1988, Noisy-OR has been augmented with several extensions. It was later modified to deal effectively with various dependent nodes having multiple states. However, it still has the limitation of developing the visual modular structure and complete causal relationship [43]. The doubly truncated normal distributions were also found to have alleviated the elicitation encumbrance through ranked nodes [44].

Similarly, deriving the prior probabilities from the accident's past data is a well-recognized technique. Data from past accidents in the arctic region were used in BNs to identify the most profound causal members in a significant event [4]. This study was useful in determining the prominent factors in accidents, which then could be monitored and given due attention in the decision-making process to create more effective safety regulations. To better investigate the threat of ship-ice collisions in arctic waters, an object-oriented Bayesian network (OOBN) was modelled and adopted [1]. This methodology was favored because of its simplicity of construction, its reusability and its modification suppleness. Furthermore, OOBNs are considered to be less complex and are associated with the ability to represent the developing modular intricacy. Likewise, to determine the most significant factors that lead to ship detentions in port state control (PSC) inspections, the data of past inspection reports were modelled through data-driven Bayesian networks [2].

Data-based BN models have also been used to interrelate various accident-causing agents and their specific impact on resulting fatalities. Past data from the Portuguese Maritime Authority was used, finally selecting 857 accident reports which justified the criteria of selected accident scenario and the developed BN model was run to relate the various ship types, seasons, time and location of accidents with the resulting fatalities [18], [45]. A similar study, one based on data from past accidents, was conducted to specify the most significant causal factors in accidents in Hong Kong port waters, however, the methodology used was negative binomial regression [19].

As mentioned earlier, the Hong Kong port is one of the safest and busiest ports in the world. Yet, no analysis of accidents in Hong Kong Port and open waters has been conducted. The only reliable study found in the literature was conducted by Yip in 2008, however it was confined to port waters and did not consider accidents occurring in open waters near Hong Kong. The present study is aimed to fill this gap and evaluate the effects of various factors on accident frequency and resulting fatalities in both Hong Kong port and open waters using Bayesian networks.

III. METHODOLOGY

Based on a combination of graph and probability theory, BNs are deliberated to be puissant tools for assessing uncertain and vague information associated with variables under consideration. This information can be processed through various inference systems like artificial intelligence, probability theory, graph theory and decision analysis [46]. BNs have the ability to process the data and vagueness of all states of a variable through inference in a probabilistic system. Attributed to its diverse capabilities, BNs provide an effective method for evaluating maritime risk [38]. BNs offer support for decision-making processes by providing a scrupulous, consistent and systemized assessment. However, the conformance of the methodology to the problem under study needs to be evaluated.

The basic features of BN model development include recognizing the influential factors or variables, determining the causal relationship between them and giving these variables a proper visual representation. Quantification of these relationships is achieved through the incorporation of data from past accidents. These data were utilized through parameter estimation, and all the probabilistic inferences are determined. Complete model development, quantification and inference were done in the BayesiaLab 8 Academic version software, which provides a reliable and effective inference environment. The detailed methodology is described below.

A. NODES AND DEPENDENCIES SPECIFICATION THROUGH DATA, LITERATURE AND EXPERT JUDGMENT

To initiate the development of the BN model, the first step is to specify which variables affect the study. Moreover, the dependency of these variables on one another needs to be determined and represented graphically. Graphical representation is achieved through nodes and arcs, where nodes signify the variables and arcs characterize dependency. This graphical representation, called direct acyclic graphs (DAGs), is of immense importance in determining the cause-consequence relationship and inferences. It is an enormously difficult task to determine these relationships through mathematical expressions and equations. Causal variables are called parent nodes, while the initiated consequence variables are called child nodes. The arcs originate from parent nodes and terminate at child nodes.

Data availability is pivotal in developing a reliable BN. Data can be gathered from accident databases, concerned authorities and regulatory institutions, as well as available literature which focuses on the same or related issues and offers expert judgment on it. Expert judgment has a fundamental role in replacing the missing data, which however can be replaced in case of data availability. However, the reliability and practicality of the models need to be improved to enhance decision-making and reduce uncertainty and vagueness. This can be achieved through the assortment, elicitation and use of available data.

The government of Hong Kong has maintained a database of accident reports that occurred either at the Hong Kong port or in waters in their jurisdiction. Whenever there is an accident in these waters, an investigation team is assigned the task of conducting a detailed investigation. This investigation determines the possible factors that led to the accident. It provides information on the type of accident that occurred, the type of ship involved, the losses and fatalities that occurred and the associated prevailing conditions of humans, ships and weather and rescue options. Moreover, certain published reports have data on the occurrences of various types of accidents and the types of ships involved, along with provision of information on maritime traffic counts. All of this information serves as potential data for BN modelling.

However, these accident reports were scrutinized to isolate and remove those reports which were lacking the required data and did not conform to the criteria developed for the selection of reports in compliance with the variables and the selection of corresponding states. Authors of previous studies like [2], [18], [19], [32], [45] have developed a criterion for nodes and states selection. Based on these criteria, accident causation factors and their cause sequence were identified for this study, and the model BN network was developed. The developed network was further discussed with experts from academia and industry until a final version was prepared and agreed upon.

B. GENERATING PROBABILITIES AND CPTS

After outlining the nodes as per the corresponding variables and defining the arcs as per the causal associations amid the variables, the conditional probability tables (CPTs) for the nodes must be developed. These CPTs could be developed either from the available data, expert judgment or through an amalgamation of these two approaches. For a set of variables such that $X= (X1, \ldots\ldots, Xn)$, the variable is binary, having values of 0 and 1, such that Xj is considered to have occurred if its value equals 1. Attributed to the causal relationship in the directed acyclic graph, the network has various conditional probabilities or parameters, which for a given variable Xj having parents $X\pi(j)$, is represented by $p(Xj/X\pi(j))$. Due to the causal relationship between the networks, each network or structure has a specific joint probability distribution $\Pr(X)$, which per factorization is given as,

$$p_r(x) = \prod_{j=1}^{n} p\left(x_j / X\pi\ (j)\right) \tag{1}$$

However, in this study, we have accident reports which have been organized into a proper data set, such that no data is missing. In that scenario, the probabilities and CPTs are calculated through the parameter estimation utilizing maximum likelihood estimation [47]. In order to estimate the parameters from the data set D, let the number of observations in this data set be m (Xj, Xπ (j)). Moreover, the variable Xj has taken a value of xj, whereas its parents Xπ (j) have adopted the pattern of xπ(j). Considering the various parameters unconnected, their estimation gets simplified and turns to a single variable with its corresponding parent. The typical way to estimate a parameter p (xj/xπ(j)) is given as,

$$\widehat{p}\left(x_j \mid X_{\pi(j)}\right) = \frac{m\left(x_j X_{\pi(j)}\right)}{m\left(x_{\pi(j)}\right)} \tag{2}$$

The maximization of the log-likelihood l (p/$\mathcal{D}$) of the parameter p in a given network for the associated data set is

$$l\left(p|\mathcal{D}\right) = \sum_{j=1}^{n} \sum_{xj|x_{\pi(j)}} m\left(x_j, X_{\pi(j)}\right) * \log p\left(x_j, X_{\pi(j)}\right) \tag{3}$$

C. SENSITIVITY ANALYSIS AND MODEL VALIDATION

In a BN model, the analysts may be interested in identifying factors or parameters that are responsible for a certain consequence. In order to identify the rationality and strength of these connections, specific changes are made in the probabilistic entities. In sensitivity analysis, the nature and magnitude of the effect of a parent node on the child node or vice versa, can be determined. One of the key features of sensitivity analysis in a model is the number of parameters considered [48]. The simplest of the cases involves making changes only to a single parameter in the network. This is an easy mode of analysis, but one that is not completely reliable.

The second approach is to consider multiple parameters in a single CPT. However, in order to do this a complete understanding of joint probability distribution and network parameter is required. The most reliable and complex approach is to consider parameters in multiple CPTs. The most anticipated sensitivity analysis in this regard has to be holistic, such that the interaction and influence of all the parameters in the analysis are considered [49]. Therefore, the BNs are considered to demonstrate robustness to reasonable variations in the CPTs.

In this study, the sensitivity analysis of the constructed BN model is conducted through the utilization of a sensitivity analysis feature offered by the BaesiaLab software employing tornado charts [50]. The sensitivity and nature of the relationship between various nodes of the network are represented through tornado charts with the option to select various numbers of parameters. Furthermore, to evaluate the degree of confidence and reliability in the results produced by the model, it has to satisfy the following conditions [2], [5], [51], [52].

An increase or decrease in the prior probabilities of the parent nodes shall result in the corresponding posterior probabilities of the child nodes.

The denomination of the influence generated by the variations in probabilities for the set evidence is greater than that of the sub-factors.

IV. SCENARIO ANALYSIS

The port of Hong Kong was the world's busiest port in the period considered in this study, 1999 to 2004. Between 2005 and 2017 it was among the top five busiest ports in the world. Out of the 185,420 ships arriving in 2017, 26,793 were ocean vessels. Ocean vessels are categorized as either ocean cargo vessels or, ocean passenger vessels. The natural and geographic conditions of the harbor have played a profound role in the growth of the Hong Kong port. Furthermore, these conditions provide an effective natural shelter against strong winds from the north and east [53].

Moreover, associated deep-water approaches and calm waters also enhance the functionality and safety of the Hong Kong port. Due to these reasons, the port serves a higher volume of traffic with a variety of sizes and types of ships. The port receives a high proportion of passenger vessels encompassing a variety of speedboats and ferries. Also, it has various maritime amenities in close proximity. The port is associated with multiple water approaches and mooring bays, which makes it attractive to a large number of ships. Figure 1 depicts the volumes of different categories of ships that arrive. The port authorities work to ensure a smooth routine for ocean-going vessels to maintain proper control.

