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Real-time risk monitoring of ship pilotage operations: Automating BN risk model development

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The maritime industry is evolving further with new technologies and services, such as autonomous ships and remote pilotage operations, under development. Whilst these services may bring new opportunities and benefits, the ability to manage risks becomes increasingly vital. Furthermore, these new technologies and services require risk models of a dynamic nature, which can incorporate ongoing systemic changes and provide risk estimation in real time. Hence, this paper presents a novel approach, which extracts the incident data and automatically establishes a real-time Bayesian risk model. The model consists of a clear hierarchy denoting a chain of risk events, i.e., root causes, hazards, accidents, and losses. The resulting risk model provides an estimation of the posterior probability of occurrence of all variables in the Bayesian network. These results are next plotted and monitored with Graphical user interface application to monitor the critical factors leading to losses and thus requiring risk control in real time. The effectiveness of the method is afterward demonstrated using a case study of ship pilotage operations. The resulted model shows the probability of occurrence of risk events such as accidents, losses, hazardous scenarios and causal factors.
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Keywords: Real-time risk model, Bayesian Network, Risk analysis, Ship Pilotage, Maritime Pilotage.

1. Introduction

Maritime transportation is considered the most important means of transportation as it enables over 80% of the total global trade (UNCTAD 2022). As a result, maritime stakeholders should monitor and manage risks in such an important and safety-critical field. Furthermore, the developments of new services such as Remote pilotage and autonomous ships have increased the system complexity due to increased software control and higher systemic interactions (Lahtinen et al. 2020; Basnet et al. 2023). Hence, safety engineers are striving to develop and implement novel risk monitoring and mitigating methods/tools that can handle the increased system complexity.

Bayesian Network (BN) has been increasingly used in the maritime community for developing risk models. Examples constitute the evaluation of the pollution risk caused by ship operations (Bayazit and Kaptan 2023), reliability assessment of ship machinery systems in different autonomy levels (BahooToroody et al. 2022), and risk analysis of ship mooring operations (Kaushik and Kumar 2023). Compared to other methods such as Fault Trees Analysis, BNs advantages include effective handling of common cause failures (Mahboob and Straub 2011), easier depiction of multi-state components (Khakzad, Khan, and Amyotte 2011), providing easy to understand graphical cause-effect structure (Bayazit and Kaptan 2023), and the ability to combine heterogeneous datasets (Cao et al. 2023).

The process of developing a risk model is time-consuming and requires extensive resources (Kraaijeveld et al. 2005; Zhang and Mahadevan 2021; Xiao-xuan, Hui, and Shuo 2007). So far, the automatic generation of risk models such as FTA models has been conducted with the usage of Model-based System Engineering (MBSE) languages (Mhenni, Nguyen, and Choley 2014), and with text mining (Mukherjee and Chakraborty 2007). For the automatic generation of BN, few studies used inputs such as bow-tie results (Li, Xu, and Shuai 2020), and system models and fault trees (Parhizkar et al. 2020) However, there is a lack of studies that automate the development of the BN models using an incident database. Furthermore, none of these studies focused on developing a real-time risk monitoring tool for generic maritime operations such as ship pilotage.

In this paper, a methodology for developing a real-time BN risk model using an incident database is proposed. The methodology combines the usage of a Graphical User Interface (GUI), programming language, BN development and inference package, and diagraming package. Furthermore, the methodology uses Noisy-OR gates to determine the conditional probabilities of the BN variables. The Noisy-OR gates can reduce the modeling and computational complexities of the large BN models (BayesFusion 2020; Pearl 1988), which has been demonstrated in several studies such as Basnet et al. (2023); Abaei et al. (2019); Ji et al. (2022).

