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Arctic shipping accident scenario analysis using Bayesian Network approach

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ABSTRACT

This paper presents a methodology for the analysis of Arctic shipping accident scenarios using Bayesian Networks (BN). The proposed methodology is applied to a scenario involving a collision between a vessel and an iceberg. The study aims to identify the most significant causative factors to the potential accident scenarios. It is achieved by undertaking a sensitivity analysis study. The results inform the development of measures to avoid and control accidents during Arctic shipping.

1. Introduction

Increased shipping traffic in the Arctic may result in higher probability of accidents (Davidson et al., 2006; Anon, 2010). Transportation in the Arctic is faced with particular risk factors, including extremely low temperatures and drifting ice (Johansson et al., 2013; Goerlandt et al., 2015). Responses to accidents in the Arctic can be slow because of the remoteness of the region (Jensen, 2007). In the review of Zhang and Thai (2016), they pointed out that most shipping accidents are mainly low probability-high consequence in nature. It is therefore important to predict the chances of an accident in this region, which can inform countermeasure design to prevent and control such occurrences (Jensen, 2007).

Researchers have dedicated effort to understanding how and why accidents occur. As a result, theories and models of accident causation have been postulated (Katsakiori et al., 2009). Fig. 1 shows the evolution and development of accident models over the past decades.

Linear models depict accidents as a domino effect, in which one factor leads to the next factor and subsequently to another until it eventually results in an accident. Complex non-linear models describe accidents as a joint effect of multiple factors acting simultaneously. Epidemiological models consider an accident as the outcome of a combination of factors, some evident and some latent, that exist together in space and time (Anon, 2012). Table 1 summarises the models that have been used over recent decades. The importance of Table 1 is to show potential tools available for modeling accidents and how BN, Fault Tree, FRAM and other probabilistic modeling approaches have been implemented. Other popular models of accident causation include the SHEL (Software-Hardware-Environment-Livewire) Model, the CFAC (Contributing Factors in Accident Causation), and MORT (Management Oversight and Risk Tree) (Lehto and Salvendy, 1991). While these accident models are detailed, they are complex and take a lot of time to build. As a first step to decision making, simpler, time-efficient methodologies are required. The reviewed models also rely heavily on data for success. In the context of Arctic shipping, there is a general lack of data. The present study is focused on presenting a methodology that is simple and easy to execute. It is meant to be used mainly as a first step for envisaging an Arctic shipping accident, and making a decision on how to mitigate the potential consequences.

The method aims at forecasting possible Arctic shipping accident scenarios from past accident data using a Bayesian Network based methodology. In this methodology, the probabilities can be updated as new information becomes available. Potential contributory factors can be identified and subsequently controlled through the use of relevant safety measures. The use of a Bayesian Network provides the flexibility of considering interdependencies and conditionality of factors involved in the envisaged Arctic shipping scenarios. It also provides the analyst with a tool to represent multivariate state of causal factors compared to binary states in a tool like the Fault Tree. The modeller also has the flexibility of using expert elicitation. This is very important when data is scarce, as is the case for Arctic shipping. The details of the advantages and the use of the Bayesian Network approach are further elaborated in Zhang and Thai (2016).

The rest of this paper is organized as described following. Section 2 reviews accident modeling tools with emphasis on Bayesian Network.

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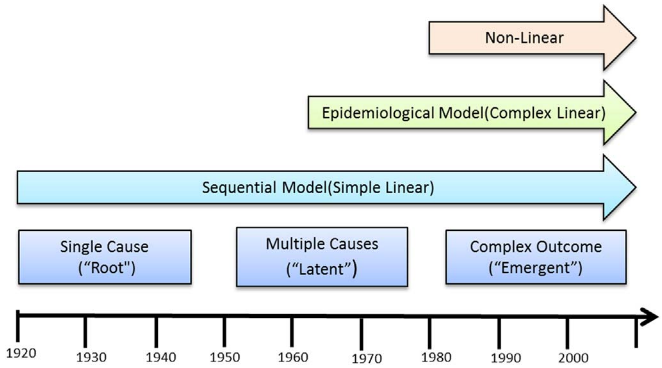

Fig. 1. History of accident modeling (after Hollnagel, 2010).

Section 3 presents the proposed methodology with an illustration of its applicability to an Arctic shipping accident scenario: collision with an iceberg. A discussion of the results is presented in Section 4 and conclusions in Section 5.