Even though the port of Hong Kong is considered to be one of the safest ports in the world, such a huge amount of maritime traffic inevitably leads to accidents. The marine department of Hong Kong has an effective mechanism for reporting these accidents. Every time an accident takes place an investigation is initiated to determine the possible causes and to develop recommendations for improvements in order to avoid such accidents in future. Figure 2 represents the number of accidents that have occurred in Hong Kong waters in the time period considered for this study.

These accident reports have been organized into a database of marine accidents. Analyzing all these reports from 1999 to 2017, give insight into the risks that normally prevail in this region along with various other aspects of maritime accidents. These accidents have been broadly classified as collision, contact, grounding, foundering, sinking, equipment damage, machinery failure, extreme or heavy weather conditions, and other. However, the occurrence of accidents of each type varies from time to time and prevailing weather, ship and crew conditions. Figure 3 represents a graphical representation of the most prominent accidents in the data considered.

Assessing oil spills from tankers using real data from the past, the most significant factors or types of accidents found were collision, grounding, equipment failure, fire and explosion and ship sinking [54]. Maritime accidents are normally classified according to and attributed to their primary causal

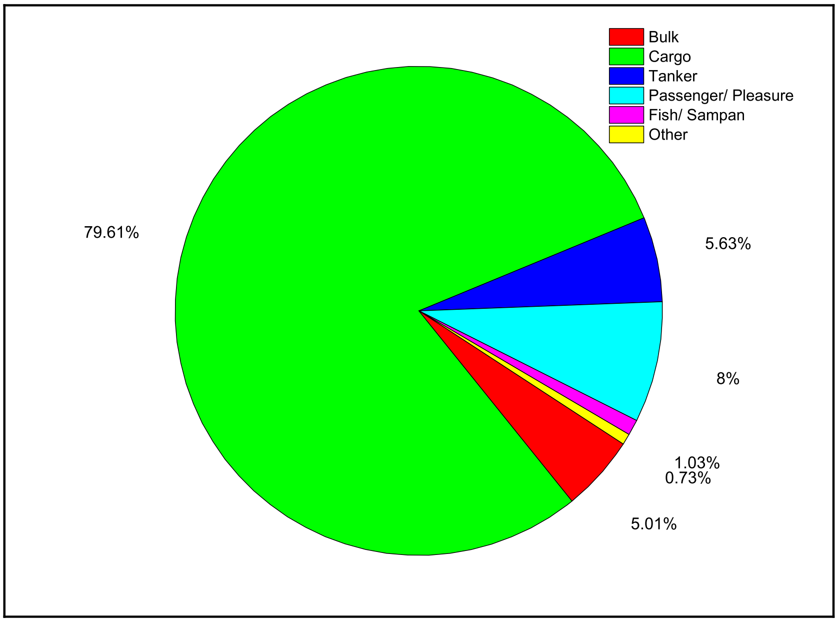

FIGURE 1. Percentages of different categories of ships at Hong Kong port.

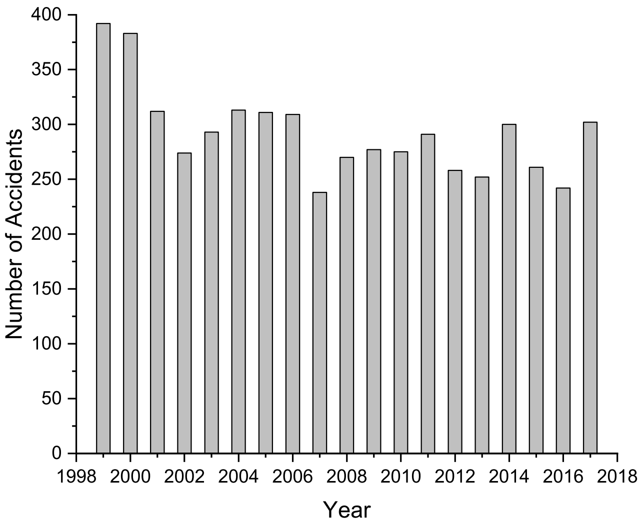

FIGURE 2. Number of accidents occurring in Hong Kong waters.

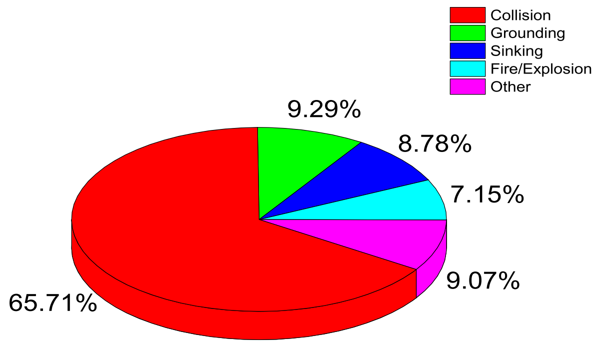

FIGURE 3. The most common type of maritime accidents.

factors, which are referred to as called first event. These first events could be improper maintenance, extreme weather conditions, and human errors [19], [55]. Human error, crew skill level, ship and environmental factors were considered while analyzing the process risk evolution of the LNG-fueled ships [56]. A study focused on maritime accidents in the Portuguese waters indicates that human error, material factors and sea and weather conditions are the most prominent accident-causing factors [57]. Another study analyzing maritime accidents in Portuguese waters assessed the contribution of each factor in accident causation along with the effect of geo-position, time of the day, month and year [18]. Various weather windows for maritime operations in black sea were analyzed considering the wave and wind factors data in different seasons [58]. The effects of all these factors were evaluated with the type of ship and its flag together with resulting fatalities and injuries.

An analysis of accidents involving passenger ships considered various aspects of human error [6]. Human error was differentiated into errors and violations. Errors were the result of a decision based on skill and perception, while violations were regarded as actions contravening regulations and procedures and instances of abuse of authority. Ship type, flag, age and size were used in an analysis to determine their quantitative contribution to the risk of a ship accident [5].

A study focused on ship collisions with icebergs in arctic regions determined that human error, including miscommunication and lack of maintenance and equipment failure were the primary factors in such accidents [4]. Furthermore, the study recommends that in order to avoid such accidents crews should be experienced, have good training, follow the navigation rules and standards, and machines should be properly designed and maintained. A similar study in this regard uses variables like weather, visibility, high winds, fog, seasons, fatigue, speed, inadequate knowledge,

TABLE 1. Risk scores as per the death toll.

Sjk score	Consequences of an accident (death toll)
41-100	More than 10 deaths
16-40	3 to 9 deaths
8-15	1 to 2 deaths
1-7	Striking, significant, disabled, serious

training and decisions to evaluate accident occurrence in Arctic waters [1]. A study conducted to ascertain the elements that effect the probability of ship collisions indicates that the person on watch has a significant role in avoiding accidents [15]. Moreover, danger detection, situation assessment, personal conditions and changing the course in an accident situation were found as to be the most influential variables.

V. ACCIDENT ANALYSIS IN HONG KONG WATERS

The smooth movement of maritime traffic is complex and requires intense collaboration in this multi-task operation. Depending on the environment in which they operate and the goods these ships carry, any mishap or accident could potentially result in loss of life and property along with environmental pollution. Hence, it is of utmost importance to pay considerable attention to the risks associated with maritime traffic. These risks include ship crew and other associated manpower, type, age, size and origin of vessels along with the different kinds of equipment and machines that make possible the movement of ship traffic around the globe. This analysis is carried out to determine the profound risks and factors associated with accidents occurring in Hong Kong waters. This is achieved in accordance with the defined risk benchmarks and tolerable hazard limits (THRs) in order to define the integrated and individual improvements required to abrogate potential risks.

BNs are a risk evaluation tool that best captures the cause-consequence relationship. The tolerable hazard rates concept is used to assess the latent threats to maritime traffic operations. These consequences are assessed in terms of life and property losses. The accumulated losses forecasted for a specific accident are then compared against these THRs, also called the ASPL (Acceptable Safety Performance Limit).

The tolerable hazard limits for each accident are determined and expressed in terms of the severity of the consequences in terms of both loss of property and life. The severity Sjk of the accident Ajk is depicted as follows:

Sjk (property loss) = equipment impairment cost + ship impairment cost + other loss cost + death and corresponding number of impairments

TABLE 2. Variable states and nodes.

No.	Node	States
1	Visibility	Bad (1) Good (0)
2	Navigational Conditions	Bad (1) Good (0)
3	Wind Force	<4 (0) 4-7 (1) >7 (2)
4	Speed	Unsafe (1) Safe (0)
5	Rules	Following (0) Violation (1)
6	Hazard Identification	Right Judgment (0) Wrong Judgment (1)
7	Attitude	Careful (0) Negligence (1)
8	Crew	No Problem (0) Less Personnel (1) Inadequate training (2)
9	Season	Dry (0) Wet (1)
10	Accident Type	Collision (0) Sinking/Grounding (1) Fire/Explosion (2) Machine/Equipment failure (3) Other (4)
11	Ship Type	Bulk (0) Cargo (1) Tanker (2) Passenger/Pleasure (3) Fish/Sampan (4) Other (5)
12	Consequence	1-7 (0) 8-15 (1) >15 (2)
13	Location	Inside Port (0) Outside Port (1)
14	Time	Day (0) Night (1)
15	Registry	Local (0) Hong Kong (1) Mainland China (2) Foreign (3)
16	Ship Age	<8 (0) 8-15 (1) >15 (2)

Sjk (deaths) = actual number of deaths + number of injured equivalents transformed to an actual number of deaths + all costs comparable to the number of deaths

Hence, the risk can be defined as a product of the probability and consequence severity of the Accident-Risk = the chance of an accident * the consequences of an accident.

