

The Effects of Safety Culture on Ship Collision Risk

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Abstract – The paper presents an approach to estimating the effects of safety culture on maritime accident risk expressed as the number of ship collisions in a sea area. The problem is approached probabilistically with a Bayesian belief network technique that combines qualitative and quantitative modeling. According to the preliminary results of the model, having poor safety culture onboard would increase the number of collisions by approximately 20 % compared with ships with an excellent safety culture. Although the model needs improvement and validation, it shows potential to serve as an aid for decision makers within maritime risk management.

Keywords

Maritime safety, safety culture, Bayesian networks, accident causation

INTRODUCTION

The majority of maritime traffic accidents are due to human failure. Instead of solely focusing on errors made by the mariner, modern human error theories emphasize the role of organisation as a latent cause behind accidents. Although several actions for improving the safety of maritime traffic have recently been conducted, some of them even targeting the organisational level such as the implementation of International Safety Management (ISM) Code, in general the safety culture has still not reached the level of other domains such as aviation.

The common definition of risk is that the risk equals the product of the probability of an unwanted event and the magnitude of its consequences. This paper studies maritime transportation risk by focusing on the probability element. The number of impact accidents in certain water area is commonly estimated using the approach originally presented by Fujii et al. (1971, 1974) and Macduff (1974). The approach models the number of accidents as a product of the so-called number of geometrical

accident candidates and a causation probability. The number of geometrical collision or grounding candidates is describing the theoretical number of collisions or groundings given the ship traffic properties of the area, such as the historical ship tracks, speeds and sizes, and the assumption that the ships are not performing any evasive manoeuvres. For collisions, it is thus estimating the number of times two ships are on a collision course within the time period under examination. There are various approaches to estimating the number of geometrical collision candidates, such as (Pedersen, 1995), (Montewka et al., 2010) and (Goerlandt et al., 2011).

The causation probability describes the probability that the ships do not make any evasive manoeuvres given that they are on a collision course. It is thus conditional on the approach used for geometrical collision candidate estimation. The causation probability is affected by various variables that are related to the mariners and the organisation, the conditions on board and outside the ship, and to technical reliability.

Due to the causal dependencies between the variables being often complicated, and due to the variation between the ships and between companies, the causation probability inevitably includes uncertainty. For example, the impact of the organization on the safety of maritime traffic is hard to assess, especially in a quantitative way. When considering the safety culture, even the concept is not clearly defined (Mohaghegh-Ahmadabadi, 2007; Guldenmund, 2010) and its impacts are challenging to measure precisely (Guldenmund, 2010). The uncertainty the causation probability includes can thus be divided into the following groups:

- Uncertainty due to incomplete knowledge of the variables affecting the causation probability,
- Uncertainty due to incomplete knowledge of the dependencies and causal relations between the variables,
- Uncertainty due to incomplete knowledge of the strength of the dependencies between the variables, and
- Uncertainty due to variation between ships and encounter situations.

These uncertainties should not be neglected, when estimating the number of ship collisions and when

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modelling the causation probability. One approach to taking the uncertainty into account is to model the accident causation probabilistically. For this, traditional risk analysis tools such as fault trees and event trees can be utilized (e.g. Pedersen, 1995; Rosqvist et al., 2002). In order to model more complicated variable dependencies, these techniques may not be sufficient. A more suitable approach might be to apply Bayesian belief networks. The utilization of Bayesian networks in Step 3 of the Formal Safety Assessment, the definition of risk control measures have been suggested to International Maritime Organization (IMO, 2006). Bayesian networks have been applied in causation probability estimation (e.g. Friis-Hansen & Simonsen, 2002; Det Norske Veritas, 2003; Rambøll, 2006). However, in these studies the role of organization or the safety culture was not examined. The effects of safety culture or safety climate have been modelled quantitatively in other fields, also with Bayesian networks (e.g. Zhou et al., 2006; Mohaghegh-Ahmadabadi, 2007;). In this paper, an approach to examining the effects of safety culture level on accident causation in a maritime traffic risk is described and some results from a preliminary model are presented. The approach provides a means to analyse how much

improvements in the ships' safety culture level would reduce the probability of ship collisions in the Gulf of Finland.

BAYESIAN NETWORKS

The structure of a Bayesian network model is a directed graph, where the nodes of the graph represent the model variables and the arcs between the nodes the dependencies (Jensen & Nielsen, 2007). The network cannot contain any directed cycles, i.e., from any node there must not be a way to loop back to the same node by following a sequence of network arcs. The network variables are discrete, i.e., each node consists of a finite number of mutually exclusive states. Each state has a probability of occurrence and it 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 probabilities of all states with all parent node state combinations form the probability table of a node. The network structure, the graph, can be perceived as the qualitative part of the model, whereas the probability tables add the quantitative dimension to the model (Darwiche, 2009).

