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A probabilistic model for accidental cargo oil outflow from product tankers in a ship–ship collision

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A B S T R A C T

In risk assessment of maritime transportation, estimation of accidental oil outflow from tankers is important for assessing environmental impacts. However, there typically is limited data concerning the specific structural design and tank arrangement of ships operating in a given area. Moreover, there is uncertainty about the accident scenarios potentially emerging from ship encounters. This paper proposes a Bayesian network (BN) model for reasoning under uncertainty for the assessment of accidental cargo oil outflow in a ship–ship collision where a product tanker is struck. The BN combines a model linking impact scenarios to damage extent with a model for estimating the tank layouts based on limited information regarding the ship. The methodology for constructing the model is presented and output for two accident scenarios is shown. The discussion elaborates on the issue of model validation, both in terms of the BN and in light of the adopted uncertainty/bias-based risk perspective.

1. Introduction

While major accidental oil spills from tankers are relatively rare occurrences, the transportation of oil remains one of the main concerns for the various stakeholders in the protection of the marine environment (Dalton and Jin, 2010). Not only can oil spills have a devastating effect on the marine ecosystem (Lecklin et al., 2011), they involve high acute costs through clean-up operations (Montewka et al., 2013c), have a considerable impact on affected economic activities (Crotts and Mazanec, 2013; Garcia Negro et al., 2009) and can have cultural and behavioral effects on local communities (Miraglia, 2002).

As an aid in maritime transportation risk management, methods for quantitative risk assessment of maritime traffic have been developed (Ozbaṣ, 2013). These provide insight in the spatial distribution of accidental risk of ship traffic, which can, when coupled to environmental sensitivity and risk analysis (Delpeche-Ellmann and Soomere, 2013; Singkran, 2013), provide input to maritime spatial planning (Frazao Santos et al., 2013) and planning of oil combating resources (Lee and Jung, 2013). Risk assessment methods can also be used to assess the effect of proposed risk control options (van Dorp and Merrick, 2011).

Worldwide, ship groundings, collisions and fires are the most frequently occurring accident types (Guedes Soares and Teixeira, 2001) and also in the Gulf of Finland, groundings and collisions represent the majority of the accident types (Kujala et al., 2009). Assessing oil spills from such accidents thus is an important aspect of maritime risk assessment. In this paper, we limit the scope to cargo oil spill size assessment of a product tanker in a ship–ship collision, i.e. vessels with a deadweight between 10 k and 60 k (Evangelista, 2002).

A number of oil spill models have been developed. Przywarty (2008) and Gucma and Przywarty (2008) report on an oil spill model based on the analysis of accident statistics, which cannot account for specific traffic characteristics. IMO (2003, 1995) presents a model for measuring the outflow performance of a particular vessel design against a reference double-hull design. Its applicability in maritime risk assessment is limited because (i) the model uses a single set of damage extent PDFs from single-hull accidents, (ii) these PDFs are treated as independent random variables in generating damage scenarios, ignoring existing correlations in realistic damage extents (Brown, 2002), and (iii) the model cannot account for the specific conditions of impact in ship–ship collisions, even though impact conditions have a significant influence on the probability of oil outflow (Goerlandt et al., 2012). Nonetheless, this model has been used to estimate oil outflow using a probabilistic regression type model (Montewka et al., 2010). To alleviate some of these limitations, van de Wiel and van Dorp (2011) present a regression model for the evaluation of the damage extent and accidental oil outflow conditional to the impact conditions. Their
The model is based on oil outflow calculations of a large set of damage scenarios for four generic tanker designs, as reported by NRC (2001). The damage cases are based on a ship collision damage procedure model by Brown and Chen (2002), and the resulting regression model explicitly links impact conditions with oil outflow. However, this model is limited due to the assumption of a predefined tanker layout.

The model presented in this paper extends the tanker cargo oil outflow modeling literature on two accounts. First, the model integrates impact scenario variables to damage extents and oil outflows of a range of product tankers with different tank layouts, dropping the predefined tank layout assumption inherent in the model by van de Wiel and van Dop (2011). The model is constructed such that a reasonable estimate of tank layouts is possible even when limited data is available of the vessels under consideration, as typically available in AIS data. The model links impact conditions with oil outflows such that a probabilistic oil outflow can be determined which depends on the local traffic composition in terms of vessel sizes and speeds. Second, Bayesian networks (BNs) are applied as a methodology for probabilistically mapping impact conditions and ship data to oil outflows.

