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Bayesian networks for maritime traffic accident prevention: Benefits and challenges

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ABSTRACT

Bayesian networks are quantitative modeling tools whose applications to the maritime traffic safety context are becoming more popular. This paper discusses the utilization of Bayesian networks in maritime safety modeling. Based on literature and the author's own experiences, the paper studies what Bayesian networks can offer to maritime accident prevention and safety modeling and discusses a few challenges in their application to this context. It is argued that the capability of representing rather complex, not necessarily causal but uncertain relationships makes Bayesian networks an attractive modeling tool for the maritime safety and accidents. Furthermore, as the maritime accident and safety data is still rather scarce and has some quality problems, the possibility to combine data with expert knowledge and the easy way of updating the model after acquiring more evidence further enhance their feasibility. However, eliciting the probabilities from the maritime experts might be challenging and the model validation can be tricky. It is concluded that with the utilization of several data sources, Bayesian updating, dynamic modeling, and hidden nodes for latent variables, Bayesian networks are rather well-suited tools for the maritime safety management and decision-making.

1. Introduction

While Bayesian networks (BNs) have been around for a few decades, in the past few years the amount of literature on BN applications to maritime traffic safety modeling has been rapidly increasing. As an example, Fig. 1 shows the number of publications in the Scopus database[1] published between 2004 and 2013 with either “maritime traffic safety”, “maritime safety”, “marine traffic safety”, or “ship safety” and “bayesian network”, “bayesian belief network”, or “bayes net” included in them. The percentages of documents containing the term “maritime traffic safety”, “maritime safety”, “marine traffic safety”, or “ship safety” which also mention the aforementioned Bayesian network term(s) are presented in Fig. 2. Although in some of the publications, maritime safety had only been referred to and the paper had been focusing on another topic, the figures suggest that there is a growing interest in the maritime traffic BN modeling, especially in Europe and Asia (Table 1).

When considering the topics of Fig. 1 and some other published BN models, it can be summarized that they have covered various maritime traffic safety and risk matters such as the ship-ship collision or grounding occurrence (Friis-Hansen and Simonsen, 2002; Det Norske Veritas, 2003; Rambøll, 2006; Hänninen and Kujala, 2012; Hänninen et al., 2014a; Akhtar and Utne, 2014), accidents and their consequences (Antao et al., 2009; Hänninen et al., 2013; Kelangath et al., 2011; Li et al., 2014; Goerlandt and Montewka, 2014; Montewka et al., 2014; Konovessis et al., 2013; Zhang et al., 2013; Kristiansen, 2010), post-accident procedures and their costs (Eleye-Datubo et al., 2006; Montewka et al., 2013; Lehikoinen et al., 2013; Sarshar et al., 2013a; Norrington et al., 2008), human reliability analysis (Martins and Maturana, 2013) safety inspection findings (Hänninen and Kujala, 2014), safety management (Hänninen et al., 2014b) and other maritime organizational aspects (Trucco et al., 2008). The main purpose of the models has been either in characterizing the overall patterns between the model variables or performing inference on certain variables of interest.

While Bayesian networks offer several benefits over other modeling approaches, they have their limitations as well. The advantages and challenges of using BNs in the context of environmental modeling have been discussed earlier by Uusitalo (2007) and Aguilera et al. (2011). Weber et al. (2012) present some pros and cons in BN applications within dependability, risk analysis and

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[1] http://www.scopus.com/.

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0001-4575/

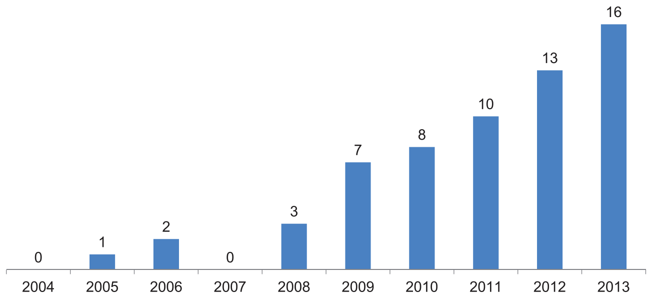

Fig. 1. The number of publications between 2004 and 2013 in Scopus given a search query (ALL("maritime traffic safety" AND "bayesian network") OR ALL("maritime traffic safety" AND "bayesian belief network") OR ALL("maritime traffic safety" AND "bayes net") OR ALL("maritime safety" AND "bayesian network") OR ALL("maritime safety" AND "bayesian belief network") OR ALL("maritime safety" AND "bayes net") OR ALL("marine traffic safety" AND "bayesian network") OR ALL("marine traffic safety" AND "bayesian belief network") OR ALL("marine traffic safety" AND "bayes net") OR ALL("ship safety" AND "bayesian network") OR ALL("ship safety" AND "bayesian belief network") OR ALL("ship safety" AND "bayes net")).