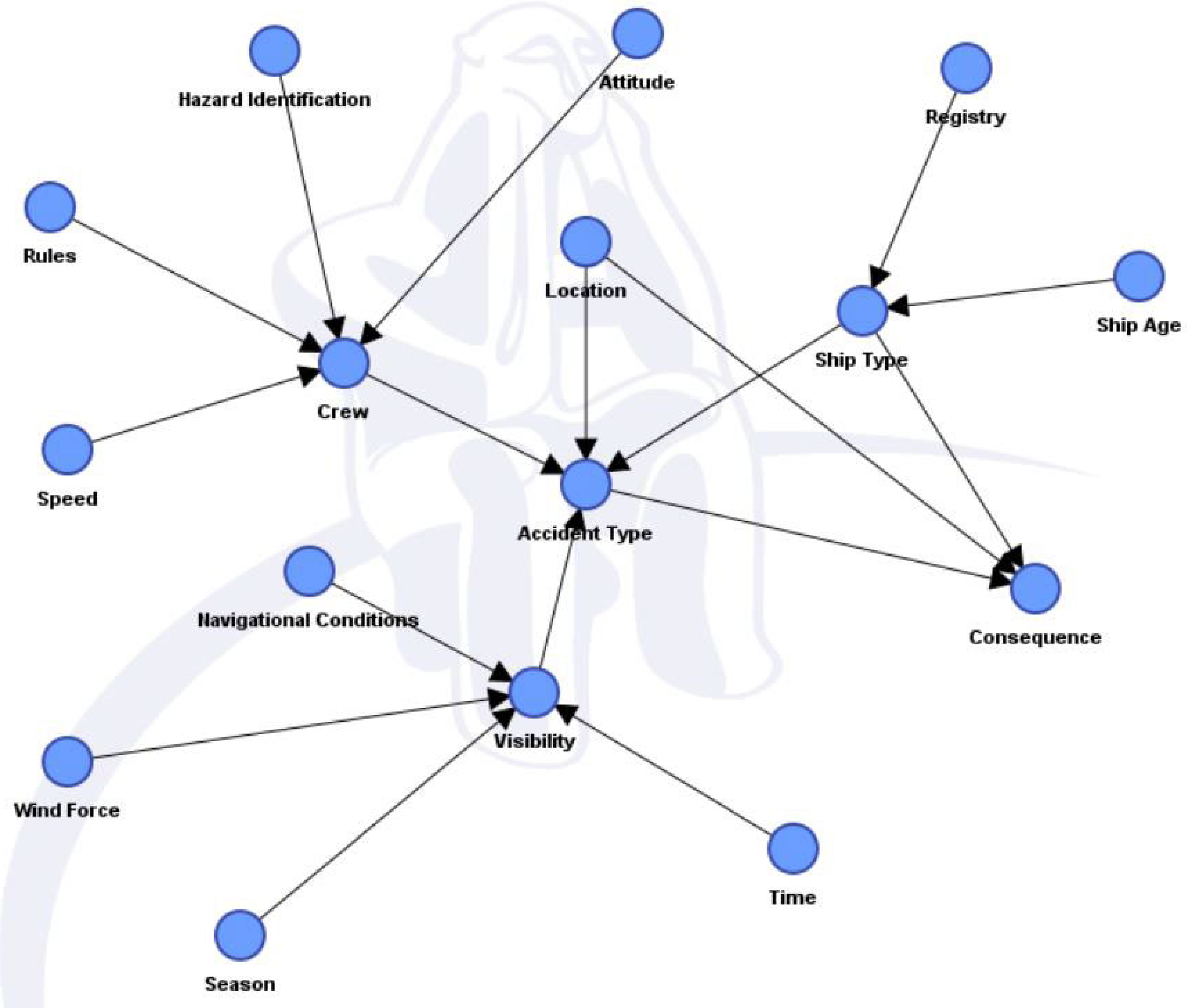

FIGURE 4. DAG of the proposed model.

However, in this study, we have focused only on the injuries and fatalities caused by the respective accident and ship types in the prevailing conditions.

The specific evaluation criteria are:

During the sorting and classification of the accident reports as per the defined criteria, the authors concluded that accidents with a death toll of more than ten were less than.05% during the period under consideration. Therefore, deaths of more than ten were not considered as this would generate a very minimal or negligible occurrence probability.

A. SPECIFYING NODES AND STATES OF BN

In order to ascertain the related nodes and states for this study, a comprehensive literature review was conducted to examine studies of this domain. A scenario analysis of the accidents that occurred in Hong Kong waters specifically and other oceans in general was also completed. After that, all the potential nodes and states were put to expert judgment. These experts were from both academia and the maritime traffic industry. The nodes and their corresponding selected states are given in the table below and have a total of 16 nodes. Each state has a variable amount of states corresponding to its nature. The states were also assigned with numbers in parenthesis so that they could be easily sorted to the corresponding states and nodes in the BayesiaLab software environment.

In the accident type node, the state "other" represents accidents like falling from stairs, falling overboard, electrocution, being hit or crushed by machinery, and death by suffocation due to lack of oxygen or exposure to hazardous gases in ship compartments or tankers. Moreover, "other" includes falling into the water during inspections or other activities at a port or falling into the water while under the effects of alcohol. The involved nodes as per their causal nature have been depicted in a DAG (Directed Acyclic Graph) in the BayesiaLab Environment.

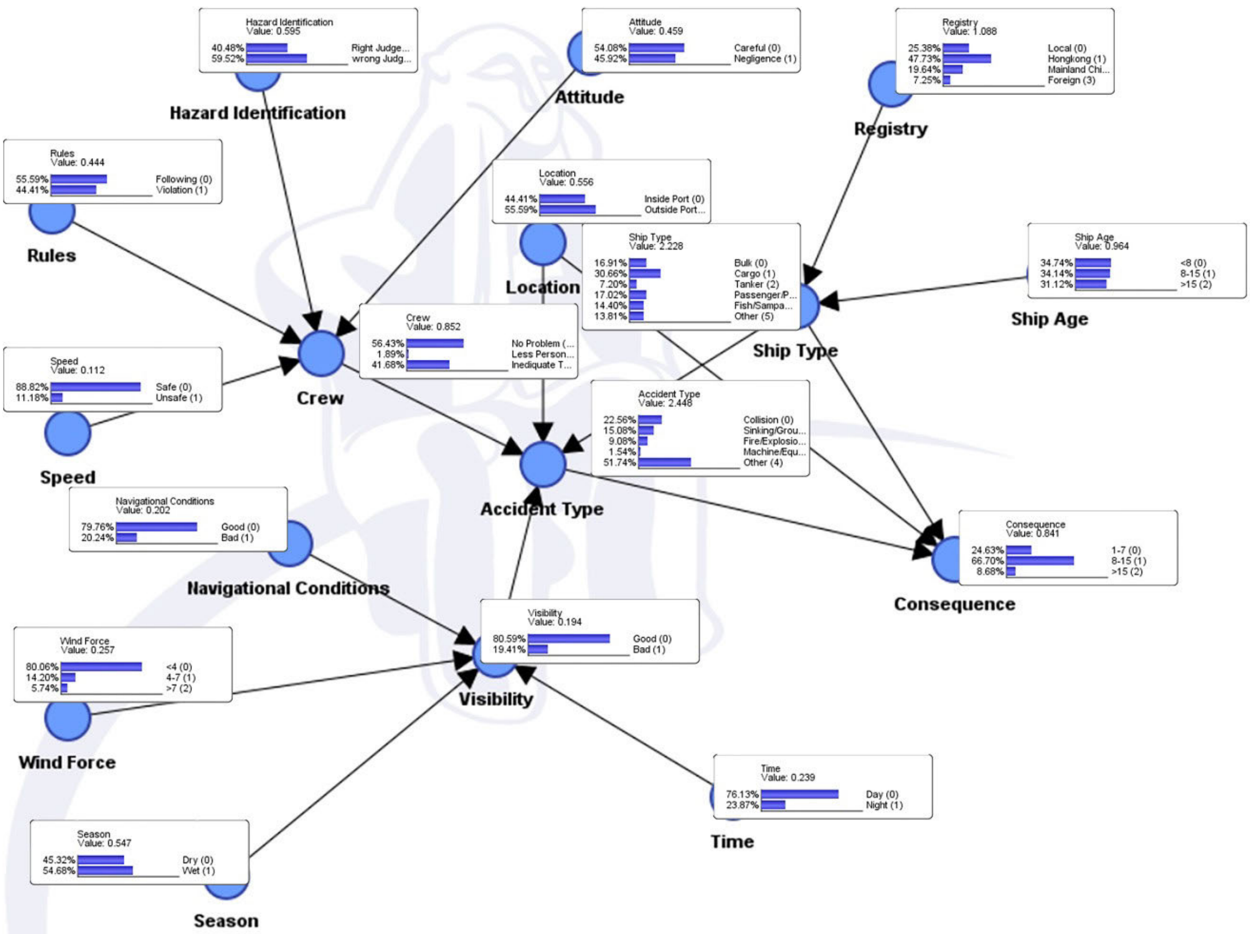

FIGURE 5. **Inference under normal conditions.**

All reports from the period under consideration which conformed to the suitability criteria were arranged into a database or data file. This file was then associated with the model graph in the software environment. After that, the parameter estimation feature of the software was used to estimate all the probabilities and CPTs.

B. RESULTS AND DISCUSSION

From the inference results generated by the BayesiaLab, it is evident that under normal conditions, that the accident category ''other'' has the highest probability 0.5174. ''Collision'' was the next highest at 0.2256. Under these conditions and the corresponding major types of accidents, the most prevailing consequence score is ''8-15'', which stands for the death of one to two people. Looking at the contributory factors, cargo ships had the highest probability of being involved in these conditions, with a contribution probability of 0.3066. Passenger ships came next with a contribution of 0.1702. Looking at the sub-factors for the type of ship, ships less than 8 years of age at the time of the accident had the highest involvement in accidents.

