# Bayesian network modeling of potential patterns in maritime safety performance

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**A!** Aalto University

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**Abstract**

Although major maritime accidents occur rather rarely, they can produce severe consequences. Safety management aims at preventing such accidents. For monitoring and improving safety, safety management requires knowledge on the safety performance. Information on various variables which are potentially related to safety and a description of how the variables interact, or which types of patterns the interactions constitute, could be beneficial for increasing that knowledge. However, these patterns might not be apparent, as maritime traffic and its safety are complicated systems.

Utilizing Bayesian network modeling approach, this thesis explores potential patterns between variables related to maritime safety. The decision-makers can then exploit this information as a starting point for analyses of the mechanisms which have generated these patterns and of what the patterns tell about safety. The thesis models safety-performance patterns from different, complementing angles. The work begins with examining the feasibility of maritime accident causation pattern models for the exploration of safety performance. This includes analyzing an existing causal collision model and assessing the feasibility of accident and incident data for collision and grounding cause pattern learning. The focus then shifts to patterns present in multiple safety indicator data, before the analysis is extended to safety management patterns and safety management dependencies with safety performance.

While causal pattern modeling is found questionable, Port State Control inspections have potential to act as a valuable data source for safety performance information. However, the inspections in Finnish ports have resulted in few deficiencies and thus the data contains only weak patterns. It might be worth evaluating whether the Port State Control could be developed so that the inspections would produce data on more detailed safety performance differences between different ships. On the other hand, maritime safety management seems to be a rather tightly coupled system with several properly functioning subareas but inadequate as a whole.

Regarding the application of Bayesian networks for the pattern modeling problem, the thesis concludes that with their capability to express uncertain, rather complex dependencies and to combine data with expert knowledge, Bayesian networks offer an attractive tool for such a task. As the amount of collected and shared data is slowly increasing within the maritime community, the Bayesian network models can be easily updated with new information, and thus their quality and worth for decision-support could be improved.

**Tiivistelmä**

Merkittävät laivaonnettomuudet ovat melko harvinaisia, mutta niiden seuraukset voivat olla vakavia. Turvallisuusjohtamisella pyritään estämään tämänkaltaiset onnettomuudet. Jotta turvallisuusjohtaminen pystyy seuraamaan ja parantamaan turvallisuutta, se tarvitsee tietoa turvallisuuden tilasta. Tilan määrittämiseksi voisi olla hyödyllistä tarkastella turvallisuuteen liittyviä tekijöitä ja niiden välisiä riippuvuuksia. Ne eivät kuitenkaan välttämättä ole ilmeisiä, sillä merenkulku ja sen turvallisuus ovat monimutkaisia kokonaisuuksia.

Työssä tutkitaan meriturvallisuuteen liittyvien tekijöiden välisiä riippuvuuksia Bayes-verkkomallinnuksen keinoin. Päätöksentekijät voivat hyödyntää havaittuja riippuvuuksia analysoidessaan mahdollisia tekijöitä kytköksien taustalla ja sitä, mitä riippuvuudet kertovat turvallisuuden tilasta. Riippuvuuksia mallinnetaan useasta toisiaan täydentävästä näkökulmasta. Aluksi tutkitaan onnettomuuksien syysuhteisten riippuvuuksien mallintamista turvallisuuden tilan arvioinnissa kahdella eri lähestymistavalla. Sen jälkeen etsitään riippuvuuksia aineistosta, joka sisältää useita turvallisuutta mittaavia indikaattoreita. Lopuksi analyysi laajennetaan käsittämään turvallisuusjohtamisen sisäiset sekä sen ja turvallisuuden väliset riippuvuudet.

Työssä havaitaan, että syysuhteisten riippuvuuksien mallintaminen on kyseenalaista. Sen sijaan satamavaltiotarkastukset voisivat sopia tiedonlähteeksi turvallisuuden tilan arviointiin, mutta valitettavasti Suomen satamissa kerätty tarkastusaineisto sisältää vain vähän havaittuja puutteita. Siksi erityyppisten puutteiden väliset riippuvuudet eivät ole kovin selkeitä. Olisikin syytä tutkia, voiko tarkastuksia kehittää niin, että ne tuottaisivat tietoa nykyistä pienemmistä turvallisuuseroista alusten välillä. Toisaalta huomataan, että merenkulun turvallisuusjohtamisen osa-alueet ovat tiiviisti linkittyneitä. Useat niistä toimivat asianmukaisesti, mutta kokonaisuutena turvallisuusjohtaminen ei vielä ole riittävän hyvällä tasolla.

Tarkasteltaessa Bayes-verkkojen soveltuvuutta meriturvallisuuden mallinnukseen todetaan, että verkkojen kyky kuvata epävarmuutta sisältäviä, melko monimutkaisia vuorovaikutuksia ja yhdistää dataa asiantuntijatietämykseen tarjoaa houkuttelevan työkalun turvallisuusriippuvuuksien kuvaamiseen. Merenkulussa kerättävän ja jaettavan tiedon määrä on hitaasti kasvamassa, ja Bayes-verkkomalleja voidaan vaivatta päivittää, kun lisää aineistoa on saatavilla. Näin voidaan parantaa mallien laatua ja hyödyllisyyttä päätöksenteon tukena.

# Preface

My voyage in the sea of maritime safety has been long but oh so enlightening. I am thankful for my supervisor and instructor, professor Pentti Kujala, for recruiting me to his maritime safety research crew although I knew nothing about ships. After this journey, I might know a tiny bit more (although I still do not remember what is pitch, yaw, or heave). I especially appreciate how Pentti has patiently trusted me and given me freedom in figuring out my thesis waypoints, while still ensuring that the path would lead somewhere. My other instructor, professor Sakari Kuikka from the University of Helsinki has kindly shared his wisdom combined with that of his excellent research group. Thank you for this opportunity.

I am thankful to my co-authors for their contributions to the articles. I also want to express my gratitude to Professor Stein Haugen and Associate professor Marek J. Druzdzel who acted as the pre-examiners of this thesis and provided useful remarks. Special thanks to professor Petri Varsta for comments and valuable feedback on the thesis draft.

I have been privileged to work within two research teams. The one in Otaniemi has taught me many things about ships, science, and the wonders and horrors of academia. I am especially grateful for the peer support from the current and former colleagues, without forgetting the important help of the secretary team. Kotka Maritime Research Centre was my primary workplace for the most of the thesis years and is the nest of my other research team. From the talented people there I have learned about multidisciplinarity and project work, but also that a coffee break is not a

coffee break unless cougars are mentioned.

While I surely have enjoyed the sea of maritime safety, luckily it has not been my whole world. I have the best friends who can make me forget work when needed. All my people, both in Hamina and here, thank you. Additionally, when in desperate need for something completely different, I have had zumba (with Anssi), the tunes of punk rock, the town of Stars Hollow, and more recently, burlesque and the lovely Shangrilettes.

I am thankful for my parents Helena and Rauno for their support and for never telling me what I should do or what I could not do (or being so good at it that I still have not noticed), and for my brother, Jussi, for a being role model of how to succeed in studying without really trying. Finally, I want to thank Harri. I am grateful for your expertise with words and writing, but more importantly, for your patience when I was stressed and annoying, for the support and cheering up when I was down and wanted to give up, and for all the great times we have had so far. Thanks for being onboard the same ship with me. Purr.

Espoo, December 18, 2014,


Maria Hänninen

# Contents

# List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

**I** Hänninen, Maria and Kujala, Pentti. Influences of variables on ship collision probability in a Bayesian belief network model. *Reliability Engineering & System Safety*, 102, 27–40, June 2012.

**II** Hänninen, Maria; Sladojevic, Marina; Tirunagari, Santosh and Kujala, Pentti. Feasibility of collision and grounding data for probabilistic accident modeling. In *6th International Conference on Collision and Grounding of Ships and Offshore Structures, ICCGS*, Trondheim, Norway, 17–19 June 2013, 1–8, 2013.