2. Related methods

2.1. Bayesian Networks

BNs have been described in depth by Pearl (1988). In a nutshell, BNs are Directed Acyclic Graphs based on Bayes theorem, which is used for probabilistic reasoning. Each node in a BN represents a variable with multiple states, each arc in BN shows the dependency between the variables, and Conditional Probability tables represent the conditional probabilities of a variable given its parents (BahooToroody et al. 2019; Chaal et al. 2022). The BN graph is directed with an arrow leading from a parent variable to a child variable. The BN is a representation of a distribution, which is defined as Eq.(1) (Neapolitan 2004):

$$p(x_1, \ldots, x_D) = \prod_{i=1}^{D} p(x_i | pa(x_i)) \qquad (1)$$

where $p(x_1, \ldots, x_D)$ is a joint probability distribution and $pa(x_i)$ is the parent set of the variable.

2.2. Noisy-OR gates

The Noisy-OR gates, proposed by Pearl (1988), is a technique for calculating the conditional probability of Boolean variables under the following assumptions i) the variables have a cause-and-effect relationship, ii) the variables are mutually exclusive, and iii) the event occurs if and only if, at least one cause has occurred (Abaei et al. 2019; Neapolitan 2004). Under these assumptions, the conditional probability can be determined with Eq.(2) (Oniśko, Druzdzel, and Wasyluk 2001):

$$p_i = \Pr(\, y \mid \bar{x}_1, \bar{x}_2 \ldots x_i \ldots, \bar{x}_{\{n-1\}}, \bar{x}_n) \qquad (2)$$

where p_i denotes the probability that a variable Y occurs if the cause x_i is present and all other causes are absent.

3. Methodology

Fig. 1 presents the steps of the methodology and required methods/tools with examples necessary to execute each of the steps. In Step 1 of the proposed methodology, a GUI is developed for capturing the chain of risk events (details of the incidents) and the total number of operations. This represents a standard incident database, where the incidents are recorded and stored. Then in Step 2, a programming language is used to extract the information from the database and calculate the prior probability of occurrence of each risk event. Next in Step 3, a BN model is developed using a BN package. The information extracted in Step 2 is used in this step as input to develop the BN structure and update the CPT. After developing the BN model, the BN package is used in Step 4 to estimate the posterior probability of occurrence of the risk events. In Step 5, the posterior probability of occurrence of the risk events is plotted to identify the critical events requiring risk control. Finally in Step 6, a GUI is developed for stakeholders, which presents the developed visualizations for risk monitoring. To execute the tasks specified in each of the steps, a programming language is used to generate a script. These scripts are then combined to automate the steps of the methodology to provide real-time BN development and risk monitoring features. The script then runs in the background at each specified time interval to provide the visualizations of risk events that update in real-time. This study does not provide a thorough description of the steps necessary to utilize the programming language and associated packages due to space limitations.

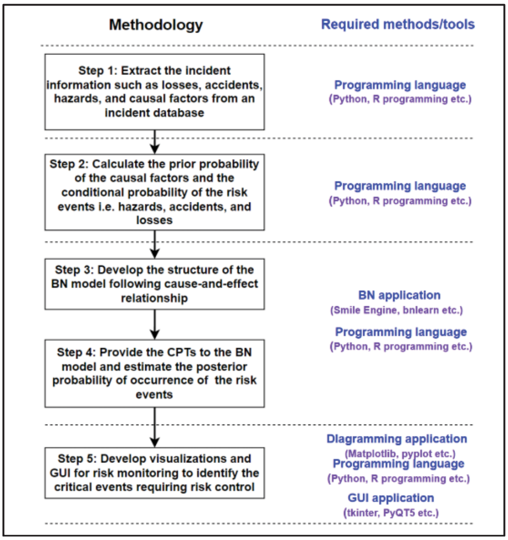

Fig. 1. The steps of the proposed methodology for developing a real time BN risk model using an incident database.

3.1.1. *Step 1: Extract the incident information such as losses, accident, hazards and causal factors from the incident database.*

In this step, the incident information of a specific timeframe is extracted and stored as variables using a programming language such as Python or R programming. The variables include the information of the incident such as occurred losses, accidents, hazards, and causal factors. In addition, the total number of operations in this specific timeframe is extracted, which will be used in step 2 for calculating the prior probability. The timeframe for the extraction is decided based on the availability of the resources and the purpose of the risk model.