Hong Kong registered ships were the most likely to be involved in accidents. A majority of these accidents took place in open waters, however, the accidents that took place inside port waters were also not minimal. Analyzing the human or crew factor, it can be seen that in the majority of the cases, the crew had no problems. However, negligence, lack of training and improper judgment played the greatest role in accident causation from the human perspective. These accidents could be reduced by developing a good understanding of rules and regulations and by developing a more effective way of communicating between ships. Similarly, an accurate assessment of threats and accurate risk information combined with rapid response times in rescue operations could also help to significantly reduce casualties. Around 80% of the accidents took place during the day, in good visibility, under normal navigational conditions, and with a wind force of less than four, but majority of accidents took place in the wet season.

Now, if the evidence is set such that 100% of the accidents take place inside the port environment, the highest accident type is ''other'' with a probability of 0.7134. The prominence of this type of accident in this scenario is understandable as it encompasses a wide range of accidents involving individuals aboard ships at port.

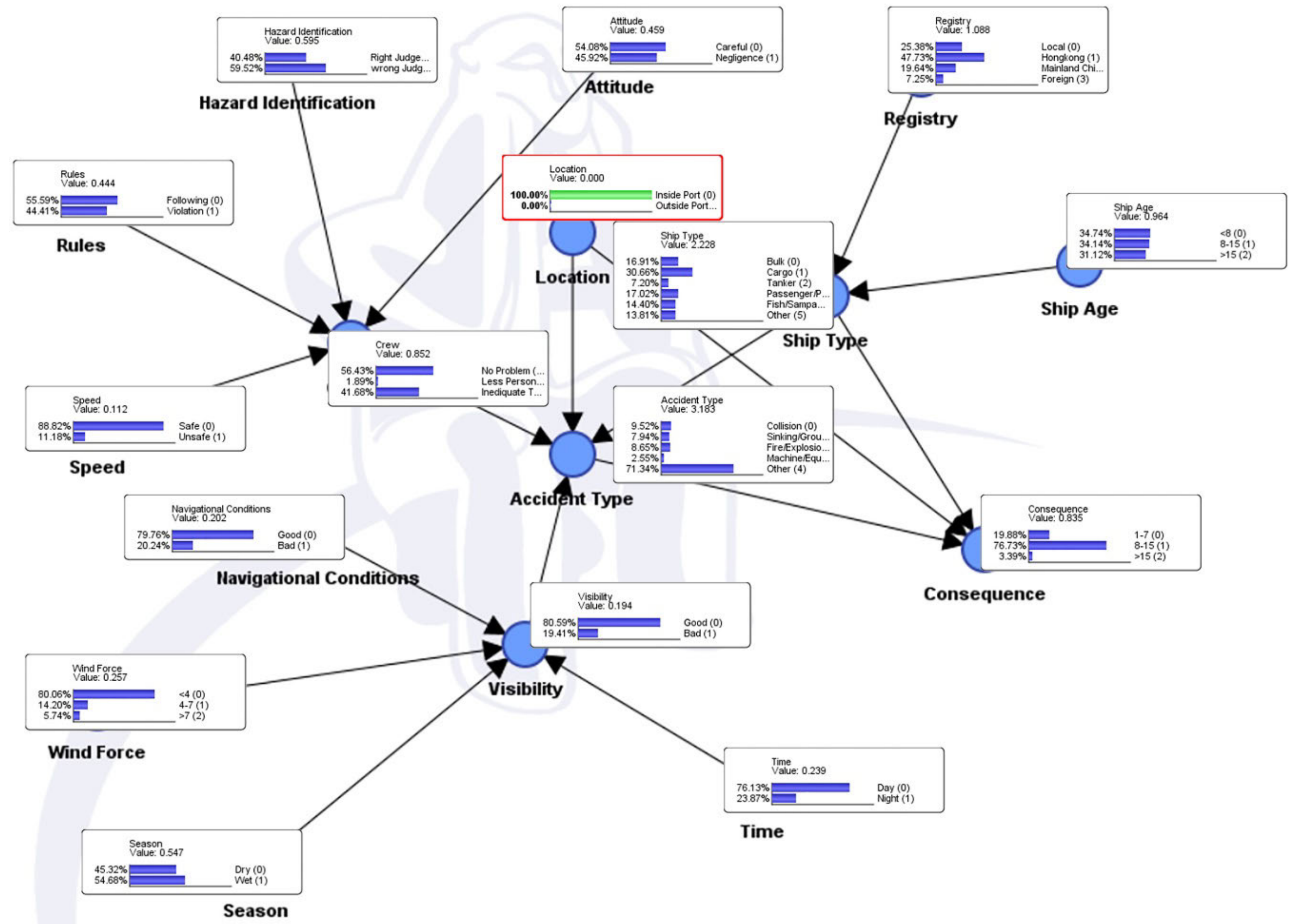

FIGURE 6. Inference results for evidence set at "Inside Port".

In this scenario, "8-15" is the consequence with the highest probability, and it increased by more than 10% (p = 0.7673). The state "8-15" represents 1-2 people killed in the accident. This trend also makes sense as the majority of fatalities caused by these types of accidents remains at one or two people killed. Moreover, since these accidents occurred in the port environment, they could be inspected and controlled more efficiently because required facilities are more easily accessible as compared to ships in open waters. Ship age does not play a significant role in this scenario; all three states have almost the same level of contribution probability. The remaining factors, like ship registry, inadequate training, negligence, and wrong judgment, remains unchanged and have the same high level of contributions. The reason for this could be that in the majority of the cases the personnel involved have not paid sufficient attention to safety requirements. Most of the times, they were found working without safety shoes, helmets and belts. Workers were found to have been working in close proximity to or inside the range of cranes and other machinery.

Furthermore, in the cleaning of tanks and ships, workers involved in accidents were negligent in checking for oxygen availability and the presence of toxic gases. During the analysis of reports for this study, it was observed that in the majority of such accidents, the workers or staff lost their lives because they were either lacking in training or were negligent towards the rules and recommendations. Thus, it is profoundly important to train-personnel in order to enhance their professionalism, integrity, and general situation management capability. The crew should be tested specifically on such scenarios and their performance should be recorded in their technical files and performance reports. In order to avoid such accidents, due attention should be paid not only to their professional and technical excellence but also to the enhancement of their psychological strength, readiness and response patterns.

Similarly, when looking only at accidents occurring in open waters, the accident probability of "other" is reduced by around 15% (p=0.3608) compared to normal conditions and by 50% (p=0.7134) in comparison to all accidents taking place inside port waters. The probability of collision increases by 10% (p=0.3298) in this scenario, while "sinking/grounding" increases by 5% (p=0.208). Looking at the consequences of this scenario, the probability of "8-15"

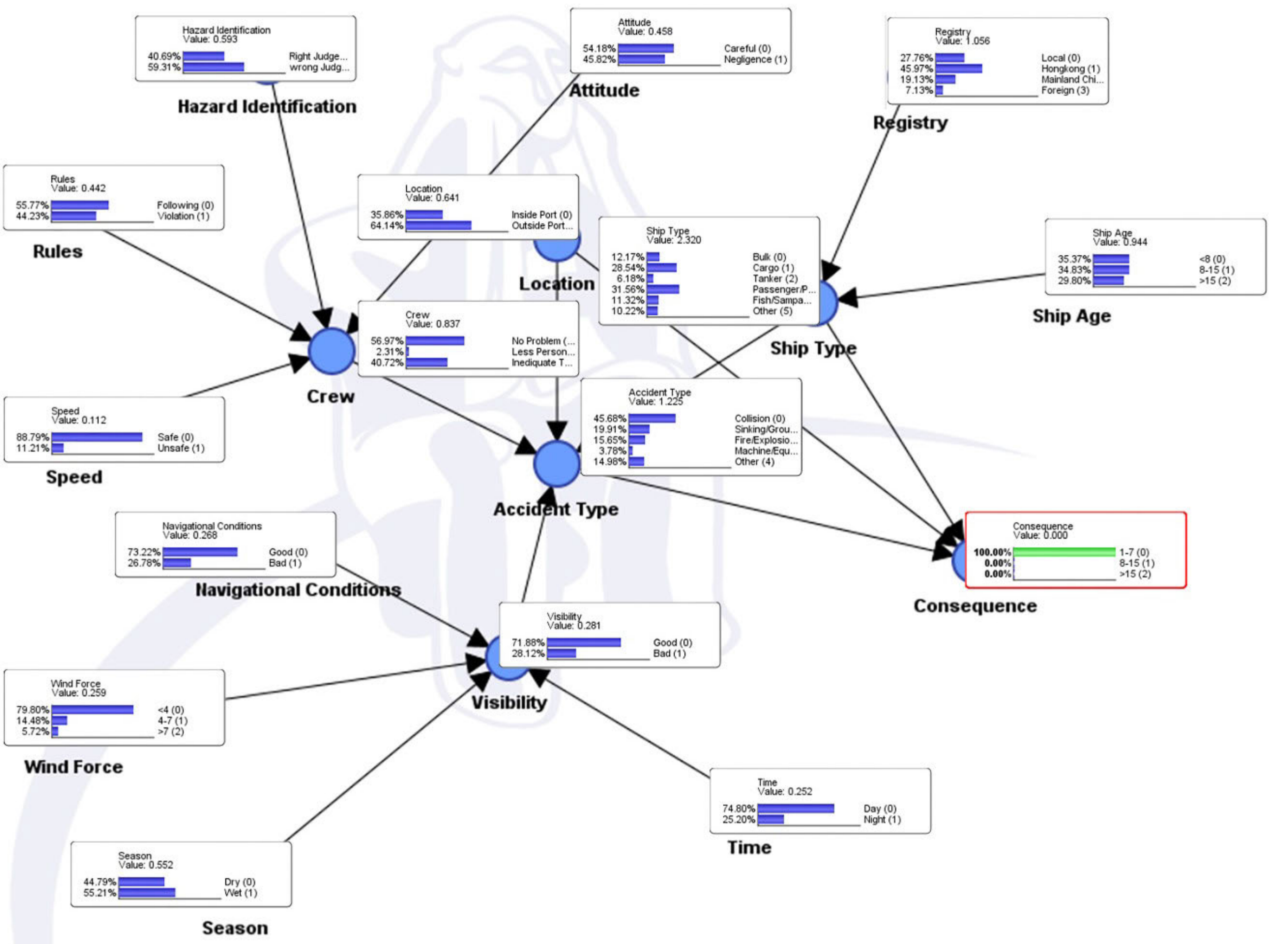

FIGURE 7. Inference results while evidence set at "1-7".

decreased by 8% (p=0.587) while the occurrence probability of both "1-7" (p=0.284) and ">15" (p=0.129) increases by 4%, meaning that for accidents outside port waters there is a higher chance of injuries and fatalities involving more than two people.