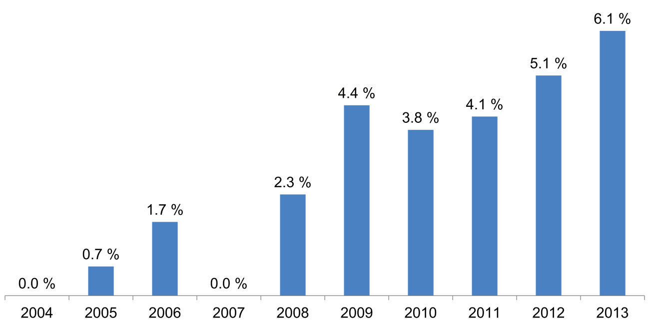

Fig. 2. The percentages of Scopus publications containing the term "maritime traffic safety", "maritime safety", "marine traffic safety", or "ship safety" which also include "bayesian network", "bayesian belief network", or "bayes net".

Table 1
The countries of Fig. 1 publications. Note that the total number is higher than the number of publications because the countries of all authors have been taken into account.

Country	No. of publications
United Kingdom	19
Finland	15
China	10
Singapore	5
Canada	3
Norway	3
South Korea	3
France	2
Hong Kong	2
Portugal	2
Brazil	1
Germany	1
Greece	1
India	1
Italy	1
Russian Federation	1
Sri Lanka	1
Turkey	1

maintenance areas. Although many of the characteristics described in those papers are universally relevant to any BN application area, the maritime traffic safety modeling features some specific matters to consider. This paper studies what BNs can offer to those matters and discusses a few challenges in the maritime traffic safety and accident prevention application. The evaluation is based on literature on BNs and their maritime traffic safety applications and the author's own experiences in constructing maritime safety BN models. The actual procedures of constructing BN models are not addressed, as many tutorials and guidebooks provide descriptions for those (e.g. Darwiche, 2009; Jensen and Nielsen, 2007; Heckerman, 1998; Daly et al., 2011; Chen and Pollino, 2012). Also, practical BN tools and software are not described in detail.

The rest of the paper is organized as follows. The next section gives a brief introduction to Bayesian networks. Section 3 focuses on applying BNs in the maritime accident prevention context; after discussing the main benefits in Section 3.1, some challenges and suggested ways to overcome them are presented in Section 3.2. Finally, Section 4 draws conclusions and provides suggestions for further studies.

2. Bayesian networks

Bayesian networks, also known as belief networks, Bayesian nets, and probabilistic directed acyclic graphs, are a technique for graphically representing a joint probability distribution of a selected set of variables (Pearl, 1988). The structure of a Bayesian network model is a directed graph, where the nodes represent the model variables and the links between the nodes the dependencies. The network is acyclic, i.e. from any node there must not be a way to loop back to the same node. Each network node consists of a finite number of mutually exclusive states. Each of these states has a probability of occurrence which depends on the current states of the variable's possible parent nodes, i.e. the variables with a direct link to the variable in question. The network structure, the graph, can be perceived as a qualitative part of the model, whereas the probability parameters add a quantitative dimension to the model (Darwiche, 2009).

Compared to other modeling techniques, BNs have been accredited for several factors such as their ability to combine data with expert knowledge, handle missing data, avoid overfitting, and present causal relationships while also providing a graphical representation which is easily understandable (e.g. Heckerman, 1998; Uusitalo, 2007). On the other hand, the relatively high number of probability parameters in already a rather simple model and the acyclicity and discrete (or discretized) variables have been stated as drawbacks of the BNs (Uusitalo, 2007; Chen and Pollino, 2012; Jensen and Nielsen, 2007). Although all of the general pros and cons apply to maritime accident prevention BN models as well, the ones which are especially relevant are discussed in the following section. Some of the addressed aspects are more related to BN properties, while some of the challenges rise from the application area, maritime traffic accidents and safety.