3.1.2. *Step 2: Calculate the prior probability of causal factors and the conditional probability of the risk nodes i.e., hazards, accidents, and losses.*

After extracting the incident information, the prior probability of each event is estimated sequentially using a programming language. For the root causes, which are the causal factors (CF) of the incidents, the prior probability of CF occurring can be calculated using $\frac{Number\ of\ CF\ occurrences}{Total\ number\ of\ operations}$. Then for the probability of occurrence of the risk nodes, the Noisy-OR gates as specified in Section 2.2 should be used. These are the conditional probabilities representing the relationships between the BN variables, i.e., how the occurrence of each variable affects the occurrence of other variables.

3.1.3. *Step 3: Develop the structure of the BN model following cause-and-effect relationship.*

In step 3, the hierarchical structure of the BN risk model is developed. For this purpose, a BN development package such as Smile engine (BayesFusion 2021) in Python or Bnlearn (Scutari, Scutari, and MMPC 2019) in R programming can be used. For each of the variables in the BN model, the states of the variable such as True/False and Occurred/Not occurred are then added. The developed BN model includes all the variables extracted in Step 1 and follows the cause-and-effect relationship between the variables. The structure of systemic model based on System-Theoretic Process Analysis method (STPA) is used in this methodology (Leveson and Thomas 2018). Fig. 2 presents an example hierarchical structure of STPA based BN risk model (adapted from Basnet et al. (2023)).

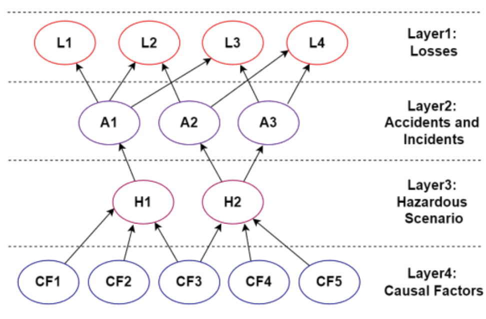

Fig. 2. An example hierarchical structure of a BN risk model (adapted from Basnet et al. (2023))

3.1.4. *Step 4: Provide the CPTs to the BN model and estimate the posterior probability of occurrence of the risk events.*

The prior probabilities calculated in Step 2 are then added to the CPTs of each variable in the BN model. Next, the inference algorithms provided in the BN packages, i.e., Smile engine, and Bnlearn are used to estimate the posterior probability of occurrence of the risk events.

3.1.5. Step 5: Develop visualizations and GUI for risk monitoring to identify the critical events requiring risk control.

The estimated posterior probabilities from Step 4 are then plotted next to visualize and easily identify the critical events requiring risk control measures. For plotting the results, diagraming packages such as Matplotlib (Barrett et al. 2005) in Python and Ggplot2 (Wickham, Chang, and Wickham 2016) in R programming should be used.

In this final step, a GUI tool is developed to display the developed graphs. The complete developed script is then automated to run at regular intervals using a windows task scheduler (Choi 2021). This automation includes extracting incident information, calculating probabilities, creating the Bayesian network model, updating probabilities, estimating posterior probabilities, and generating visualizations. Depending on the specified interval such as every few seconds, the tool will run, estimate and display the results in the current timeframe, making it real-time.

4. Illustrative case study – Ship pilotage operation

The proposed methodology has been illustrated in this study by developing a real-time risk monitoring tool for ship pilotage operation. For executing each of the steps, python has been used.