These trends might be explained by the fact that sources of help are far away when accidents occur in open waters and victims are mostly rescued by passing ships. There is more chance of drowning and increased multiple fatalities because of the hazards posed by deep and open waters along with limitations in a ship's ability to communicate with authorities that could help and initiate rescue operations. By the time authorities receive information about the accident and launch a rescue mission, the damage is already done.

In order to determine the dependability relationship between nodes with respect to the consequence type "1-7", the evidence is set at this state. Looking at the inference it could be concluded that the highest contributor among accident type is "collision" whose occurrence probability doubles. The "sinking/ground" and "fire/explosion" states also experience a considerable increase. The occurrence probability of "other" declined by 36.76% (p=0.149). This change can be understood by looking at the types of ships involved in the recorded accidents. The rate of accidents for passenger/pleasure vessels almost doubled in this scenario. Since passenger and pleasure vessels are not associated with huge cargo or hazardous gases and materials, there is a reduction in accidents involving these vessels and port activities like loading/unloading or ship and tank cleaning. This increase in passenger ships, and reduction in the risky activities associated with the cargo ships reduce the occurrence of "other", which is common with cargo ships in the port environment. Supporting evidence in this scenario is that the occurrence probability of accidents taking place in open waters increases by 8.55% (p=0.641).

Moreover, meteorological conditions and visibility also seem to have an effect on accident occurrence in this case. Hence, to enhance ship safety in such situations, due attention must be given to the visibility in the vicinity along with the weather conditions that affect navigation at sea. Therefore, the ship crew and company staff shall pay proper attention to the meteorological department forecasts and weather reports. Failure to do so could result in accidents, loss of lives and property, and damage to the environment.

Setting the evidence at "8-15", results in the "other" types of accidents increasing by around 20% (p=0.711). At the

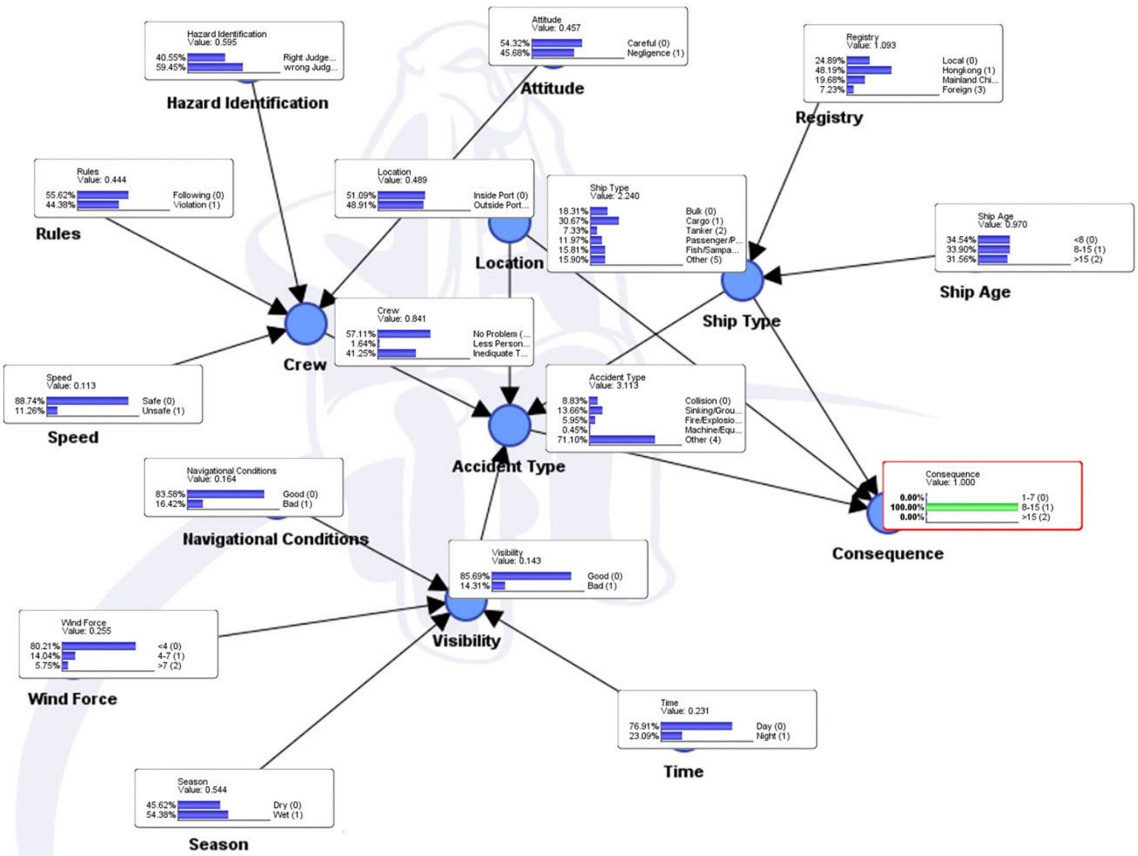

FIGURE 8. Inference results with evidence set at "8-15".

same time, the occurrence probability for all other types of accidents drops. The probability of "inside port" in the location node also increases, which is congruent to the trend developed and observed. For this scenario, the probability of good visibility increases because this class of accidents is not affected by bad weather and navigational conditions. Such accidents mostly occur due to falls, slips, contact with sharp objects, or by being hit or crushed by machinery and ropes. This trend is also bolstered by the type of ship involved, as the most contributing type of ships in this scenario are cargo and bulk, which are associated with these activities and accidents.

Similarly, if the probability of the state ">15" is set at 1, the accident type which most contribute to fatalities involving more than two people are "collision" which increase by around 40% (p=0.624), and "fire/explosion" which increases by 5% (p=0.145). A majority of these accidents took place outside the port waters, with the bad visibility and inadequate training of the crew as the most contributory factors. The most prominent sub-factors were bad navigational conditions with an increase in nighttime accidents. Furthermore, negligence of the ship crew was also among the most significant sub-factors. The majority of ships involved in these accidents were registered locally and in Hong Kong.

It is of pivotal importance to contemplate the presence of risks under such circumstances, specifically while pilotage operations are underway. The captain, officer of the watch and other prominent support staff should assess the external environment with respect to factors such as visibility, current and wind strength. They should communicate with and accept help from all relevant authorities within their scope to accidents. All crew and supporting staff members should be made fully aware of the situation and be instructed to be very careful and attentive. They must receive sufficient training and information on the enactment of protective and counter measures.

While analyzing the evidence regarding the type of accidents, when the probability of collision is set to 1, cargo and passenger ships were revealed to be the vessel type most commonly involved in such accidents. In particular, passenger ships saw the highest increase, making the most significant factor in collisions. Looking at the consequences of this scenario, the probability of injuries is doubled. However, the most interesting and critical aspect is that the probability of ">15," in which more than two deaths were reported tripled. The majority of these accidents take place outside of port waters. This evidence suggests that ship crews, liner companies, port authorities and the coast guard should devise and implement policies that could initiate early warning and