**III** Hänninen, Maria and Kujala, Pentti. Bayesian network modeling of Port State Control inspection findings and ship accident involvement. *Expert Systems with Applications*, 41, 1632–1646, March 2014.

**IV** Hänninen, Maria; Valdez Banda, Osiris A. and Kujala, Pentti. Bayesian network model of maritime safety management. *Expert Systems with Applications*, 41, 7837–7846, December 2014.

**V** Hänninen, Maria. Bayesian networks for maritime traffic accident prevention: Benefits and challenges. *Accident Analysis & Prevention*, 73, 305–312, December 2014.

# Author's Contribution

**Publication I: "Influences of variables on ship collision probability in a Bayesian belief network model"**

Kujala suggested the idea to the manuscript and gave valuable comments and suggestions. The author selected the methods, carried out the analyses, and was the main contributor to the manuscript.

**Publication II: "Feasibility of collision and grounding data for probabilistic accident modeling"**

The author developed the idea, carried out the case study analyses, and was the main contributor to the manuscript. Sladojevic and Tirunagari contributed to the manuscript. Kujala provided valuable comments and suggestions.

**Publication III: "Bayesian network modeling of Port State Control inspection findings and ship accident involvement"**

The author developed the idea, carried out the analyses and was the main contributor to the manuscript. Kujala provided valuable comments and suggestions.

**Publication IV: "Bayesian network model of maritime safety management"**

The author presented the idea and the methodology to construct the safety management model parameters. Further, the author constructed the main

model, carried out the analyses with the model, and was the main contributor to the manuscript. Valdez Banda defined the safety management variables, established their links, conducted the expert elicitations, and contributed to the manuscript. Kujala provided valuable comments and suggestions.

**Publication V: "Bayesian networks for maritime traffic accident prevention: Benefits and challenges"**

The author was the sole contributor to the manuscript.

# Original Features

This thesis focuses on exploring potential dependency patterns between different types of variables all related to the safety performance in the maritime traffic. The patterns are probabilistic and modeled with Bayesian networks. The following features of this thesis are believed to be original:

1. Conducting a detailed analysis on a causation probability model, studying the feasibility of available maritime accident cause data for learning patterns between causes and finding that causal collision and grounding pattern modelling is problematic and questionable (**PI**, **PII**, **PV**)

2. Constructing a Bayesian network model for capturing patterns between different types of deficiencies detected in Port State Control inspections and discovering that the Finnish inspection data contains weak patterns (**PIII**)

3. Analyzing patterns between the Port State Control inspection findings, accident involvement, and incidents and violations reported by the Vessel Traffic Service; recognizing that the most informative deficiency-related information for a ship's accident involvement is the number deficiencies related to structural conditions (**PIII**)

4. Modeling ship safety performance as a hidden Bayesian network variable and estimating its state with safety indicators (**PIII**, **PIV**)

5. Utilizing current norms and standards in establishing a model for describing patterns within maritime safety management (**PIV**)

6. Applying Bayesian networks as the modeling technique to describe and analyze safety management; revealing that the overall safety management quality in Finnish waters has room for improvement,

and that the strongest safety-management related signal for adequate overall safety management is that of having a good IT system for safety management purposes (**PIV**)

7. Linking a maritime safety management Bayesian network to Port State Control inspection findings, accident involvement, and incidents and violations reported by the Vessel Traffic Service; finding that if no deficiencies have been discovered during a Port State Control inspection, the adequacy of the safety management is almost twice as probable as without knowledge on the inspection history (**PIV**)

8. Concluding that the exploration of maritime safety-performance patterns suffers for example from incomplete understanding of safety, lack of data and problems related to expert judgment; arguing that Bayesian networks with their capability to express uncertain, rather complex dependencies and to combine data and expert knowledge offer an attractive tool for such an exploration task (**PV**)

# Abbreviations

**AIC**  Akaike information criterion

**BIC**  Bayesian information criterion

**BN**  Bayesian network

**DAG**  directed acyclic graph

**EM**  expectation-maximization

**ISM**  International Safety Management

**NPC**  Necessary Path Condition

**PSC**  Port State Control

**VTS**  vessel traffic service

# Special Terms

**accident occurrence model** Describes the dependencies between certain variables and whether an accident occurs or not

**accident model** Describes mechanisms (such as accident causes, consequences, or circumstances) within accident(s)

**causation probability** A concept related to the Fujii-Macduff-Pedersen approach to ship-ship collision and grounding frequency estimation (Fujii et al., 1974; MacDuff, 1974; Pedersen, 1995), which describes the probability that, given a collision or grounding candidate situation, the ship(s) will fail to avoid the collision or grounding

**collision candidate** A concept related to the Fujii-Macduff-Pedersen approach to ship-ship collision frequency estimation (Fujii et al., 1974; MacDuff, 1974; Pedersen, 1995), which describes whether two ships are on a collision course

**empty graph** A Bayesian network model with no arcs between the model variables; a model of independent variables

**overall safety management level** A Bayesian network variable in Publication IV which is 'inadequate' when one or more maritime safety management subareas are 'poor' and 'adequate' when all subareas are at least on an average level

**parent node** Given two Bayesian network variables $X$ and $Y$ and an arc $X \rightarrow Y$, $X$ is called the parent node of $Y$ and $Y$ the child of $X$

**pattern** An interesting regularity amongst a set of variables

**safety state**  A hidden variable which represents the ship's unobservable safety perfomance in models of Publication III. In Publication IV, the same variable is entitled 'Safety'

**safety indicator**  A qualitative or quantitative measure which seeks to produce information on the safety performance of a system, adapted from (Reiman & Pietikäinen, 2012)

**safety performance**  A directly unobservable system property which reflects in which ways and to what extent the system is safe

**safety management**  A subarea of organizational management where the aim is to develop, plan, realize and follow operations for preventing accidents and minimizing risks related to the safety of people, environment or property

**structure learning algorithm**  An algorithm for learning the arcs between the Bayesian network model variables from data

**symmetrical uncertainty coefficient**  A measure of how informative two variables $X$ and $Y$ are for each other, introduced by Theil (1970); it is a weighted average of how large a proportion of the entropy of $X$ can be decreased with observing $Y$, given the opposite roles of $X$ and $Y$

# 1. Introduction

## 1.1 Background and motivation

Shipping is one of the main modes of transport in the world. Maritime transportation is especially important for Finland; in 2013, 78% of Finland's import and 89% of its export trade was transported with ships (Finnish Customs, 2014).

Although major maritime accidents occur rather rarely, they can produce severe and expensive consequences (Hartman et al., 1991; Helle et al., 2011; Montewka et al., 2014, 2013). Safety management aims at preventing such accidents. It plans operations for ensuring the safety of people, environment or property and then implements these actions while continuously monitoring and developing them further. While the term *safety* has several definitions, this thesis adopts the view of Besnard & Hollnagel (2014): "safety is the system property that is necessary and sufficient to ensure that the number of events that could be harmful to workers, the public, or the environment is acceptably low."

The aforementioned definition implies that safety is an abstract and vague concept and thus cannot be directly observed. Yet, for monitoring and improving safety, safety management requires some kind of knowledge on the system's safety performance, that is, in which ways and to what extent the system is safe. Information on various features or variables which are potentially related to safety and a description of how these variables interact, or which types of patterns the interactions constitute, could be beneficial for increasing that knowledge. However, these safety variable patterns might not be apparent, as getting a ship safely from her departure port to the destination includes either direct or indirect interaction with several elements including technical, environmental, individual,

organizational, economic, regulatory and political factors. Whereas these factors might already form complicated systems by themselves, they further interact in complex, uncertain and partly uncontrollable ways.

The theoretical models of accident causation within a complex sociotechnical system such as ship operation differ in their views on how accidents occur (e.g. Dekker, 2002; Heinrich, 1931; Hollnagel, 1998, 2009; Leveson, 2004; Perrow, 1984; Rasmussen, 1997; Reason, 1990); for summaries, see (Lundberg et al., 2009; Qureshi, 2007). Whereas the earliest accident models presented accident causation as a linear chain of events with an underlying root cause, the most recently introduced and arguably currently dominating (Underwood & Waterson, 2013) systemic accident models maintain that describing accident cause-effect relationships in a complex socio-technical system is not advisable (Dekker, 2011; Hollnagel, 2009; Leveson, 2011).

