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Human fatigue's effect on the risk of maritime groundings – A Bayesian Network modeling approach

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ABSTRACT

The article introduces a general method for developing a Bayesian Network (BN) for modeling the risk of maritime ship accidents. A BN of human fatigue in the bridge management team and the risk of ship grounding is proposed. The qualitative part of the BN has been structured based on modifying the Human Factor Analysis and Classification System (HFACS). The quantitative part is based upon correlation analysis of fatigue-related factors identified from 93 accident investigation reports. The BN model shows that fatigue has a significant effect on the probability of grounding. A fatigued operator raises the probability of grounding of a large ship in long transit with 23%. Compared to the two watch system (6–6 and 12–12), the 8–4–4–8 watch system seems to generate the least fatigue. However, when manning level, which is influenced by the various watch schemes, is taken into account, the two watch system is preferable, leading to less fatigue and fewer groundings. The strongest fatigue-related factors related to top management are vessel certifications, manning resources, and quality control.

1. Introduction

High safety performance has become increasingly important in many high-risk industries. Nuclear power, the chemical industry, offshore oil and gas production and air traffic control are some example of such industries, but almost no research has focused on shipping (Håvold and Nesset, 2009). Maritime transportation has a history of accidents. Although today's ships are highly equipped with navigation technology, information from the International Union of Marine Insurance (IUMI) indicate that the number of shipping accidents is increasing, and the reasons are attributed to the humans on board (Nilsson et al., 2009). Work conditions and organization are elements in a system that are presumed to contribute to accidents (García-Herrero et al., 2012). In general, seafarers are reported to experience more accidents than the onshore population (Roberts and Hansen, 2002). There is no consensus on the statistical distribution of the causes to shipping accidents due to the different viewpoints of accident analysis and investigation approaches. However, human errors, technical and mechanical failures are typically underlined as the main group of causes (Celik et al., 2009). An important reason for human error is considered to be human fatigue (Gould and Koefoed, 2007; Lützhöft et al., 2007; Xhelilaj and Lapa, 2010; Dorrian et al., 2011; Akhtar and Utne, submitted for publication). In 2006, Norway experienced 88 ship groundings. In 8 of them the watch keepers had fallen asleep (Gould and Koefoed, 2007). Understanding and prevention of shipping accidents is still a focal matter of maritime interest and importance. The true extent of human fatigue, its causes and mechanisms in transportation, are unknown. The scholars disagree because human fatigue is a multi-dimensional construct and its effects on cognitive performance are therefore also complex. In general, they agree that statistics underestimate the true magnitude of the problem because of underreporting (Williamson et al., 2009). The poorly detailed and non- uniform accident databases scattered around the world also hinder a pure statistical approach (Li and Wonham, 2001; Hassel et al., 2011). Yet, even though it has not been proven, studies do point to a strong connection between fatigue and the risk of accidents (Rothblum et al., 2002; Jensen et al., 2004; Xhelilaj and Lapa, 2010).

Fatigue can be classified into physical and cognitive (mental) categories. Mental fatigue is believed to be psychological in nature, whereas physical fatigue is considered synonymous with muscle fatigue (Grandjean, 1979; Lal and Craig, 2001). Both physical and mental fatigue causes decline in alertness, mental concentration, and motivation. Fatigue decreases the speed of cognitive processing, and thus the major symptom of mental fatigue is a general sensation of weariness, increase in reaction time, lower vigilance and disinclination for any kind of activity (Grandjean, 1979; Sneddon et al., 2012). Psychological distress is shown to be most aggravated in workers who face high demands in their jobs with,

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for instance, excessive work load, confined spaces and poor thermal conditions (García-Herrero et al., 2012).

Human fatigue lacks a clearly defined and agreed upon definition, even though it has long been a topic of research. A definition of maritime human fatigue is "a *biological drive for recuperative rest*" (Desmond and Hancock, 2001; Noy et al., 2009; Williamson et al., 2009). However, a broader definition of fatigue is "*subjective experience of someone who is obliged to continue working beyond the point at which they feel confident of performing a task efficiently*" (Smith et al., 2001). Human fatigue is difficult to measure and even more difficult to state as a cause to an accident. Therefore accident investigation reports are often reluctant assigning any large importance to human fatigue. Therefore, by analyzing accident investigation reports (as done in this study), one has to rely on the subjective reports from people involved. Whether or not human fatigue is likely to have been present has to be assessed based on the mentioned fatigue influencing factors in the reports. The latter definition is therefore used in this study. The definition also covers both the mental and the physical fatigue. Throughout the article when fatigue is mentioned, it is referred to human fatigue.