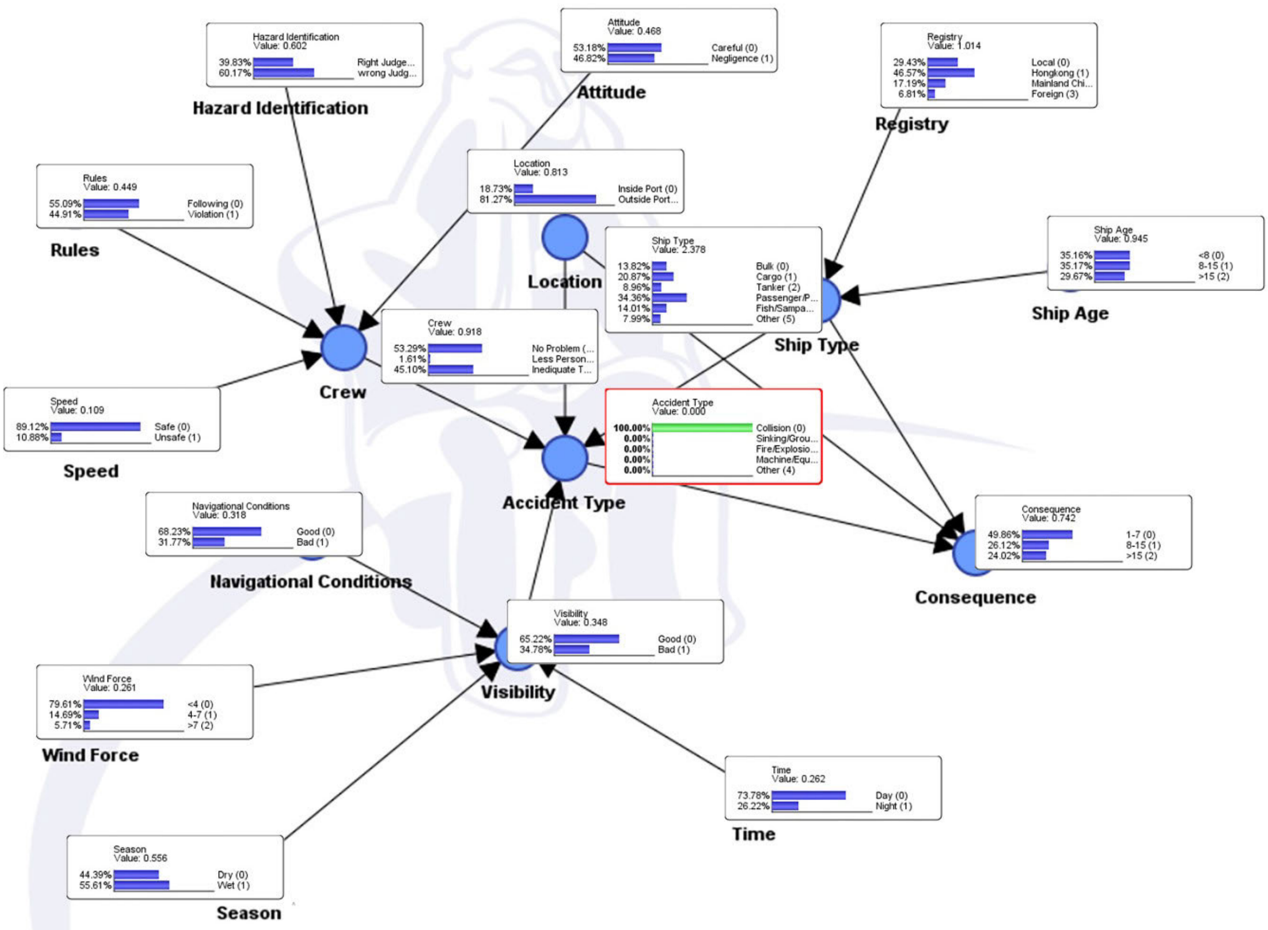

FIGURE 9. Inference results for target set at "Collision".

rapid rescue systems. The crews of cargo and passenger watercraft specifically should be highly trained to avoid collision accidents.

Following the navigational rules defined by International Maritime Organization (IMO) and the vessel traffic service (VTS) has a remarkable significance in reducing the collisions. Violation of these rules on the part of ship captains and officers of the watch can lead to serious confusion, which in turn can lead to catastrophic accidents. The ship crew must remain in communication at all times with the vessel traffic services, meteorological departments, radar systems and other concerned port and government authorities. When accidents do occur, the concerned authorities must be informed immediately with accurate information with regards to the situation and type of accident. The authorities must devise an efficient rapid response group that can effectively reduce loss of life and other negative impacts.

Setting the evidence at ''sinking/grounding,'' the most prominent ships in this regard are ''cargo'' and ''fish/sampan''. Fishing vessels are the most contributing ships in this scenario as their probability doubles. One to two deaths and injuries is the most frequently seen consequence in this scenario. The most prominent causation factors are visibility and bad navigational conditions along with negligence, violation of rules and lack of training on the part of the crew. This trend is very relevant as the majority of local fisherman do not have basic lifesaving gear available to them. Furthermore, they either lack access to information on weather and sea conditions, or if they are informed many neglect to heed it. Local and Mainland Chinese vessels show an increased probability to be involved in such accidents; however, Hong Kong vessels are also involved in a major portion of reported accidents.

When the ''fire/explosion'' probability is set at 1, the main increase in the inferred probabilities is for tankers. This scenario is also very common for cargo vessels. One possible explanation for this is the abundance of inflammable and hazardous materials being transported on cargo ships and tankers. Looking at the trends observed in the consequence node, the state representing injuries experienced a huge increase in its probability. The state representing more than two fatalities also showed a significant increase in its probability. The interesting trend observed in this scenario is that the majority of these accidents took place in good visibility and navigational conditions. Although inadequate training, violation of rules and negligence had a significant occurrence probability in this scenario, their probability decreased when

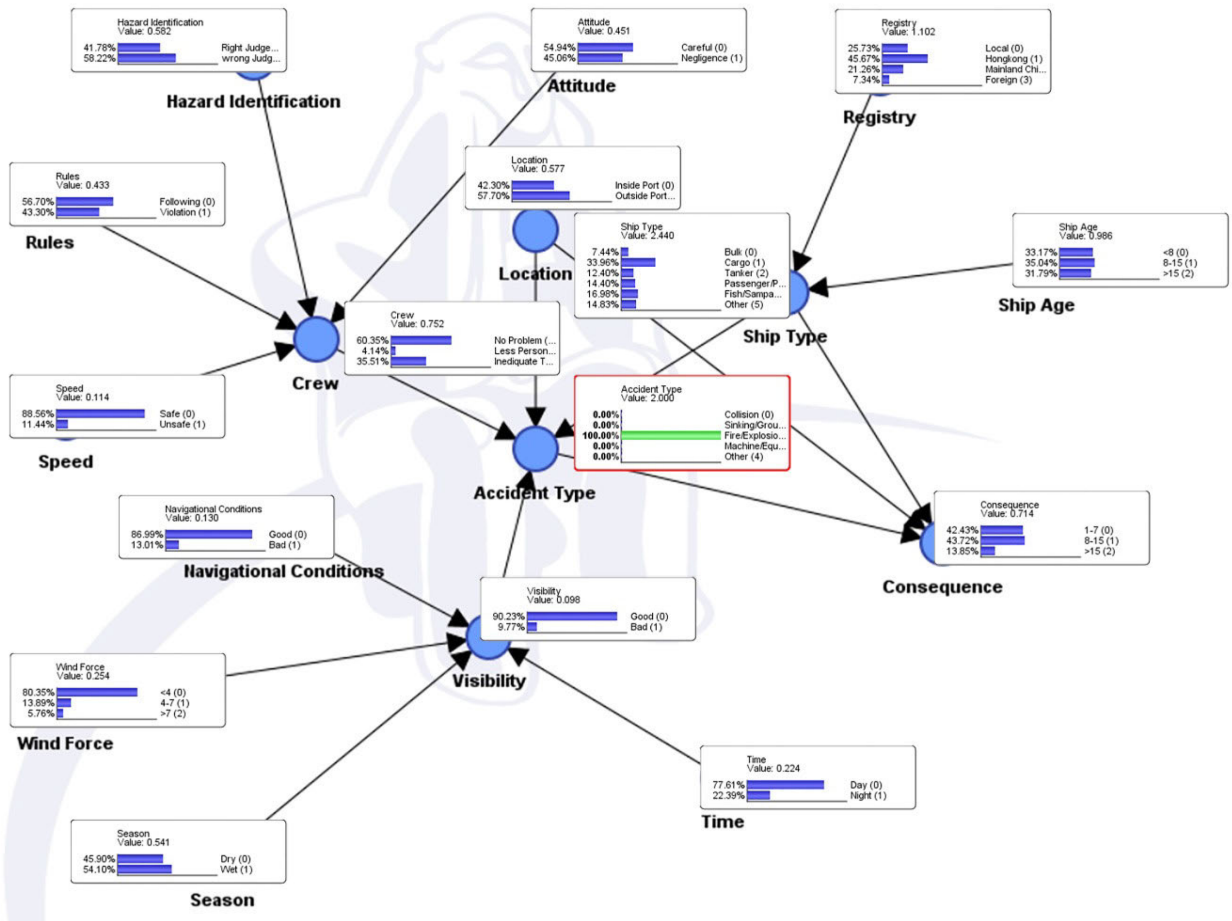

FIGURE 10. Inference results for evidence set at "fire/explosion".

compared to the accident likelihood under normal conditions in this model.

Considering ship type, it appears that "cargo" was the most prominent contributing factor. When setting the evidence at cargo ships, the most common types of accidents were "collision," "grounding/sinking," and "other." However, when the evidence is not set at cargo ships, collisions drop significantly while sinking and grounding increased. In this scenario, "8-15" remains the most common consequence but there is also a noticeable increase in the probability of accidents resulting in more than two deaths. The interesting dimension in this scenario is the huge increase in the involvement of Mainland Chinese ships in cargo accidents.

Hong Kong registered ships remain the ship type most likely to be involved in an accident, however, this could be attributed to the volume of traffic associated with them. Such an increase in the magnitude of accident likelihood for Mainland Chinese cargo vessels is a matter of concern and should be addressed with proper measures. Issues with respect to training and attentive attitude of crew members should be given priority to avoid accidents. Correctly judging situations and hazard together with early detection and communicating the problems make a huge positive impact on safety outcomes. Moreover, the quality and means of communication with the other ship involved in an accident also need to be improved. Another prominent aspect in the collision scenario is the understanding of responsibility, rules and classification of ships for the captains and officers of the watch involved. Following the defined rules in this matter is of utmost importance. They should know and follow the rules of priority and give way classifications; this could significantly help in reducing accidents and fatalities.

Attributed to the wide range of factors considered in this study, it can be extensively employed to maritime transportation risks in the Hong Kong waters. Since this study is conducted on the basis of real data applied to open waters and the port environment, its reliability and effectiveness holds a significant value. The nodes, states and their causal relationships were also developed in concurrence to the available literature and then finalized by expert opinion, which also enhances the significance of this study. This study has a novel contribution to the Hong Kong waters as the accident risk have been associated to various factors from the most prominent dimensions like environment, human, ship, time, geography and registry of the ships. It is an interesting and prominent association as each type of accident can be assessed from the range of parameters considered. Moreover, BN environment facilitates to assess the mutual effect of various factors on the

TABLE 3. Sensitivity analysis for the accident type and consequence.