Instead of examining safety through controversial cause-effect chains and their likelihoods, safety indicators can be utilized in assessing safety performance. A safety indicator is an observable variable, which is considered to somehow measure the directly unobservable safety performance of the system (e.g. Øien et al., 2011). An indicator can be either quantitative or qualitative (Reiman & Pietikäinen, 2012); for example, a recording of the number of certain occurred events or a qualitative result from a safety survey can serve as an indicator. By collecting data on indicators, the current safety performance and the effects of improvements can be monitored. However, as its name suggests, an indicator is always merely indicatory of the intrinsic safety performance (Mearns, 2009; Reiman & Pietikäinen, 2012). Furthermore, a single indicator might not provide useful information until considered together with other safety indicators (Bailey & Hewson, 2004; IAEA, 2000); information on the system's safety performance then arises from the patterns between several safety indicators.

## 1.2   State of the art

An ultimate indicator of poor maritime safety performance is that of having an accident. In the Baltic Sea, accidents have mainly been groundings and ship-ship collisions (Helsinki Commission, 2012; Kujala et al., 2009). Patterns within maritime accidents have been modeled for example by Antao et al. (2009), Kokotos & Linardatos (2011), Le Blanc &

Rucks (1996), Le Blanc et al. (2001), Grech et al. (2002), Tzannatos & Kokotos (2009), Hashemi et al. (1995), and Kelangath et al. (2011). While these studies have provided dependency descriptions of variables related to weather, location and ship particulars, for example, they have not presented any patterns between several causes of an accident.

Regardless of the included model variables, the problem with any accident model is that it does not answer whether the patterns are present in accidents only or if they exist in safe operation as well. The underlying mechanisms producing these patterns may have been considered contributory to accidents in hindsight, although in reality they were also present in normal operations (Reiman & Rollenhagen, 2011). Thus, an accident model cannot be used for distinguishing ships by their safety performance; it does not serve as a basis for evaluating how indicative the model variables and their interdependencies are for safety performance assessment.

Maritime accident occurrence models can be seen as safety performance estimator models, where the safety performance is indicated by the estimation of how likely the ship is estimated to have an accident. The models estimating accident occurrences can be divided into two types: deductive and inductive models, in other words, theory-based and data-based models. Whereas the deductive or theory-based models attempt to describe the ship movements and encounter situations in a certain sea area and to estimate how probably they result in an accident, the inductive or data-based models utilize past accident and other variable data and predict the accident probability based on other variables selected.

Maritime traffic risk assessments typically apply deductive modeling (Li et al., 2012). More specifically, the most common approach for estimating how likely it is that the ships will collide or run aground is to use two concepts referred to as the number of collision candidates and causation probability (see Fujii et al., 1974; Goerlandt & Kujala, 2011; MacDuff, 1974; Montewka et al., 2010; Pedersen, 1995). The collision or grounding probability (or in this case, rate) equals the product of the aforementioned quantities. In brief, the number of collision candidates describes how frequently the ships are navigating in the considered area in such a way that it is geometrically possible for them to meet; it thus depends on ship traffic properties such as the number of ships, their routes, speeds, and sizes. Furthermore, blind navigation assumption is used; the concept describes the number of accidents, if the ships are assumed to make no

evasive maneuvers but just continue navigating with their current speed and heading until they hit the other ship (or shoal).

The factors which are affecting whether an accident actually occurs in an encounter, that is, whether the ship(s) will not make successful evasive maneuvers, are then influencing through the causation probability. The causation probability, especially in the beginning, was an estimated constant based on the difference in the number of collision candidates and statistics-based accident frequency (Fujii et al., 1974; MacDuff, 1974; Montewka et al., 2012), later on it has been derived with a model, typically a fault tree (Asami & Kaneko, 2013; Fowler & Sørgård, 2000; Pedersen, 1995; Rosqvist et al., 2002) or a Bayesian network (Det Norske Veritas, 2003; Friis-Hansen & Simonsen, 2002; Hänninen et al., 2014; Rambøll, 2006). These models have been causal descriptions of how several factors have been assumed to affect the causation probability, and they have been mainly based on expert knowledge.

While previous studies have compared the resulting causation probability value to other published values, but the causation probability models' validity has not been explicitly addressed. Further, as was already mentioned, the most recent theoretical accident models do not support causal modeling. Moreover, Goerlandt & Kujala (2014) recently criticized the validity of the approach of estimating the maritime impact accident occurrence probability with the collision candidate-causation probability approach.

The inductive-based accident occurrence estimation statistically links past accident probability to one or more explanatory variables without attempting to mimic the actual cause-effect mechanisms leading to the accident. In the literature, the maritime accident probability and its dependence on factors such as ship age, size, type, flag, classification society membership and number of Port State Control (PSC) inspections has been predicted with logistic regression models (Knapp & Franses, 2007a; Li et al., 2014) and neural networks (Soma, 2004). Regression models have also been applied to statistical linking of accident probability and organizational aspects such as safety climate (Lu & Tsai, 2008) and to the level of performance on the objectives for the three safety-related decision contexts (Merrick & Grabowski, 2014). In addition to accident probability estimation, logistic regression has been utilized in predicting other safety indicators such as PSC detention probability (Knapp & Franses, 2007b) and certain PSC deficiency type probability (Mejia Jr et al., 2010) based

on selected ship properties such as age and flag. Cariou & Mejia Jr. (2008), Soma (2004) and Grabowski et al. (2010) have also carried out prediction of safety indicators other than the accident occurrence probability.

As all these models target at predicting accident occurrence probability or some other safety indicator, they are optimized for reaching that target at the expense of describing the interdependencies between the other variables as validly as possible. Thus this type of a predictive model might not necessarily capture all patterns between the variables and might provide less information on the overall system safety performance features. In case the safety management would benefit from information on these other dependencies between the variables, a descriptive model which has no single outcome variable but focuses on identifying overall or local relationships among the variables might be more suitable than a predictive model.

One descriptive modeling technique, which can also be utilized for prediction, is Bayesian networks (BNs) (Lauritzen & Spiegelhalter, 1988; Pearl, 1988). BNs are capable of presenting relatively complex, not necessarily causal dependencies and they can cope with uncertainty and unobservable variables. In addition, BNs are able to combine learning from data with expert knowledge. In brief, a BN graphically represents the joint probability distribution of a set of variables (Darwiche, 2009). The structure of a BN model is a directed acyclic graph (DAG). The nodes of the DAG represent the model variables and the arcs between the nodes describe the direct variable dependencies. 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 potential parent node nodes, i.e., the variables with an arc to the variable in question. The BN structure can be based on expert knowledge, or it can be learned from data. The structure learning algorithms can be roughly divided into two groups: the constraint-based approaches and the 'score-and-search' approaches (Daly et al., 2011). Whereas the constraint-based methods check conditional independencies between the model variables present in the data and build a structure correspondingly, the latter type algorithms return a model which maximizes a chosen score metric from a set of BN candidates. As with the structure, the network probabilities can be extracted from experts or from data.

Although BNs have been utilized in describing causal dependencies in maritime accident occurrence (Det Norske Veritas, 2003; Friis-Hansen &

Simonsen, 2002; Hänninen et al., 2014; Martins & Maturana, 2013; Ram-
bøll, 2006; Trucco et al., 2008), the models have been deductive. The
causal dependencies encoded within the models have been based on ex-
pert knowledge or a theoretical human reliability framework. These mod-
els have included several variables which are not directly observable and
rather vague, such as 'competence' (Det Norske Veritas, 2003; Hänninen
et al., 2014), 'human failure' (Rambøll, 2006) and 'quality of life' (Martins
& Maturana, 2013). To the author's knowledge, BN application to in-
ductive modeling of any potential connections between multiple maritime
safety indicators, such as PSC findings and vessel traffic service (VTS)
reportings, by learning the model from indicator data remain absent.