A Bayesian network model can be constructed based on expert knowledge, by learning the network automatically from data, or with a combination of



Figure 1 The structure of the main model

these. Bayesian networks can be extended into Influence Diagrams by adding decision variables and utility variables into the network. Decision variables describe the decisions whose effects one wants to examine. The effects can be studied on probability level, i.e., how the probability distributions or the most probable states of the network variables change, or, if utility variables are present, as expected utilities given the decision. In other words, Influence diagrams can be utilized in performing cost-benefit-analysis.

MODEL

The model utilized in this paper for demonstrating the analysis of the effects of safety culture on collision risk is producing the collision causation probability as an output. The causation probability model is an Influence Diagram model that contains two instances of a *Loss of control* sub model, an instance for each of the encountering ships. The structure of the main model can be seen in Figure 1. The model is very similar with the one that has been presented by the author in (Hänninen and Kujala, unpubl.). The model variables related to the ship traffic image and the environment are reflecting the circumstances of the Gulf of Finland. This paper demonstrates the application of the model to studying safety culture effects. For this reason, the model presented in this paper has a decision variable for manipulating the safety culture level. The safety culture variable, its manipulation and the following effects are described in this paper. For more detailed descriptions of the other model variables, see (Hänninen and Kujala, unpubl.).

The *Safety culture* variable describes how well the ship operator addresses various safety issues such as standard of equipment, maintenance routines, work procedures, instructions, working conditions, training and attitude and how well a proper safety mindset among its employees is encouraged. The states of the safety culture are *excellent*, *standard* and *poor*. The probability distribution over the states given the current traffic situation depends on the ship type (passenger vessel, high speed craft, cargo vessel, tanker, other ship) and is based on a study by Det Norske Veritas (2006). In the model, there are separate safety culture variables for the two encountering ships (*ship A* and *ship B*). Separate variables allow unique safety culture distributions to be assigned to the encountering ships, but in this study the distributions are kept identical.

In the model, the *Safety culture* variable has a direct influence on the variables *Maintenance routines*, *Duties*, *Incapacitated*, *Competence*, *Communication level*, *Bridge Resource Management (BRM)* and *Other distractions*. The magnitude of the influence is based on (DNV, 2003; 2006) with the assumption

that the differences between ship types in DNV's parameters for the variables *Maintenance routines*, *Bridge Resource Management*, *Communication level* and *Incapacitated* were due to the difference in safety culture levels between ship types. For a detailed description of the magnitude of the influence, see the probability tables of the influenced variables in (Hänninen and Kujala, unpubl.).

With the decision variable *Manipulate safety culture*, one can set the distributions of ships' safety culture level. The variable has four demonstrative states: *no change*, *allow poor*, *improve moderately* and *demand excellence*. The effect of these states on the distribution of *Safety culture* variable can be seen in Table 1. *Allow poor* sets the safety culture of the ships to poor. It reflects the situation when there are basically no requirements for the ships' safety culture and all ships are allowed to have poor safety culture, i.e., "the worst-case scenario". *Improve moderately* sets the probability of *poor* safety culture to zero while the probability of *standard* safety culture remains unchanged (0.5). *Demand excellence* sets the safety culture level to excellent, corresponding to a situation where an excellent safety culture is required for all ships, and that they have achieved it. These manipulations are not conditional on the ship type.

The model does not include utility variables. Thus the effects of the decision variable are examined as changes in the variables' probability distributions. When examining the resulting causation probabilities, it should be noted that the model has been built with the assumption of utilizing Pedersen's (1995) model for the collision candidate estimation. For the modelling, Hugin Expert software (Madsen et al., 2005) is applied.

RESULTS

The effects of manipulating the safety culture can be examined on any of the network variables. As an example, the probability of a ship losing control, a ship having a steering failure, and the ships colliding, i.e., the causation probability, for the four alternative states of safety culture manipulation are presented in Table 2. From the table it can be seen that with the default safety culture level distribution in the Gulf of Finland, the estimated causation probability is 9.9E-05. If all ships had an excellent safety culture, the causation probability is estimated to be 9.0E-05, whereas having poor safety culture increases the causation probability to 1.1E-04.