3. Bayesian networks in maritime accident prevention modeling

3.1. Benefits

3.1.1. Suitability for complex system modeling

The latest theoretical accident models for complex socio-technical systems state that accidents are a result of complex, at least partially unknown interactions in the system (see e.g. Dekker, 2002, 2011; Leveson, 2004; Hollnagel, 2009). Furthermore, they state that accidents cannot be described with linear cause-effect relationships, where removing one falsely component would prevent the accident occurrence (Leveson, 2004).

Bayesian networks enable presenting rather complex systems. For example, Trucco et al. (2008) included 71 nodes and 113 links in their maritime organizational effects BN, and the ship-ship collision causation model evaluated by the author in Hänninen and Kujala (2012) consisted of 100 nodes and 179 links. When considering the number of probability parameters, The Port State Control deficiency model, constructed by the author with a repeated hill-climbing BN structure learning algorithm (see Hänninen and Kujala, 2014), contained 420 probability parameters, out of which 239 were independent. Moreover, the model of Hänninen and Kujala (2012) included 2336 independent parameters and 3711 parameters in total.

Bayesian networks are acyclic and directed by definition. This sets some limitations when modeling dependencies which are cyclic or two-way in the reality. For example, one of the key aspects of safety management is continuous improvement (Lappalainen et al., 2011). The safety of the system is monitored and evaluated and the results are then utilized by making changes to certain aspects of the safety management. This type of a feedback loop could not be encoded into a safety management BN model. To some extent, this shortcoming could be tackled with dynamic BNs (see Section 3.1.5). Sometimes the problems with two-way dependencies could be resolved with hidden nodes (Section 3.1.3).

Besides the acyclicity, in practice the BN model complexity is only limited by the computational power and memory capacity. However, another question is then how many variables, states and dependencies are reasonable to include in a model and which features' effects could be considered only implicitly in the uncertain dependencies. This leads to the next BN benefit, the incorporation of the problem uncertainties.

3.1.2. Coping with uncertainty

The complex nature of what makes a maritime traffic system – or a single ship – safe, inevitably introduces uncertainty. All potentially relevant factors and their complex interactions could not be observed or measured, and thus it might be very unlikely to capture data on all of them. On the other hand, if experts are serving as the source of data, their knowledge might be incomplete. Furthermore, although maritime traffic safety regulations set certain bounds to the vessels, the crew, and to the shipping companies, different ships, shipping companies, or flags can vary widely in their safety performance (Li and Wonham, 1999; Håvold, 2005; Ek and Akselsson, 2005; Knapp and Franses, 2007). Finally, a model is always a simplification of the reality, and the chosen modeling technique, the set of variables and their interactions can never capture a perfect picture of the problem to be modeled. Thus a maritime traffic safety model will always include uncertainty due to lack of data, incomplete knowledge, variability, the chosen modeling technique, and the applied assumptions and problem boundaries.

BNs are capable of including at least some of the aforementioned uncertainty in the form of probabilities. As each variable and dependency is probabilistic, the model users are able to see the uncertainty in the estimates and take that into consideration in the decision-making. A good example of the uncertainty effects was presented by Goerlandt and Montewka (2014). Their paper stated that two of the variables which affect an oil outflow resulting from a ship collision, the relative impact location and impact angle, contain significant uncertainty. They then demonstrated how this uncertainty affects the outflow estimate by systematically varying the values of these two variables and reporting the results from the BN model.

While BNs treat uncertainty explicitly, they also offer a way to decrease it. The Bayesian approach enables the combination of expert knowledge with data and updating the model parameters when more data has been collected or observed. The effects of potential biases in the data and elicited expert knowledge could thus be minimized by not relying only on a single information source.

3.1.3. Relaxation of causality

Contrary to fault trees and event trees, the traditional risk and safety modeling techniques, BN models do not restrict to describing events; the nodes can represent any kind of factor seen relevant to the problem. Furthermore, the (lack of) links merely represent conditional (in)dependence assumptions. Thus, the directed links between the variables do not necessary need to be direct causal connections (e.g. Pearl, 1988; Darwiche, 2009).

For example, a link between two variables could describe a dependence stemming from an unknown common cause. In the maritime safety context, this could occur when modeling dependencies between several safety indicators: one indicator is not a cause of another indicator, but still the indicators are not independent, because their values depend (or assumed to depend) on the level of safety. If a BN model was to be constructed and it would only include the indicator variables and not the safety itself, the indicator correlations were then modeled with links between the indicators.