4.1. Description

Ship pilotage operation is a mandatory service where an expert (pilot) assists ship crews in safely navigating through congested waters. Hence, it is a safety-critical task for enhancing maritime safety in areas prone to incidents and accidents due to congested traffic and shallow water depths (Lahtinen et al. 2020). The ongoing development of remote pilotage in European countries allows pilots to assist ship masters from shore. It is expected that in remote pilotage, there will be many common systems and processes with the current pilotage operations (Basnet et al. 2023). Hence, it is crucial to analyze risk factors in ship pilotage to improve the implementation of remote pilotage in the future.

4.2. Application of the Methodology and results

4.2.1. Step 1: Extract the incident information such as losses, accidents, hazards, and causal factors from the incident database.

All the pilotage incident observations reported during a year (from 10th June 2020 to 10th June 2021) in Finnish fairways were extracted from the database provided by Finnpilot Pilotage Ltd, which is a Finnish state-owned company providing pilotage services in Finland. A python script was developed that checks the stored database file at Finnpilot, extracts the relevant information from each incident, and saves it as a unique observation. An example of observation is provided below:

Observation 1: Ship stoppage during pilotage
Losses: Potential financial losses.
Accidents and Incidents: delay in operation
Hazardous scenario: Lack of requisites for pilotage
Causal factors: Main engine failure

For the afore-mentioned year, a total of 169 observations were extracted from the incident database. This resulted in the identification of two types of losses, four types of accidents and incidents, seven hazardous scenarios, and 20 causal factors. Furthermore, the total number of pilotages conducted in this period was determined to be 21450. In reference to existing BN studies, and the feature of BN for being applicable even for lack or lower number of data (Bayazit and Kaptan 2023; Basnet et al. 2023), the 169 observations from 21450 pilotages in this study are considered sufficient to populate the BN.

4.2.2. Step 2: Calculate the prior probability of causal factors and the conditional probability of the risk nodes i.e., hazards, accidents, and losses.

The prior probabilities of each event extracted in Step 1 were then calculated. Table 1 presents the prior probabilities of the extracted causal factors in ship pilotage operation from an incident database. The table shows that the prior probabilities of main engine failure and human error are higher than the other causal factors. Table 2 then presents an example of a CPT table for a hazard "H3: Violation of minimum separation standards in route", which presents the probability of this variable occurring i.e., P(State=True) given the causal factor has occurred.

Table 1: The prior probabilities of the causal factors of pilotage incidents in Finnish fairways during a year (from 10th June 2020 to 10th June 2021)

Causal Factors	P(State=True)

Propulsion or Thruster failure	0.00097
Main engine failure	0.00214
Autopilot failure	0.00023
Human error	0.0013
Weather forecast_issue	4.662e-05
Lights failure	0.00023
Gyro failure	0.00093
RADAR failure	0.00047
Engine failure	4.662e-05
Design issue	9.324e-05
Power failure	0.00042
Control station failure	9.324e-05
ECDIS failure	0.00023
Rudder failure	0.00028
Unknown cause	9.324e-05
Insufficient visibility	9.324e-05
AIS failure	9.324e-05
Pilot Plug or PPU failure	0.00014
Fairway equipment failure	9.324e-05
Frozen windows	4.662e-05

Table 2: The Conditional probability table of a hazard "H3- Violation of minimum separation standards in route" given the occurrence of the causal factors p(H/CF)

Causal Factors (CF)	H3-True	H3-False
Human error- True	0.27586	0.72414
ECDIS failure- True	0.14286	0.85714
Propulsion or Thruster failure-True	0.04	0.96
Main engine failure-True	0.02740	0.97260
Unknown cause-True	0.5	0.5

4.2.3. *Step 3: Develop the structure of the BN model.*

For each variable extracted in Step 1, a node was then added to the BN model using the Smile engine package in python. For all of these variables, two states: True and False denoting the occurrence or non-occurrence of the event were added. The process specified throughout the python wrapper documentation provided in BayesFusion (2021) was used during the BN development. Fig. 3 shows a section of the developed BN systemic risk model, which follows a hierarchical structure of STPA (see Fig. 2).