Target Node	State	Difference in Probability (Max and Min)						
		Location	Ship Type	Visibility	Navigational Conditions	Crew	Registry	Accident Type
Accident Type	Collision	.235	.325	.222	.162	.052	.064	
	Sinking/Grounding	.128	.247	.083	.060	.028	.053	
	Fire/Explosion	.007	.124	.055	.040	.122	.011	
	Other	.353	.333	.286	.210	.180	.087	
Consequence	0-7	.085	.280	.137	.100	.060	.032	.535
	8-15	.181	.300	.080	.158	.096	.019	.720
	>15	.095	.060	.218	.058	.044	.0159	.230

accident causation and its consequence, which is new for the Hong Kong waters and has prominent meaning with respect to the peculiar conditions of the considered region. This study offers a detailed understanding on the various considered types of accidents providing information about the significance of accident locality and effect of geographic positions on the variations in accident consequence. Also, the type of ship is not only associated with the type of accident, but with the consequence too which offers practical guidelines to the ship owner and liner companies as to which type of accident they are more prone to along with the possible reasons and the severity and type of consequences. This feature enables the involved authorities to arrange specific measures related to facilities, protection and insurances to avoid and recover the losses. Apart from that, this study offers practical understanding to the Hong Kong port authorities on which type of accidents are common in which locality and what are the resulting patterns in consequences. This information will help them with making more target oriented policies and resource allocation. The other most prominent aspect of this study is the identification of the ''other'' accidents as the most significant issue having more severe consequences inside port waters with the causing factors mainly associated to human. This trend in results can enable the Hong Kong port authorities to design and enforce safety procedures and policies not only on their staff, but at the crew of arriving ships and significantly reduce not only the occurrence of these accidents, but also control the scale and severity of the consequences because the trending reasons and scenarios for these accidents have been elaborated in detail in this study.

C. SENSITIVITY ANALYSIS

As discussed earlier, sensitivity analysis is conducted to determine the most critical parameters or elements in a model or accident scenario. Generally, the most critical variables or states have higher probabilities of occurrence and contribution as compared to other parameters involved in a scenario. However, there is no specific or defined amount of variation that would make a variable worthy of consideration and be affected by the likelihood or probability of other parameters involved. Sensitivity analysis has a significant role in the prioritization of factors in order to avoid or decrease the happening of accidents and minimize their consequences. Still, factor prioritization and selection is more greatly reliant on the decision-maker than the analyst or forecaster.

The consequence and type of accident nodes are fixed as target nodes to conduct the sensitivity analysis of the constructed BN model. The BayesiaLab sensitivity analysis is given through the tornado charts identifying those variables which are most critical from the perspective of their effect on the set target. These tornado charts were then transformed into a table giving quantitative difference between the occurrence probability of the target nodes and states in response to the maximum and minimum contribution and probability of the respective variables. This was also verified by setting evidence at each state and variable of the model against the concerned target nodes [29]. Those variables which depicted the most prominent and maximum sensitivity for the set target nodes have been presented in Table 3. In other words, variables with the largest probability difference are the most critical factors requiring immediate and proper attention. It is evident from the table below that location, ship type, visibility, crew and navigational conditions are the most critical variables for the different types of accidents.

Similarly, analyzing the sensitivity analysis for the consequence node, it can be observed that ship type, location of the accident, visibility and navigational conditions at the time of accident and the performance of ship crew played the most critical role in defining the type and magnitude or severity for the considered types of accidents.

VI. CONCLUSION

This study was based on the present literature, expert judgment and past accidents data using BN environment to develop a model for the risk assessment and decision support of sustainable traffic safety in Hong Kong waters. The objective was to fill the gap in the maritime transportation and safety science literature regarding the sustainable traffic safety in Hong Kong waters. The adopted methodology consisted of the identification and selection of various causation factors to the accident risk through available literature and expert judgment, incorporating the past accident data to conduct analysis and inference in the BN environment, and classifying the respective consequences against the resulting risk in the form of defined risk categories. The most prominent conclusions of this study are,

1. Under normal conditions, without setting evidence at any variable, accident category ''other'' has the highest probability of 0.5174 being second by ''Collision'' with a probability of 0.2256. The highest resulting consequence associated was ''8-15'' indicating death of one or two people. While, cargo and passenger ships had the highest involvement.
2. With respect to the consequences, passenger ships were found associated with high rate of injuries. Similarly, accidents inside port waters had higher percentage of 1-2 deaths with the human factor as most significant cause. Accidents with more than two deaths were found associated with cargo ships and tankers taking place in open waters.
3. Coming to the involvement in type of accidents, cargo and passenger ships had the highest involvement in ''Collision''. While cargo and fish/sampan had the highest association with ''Sinking/Grounding''. Moreover, tankers and cargo ships had the highest involvement in ''Fire/Explosion''.
4. While determining the most sensitive factors, ship type, location, visibility, navigational conditions, crew performance and registry of the ship were the most critical factors for both the set target nodes, type of accident and the consequence.

In summary, this study was focused at the risk assessment for traffic in Hong Kong waters and providing a decision support for the preventive and management measures. The results will be useful in reducing casualties and property losses in maritime accidents. This will be especially valuable in situations where there is high maritime traffic yet limited resources available, as in the case of Hong Kong. The results of this study could help to improve the allocation of rescue resources and to devise better rescue plans. This study could further be improved by analyzing the complex and interdependent nature of the causative factors for the individual types of accidents and ships. Moreover, the effect of various dimensions of human factors needs to be quantified in order to control and prevent the accidents of fishing vessels and those in port environment.

AUTHOR CONTRIBUTIONS

RU Khan and J.Y identified the major factors, conceptualized and developed the model. RU. Khan run the model, analyzed the results and wrote the manuscript. H.L worked on the determination of prominent factors and defining the data pattern. FS.M helped in identifying the causation factors and arranged all the data as per the described criteria and software pattern requirements. J.Y supervised the overall study. All authors reviewed the manuscript.

CONFLICTS OF INTEREST

Authors declare no conflict of interest.

REFERENCES

[1] B. Khan, F. Khan, B. Veitch, and M. Yang, ''An operational risk analysis tool to analyze marine transportation in arctic waters,'' *Rel. Eng. Syst. Saf.*, vol. 169, pp. 485–502, Jan. 2018.
[2] Z. Yang, Z. Yang, and J. Yin, ''Realising advanced risk-based port state control inspection using data-driven Bayesian networks,'' *Transp. Res. A, Policy Pract.*, vol. 110, pp. 38–56, Apr. 2018.
[3] G. Zhang and V. V. Thai, ''Expert elicitation and Bayesian network modeling for shipping accidents: A literature review,'' *Saf. Sci.*, vol. 87, pp. 53–62, Aug. 2016.
[4] M. Afenyo, F. Khan, B. Veitch, and M. Yang, ''Arctic shipping accident scenario analysis using Bayesian network approach,'' *Ocean Eng.*, vol. 133, pp. 224–230, Mar. 2017.
[5] K. X. Li, J. Yin, and L. Fan, ''Ship safety index,'' *Transp. Res. A, Policy Pract.*, vol. 66, pp. 75–87, Jan. 2014.
[6] Ö. Ugurlu, S. Yildiz, S. Loughney, and J. Wang, ''Modified human factor analysis and classification system for passenger vessel accidents (HFACS-PV),'' *Ocean Eng.*, vol. 161, pp. 47–61, Aug. 2018.
[7] D. Konovessis and D. Vassalos, ''Risk evaluation for RoPax vessels,'' *Proc. Inst. Mech. Eng. M, J. Eng. Maritime Environ.*, vol. 222, no. 1, pp. 13–26, Feb. 2008.
[8] S. García-Herrero, M. A. Mariscal, J. García-Rodríguez, and D. O. Ritzel, ''Working conditions, psychological/physical symptoms and occupational accidents. Bayesian network models,'' *Saf. Sci.*, vol. 50, no. 9, pp. 1760–1774, Nov. 2012.
[9] M. Celik, S. M. Lavasani, and J. Wang, ''A risk-based modelling approach to enhance shipping accident investigation,'' *Saf. Sci.*, vol. 48, no. 1, pp. 18–27, Jan. 2010.
[10] M. Hänninen, O. A. V. Banda, and P. Kujala, ''Bayesian network model of maritime safety management,'' *Expert Syst. Appl.*, vol. 41, no. 17, pp. 7837–7846, Dec. 2014.
[11] U. Peter and W. Patrick, ''Accident analysis models and methods: Guidance for safety professionals,'' Loughborough Univ., Loughborough, U.K., 2013.
[12] F. Goerlandt and J. Montewka, ''Maritime transportation risk analysis: Review and analysis in light of some foundational issues,'' *Rel. Eng. Syst. Saf.*, vol. 138, pp. 115–134, Jun. 2015.
[13] R. Flage and T. Aven, ''Emerging risk—Conceptual definition and a relation to black swan type of events,'' *Rel. Eng. Syst. Saf.*, vol. 144, pp. 61–67, Dec. 2015.
[14] D. Zhang, ''Challenges and new developments in maritime risk assessment,'' in *Proc. Probabilistic Saf. Assessment Manage. Conf.*, Honolulu, HI, USA, 2014, pp. 22–27.
[15] M. Hänninen and P. Kujala, ''Influences of variables on ship collision probability in a Bayesian belief network model,'' *Rel. Eng. Syst. Saf.*, vol. 102, pp. 27–40, Jun. 2012.
[16] J. Montewka, S. Ehlers, F. Goerlandt, T. Hinz, K. Tabri, and P. Kujala, ''A framework for risk assessment for maritime transportation systems—A case study for open sea collisions involving RoPax vessels,'' *Rel. Eng. Syst. Saf.*, vol. 124, pp. 142–157, Apr. 2014.
[17] P. Trucco, E. Cagno, F. Ruggeri, and O. Grande, ''A Bayesian belief network modelling of organisational factors in risk analysis: A case study in maritime transportation,'' *Rel. Eng. Syst. Saf.*, vol. 93, no. 6, pp. 845–856, Jun. 2008.
[18] P. Antão, O. Grande, P. Trucco, C. G. Soares, S. Martorell, and J. Barnett, ''Analysis of maritime accident data with BBN models,'' in *Safety, Reliability and Risk Analysis: Theory, Methods and Applications*. S. Martorell *et al.*, Eds. London, U.K.: Taylor & Francis, 2009, pp. 3265–3273.
[19] T. L. Yip, ''Port traffic risks—A study of accidents in hong kong waters,'' *Transp. Res. E, Logistics Transp. Rev.*, vol. 44, no. 5, pp. 921–931, Sep. 2008.
[20] J. Pearl, ''Statistics and causal inference: A review,'' *Test*, vol. 12, no. 2, pp. 281–345, Dec. 2003.
[21] J. Ren, I. Jenkinson, J. Wang, D. L. Xu, and J. B. Yang, ''An offshore risk analysis method using fuzzy Bayesian network,'' *J. Offshore Mech. Arctic Eng.*, vol. 131, no. 4, pp. 1–28, Sep. 2009.
[22] P. Damien and K. Kockelman, ''Preface to special issue,'' *Transp. Res. B, Methodol.*, vol. 44, no. 5, pp. 631–632, 2010.
[23] M. M. Abaei, R. Abbassi, V. Garaniya, S. Chai, and F. Khan, ''Reliability assessment of marine floating structures using Bayesian network,'' *Appl. Ocean Res.*, vol. 76, pp. 51–60, Jul. 2018.
[24] M. M. Abaei, E. Arzaghi, R. Abbassi, V. Garaniya, S. Chai, and F. Khan, ''A robust risk assessment methodology for safety analysis of marine structures under storm conditions,'' *Ocean Eng.*, vol. 156, pp. 167–178, May 2018.