On the other hand, it is also possible to include common causes as hidden nodes in a BN model. A hidden node denotes a latent variable for which there is no data available. Details on how BNs handle hidden nodes are considered out of the scope of this paper; more information can be found in Neapolitan (2004). An example of using hidden nodes in the maritime accident prevention context can be found in a previous paper by the author (Hänninen and Kujala, 2014), where maritime safety indicator BN models were constructed with and without a hidden node, which was representing the ship safety level.

3.1.4. Versatility

A BN model is very versatile and the same model can be utilized in multiple ways. As a BN describes the joint probability distribution over the network variables, it is possible to examine the marginal or conditional probability distribution of any model variable; a BN does not have a designated target variable.

Once the network structure and the probability parameters have been defined, the model can be applied to several types of system investigations and reasoning, for which Bayesian networks software enable fast responses to. According to Darwiche (2009), BNs can be utilized in finding a probability of a certain variable instantiation (such as the probability of inadequate safety management level), the posterior marginal distribution of a certain variable or variables after some evidence (the probability of inadequate safety management level given poor management commitment), or the most probable network variable or variable subset instantiation given some evidence (in which states the other model variables most probably are, if the safety management level is inadequate). The queries to be performed naturally depend on why the BN has been constructed. Different queries are relevant when the aim is at descriptive modeling of the system characteristics, in which case all model variables and their dependencies are under interest, compared to when one wants to predict the value of one particular variable based on the others, for example.

In addition to performing queries described above, the BN model properties can be analyzed with sensitivity and mutual information analyses. Sensitivity analysis examines how small changes in the probability parameters affect another parameter. The mutual information analysis seeks to find how much uncertainty in one model variable can be removed by observing the state of another variable. According to Woodberry et al. (2004), both mutual information analysis and sensitivity analysis should be conducted in order to investigate the BN model properties thoroughly. Many BN software such as HUGIN Expert (Madsen et al., 2005) and GeNIe (Druzdzel, 1999) include tools for carrying out the analyses.

The author performed a series of posterior marginal distribution queries and applied and discussed the sensitivity and mutual information analyses techniques within a ship collision occurrence model validation context in Hänninen and Kujala (2012). Sensitivity and mutual information analyses were also performed by Montewka et al. (2014) for validating their RoPax ship collision risk framework. A third example of a BN sensitivity analysis application is presented in Goerlandt and Montewka (2014), where it was conducted as a part of validating the tanker oil outflow model. Validation is further discussed in Section 3.2.5.

3.1.5. Capability of dynamic modeling

BN models can be utilized for describing uncertain dynamic systems as well (e.g. Kjaerulff, 1992). In that case, the model includes multiple copies of the same variable which describe the variable states over time. Some BN software provide special tools for dynamic Bayesian network (DBN) construction. For instance, in GeNIe (Druzdzel, 1999) the user creates a model for one time step and sets the temporal probabilistic links between the time slices, and the software then constructs the variable copies for each time slice. It is then possible to analyze the dynamic behavior of the modeled system.

In the maritime domain, Sarshar et al. (2013b) modeled panic in ship fire evacuation using a DBN. In the military context, DBNs have been proposed for identifying air targets approaching a combat vessels (Wiggers et al., 2011). However, it seems that the full potential of the DBNs in maritime safety modeling has not been recognized yet.

3.1.6. Extendable to a decision problem model

A basic BN model can be a useful tool in maritime safety decision making. Nevertheless, they can also be extended into a full decision problem model. An influence diagram (ID) can be constructed from a causal BN by adding decision variables and utility variables. Decision variables describe the decisions or interventions whose effects one wants to examine with the model. These could be for instance novel risk-control alternatives. Utility variables describe the costs and benefits related to some of the network variables, measured in some common unit such as monetary values. The utility nodes are not necessary for performing decision analysis; without them, the effects of the intervention or a decision can be evaluated on a probability level, i.e. how the probability distributions or the most probable states of the network variables change. In case utility variables are also included, the model describes the influence as an expected utility given the decision alternatives. Thus, IDs can be utilized in maritime safety related cost-benefit analyses.

Compared to other techniques such as decision trees, IDs provide a more compact representation of a decision analytic problem (see e.g. Parnell and Bresnick, 2013). In the maritime safety domain, the utilization of IDs when defining risk-control options within the Formal Safety Assessment procedure (FSA, see International Maritime Organization, 2002) has been suggested to International Maritime Organization (2006).