   As a part of evaluating safety performance, safety management requires
also that the safety management procedures themselves are assessed.
Maritime safety management is a broad topic and consists of several sub-
areas, as the safety management standards and guidelines (International
Maritime Organization, 2013; OCIMF, 2008) indicate. A model describing
these subareas, how they interact, and how strongly safety management
and safety performance are linked could provide useful information about
the patterns within the safety management. While safety culture subarea
connections have been described in the literature (Ek et al., 2014; Håvold,
2005; Oltedal & McArthur, 2011), detailed models of patterns between
the maritime safety management subareas and further between safety
management and maritime safety performance have not been published
yet.

   Table 1.1 summarizes the research gaps in the literature regarding the
models of patterns within accidents, accident occurrence, other safety in-
dicators, and safety management. It can be concluded that the causa-
tion patterns presented in the probability estimation of studies collision
and grounding occurrence need further validation. On the other hand,
detailed patterns between several maritime safety indicators and safety
management and those within the maritime safety management have not
yet been explored.

## 1.3   Objectives and the scope of the work

This thesis aims at identifying potential patterns between variables re-
lated to the safety performance in the maritime traffic using BNs. More
specifically, the thesis seeks to find information on interdependencies be-

**Table 1.1.** Limitations of the existing maritime safety performance models addressed in this thesis

| Safety performance pattern models | | | |
|---|---|---|---|
| Accidents and accident occurrence | | Other safety performance indicators | Safety management quality |
| Theory-based models | Data-based models | | |
| • Controversial theoretical background <br> • Unmeasurable or abstract variables <br> • Not fully validated | • Accident occurrence models targeted at predicting the accident rate, not at presenting all associations <br> • Accident models not describing patterns between accident causes | • Models not describing patterns between several safety indicators <br> • No BN applications | • Models not describing patterns within maritime safety management <br> • No BN applications |

tween several safety indicators which are reflecting different and potentially supporting views to safety performance. The decision-makers can then utilize this information as a starting point for further analyses of the mechanisms which have generated these patterns. Moreover, they can ponder what the patterns tell about safety and how this information could be used in safety management. The term *pattern* refers to an interesting regularity amongst a certain set of variables. These regularities can stem from direct causal dependencies between the variables, from common hidden causes, or from statistical associations due to any reason; the thesis does not assign any restriction or interpretation to the variable dependencies. Furthermore, the patterns are allowed to be uncertain, whether due to variability or lack of knowledge, and the uncertainties are expressed with probabilities. The purpose is to potentially reveal patterns which are not necessarily visible when looking at the raw data or in the experts' beliefs on local variable dependencies. The term *potential* in the title reflects both the probabilistic nature of the patterns and the fact that the models feature safety indicators and thus the discovered patterns can also be considered indicatory of the safety performance itself.

Figure 1.1 demonstrates the thesis' aim through a simplified example. Figure 1.1(a) presents an imaginary data on how ships with and without accidents and incidents are distributed over two other discrete safety indicator variables. Figure 1.1(b) then shows a BN learned from the data by using the Necessary Path Condition (NPC) structure learning algorithm. Figures 1.1(c)–1.1(f) demonstrate some patterns captured within

the model. For example, one could discover simple patterns between these four variables, patterns such as a positive correlation between indicators A and B (Figures 1.1(c), 1.1(d)) and a larger accident involvement probability in cases where the VTS has reported a violation or incident for the ship than in cases where it has not done so (Figures 1.1(e), 1.1(f)). In the thesis however, the examined patterns are between a larger number of variables than in this demonstrative example.

The included articles model maritime safety performance patterns from different, complementing angles. The presented models thus all describe safety performance but have different variables, data sources, and interpretations for the encoded dependencies (see Figure 1.2. The set of views to safety performance the articles jointly form cannot be claimed to provide a complete representation of the maritime safety performance features, but the set covers both the traditional view to safety, that is, through accidents, and views to safety features within ships of all safety performance levels, within their normal operations. Furthermore, the thesis utilizes all relevant statistical data available at the time of conducting the research, augmented with expert views.

The work begins with examining the usability and credibility of maritime accident causation pattern models for safety performance exploration by analyzing a state of the art collision causal model (Publication I) and assessing the feasibility of accident and incident data to collision and grounding cause pattern modeling (Publication II). It then shifts the focus to patterns present in multiple safety indicator data (Publication III). The set of safety indicators includes the number of deficiencies of various types detected in PSC inspection, ship's involvement in accidents, and whether or not VTS has reported the ship conducting a violation or having an incident. Next, the analysis is extended to safety management patterns and safety management dependencies with safety performance (Publication IV). The last article (Publication V) presents a discussion on some of the challenges of maritime safety performance pattern modeling and applying BNs to the problem. The research questions of the articles are as follows:

**PI** What types of patterns are present in an expert-based ship-ship collision causation model? How valid are the patterns and the model?

**PII** Are maritime accident and incident data suitable sources for collision and grounding cause modeling? Can a Bayesian network pre-

(a)



(b)



(c)



(d)



(e)



(f)
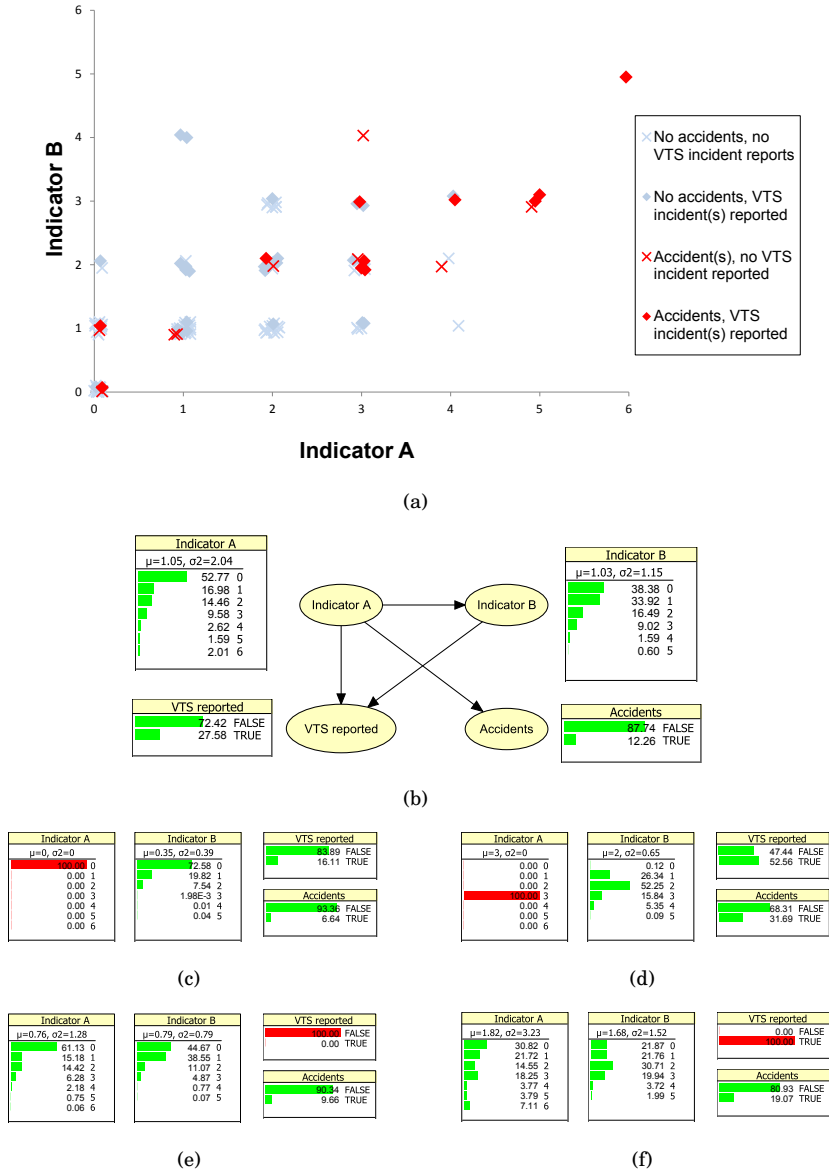
**Figure 1.1.** The aim of the thesis demonstrated with a simple example. (a) An example of imaginary data on how ships with and without accidents and incidents are distributed over two other discrete safety indicator variables (some noise has been added in order to show overlapping data points). (b) A BN learned from the data of (a); the green bars and the numbers in front of the variable state names describe the state probabilities as percentages. (c)–(f) Some example variable dependency patterns captured by the model. A red column denotes that the variable has been observed to be in this state

**Figure 1.2.** The aim of the thesis: discovering potential patterns in several maritime-safety related data and expert knowledge, the patterns then reflecting safety performance from different angles

dicting accident cause patterns be built from categorical cause data?