2. Bayesian Network

In Friis-Hansen (2000), the use of BN for risk analysis was studied. The outcome of the proposed model was compared to the output from an Event Tree analysis. The proposed tool was applied to a helicopter landing on a cruise ship. In the same study, BN was applied to diagnose misfire and leakage in a marine diesel engine. The study also attempted to combine BN with structural reliability methods, and regression methods for requalifying a pipeline in the North Sea. Another application of BN in maritime operation was made by Liwåg (2015), who applied BN to model the operation of Military Ocean Patrol Vessels with consideration of the potential threats during operations. The outcome of the study was information for ship design to enhance survivability and endurance. While the main aim of the study was to evaluate operational risk and show how both aleatory and epistemic uncertainty contribute to the output of such a model, it is a good example of the efficiency of a BN application to a security problem. Pristrom et al. (2016) also presented a BN based model that sought to estimate the probability of a ship getting hijacked off the east coast of Africa or off western India. The overall goal of this study was to provide a tool for stakeholders to make economic decisions in the context of ship operation. An elaborate BN for the Maritime Transport System (MTS) was also presented by Trucco et al. (2008). A study by Musharraf et al. (2013) applied a BN to a generic scenario of an offshore emergency evacuation in the context of estimating human error probability. The study shows the effectiveness of BN for estimating such probabilities. In a study by Weber et al. (2012), the authors presented a review of BN and some notable applications in other industries, to which the interested reader may refer. The focus of the present study is using BN to forecast Arctic shipping accident scenario's based on past accident data. The goal of this approach is to enable identification of priorities for allocation of resources for response and mitigation.

The proposed method in this paper, discussed later in Section 3, is used mainly to forecast accident scenarios from past accident data. The advantages of making the method Bayesian based is discussed in the context of the advantages the BN has over tools like the Fault Tree and the Event Tree.

The Bayesian Network (BN) is a probabilistic graphical based network, mainly for describing knowledge uncertainty (Martin et al., 2009; Jensen et al., 2009; Ben-Gal, 2007). BN follows a Direct Acyclic Graph (DAG) structure and is made up of nodes and edges (arrows). The node is representative of random variables while the edges are the probabilistic relationships between these variables. The relationships in the BN describes dependency among the variables. In its simplest form, it is represented as two nodes which depict the random variables. These nodes are connected by directed edges. A line from Y_i to Y_j depicts dependence between the two variables. A simple interpretation of this connection is that the variable Y_i has an impact on Y_j. Y_j is called the child of Y_i. Y_i is the parent of Y_j.

The DAG is basically the qualitative description of the BN. The quantitative relationship is described using the conditional probability table (CPT) for discrete random variables. The basis of the Bayesian Network is the Bayes theory, which is expressed as:

$$P(A \mid E) = \frac{P(E \mid A)P(A)}{P(E)} \tag{1}$$

where $P(A \mid E)$ is referred to as the posterior, thus how likely A is, given an evidence of E, $P(EAA)$ is the likelihood which represents how likely

Table 1
Accident models and description.

Model	Description
Heinrich Domino Model	This model describes an accident as a linear one-by-one progression that occurs in a fixed and logical pattern. The premise here is that human errors cause accidents. The factor preceding the accident (the unsafe act or the mechanical or physical hazard) should receive the most attention (Weaver, 1971; Bird, 1974; Adams, 1976).
Kletz Model	This is an accident investigation model. It involves the sequences of decisions and actions that resulted in the accident. It shows against each step, the possible recommendations from investigations (Kletz, 2001).
Swiss Cheese Model	This model describes an accident as the outcome of failures at several stages, a complex combination of unsafe acts by front line operators and latent conditions. The system is depicted as a stack of Swiss cheese. Each slice is a safety barrier and an alignment of the holes in the slice means failure of the system (Reason et al., 2006).
Offshore Occupational Accident Frequency Prediction Model	The idea behind this model is that occupational accidents come from unacceptable interaction between the worker and the working environment. The behaviour of workers is influenced by corporate philosophy, workplace environment, and procedures (Attwood et al., 2006).
Human and Organizational Factor (HOF) Model	This model is based on the idea that the cause of an accident is a result of a chain of errors. An individual error may not be sufficient to cause severe impact unless it is through a combination of multiple latent errors. The focus of this methodology is the demonstration of how root cause, trigger event, incident, accident, and consequence levels are logically related (Ren et al., 2008).
Loss Causation Model	This model is organized in such a way that it establishes a hierarchy of events relative to their respective precursor conditions. The analysis starts with the harm caused to a person and then goes back through a series of processes that resulted in the loss. A failure at any point in the model will result in the progression of loss (Kujath et al., 2010).
SHIPP Model	The goal of the SHIPP methodology is to detect hazards, assess them, forecast, avert their occurrences, and continue monitoring the occurrences. The model relies on process history, accident precursor information, and accident causation modeling. A notable capacity of this methodology is its use to assess the risk of an entire process system and sub-systems. It is also a good tool for identifying the system's concealed interactions and their effects (Rathnayaka et al., 2011)
Functional Resonance Accident Model (FRAM)	This is a complex non-linear model. It describes the non-sequential nature of accidents. It has been applied, for example in the aviation industry (Hollnagel, 2004).