In the maritime traffic accident context, examples of applying IDs can be found in oil accident cleanup procedures optimization. Lehikoinen et al. (2013) modeled how the Finnish oil-combatting vessels should be located for an optimal cleanup given a hypothetical oil accident in the Gulf of Finland. Montewka et al. (2013) developed an ID for the cleanup cost estimation. In their model, the decision variables were representing whether different oil-combatting vessels were participating in the cleaning, and whether to use oil spill containment booms.

3.2. Challenges

3.2.1. Incomplete understanding of safety and accident occurrence

One major challenge when attempting to model causal relationships of maritime accident occurrence stems from a controversial theoretical background. The views on how and why accidents in complex socio-technical systems occur are not yet established; for a review of the different theoretical accident frameworks, see Qureshi (2007). Moreover, as was already mentioned in Section 3.1.1, the latest views do not support cause-effect modeling. Furthermore, these views also state that the initiating event in a chain-of-events model, the so-called root cause, is arbitrary, as one could always go further in the analysis (Leveson, 2004), and the existence of such root cause is a misunderstanding (Hollnagel, 2004; Hollnagel et al., 2006). Regarding maritime accident occurrence, the reliability of certain ship-ship collision frequency approaches has been questioned (Goerlandt and Kujala, 2014).

The controversies in the theoretical understanding on accident occurrence are a challenge to all causal accident models, not only for those implemented with BNs. In fact, BNs might be a very attractive approach if a causal model is needed due to its capability to include uncertainty in the model (Section 3.1.2). However, in order to model a complex system where “everything can affect everything”, one should establish a fully connected BN, meaning that there should be direct links between all variables. It should be noted that a link between two variables does not mean that the variables are necessarily heavily dependent; the probability parameters could have been defined in such a way that the dependency is very weak and uncertain. On the other hand, depending on the presence of other links in the model, an absent direct link between two variables could make the variables independent. In practice however, it is not necessarily possible or meaningful to construct a fully connected BN for a complex accident representation. The analyst must then decide how weak (assumed) dependencies are included and which are omitted. The selected variables and threshold for the strength of dependency to be encoded might have an effect on the results.

3.2.2. Scarce data

Maritime traffic accidents are fortunately rather rare events. For example, approximately 0.7 accidents per 1000 port ship calls had occurred in the Gulf of Finland (Kujala et al., 2009; Kuronen et al., 2009). This means that the data on maritime accidents is rather limited. Unfortunately, the amount of data cannot be increased by gathering data from a very long time period because the rules, regulations, and the safety culture itself could have been changed within the covered time, and the complete dataset would not necessarily represent a similar underlying phenomenon. On the other hand, as was discussed earlier, the accident mechanisms have been considered complex with potentially several involved factors. Thus, we are facing a modeling problem of a large number of variables but relatively few data on them.

In addition to rare occurrence, the amount of maritime accident data is limited due to underreporting (Psarros et al., 2010). When Hassel et al. (2011) compared accident data from different databases, they found that the number of unreported accidents comprised roughly 50% of all occurred accidents. Other studies have found that also incidents and near accidents are not fully reported (Devanney, 2008; Oltedal, 2010; Lappalainen et al., 2011; Bhattacharya, 2012).

Unfortunately, several of the accidents which have actually been reported suffer from missing data. For example, ship size information had been included in 58% of the Gulf of Finland ship accidents stored in HELCOM’s accident database (Hänninen et al., 2013). Moreover, an accident cause, ice conditions or pilot presence had been reported in less than half of the cases. As another example, the former Finnish maritime accident database DAMA enabled reporting up to four causes for an accident. However, in only 15% of the collisions and groundings more than one cause had been reported (Hänninen et al., 2013). The missing information is further discussed in the following subsection, together with other data quality related problems.

As the accidents are rare and underreported, maritime accident prevention and safety management could benefit from models which are not describing accidents but other factors indicative of maritime safety level, and for which there is more data available. One set of potential ship safety indicators results from Port State Control inspections. Port State Control (PSC) inspection checks the condition, the equipment, manning and the operation of foreign state vessels for verifying that the aforementioned aspects on board comply with international regulations (International Maritime Organization, 2011). If the inspection reveals deficiencies that pose a safety hazard, the ship may be detained at the port until the deficiencies have been rectified. The findings from an inspection are stored into a database; for example, the inspection results within Paris MoU, an agreement on a harmonized system of Port State Control covering European coastal states and the west coast of Canada, are partially available online.[2] As PSC is conducted periodically – within Paris MoU, 5–36 months after the previous inspection, depending on how "risky" the ship has been determined (Paris MoU, 2012) – there is more data, and it covers not only accident vessels but ships from all levels of safety. As an example, within 2009–2011, an average of 350 PSC inspections per year had been conducted within Finnish ports (Hänninen and Kujala, 2014). However, own experiences show that the data might not be very informative for complex BN construction (see Section 3.2.3).