**PIII** What kind of and how strong potential dependencies can be found between PSC deficiencies, ship accidents and incidents? What are the most informative variables for a ship's accident involvement?
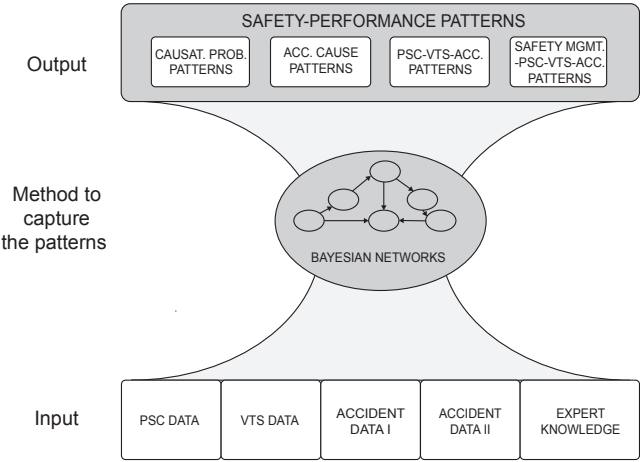
**PIV** What are the patterns related to the quality of maritime safety management and its subareas? How is safety management indicated by accidents, incidents and safety deficiencies?

**PV** What are the challenges in maritime safety performance pattern exploration and how can Bayesian networks be utilized in the pattern modeling?

Table 1.2 summarizes the subpopulations of maritime traffic addressed in Publications I–IV and the types of patterns the papers explore within these subpopulations. Lastly, Table 1.2 mentions whether the models are based on expert knowledge, learned from data, or both.

## 1.4 Limitations

Maritime safety is a very broad topic with no clear bounds on what it consists of. This thesis focuses only on selected aspects of it: an expert-based representation of collision occurrence mechanisms, reported collision and

**Table 1.2.** Details about the BN models in Publications I–IV: The subpopulation of maritime traffic the model describes, the modeled patterns and the model construction approach

| Publication | Subpopulation | Patterns | Expert-based or learned from data |
|---|---|---|---|
| I | Collision candidates | Causal mechanisms affecting collision causation probability | E |
| II | Collided or grounded ships | Dependencies between reported causes | ML |
| III | PSC-inspected ships | Dependencies between PSC deficiencies, VTS violations and incidents, and accident occurrence | ML |
| IV | PSC-inspected ships | Dependencies between the safety management subareas, PSC deficiencies, VTS violations and incidents, and accident occurrence | E & ML |

*PSC = Port State Control, VTS = vessel traffic service, E = expert knowledge, ML = machine learning (learned from data)*

grounding causes, PSC inspections, the number of past accidents and reports by VTS, and safety management in shipping. The focus is on safety performance pattern modeling, and thus aspects such as accident consequences or occupational safety are not included. As was already mentioned, the purpose is to discover and present patterns between safety indicators, and any further interpretation of these patterns and how the information could be utilized in practical safety management and decision making is not discussed.

The data and some of the expert knowledge which have been utilized are reflecting the situation in the Gulf of Finland or the maritime traffic within the Finnish waters. For example, PSC data contains only Finnish inspections, as previous research (Knapp & Franses, 2007b) suggests that the port state might influence the results. Furthermore, the accident, PSC and VTS history used as an input data are covering rather short a time period (seven, two, and five years, respectively) due to the fact that the safety regulations and inspection practices evolve over time and have a potential effects, which the models are not able to capture, on the data. While there is no reason the models could not be applied to other sea areas as well, especially after perhaps updating some model parameters, the area and time specificity should be kept in mind when examining the results.

When capturing the safety performance patterns, BNs are applied as the modeling methodology. While BNs have many features, which make them attractive for maritime safety pattern modeling, as described in Publication V, it is only one approach to modeling the problem.

# 2. Identification of Patterns within Different Maritime Safety Performance Manifestations

## 2.1 Causal patterns in ship collisions and groundings

The first maritime safety indicator under study is maritime accidents. The thesis explores patterns within the accident causation and evaluates whether cause pattern modeling provides useful and credible information on maritime safety performance. This is conducted for two cases: when the dependencies between model variables are causal and are based on expert knowledge (Publication I), and when the variable associations are purely statistical and learned directly from data (Publication II).

Publication I focuses on the causal relationships within a causation probability model largely derived from literature (Det Norske Veritas, 2003, 2006). The model can be considered as the state of the art in causal ship collision occurrence modeling, as it is the most complicated representation of a phenomenon judged as complex in reality and as it considers also some organizational aspects and includes uncertainty of the dependencies in the form of probabilities. In the light of accident theories, the analyzed model can be seen as epidemiological: it is relatively complex and does not present one root cause, yet its dependencies can be interpreted as causal.

Publication I studies the variable dependencies within the model in detail. It examines how much the observations of the other model variables affect the causation probability, how sensitive the causation probability is to changes in the probability distributions of the other variables and how much uncertainty in the collision occurrence can be removed by observing the model variables.

It is found that while some of the features of the model variable dependencies seem plausible when compared to those in the literature, most

of them are difficult to validate due to the abstract and unmeasurable nature of the variables. More importantly, the validity of the whole causation probability concept and its application to safety performance estimation can be questioned, as it is a rather vague and artificial entity. It is conditional on "being a collision candidate, given a blind navigation assumption" (see Section 1.2), which is a fictional factor (Goerlandt & Kujala, 2014). It thus seems questionable to describe causal patterns behind a concept which has been defined based on a fictional property and is not based on any established theory. Although the uncertainty in the causal links, expressed as probabilities, could be considered a systemic property of the model, the model aims at describing causal mechanisms leading to collision. Consequently, the model is not in line with the latest accident theories for complex systems (see Section 1). Thus it is concluded that, although the model might provide some information for preventive maritime safety management, it should at least be accompanied by other views to maritime safety performance.

Publication II addresses the feasibility of maritime traffic accident and incident data for pattern modeling of collision and grounding accidents, especially between their causal factors. Furthermore, it conducts a case study of learning a BN model from accident cause data. The purpose of this case study is to evaluate whether the data provides adequate information for such predictive collision and grounding cause pattern modeling.

The feasibility is evaluated based on how well the BN model matches to unseen accident cases and how it performs in classification of the accidents into collision and grounding cases based on the accident cause(s). The structure of the model is learned with the NPC algorithm (Steck, 2001). This constraint-based algorithm is chosen because of the interest in the model variable dependencies and independencies. The model parameters are learned with the expectation-maximization (EM) algorithm (Dempster et al., 1977). The predictive quality is checked by dividing the accident data into separate training and test sets and examining how well the training-set-based model performs with the test data compared to the so-called empty graph model with no dependencies between its variables. In addition, the model's ability to correctly classify test set cases as collisions is evaluated.