Grounding can be categorized into drift and power grounding. Drift grounding, which is defined as grounding with no engine power, seldom leads to high –energy impacts. However the wave actions may break down the hull over time. Power grounding occurs with the engine running, which often means grounding in higher speed and more damage (Kristiansen, 2001). Both types of accidents are included in our study, and the risk quantification in this study is therefore for drift and power groundings combined. Further on, contact of the ship's hull with the seabed is deemed sufficient to classify a event as a grounding. It is not a requirement for the ship to actually get stranded on the seabed.

The objective of this article is to present an approach for developing a Bayesian Network (BN) for modeling the risk of maritime accidents. More specifically, the article focuses on human fatigue in a ship's Bridge Management Team (BMT) and its influence on the risk of maritime grounding accidents. There exists research on fatigue in BMT (Akhtar and Utne, submitted for publication), but since fatigue is so multi -dimensional and vague, it is regarded as a highly difficult task to measure the effect of human fatigue on the risk of maritime accidents, and to our knowledge no attempt has yet been made.

Fatigue is a complex phenomenon (IMO, 2001; Allen et al., 2008; Akhtar and Utne, submitted for publication), and looking into only a set of causes or factors individually will therefore not provide the whole picture (Smith et al., 2006). Thus, it is necessary to consider the interplay of factors when analyzing such accidents (Zhao et al., 2011). It has been argued for a more holistic and far reaching research on seafarers' fatigue (Smith et al., 2006).

Greenberg (2007) analyzed various models and techniques available in the field of accident modeling, and concluded that traditional models fall short in analyzing and evaluating phenomena that are exhibited by socio-technical systems. This is due to the difficulty of performing safety analysis when proceeding from simple components to systems and to socio-technical systems. The challenge of modeling human performance as part of a system is a problem that still is not fully solved. Human behavior is influenced by a combination of personal traits, social beliefs and the organizational system. Greenberg (2007) concluded that the most promising way is the use of probabilistic modeling, the most suitable technique being the BN, which is well adapted to model complex systems, and a range of different variables can be included into the system without too much difficulty.

The article is structured as follows: Section 2 introduces the BN method, Section 3 introduces an eighth step approach for constructing a BN and explains how the study in the article was conducted, Section 4 presents the results, and Section 5 gives the conclusions.

2. Bayesian Networks

BN is a framework for reasoning under uncertainty, and is widely used for representing uncertain knowledge (Trucco et al., 2008). BN makes complex problem analysis perspicuous since interrelations and dependencies of the model parameters become visible (Hänninen, 2008). Recently, there has been an increased interest to use BN to model phenomena involving human and organizational factors. Trucco et al. (2008) proposed a BN model of organizational factors in maritime transportation. Bearfield and Marsh (2010) made a BN model of lower consequence rail incidents, and Hänningen and Kujala (2010) examined the effects on collision probability of weather and human factors using BN. There are also other relevant studies from outside the field of maritime transport. Didem and Kayakutlu (2010) used BN to simulate the effects of management's various strategy changes in the energy sector (Cinar and Kayakutlu, 2010; Greenberg et al., 2005) applied BN to the civil aviation industry (Reuven et al., 2005).

BN relies on Bayes' theorem to propagate information between nodes which can be formulated as shown in:

$$P(Y|X) = \frac{P(X|Y) \cdot P(Y)}{P(X)} \tag{1}$$

where $P(Y)$ is the prior probability of the hypothesis, i.e., the likelihood that Y will be in a certain state, prior to consideration of any other relevant information (evidence) which is X. $P(X|Y)$ is the conditional probability (the likelihood of evidence given the hypothesis to be tested), and $P(Y|X)$ is the posterior probability of the hypothesis (the likelihood of Y being in a certain state, conditional on the evidence provided) (Kragt, 2009). The theorem connects the BN network together by the use of Y and X (Peng-cheng et al., 2012). For example, by assigning a disease to Y and a symptom X, the probability of the symptom is often easier to define given the disease. One may thereupon adopt an opposite approach to find the probability of the disease given the symptom. If the symptom X is known to be present, one may change the probability of the symptom from 0 to 1 and then update the probability of the disease. This is called setting evidence or probabilistic inference. Evidence may be set both ways. If, for instance, the disease is confirmed, one may set the probability of disease to 1 and get the probability of the symptom by updating the network by recalculating the values.

There are, however, difficulties related to BN. The BN structures are unique to the problem at hand, and they often are a product of

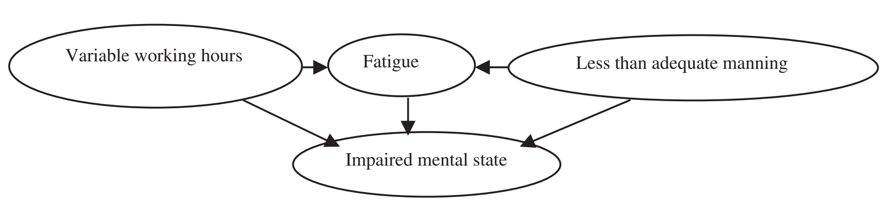

Fig. 1. A simple BN example.