The scarce data problem is further enhanced by the restricted data accessibility. Maritime safety and accident related data collection and harmonization have been increasing over the past few years (Correia, 2010; Weintrit, 2011; Storgård et al., 2012). Unfortunately, the collected data is not necessary available for an analyst, not even for academic research purposes (Devanney, 2008). As an example, only the EU member state authorities have access to the European Marine Casualty Information Platform (EMCIP), and only on data from their own country. The mentioned PSC data might not be easily available either. For example, although Paris MoU data is available online, one needs to get a written permission from the data owners, that is from each member country, to use their corresponding data.

Data scarcity is of course not a problem restricted to the BN application but affects any type of data-based modeling. As was already mentioned, BN model accuracy could be improved by combining the data with expert knowledge or other relevant data sources. On the other hand, a model performance could potentially be increased by creating artificial accident cases. For example, if the purpose of a data-based BN model was to compare the patterns of accident vessels to those of more common "safe" ships, utilization of oversampling methods such as the one proposed by Chawla et al. (2002) might increase the correct recognition of accident patters. However, the analyst should be careful with oversampling as it could yield an overfitted BN.

3.2.3. Problems with data quality

Various studies have raised a question on the quality of maritime safety related data. In addition to the already mentioned missing data, maritime accident databases have been found to include errors in their contents (Salmi, 2010).

In Hänninen et al. (2013), the author evaluated the feasibility of categorical ship collision and grounding cause data for BN modeling. A 38-variable model consisting of 37 different cause type variables and an accident type variable, all derived from the former Finnish maritime accident database DAMA, was constructed with a Necessary Path Condition (NPC) structure learning algorithm (Steck and Tresp, 1999) and expectation-maximization (EM) method (Dempster et al., 1977) for the parameter estimation. For evaluating the quality of the resulting model, the accident dataset was divided into a training set for learning the model and a smaller test set for evaluating how well the resulted model performed with unseen data. From the training data, the algorithm learned a network of ten connected variables (including the event type and nine cause types), 17 unconnected cause type variables, and five pairs of dependent causes. When the resulted model was evaluated based on how well the model fitted into the test set and predicted the correct accident type, it was found that the BN was not clearly superior to a model with no links between any of the variables. To summarize, the cause information contained in the accident database was not found very informative for establishing a cause dependency BN for collisions and groundings.

Accident investigation reports form another data source which has faced criticism in the scientific literature. According to Reason (1990), the reliability of accident reports can be questioned, since they propose a simplified presentation of the events and are mostly concerned with attributing blame. Accidents with no injuries have been underreported and more severe accidents have been investigated in more detail (Gould et al., 2006). Moreover, the reports result from an investigation which has been inevitably subjective and affected by the underlying, potentially subconscious views on how accidents occur (Lundberg et al., 2009; Leveson, 2011; Reiman and Rollenhagen, 2011; Besnard and Hollnagel, 2014). Thus, as was stated by Gould et al. (2006), a high risk of bias might be present when using accident investigation reports as a source of data.

Maritime accident reports are in text format and their usage typically requires human effort in extracting the data from the text. The task can become tedious and has potential for introducing additional biases when interpreting the text (Johnson, 2000; Hyttinen et al., 2014) and further when determining how the textual description corresponds to BN variables and probabilities. In order to overcome these challenges, there have been some attempts to apply text mining techniques in extracting information from maritime accident investigation reports (Grech et al., 2002; Tirunagari et al., 2012). However, text mining can be challenging as the maritime accident reports are written in natural language with no standard template and they often contain misspellings, abbreviations, multi words (e.g. "safety culture"), and words with several meanings (e.g. "fatigue").

In the previous subsection, PSC data was mentioned as a potential input for a maritime safety BN model. In Hänninen and Kujala (2014), the author utilized PSC data for BN model construction (see also Sections 3.1.1 and 3.2.2). The target was to model potential patterns between the numbers of different types of deficiencies found in the inspections. However, the patterns in the data turned out to be rather weak. This was largely due to over 75% of the inspections discovering no deficiencies. Thus, with the current PSC inspection practices and definitions of which is to be considered as a deficiency, the theoretical potential in frequently collecting data from ships with varying safety features might be lost, or the resulting data would need supplementary information sources.