The results from the case study of Publication II suggest that the accident dataset does not contain enough information for this type of accident

cause dependency modeling. This is mainly due to the fact that in less than 15% of the accident cases more than one cause had been reported. Although the NPC algorithm learns a BN consisting of the accident type and nine causes, the dependencies in the network are rather weak: the log-likelihood score of the model is only slightly better than the one of the empty graph. Moreover, Akaike information criterion (AIC) and Bayesian information criterion (BIC) scores, which reward for a good model fit but penalize a model for its complexity, to some extent prefer the empty graph. Publication II concludes that, at this moment, an accident database which would allow the probabilistic modeling of dependencies between several accident causes is not yet available for the maritime safety research community. On the other hand, if the purpose were to classify accidents into collisions and groundings based on their causes, other modeling approach than BNs might be more feasible. This is further discussed in Publication V.

## 2.2   Port State Control inspection results as safety indicators

Given the aforementioned problems in accident cause pattern modeling, the thesis shifts its focus to other safety indicator patterns. Publication III explores potential non-causal patterns in PSC inspection data. BNs are used in linking different types of PSC deficiencies to each other and to two other maritime safety indicators: ship's accident history in the Helsinki commission (HELCOM) accident database, and the incident and violation reports written by the Gulf of Finland VTS.

Two versions of BNs are learned from the data:   a) networks with the indicator variables contained in the data and b) networks with the indicator variables and an additional hidden variable *safety state*. In the latter versions, *safety state* is an abstract variable which represents the whole system of a ship in operation, which might affect safety performance, excluding the features that are already present in the model as separate variables. Constructing BNs with such a hidden variable is motivated by the idea of taking into account that accidents, incidents and deficiencies had not been directly influencing each other in reality but are manifestations of the ship's directly unobservable safety performance. Also, *safety state* can serve as a point at which other safety-related variables or Bayesian networks learned from additional data sources could logically be linked into the PSC findings and accident involvement variables. The
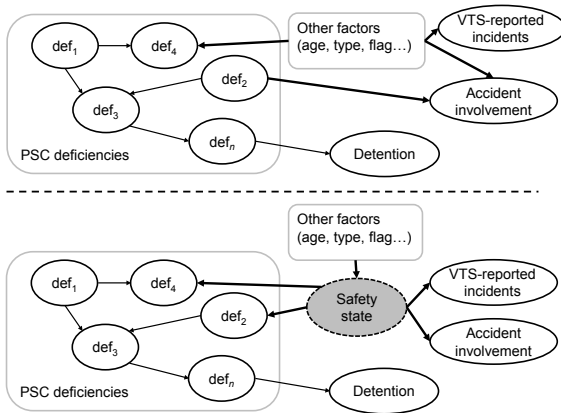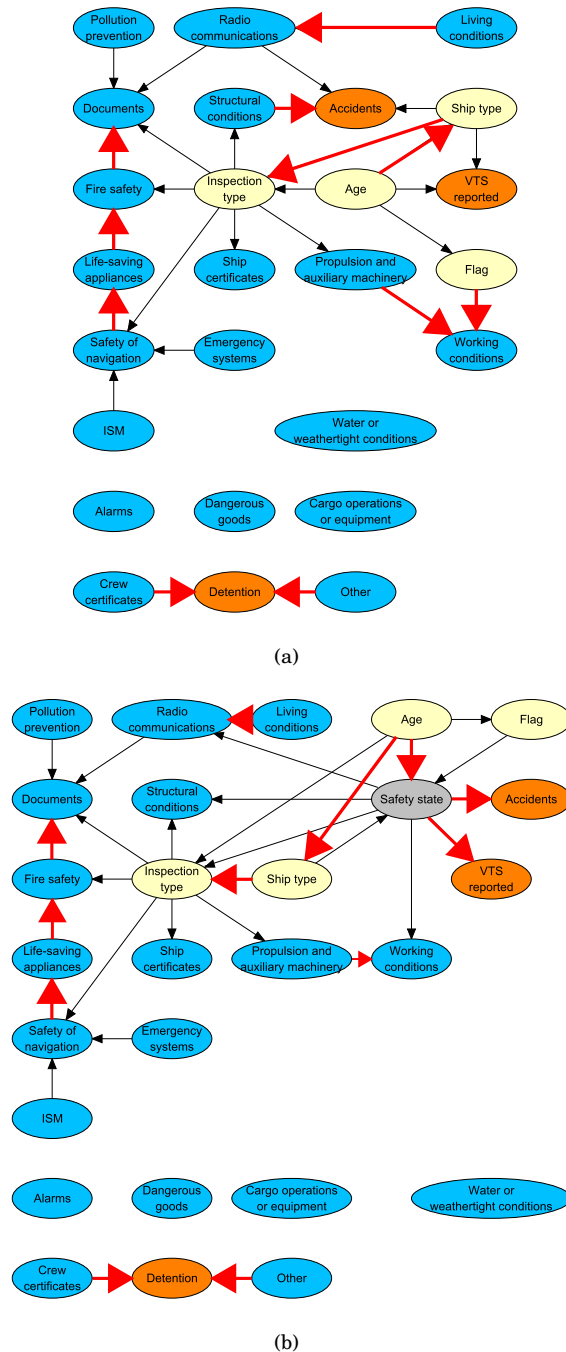
**Figure 2.1.** An illustration of where the hidden variable *Safety state* is added in models learned from data in Publication III

location of the safety state variable is demonstrated in Figure 2.1: it is inserted between the parent and/or child variables of *accident involvement* and *VTS reported* and between *flag*, *age* and *ship type* and their children.

The structures of the models without the hidden variable are determined using both a constraint-based and a score-and-search based BN structure learning algorithm. The utilization of two alternative learning methods instead of several or only one is justified by not aiming at a comparison of several different algorithms but still wanting to demonstrate potential differences in the resulting models due to the selected structure learning approach. For the contraint-based approach, NPC (Steck, 2001) algorithm, which the Hugin Expert software manual recommends over the other constraint-based alternative in the software, PC, is selected. The chosen score-based method is employing repeated hill-climbing with random restarts and the so-called BDeu metric as a score (Heckerman, 1998). The network parameters of all the models are learned with EM learning (Dempster et al., 1977). Because *safety state* is unobservable, the number of its alternative levels is unknown. Thus separate models are constructed for two to five *safety state* levels. After learning the BN models, their performances are evaluated with 10-fold cross-validation. In addition to scoring the model fit based on the log-likelihood, model-complexity penalizing AIC scores are also calculated.

The comparison of the different model alternatives resulting from the choice of structure learning algorithm and *safety state* variable inclusion and formulation finds that the hill-climbing based model with five *safety*

(a)



(b)

**Figure 2.2.** The NPC-based model (a) without and (b) with a hidden two-state *safety state* variable constructed in Publication III. The variable dependencies with the symmetrical uncertainty coefficients higher than or equal to 5.0% are marked with larger, red arrows
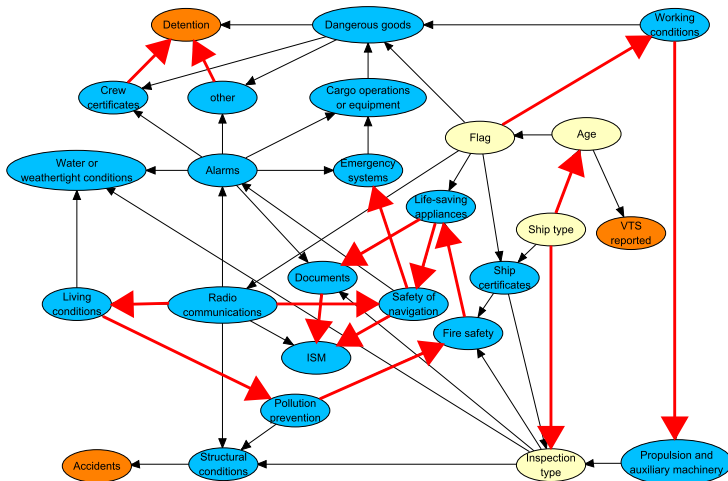
**Figure 2.3.** The hill-climbing based model without the hidden *safety state* variable constructed in Publication III. The variable dependencies with the symmetrical uncertainty coefficients higher than or equal to 5.0% are marked with larger, red arrows

*state* levels fits best to the data. On the other hand, the cross-validation results suggest that the NPC-based model that does not include the *safety state* variable generalizes best to unseen data. However, no BN variant can be considered clearly superior to the others based on the model fit or its generalizability.