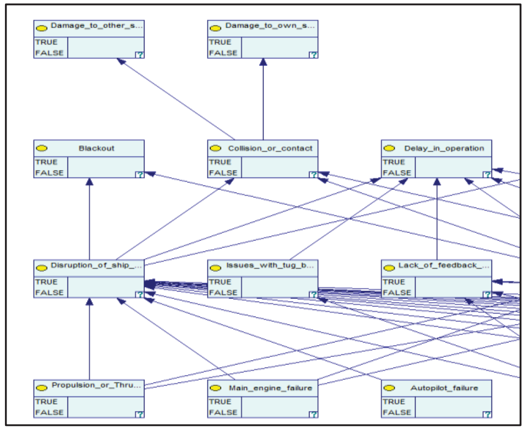

Fig. 3. A section of the BN risk model for ship pilotage in Finnish fairways

4.2.4. *Step 4: Provide the CPTs and estimate the posterior probability of occurrence of the risk events.*

The CPTs calculated in Step 2 were then added to the BN model by following the process specified in BayesFusion (2021). The model was then used to estimate the posterior probability of occurrence of the risk events. Table 3 presents the estimated probabilities of the risk events in pilotage operations in Finland. The table shows that the disruption of ship maneuverability has the highest estimated probability of occurrence of 0.0049, which is followed by delay in operation with 0.002710 and lack of requisites for operation with 0.001560. For the losses, the model shows that the probability of damage to other ships or fairway objects during pilotage is 0.000220, and damage to the own ship is 0.000044. Similarly, for accidents and incidents, the collision or contact has a probability of occurrence of 0.000390, and the blackout has 0.000420.

Table 3: The estimated posterior probabilities of occurrence of the risk events and their ranking with red denoting the critical events.

Risk event	P(State=True)
Damage to other ship or fairway objects	0.000220
Damage to own ship	0.000044
Blackout	0.000420

Collision or contact	0.000390
Delay in operation	0.002710
Partial Blackout	0.000036
Disruption of ship maneuverability	0.004900
Issues with tugboats	0.000045
Lack of feedback or information	0.000620
Lack of requisites for operation	0.001560
Violation of minimum separation standards in the route	0.000540
Wrong execution of navigation command	0.000090
Wrong feedback or information	0.000300

4.2.5. Step 5: Develop visualizations and GUI for risk monitoring to identify the critical events requiring risk control.

Finally, a GUI application was developed using the Tkinter package in python. Each tab in the GUI application displays a plot for each type of variable i.e., causal factors, accidents, hazardous situations, and losses. Fig. 4 presents an example plot of the estimated posterior probability of occurrence of accidents and incidents of pilotage operation in Finnish fairways in a Tkinter application.

The compiled script of python is then added to the windows task scheduler to run every hour. Fig. 5 shows a window for setting the windows task scheduler to run a python app every hour. Hence, the tool development that automatically updates the risk model and provides plots using incident information from the database was completed.

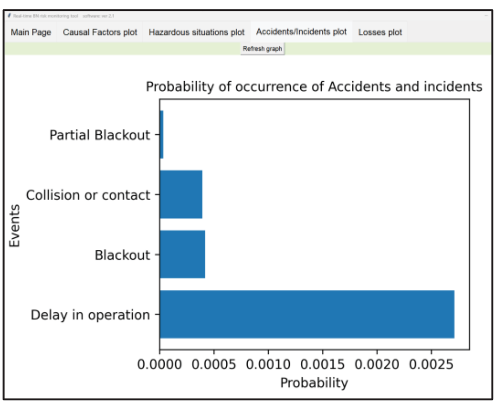

Fig. 4. A Tkinter application showing the visualizations of the estimated posterior probability of occurrence of accidents and incidents during pilotage in Finnish fairways.