3.2.4. Relying on expert judgment

As was already mentioned in Section 3.1.2, BNs can compensate the problems with data by combining it with expert knowledge. Furthermore, using the knowledge of experts is often the only way to address a risk-control problem with novel risk-control options. When making probabilistic judgments, however, people often tend to rely on heuristics, which may produce biases to the elicited quantitative information (O'Hagan et al., 2006). Nevertheless, as the expert elicitation is a scientific field of its own, there are many publications on how to calibrate the experts and avoid the biases (e.g.

[2] https://www.parismou.org/inspection-search.

Otway and Winterfeldt, 1992; Gilovich et al., 2002; Simola et al., 2005; O'Hagan et al., 2006; Speirs-Bridge et al., 2010).

Another challenge in using experts comes from the fact that the elicited information is always subjective. It reflects the expert's knowledge, which is conditional on his/her background, experience, and interpretation of the problem. For example, when the author and her colleagues modeled the effects of implementing a novel navigational service in the Gulf of Finland (Hänninen et al., 2014a), it was found that the shipping company representatives had a very different view on Vessel Traffic Service effect to accident-avoidance than the VTS operators and authorities. Another own study (Hänninen et al., 2014b) also showed differences in the experts' assessments, this time regarding maritime safety management. Nevertheless, although the resulting safety management adequacy values were different, all experts felt that it was more probable to have inadequate overall safety management than adequate. Thus, if the model had been used to guide whether to be satisfied with the current safety management or to take actions to improve it, the between-expert differences had not affected the decision.

The subjectivity of the expert opinion can also be seen as an advantage. Including the views of several experts with different background knowledge and experience might provide a richer information base than any single data source. BNs offer a way to also include the expert uncertainty in the model. By not aggregating the expert views before inserting them into the model, one could build such a BN where it is possible to analyze the system according to a single expert, or examine the results based on an expert combination. It is also possible to include different weights to the experts, according to their estimated expertise quality, for example, and see how the weights affect the outcome.

On the other hand, the model can be built in a way that it includes also the expert's uncertainty in his/her estimated value(s), at least to some extent. One alternative for this would be the integration of BNs with other approaches to uncertainty representation than probabilities. For example, Li et al. (2012) established a fuzzy BN network approach for the quantification of organizational influences in human reliability analysis context, and Eleye-Datubo et al. (2008) proposed a similar model for the maritime safety domain. Various ways to elicitic fuzzy knowledge from experts have been presented, e.g. by Cornelissen et al. (2003).

According to Rasmussen (1997), experts might only have knowledge on a local-scale interactions and cannot comprehend how the local changes affect on a system level. That is actually all that BNs require from an expert when the network parameters are to be defined: to assess the probability distribution of each variable, given its parent variable configuration. After determining each of these local dependencies, the higher level effects are then "automatically" visible when the model is run in a BN software. This modularity feature of the BNs stemming from the independence assumptions also saves space and time, because it allows expressing the joint probability of the network variables with conditional probabilities using the chain rule.

Regardless of the modularity, the number of the probability parameters can become rather high even in a relatively simple BN. The experts might feel uncomfortable or exhausted to assess hundreds or thousands probabilities, especially the ones conditional on several variables. This could have an effect on the outcome. In the previously mentioned navigational service study (Hänninen et al., 2014a), the experts had to assess 1050 probabilities in total. After constructing the models with the experts' estimations, a comparison of the BN outcomes to the experts' qualitative opinions revealed some discrepancies. Although there might have been several reasons for these conflicting views, one of them could have been the experts' exhaustion given the tedious job and limited available time.

One more challenge when building a maritime safety BN based on experts comes from the fact that the maritime safety experts can be quite busy; some studies show that the mariners and safety designated persons suffer from work overload already with their normal tasks (Knudsen, 2009; Lappalainen et al., 2011; Storgård et al., 2012). Thus it might be difficult to find enough time for the potentially rather long elicitation session. On the other hand, own experiences indicate that once an expert is present in an elicitation session, he/she is typically eager to share the knowledge at least qualitatively.

3.2.5. Validation

A typical way to validate a statistical model is to evaluate how well it performs on unseen data, i.e. check the predictive validity of the model. This is also applicable to BNs (see e.g. Hänninen and Kujala, 2014) – given that there is data to test the model with. However, especially the validation of an expert-based model can be difficult.