The result of the log-likelihood scores being higher for the BN models than for an empty graph suggest that the indicator data indeed contains patterns of variable dependencies. The variables are connected to each other with 27–53 direct arcs, depending on the applied structure learning algorithm and the inclusion of the *safety state* variable. Moreover, the accident involvement is either directly or indirectly dependent on 58–100% of the model variables and reported by the VTS on 52–100% of the variables.

The strength of the variable dependencies is evaluated by examining how much uncertainty in one variable could be reduced by knowing the state of another variable. This can be considered as a measure of how informative two variables are to each other. While in Publication III this is evaluated by calculating uncertainty coefficients, Figures 2.2–2.3 present the informativeness with their symmetrical variants known as symmetrical uncertainty coefficients (Press et al., 1992). Figures 2.2(a)–2.3 highlight the variable dependencies with symmetrical uncertainty coefficients over 5.0% in the models without the *safety state* variable and in the NPC-

based model with a two-state *safety state*. Most of the information sharing is between *crew certificates* and *detention*, *radio communications* and *living conditions*, *safety of navigation* and *life-saving appliances*, and *life-saving appliances* and *fire safety*. Furthermore, almost 30% of the uncertainty, on average, is reduced from *safety state* or *VTS reported* if the other is known. However, the patterns cannot be considered very strong, as the uncertainty reductions are generally rather small (uncertainty coefficients are less than 5% for 95–97% of the variable pairs in the aforementioned models) and the AIC scores are higher for the empty graph than for any BN model, given the cross-validation test set. This seems plausible due to the limited amount of data, but more importantly, due to the complexity of the system. Nevertheless, information on these rather weak patterns present in the data might still be valuable for safety management. When accompanied with background information on how the PSC inspections have actually yielded the observed numbers of deficiencies, the presented models provide support to analyzing what might be the underlying reasons for the weak but yet existing patterns in the data the models are reflecting and how these are related to the maritime safety.

When focusing on accident involvement, an inspected ship with no accidents is more likely a tanker or "other" ship, and less likely a passenger ship than the one which has been involved in accidents. Moreover, depending on which model is applied, the inspected ship has approximately 40–80% lower probability of containing deficiencies related to structural conditions, such as corroded or cracked ship hull, tanks or decks, inoperative steering gear, or insufficient stability information.

## 2.3 Addressing maritime safety performance through safety management patterns

While the PSC deficiency data utilized in Publication III can be considered to provide information on safety management through variables such as the numbers of the International Safety Management (ISM) Code and documents related deficiencies, it does not explicitly address the patterns within safety management itself, information which could be beneficial when self-evaluating the safety management actions. Publication IV considers safety performance from that aspect and presents a BN which models the maritime safety management subarea qualities and their dependency patterns. The safety management subareas are selected based on

content analyses of the ISM Code and two supplementary safety management descriptions: the Tanker Management Self-Assessment and a list of safety management components derived by a group of experts based on a safety management framework proposed by Grote (2012). To the author's knowledge, no maritime safety management model based on the established safety management norms or standards have been published before. The probability parameters for the safety management subareas are elicited from six maritime safety experts with diverse views on maritime safety. The experts provide individual assessments, and the variability due to potential expert differences is included in the model. The user of the model can then decide whether to examine the results based on a single expert's view or to use an expert combination.

In addition, Publication IV links the safety management to three maritime safety indicators: maritime traffic accident involvement, involvement in a violation or incident that has been reported by a VTS center and deficiencies discovered in PSC inspections. A separate BN is built containing the safety management subareas and their dependencies. It also features an output variable, *Overall safety management level*, which expresses whether the safety management in general is adequate, defined as all safety management subareas being at least on an average level. The safety management BN is then inserted as a submodel to another network which includes the safety indicators variables and a hidden *Safety* variable. *Safety* has the same interpretation as *safety state* in Publication III (see 2.2). *Overall safety management level* is assumed to directly influence the *Safety* variable, which is further linked to the safety indicator variables (Figure 2.4). The conditional probabilities for *Safety* and the three indicators are learned from data by using the assumption that accident involvement, reported by VTS and one or more PSC deficiencies is a certain indicator about the inadequacy of overall safety management level.

The resulting model suggests that the maritime safety management is a rather tightly coupled and complex system, where all subareas directly or indirectly influence each other. More specifically, five safety management subarea pairs where the subareas are most informative on each other when measured with the symmetric uncertainty coefficient are *Status of corrective actions* and *Accident and incident reporting and analysis*, *Status of preventive actions* and *Accident and incident reporting and analysis*, *Resources and personnel* and *Training*, *Maintenance* and *Ship operations*,
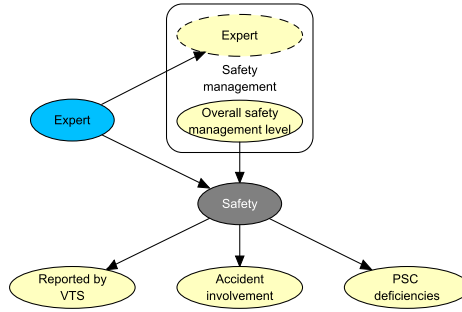
**Figure 2.4.** The structure of the main model of Publication IV, where the *Safety management* submodel, depicted with a rounded rectangle and containing maritime safety management subareas, is linked to the three safety indicators through the hidden *Safety* variable
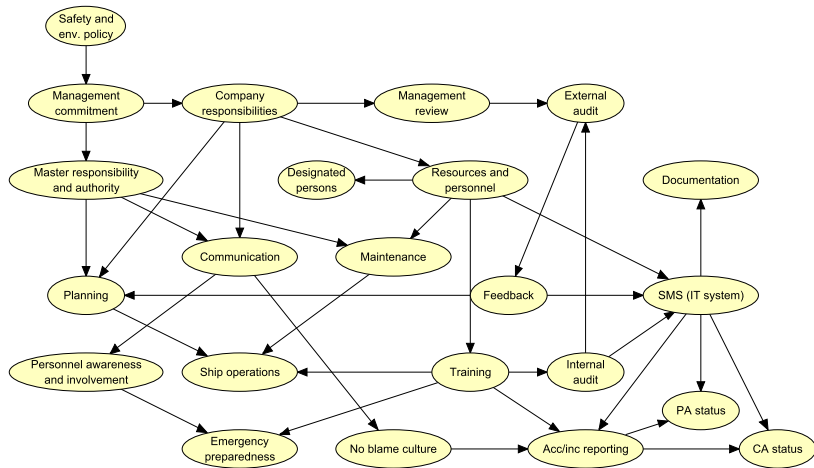


**Figure 2.5.** The dependencies between the safety management subareas in the BN submodel of Publication IV

and *No-blame culture* and *Communication*. On the other hand, a good IT system for the purposes of safety management and good level of resources and personnel are the strongest indicators of an adequate overall safety management level, whereas good safety and environmental protection policy indicates the least. This can be interpreted in a way that creating a good policy is not enough for effectively functioning safety management, and that a good IT system indicates that several other safety management subareas are also functioning properly.