[25] M. M. Abaei, R. Abbassi, V. Garaniya, E. Arzaghi, and A. B. Toroody, "A dynamic human reliability model for marine and offshore operations in harsh environments," *Ocean Eng.*, vol. 173, pp. 90–97, Feb. 2019.

[26] M. M. Abaei, E. Arzaghi, R. Abbassi, V. Garaniya, M. Javanmardi, and S. Chai, "Dynamic reliability assessment of ship grounding using Bayesian inference," *Ocean Eng.*, vol. 159, pp. 47–55, Jul. 2018.

[27] A.-A. Baksh, R. Abbassi, V. Garaniya, and F. Khan, "Marine transportation risk assessment using Bayesian network: Application to arctic waters," *Ocean Eng.*, vol. 159, pp. 422–436, Jul. 2018.

[28] W. Shi and K. X. Li, "Themes and tools of maritime transport research during 2000–2014," *Maritime Policy Manage.*, vol. 44, no. 2, pp. 151–169, Dec. 2016.

[29] A. Mazaheri, J. Montewka, and P. Kujala, "Towards an evidence-based probabilistic risk model for ship-grounding accidents," *Saf. Sci.*, vol. 86, pp. 195–210, Jul. 2016.

[30] F. Goerlandt and J. Montewka, "A framework for risk analysis of maritime transportation systems: A case study for oil spill from tankers in a ship–ship collision," *Saf. Sci.*, vol. 76, pp. 42–66, Jul. 2015.

[31] O. A. Valdez Banda, F. Goerlandt, V. Kuzmin, P. Kujala, and J. Montewka, "Risk management model of winter navigation operations," *Mar. Pollut. Bull.*, vol. 108, nos. 1–2, pp. 242–262, Jul. 2016.

[32] M. J. Akhtar and I. B. Utne, "Human fatigue's effect on the risk of maritime groundings—A Bayesian network modeling approach," *Saf. Sci.*, vol. 62, pp. 427–440, Feb. 2014.

[33] E. Akyuz and M. Celik, "A methodological extension to human reliability analysis for cargo tank cleaning operation on board chemical tanker ships," *Saf. Sci.*, vol. 75, pp. 146–155, Jun. 2015.

[34] Y. F. Wang, M. Xie, K.-S. Chin, and X. J. Fu, "Accident analysis model based on Bayesian network and evidential reasoning approach," *J. Loss Prevention Process Industries*, vol. 26, no. 1, pp. 10–21, Jan. 2013.

[35] A. John, D. Paraskevadakis, A. Bury, Z. Yang, R. Riahi, and J. Wang, "An integrated fuzzy risk assessment for seaport operations," *Saf. Sci.*, vol. 68, pp. 180–194, Oct. 2014.

[36] H. Liwång, "Survivability of an ocean patrol vessel—Analysis approach and uncertainty treatment," *Mar. Struct.*, vol. 43, pp. 1–21, Oct. 2015.

[37] S. Pristrom, Z. Yang, J. Wang, and X. Yan, "A novel flexible model for piracy and robbery assessment of merchant ship operations," *Rel. Eng. Syst. Saf.*, vol. 155, pp. 196–211, Nov. 2016.

[38] A. G. Eleye-Datubo, A. Wall, A. Saajedi, and J. Wang, "Enabling a powerful marine and offshore decision-support solution through Bayesian network technique," *Risk Anal.*, vol. 26, no. 3, pp. 695–721, Jun. 2006.

[39] M. Musharraf, J. Hassan, F. Khan, B. Veitch, S. MacKinnon, and S. Imtiaz, "Human reliability assessment during offshore emergency conditions," *Saf. Sci.*, vol. 59, pp. 19–27, Nov. 2013.

[40] C. Yeo, J. Bhandari, R. Abbassi, V. Garaniya, S. Chai, and B. Shomali, "Dynamic risk analysis of offloading process in floating liquefied natural gas (FLNG) platform using Bayesian network," *J. Loss Prevention Process Industries*, vol. 41, pp. 259–269, May 2016.

[41] L. Mkrtchyan, L. Podofillini, and V. Dang, "Overview of methods to build conditional probability tables with partial expert information for Bayesian belief networks," in *Proc. 25th Eur. Saf. Rel. Conf. Saf. Rel. Complex Eng. Syst. (ESREL)*, 2015, pp. 81–1973.

[42] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Amsterdam, The Netherlands: Elsevier, 2014.

[43] Y. Xiang, "Non-impeding noisy-AND tree causal models over multi-valued variables," *Int. J. Approx. Reasoning*, vol. 53, no. 7, pp. 988–1002, Oct. 2012.

[44] N. E. Fenton, M. Neil, and J. G. Caballero, "Using ranked nodes to model qualitative judgments in Bayesian networks," *IEEE Trans. Knowl. Data Eng.*, vol. 19, no. 10, pp. 1420–1432, Oct. 2007.

[45] P. Antão and C. Soares, "Analysis of the influence of waves in the occurrence of accidents in the portuguese coast using Bayesian belief networks," *J. Konbin*, vol. 13, no. 1, pp. 105–116, Jan. 2010.

[46] X. Wang, J. Zhu, F. Ma, C. Li, Y. Cai, and Z. Yang, "Bayesian network-based risk assessment for hazmat transportation on the middle route of the South-to-North water transfer project in China," *Stochastic Environ. Res. Risk Assessment*, vol. 30, no. 3, pp. 841–857, Jul. 2015.

[47] A. Feelders and L. C. van der Gaag, "Learning Bayesian network parameters under order constraints," *Int. J. Approx. Reasoning*, vol. 42, nos. 1–2, pp. 37–53, May 2006.

[48] H. Chan and A. Darwiche, "Sensitivity analysis in Bayesian networks: From single to multiple parameters," in *Proc. 20th Conf. Uncertainty Artif. Intell.* Ithaca, NY, USA: Cornell Univ., 2004, pp. 67–75.

[49] P. Xie, J. H. Li, X. Ou, P. Liu, and R. Levy, "Using Bayesian networks for cyber security analysis," in *Proc. IEEE/IFIP Int. Conf. Dependable Syst. Netw. (DSN)*, Jun. 2010, pp. 211–220.

[50] M.-L. How, S.-M. Cheah, Y.-J. Chan, C. A. Khor, and M. E. Say, "Artificial intelligence-enhanced decision support for informing global sustainable development: A human-centric AI-thinking approach," *Information*, vol. 11, no. 1, p. 39, 2020.

[51] K. X. Li, J. Yin, H. S. Bang, Z. Yang, and J. Wang, "Bayesian network with quantitative input for maritime risk analysis," *Transportmetrica A, Transp. Sci.*, vol. 10, no. 2, pp. 89–118, Apr. 2012.

[52] A. John, Z. Yang, R. Riahi, and J. Wang, "A risk assessment approach to improve the resilience of a seaport system using Bayesian networks," *Ocean Eng.*, vol. 111, pp. 136–147, Jan. 2016.

[53] *Port and Maritime Statistics*, Marine Dept., Hong Kong, 2017.

[54] D.-T. Su, F.-M. Tzu, and C.-H. Cheng, "Investigation of oil spills from oil tankers through grey theory: Events from 1974 to 2016," *J. Mar. Sci. Eng.*, vol. 7, no. 10, p. 373, Oct. 2019.

[55] S. Kristiansen, *Maritime Transportation: Safety Management and Risk Analysis*. Evanston, IL, USA: Routledge, 2013.

[56] S. Xuan, S. Hu, Z. Li, W. Li, and B. Li, "Dynamics simulation for process risk evolution on the bunker operation of an LNG-fueled vessel with catastrophe mathematical models," *J. Mar. Sci. Eng.*, vol. 7, no. 9, p. 299, Aug. 2019.

[57] J. Gouveia, P. Antão, and C. G. Soares, "Statistical analysis of ship accidents in the Portuguese waters," in *Proc. Edições Salamandra*, Lisboa, Portugal, vol. 1, 2007, p. 19.

[58] F Onea and L Rusu, "Long-term analysis of the black sea weather windows," *J. Mar. Sci. Eng.*, vol. 7, no. 9, p. 303, Sep. 2019.

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