Table 1. Probability table for safety culture level (identical for both ships)

Manipulate sc	Own ship type	Excellent	Standard	Poor
no change	pass	0.3	0.5	0.2
	hsc	0.3	0.5	0.2
	cargo	0.1	0.5	0.4
	tanker	0.25	0.5	0.25
	other	0.1	0.5	0.4
allow poor	pass	0	0	1.0
	hsc	0	0	1.0
	cargo	0	0	1.0
	tanker	0	0	1.0
	other	0	0	1.0
improve moderately	pass	0.5	0.5	0
	hsc	0.5	0.5	0
	cargo	0.5	0.5	0
	tanker	0.5	0.5	0
	other	0.5	0.5	0
demand excellence	pass	1.0	0	0
	hsc	1.0	0	0
	cargo	1.0	0	0
	tanker	1.0	0	0
	other	1.0	0	0

Table 2. The probability of one ship losing control, having a steering failure, and the causation probability, for the alternative states of safety culture manipulation. The values are estimates for the Gulf of Finland ship traffic

Safety culture manipulation	Loss of control, 1 ship	Steering failure, 1 ship	Causation probability
No change	6.955E-05	1.05E-06	9.887E-05
Allow poor	9.257E-05	1.14E-06	1.071E-04
Improve moderately	5.246E-05	9.75E-07	9.272E-05
Demand excellence	4.489E-05	9.30E-07	9.001E-05

Table 3. The expected time between collisions (years) in the Gulf of Finland for the safety culture manipulations

Safety culture manipulation	Years
No change	5.4
Allow poor	4.9
Improve moderately	5.7
Demand excellence	5.9

In order to examine the effect on collision frequencies, the number of geometrical collision candidates, 1890, estimated in (Ylitalo, 2010) is multiplied with the results from the model. The resulting expected times between collisions can be seen in Table 3. The results vary between 4.9 years to 5.9 years.

DISCUSSION

As can be calculated from Table 2, the probability of losing the control of a ship, given excellent safety culture level, is approximately a third of the one, given the model's current safety culture level situation. For a steering failure, the decrease in probability is 11%. Especially when considering a loss of control, the model finds improvement in the safety culture as a rather efficient way to increase maritime traffic safety. Further, the causation probability is 9% lower with all ships having excellent safety culture than with the current safety culture situation. If the two extremes are compared, all ships having a poor and all ships having an excellent safety culture, the largest effect the safety culture can have on collision probability in the model can be observed: with a poor safety culture, the causation probability is 19.0 % higher than with the "best case scenario". It means that the expected number of collisions would also increase 19.0%. The model thus suggests that the safety culture is an important factor behind ship collision risk.

The effect of changing from the current situation to letting all ships have poor safety culture is smaller than the one of changing from current to excellent. It can be explained when examining the current safety culture level distribution in the model: the distribution is leaning towards poor safety culture for cargo ships, which are almost 70 % of the whole ship traffic in the Gulf of Finland. The current safety culture in the model is thus not so far away from the "worst-case scenario".

When considering the validity of the model, the estimated accident frequency with the current safety culture level distribution seems to be in accordance with the accident statistics (Hänninen & Ylitalo, 2010). However, the magnitude of the effect of safety culture level on collision risk is more challenging to validate. Studies such as (Hänninen, 2007) and (Heijari & Tapaninen, 2010) emphasize the role of organization. Merrick et al. (2001) estimated the effect of implementing the International Safety Management (ISM) Code to be 15 % decrease in potential accident rate in Washington State Ferry traffic - and ISM Code was concluded to be the most effective risk management intervention. In light of these studies, the effects in the model are plausible. Yet, the model is still in its preliminary stages and more validation is needed.

CONCLUSIONS

The fuzziness in safety culture definition and the challenges in measuring it may raise questions if a quantitative modelling of safety culture is even possible. The Bayesian networks approach is capable of combining the qualitative information about the affecting factors and their dependencies and the quantitative information required for performing probabilistic risk analysis. In addition, the distributions and the structure of a Bayesian network can be easily updated whenever more data or knowledge is available. The purpose of this paper was to demonstrate the utilization of the model for examining the effects of the organization, especially the safety culture, on ship collision risk. At the moment, the effect of organisation on ship's proneness to collision is basically modelled with a single variable in the model - the "safety culture". For now, it is not possible to examine the effects of the various factors behind the safety culture. In the future, the model will be further developed to include these factors as well. The manipulation of the safety culture levels is not yet considered. Also the costs of the manipulation or the accidents are not included. After these improvements to the model, it will be possible to analyse the effects of more detailed factors of safety culture on collision risk and perform a thorough cost-benefit analysis of the problem.

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