When considering the associations between safety management and the three safety indicators, inadequate overall safety management level increases the probabilities of being involved in accidents and incidents and
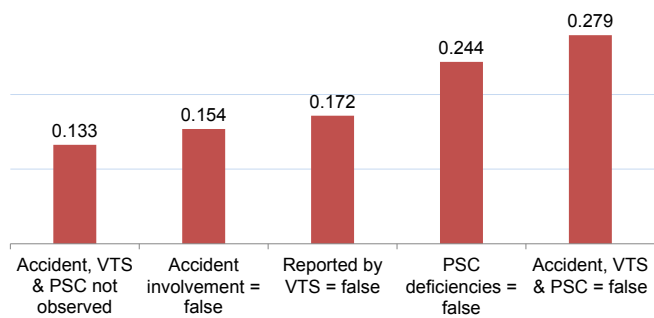
**Figure 2.6.** The probability of *Overall safety management level* being *adequate* when having no knowledge about accident, VTS incident, or PSC history; after knowing that the ship has not been involved in accidents; having not been reported by VTS to have incidents; having no PSC deficiencies; and having not had accidents, incidents or deficiencies (Publication IV) (In case there is knowledge about the ship having had deficiencies or been involved in an accident or incident, the *Overall safety management level* is inadequate)

of ship containing PSC deficiencies compared with when the overall safety management level is uncertain. If the connections are examined to the opposite direction, an adequate overall safety management level becomes more likely if the ship has had no deficiencies, no accidents or no reported incidents. Moreover, if the ship has had none of these three, the probability of adequate overall safety management level is over two times as high as when the indicators have not been observed, that is, when their true state is uncertain (Figure 2.6). Out of the three safety indicators, the most informative indicator of the adequacy of overall safety management level is whether a PSC inspection has discovered deficiencies or not.

Regarding the model validity, the proposed approach divides maritime safety management into connected subareas, which is a feature that is also present in well-established safety management system descriptions such as the ISM Code. Further, the safety management BN shares some characteristics with other nomologically adjacent models presented in the literature, such as the safety management model of Hale et al. (1997), the process industry maintenance safety model by Hale et al. (1998) and the safety culture description by Fernández-Muñiz et al. (2007). When asked about the validity of the model, experts find the structure appropriate and are satisfied with the resulting marginal distributions and some examples of how the distributions change after observing certain variables. The model thus seems to succeed in faithfully capturing the expert views. The results from the sensitivity analysis suggest that the model

is not very sensitive to changes in individual safety management subareas. On the other hand, the experts have dissimilar estimates for some of the subarea distributions, and thus the overall safety management adequacy is somewhat sensitive to which expert is selected. This also means that changing the weights of the experts from the current equal weighting affects the safety management level to some extent. Nevertheless, regardless of how the experts are weighted, the conclusion on the general quality of the safety management remains the same: the overall safety management level on vessels within Finnish waters is more likely inadequate than adequate.

## 2.4  Bayesian network utilization in pattern exploration

Given the pattern explorations described in the previous subsections, Publication V provides a synthesis of the problematic features of maritime safety performance modeling and of how such a modeling task can benefit from BN application. The detected main challenges are

- incomplete understanding of safety and accident occurrence in complex systems,

- scarce maritime safety performance data,

- problems with data quality,

- relying on expert judgment, and

- model validation.

On the other hand, several of the aforementioned challenges can be overcome, or at least taken into account, if the pattern modeling is conducted with BNs. BNs can, for example,

- model rather complex systems,

- cope with uncertainty,

- model non-causal dependencies,

- be utilized in a versatile manner,

- model dynamic systems, and

- extend to a decision problem model.

While BNs possess several attractive features, before deciding to construct a BN, one should consider whether it is worthwhile to apply quantitative modeling at all. In some cases, utilization of qualitative techniques might be more cost-effective. On the other hand, sometimes a model which estimates a single variable $Y_1$ based on $n$ other variables $\{Y_2, Y_3, ..., Y_{n+1}\}$ might be needed, and then a logistic regression model, for example, could be a better alternative. Thus, the applied method should always be selected based on what purpose the model is to serve, who will use it, and what type of data or background knowledge is available for its construction.

# 3. Conclusions

This thesis has explored and modeled patterns potentially present in data and expert views reflecting certain views of maritime safety performance. Identifying such patterns between several variables could be useful for increasing the knowledge of how the maritime traffic functions in regards to safety. The results can be utilized in evaluating the safety performance and safety features within maritime safety management and also in assessing the safety management system itself. The thesis has also discussed the challenges in maritime safety performance pattern modeling. While the thesis provides detailed information on several dependencies between two safety-performance related variables, the identification of these higher-level patterns and the exposure of certain obstacles to discovering patterns which are safety-informative are considered the main contributions of the work.

Regarding patterns in accident causes, the thesis concludes that the validity of causal accident modeling based on causation probability is questionable. If one wants to focus on accident causation patterns, maybe a more attractive approach might be to focus on statistical patterns within past accident cause data. However, at the moment such a database with rich accident cause content is not yet available. On the other hand, focusing on patterns in causes reported to accident databases does not eliminate the fact that the reported causes are someone's interpretations of the events, and thus they are conditional on the person's underlying views on accident mechanisms, which may not correspond to the state-of-the-art understanding on how accidents really occur. Also, such a model does not provide a means for safety performance estimation. For such a task, PSC inspections could provide a suitable input dataset, as they should cover ships with all safety performance levels. However, with the current inspection practices and interpretations of when a certain feature should be

reported as a safety deficiency, the patterns which can be learned from the Finnish PSC deficiency data seem to be rather weak: it is difficult to detect any patterns from a dataset consisting of mainly zeros, and learning BN models which would include rather apparent patterns such as in the imaginary example depicted in Figure 1.1 cannot be achieved. Nevertheless, given these challenges and the complexity and variability related to lack of safety and accidents, even weak patterns could be beneficial for gaining insight on certain safety (or safety-inspection-related) features, which might otherwise remain unnoticed. Also, it would be worth studying whether the Port State Control could be developed so that it would also serve as an information source for indicating more detailed safety performance differences between different ships. For example, it would be interesting to investigate whether the PSC inspections could also report positive findings such as various safety sufficiencies and abundancies. It would allow the gathering of more detailed data on "safe" ships, and the patterns related to their features could then be examined. This would follow the principles of the currently dominating systemic accident theories and recent safety management philosophy, which suggest that the safety of complex socio-technical systems should be investigated by focusing on "what goes right" instead of the lack of safety (Hollnagel, 2004, 2014).

The findings suggest that the modeling of maritime safety performance patterns is rather challenging, given the current understanding on accident occurrence and the quality and quantity of available statistical data. Luckily, the amount of data related to maritime safety is increasing, databases are being developed, and the idea of open data is becoming more popular. While this thesis found certain patterns, especially within the maritime safety management, combining multiple data sources could, in future, produce stronger safety-related patterns. On the other hand, collecting data on safety management subareas through various safety management indicators could improve the safety management BN and thus produce better decision-support for the self-assessment of safety management.

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# Errata

**Publication II**

- In Abstract, "The results indicate that the dataset does not contain enough information for the applied of modeling approach" should read "The results indicate that the dataset does not contain enough information for the applied modeling approach".

- In Section 3, "The marine traffic accident investigation reports of accidents from 1997 on and 10 older reports canbe downloaded from..." should read "The marine traffic accident investigation reports of accidents from 1997 on and 10 older reports can be downloaded from..."

- In Section 3, "Artana et al. (2005) developed and evaluated software utilizing text-mining for encountering maritimmarinee hazards as well as..." should read "Artana et al. (2005) developed and evaluated software utilizing text-mining for encountering maritime hazards as well as..."

- In Section 5.2, "Table 5 summarizes the data consististing of..." should read "Table 5 summarizes the data consisting of..."

**Publication III**

- In Section 2.2, "These links are substitude with..." should read "These links are substituted with..."

- In Section 3.3, "This Section focuses on the models with and with-

out a hidden variable which have the highest average AIC and log-likelihood scores in the cross-validation" should read "This Section focuses on the models with and without a hidden variable which have the highest average log-likelihood scores in the cross-validation".

An efficient maritime transportation system requires that the ships are operated safely. Safety management plans and implements actions which target at ensuring such safe operations. It then continuously monitors the safety and improves the actions when necessary. However, safety is an abstract concept which cannot be directly observed. Yet, safety management needs some kind of knowledge on the system's safety performance, that is, in which ways and to what extent the system is safe. This knowledge might not be gained unless one takes a look at several safety performance indicators at the same time.

This thesis aims at increasing knowledge on maritime safety performance by viewing it from different angles. It provides detailed analyses of various safety-related variable interactions and studies what kind of larger patterns these interactions produce. The decision-makers and safety managers can then use this pattern information as a starting point for analyzing the underlying maritime safety itself.

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