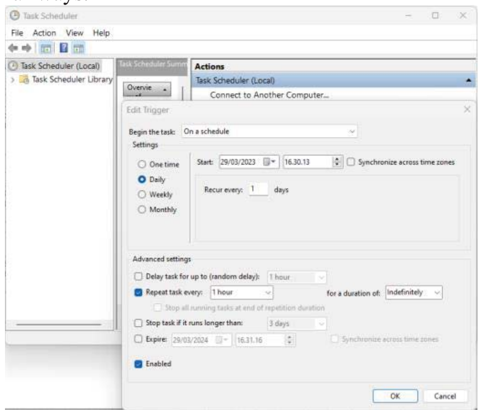

Fig. 5. Setting the windows task scheduler to run the python script every hour for real-time risk monitoring.

5. Discussions

5.1. Methodology

As most of the incidents in the maritime industry are recorded in a database, the steps proposed in this study can guide an analyst to develop a tool that can extract the required information from the database and develop a BN risk model. The model can then be used to conduct inferences to estimate the probability of occurrence of the risk events and provide visualizations to the stakeholders for risk monitoring. The usage of programming languages enabled the process since there are several packages developed to execute each of the tasks proposed in the methodology. As the outputs of each step are used as inputs in another, developing a complete script in the same programming language facilitated the automation of all of the steps. Windows task scheduler is then able to run the compiled script in every short period as specified by the developer.

Compared to other similar studies, where the inputs were generated with expert opinion (Li, Xu, and Shuai 2020), and Computational Fluid Dynamics (Jiang et al. 2021), the use of an incident database facilitated identification of the risk events and the estimation of the prior probabilities. Furthermore, the hierarchical structure of the developed BN supported the understanding of the risk events chain, thus improving risk communication. In addition, it enables the development of separate visualizations for each type of risk event, which can help the stakeholders to focus on the critical type of risk events as required. This study provided information about necessary tools and methods which are still missing in other existing real-time risk monitoring studies such as Jiang et al. (2021); Li, Xu, and Shuai (2020). This will ease the process of adapting the proposed methodology to develop new risk monitoring tools for researchers in the maritime scientific community as well as industry.

5.2. Case study

As the European ship pilotage industry moves towards remote pilotage, the need for risk management studies increases (Lahtinen et al. 2020; Basnet et al. 2023). However, the review of existing literature reveals the absence of studies focusing on developing risk monitoring tool for ship pilotage operations, highlighting the significance of this study. The developed risk monitoring tool can support the identification of the high risk factors in real time. For instance, the current risk model highlights a higher probability of main engine failure, human factors, and gyro failures as causal factors compared to others. Consequently, pilotage stakeholders can decrease incidents by implementing risk control options targeted at these specific components. The accuracy of the developed BN risk model depends on the accuracy of the data, hence the data should be enriched by adding the observations from multiple years of pilotage. For example, the current model cannot estimate the probability of grounding event because in the current dataset (from 10th June 2020 to 10th June 2021), there wasn't any observatiosn related to grounding. Furthermore, the observations can be further enhanced by reporting additional details to the incidents such as identifying further causal factors of the root nodes (e.g., fatigue, distraction for human error), and also adding the operational conditions during incidents such as weather, traffic, location and ice conditions.

6. Conclusions

The advances in the programming and software development field have facilitated the process of automating manual tasks using software and tools. Implementing such features is important for monitoring maritime systems and operations with increasing complexity. Hence, the current study proposed a methodology that uses a programming language to create a real-time risk monitoring tool that uses an incident database as input, BN for risk estimation, and risk plots for risk monitoring. The usage of an incident database as input to the BN model allows analysts to utilize already existing information to gather risk-based knowledge, and the usage of clear chain of events i.e., cause and effects improves risk understanding and risk communication. The proposed methodology was then demonstrated by developing a real-time risk monitoring tool for ship pilotage operation in Finnish fairways. The present risk model should serve as the groundwork for risk monitoring during ship pilotage and should be further enhanced by including incidents from multiple years. Furthermore, the verification and validation of the model is important for the usability, which should be conducted in the future. Furthermore, the sensitivity and the uncertainty of the BN model should be assessed.

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