Regarding model validation in general, many studies from different disciplines (e.g. Landry et al., 1983; Mengshoel, 1993; O'Keefe and O'Leary, 1993) emphasize that a proper validation should reach beyond predictive validity into aspects of model's credibility and relevance. One approach is to consider small parts of the model one by one, apply the sensitivity and/or mutual information analysis methods and/or queries mentioned in Section 3.1.4, and then evaluate if the model behavior is valid. In addition to the studies referred to in Section 3.1.4, Zhang et al. (2013) used this type of approach for partially validating their navigational risk model; they examined if small changes in probability parameters confirmed their suggested axioms for a valid BN risk model. Furthermore, Pitchforth and Mengersen (2013) have proposed a validation framework for expert-based BN models. The framework is very comprehensive, as it includes seven types of validity: nomological, face, content, concurrent, convergent, discriminant, and predictive validity. For each validity aspect, they suggest questions to be answered in order to test the validity of a BN model. In maritime safety studies, their framework has recently been partially applied by Goerlandt and Montewka (2014) and Hänninen et al. (2014b).

Interestingly, in none of the maritime safety related BN publications mentioned in Section 1, the authors had modeled the problem with an alternative technique and compared the results. It thus remains uncertain whether BNs were the optimal approach to the presented problems.

3.3. When not to apply BNs

So far Section 3 has described the benefits of applying BNs to modeling problems targeted at maritime accident prevention and then presented some challenges. The challenges however have been more related to the maritime safety modeling in general, for which BNs actually provide many ways to cope. The paper now briefly discusses when BNs might not be the best modeling tool.

As was mentioned earlier, a BN represents the joint probability distribution over its variables $Y_1, Y_2, \ldots, Y_n$: $P(Y_1, Y_2, \ldots, Y_n)$. Sometimes a model which estimates a single variable Y_1 based on n other variables $Y_2, Y_3, \ldots, Y_{n+1}$ might be needed. When the variables are probabilistic, this equals estimating $P(Y_1|Y_2, \ldots, Y_n)$. For example, one would like to know how the maritime accident probability depends on vessel age and flag. Determining this type of a conditional probability is possible with a BN (see Section 3.1.4). However, if the BN has been learned from data, the model is a result of finding a BN which best describes the joint probability (Friedman et al., 1997). In some cases, this model might not be optimal for assessing $P(Y_1|Y_2, \ldots, Y_n)$ (Friedman et al., 1997). Some ways to improve the BN performance in estimating the conditional distribution of Y_1 have been suggested in the literature (Grossman and Domingos, 2004; Madden, 2009). However, especially if the associations between the other variables Y_2, Y_3, ..., Y_{n+1} were not under interest, the task could perhaps be better suited for other methods such as decision trees, logistic regression, neural networks, or support vector machines.

Before deciding to construct a BN model, one should consider whether it is worthwhile to apply quantitative modeling at all. In some cases, the utilization of qualitative techniques might be more cost-effective. Although BNs seem to be a rather suitable technique for maritime safety representations, no modeling approach should be used as a fits-all solution. The applied method should always be selected based on to what purpose the model is to serve, who will use it, and what type of data or background knowledge is existing for its construction.

4. Conclusions

As the application of Bayesian networks in the maritime traffic context is becoming more popular, this paper examined the benefits and challenges when Bayesian networks are applied for maritime accident prevention and safety modeling. The capability of representing rather complex, not necessarily causal but uncertain relationships makes BNs an attractive modeling tool for the maritime safety and accidents. Furthermore, as the maritime accident and safety-deficiency related data is still rather scarce and difficult to obtain, the possibility to combine data with expert knowledge and the easy way of updating the model after acquiring more evidence further enhance their feasibility. However, as the model complexity increases, so does the number of probability parameters to be determined, and eliciting the probabilities from experts might become challenging. Utilizing several data sources which are somehow connected might help to remove some of potential uncertainties and biases stemming from scarce data and expert knowledge utilization. With the utilization of several data sources, Bayesian updating, dynamic modeling, and hidden nodes for latent variables, even better and more realistic tools for decision-making could be achieved. On the other hand, as maritime accidents are still rather rare and the majority of ships succeed to navigate their journeys safely, data from safe operations would not be as scarce as the accident data. Hollnagel (2014) also suggests that the safety of complex socio-technical systems should be investigated by focusing on “what goes right” instead of the lack of safety. Thus, BNs which describes normal operations in the maritime traffic might be an attractive alternative for a useful safety management tool.

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