Bayesian networks (BNs) are a kind of probabilistic graphical model which provide a natural way of modeling uncertainty in complex environments (Koller and Friedman, 2009; Pearl, 1988). BNs have been applied in a range of applications relevant for evaluating the effect of accidental oil spills from maritime transportation. Stelzenmüller et al. (2010) applied BNs along with GIS tools to support marine planning. Juntunen et al. (2005) and Lehikoinen et al. (2013) applied BNs to assess the effectiveness of oil combating technologies with respect to environmental impact of oil spills. Lecklin et al. (2011) used BNs to evaluate the biological acute and long-term impacts of an oil spill. Montewka et al. (2013c) applied BNs to determine the clean-up costs resulting from an oil spill. BNs have also been applied for modeling the consequences of other ship accident types (Montewka et al., 2013a, 2012a). The presented work can thus be seen as a natural extension to the literature concerned with evaluating the impact of oil spills using BNs.

This paper is organized as follows. In Section 2, a general outline is given of the intended application area of maritime transportation risk assessment, as well as of the adopted risk perspective. In Section 3, the overall framework for the construction of the product tanker collision oil outflow BN is outlined. In Section 4, the data, models and method for constructing the submodel linking ship size, damage extent and oil outflow is shown. In Section 5, the method for constructing the submodel linking impact conditions to damage extent is outlined. Section 6 integrates the submodels to the resulting BN, showing the results of an example impact scenario. In Section 7, a discussion on the results is made, focusing on the issue of validation.

### 2. Perspective for risk assessment in maritime transportation

As the intended application area of the model presented in this paper is risk assessment of maritime transportation, it is considered beneficial to place of this model in the larger framework of maritime risk assessment and to outline the adopted risk perspective. Especially the latter issue is important as a variety of views exist on how to perform risk assessments, and because the adopted perspective has implications on what requirements risk models have e.g. in terms of validation.

1 The Automatic Information System (AIS) is a system where navigational parameters are transmitted from ships to one another and to shore stations, allowing for improved situational awareness. It provides a rich data source for studies in maritime transportation, containing detailed information about vessel movements.

#### 2.1. Risk assessment in maritime transportation

Methods for risk assessment in maritime transportation typically aim to assess the probability of occurrence of accidental events and assess the consequences if such events happen. Methods for assessing the probability of collision e.g. include Fowler and Sørgård (2000), Friis-Hansen and Simonsen (2002) and Montewka et al. (2012b), but many others exist, see Özbay (2013). Apart from providing a picture of the spatial distribution of accident probability in the given sea area, these methods also provide a set of scenarios in terms of the encounter conditions of vessels in the sea area, which is important if a location-specific consequence assessment is sought. The general framework for maritime transportation risk assessment can be summarized as in Fig. 1.

It is well-established that in the complex, distributed maritime transportation system, knowledge is not equally available about all parts of the system (Grabowski et al., 2000; Montewka et al., 2013b). Ship sizes in terms of main dimensions and vessel encounter conditions can be estimated with reasonable accuracy based on AIS data as this data provides a comprehensive image of the maritime traffic in a given sea area. On the other hand, uncertainty exists about the more specific features of ship designs: main dimensions provide some insights but the detailed tank arrangements and hull structural parameters are typically not available for all ships operating in a given area. Furthermore, uncertainty exists in terms of how to define a ship–ship encounter which may lead to a collision: a reliability study has shown that various encounter definitions can lead to very different pictures of the spatial distribution of accident likelihoods (Goerlandt and Kujala, 2014). Likewise, there exists considerable uncertainty regarding the link between encounter conditions and impact scenarios as the process from the encounter conditions to the impact is not well understood (Goerlandt et al., 2012; Ståhlberg et al., 2013).

The presence of such uncertainty is often considered problematic (Fowler and Sørgård, 2000), but this depends on what the aim of risk assessment is understood to be and hence what perspective is taken to describe risk.

#### 2.2. An outline of some foundational risk perspectives

While risk assessment is an established tool for informing decisions, there are fundamentally different views on how to assess risk. This concerns the question of the risk perspective, i.e. the systematic approach taken to analyze and make statements about risk.

A traditional “probability of frequency” approach is suggested by Kaplan (1997). In this risk perspective, risk is described through the triplet \(<s_i, p_i, c_i>\), where \(s_i\) is the ith scenario, \(p_i\) the probability of
that scenario and \( c_i \) the consequence of the \( i \)th scenario. An important characteristic of this definition is that the risk is described through probabilities.

Schematically, the risk perspective consists of events \( A \), consequences \( C \) and probabilities \( P \) and can be summarized as:

\[
\text{Risk} \sim (A, C, P, B(P_f))
\]  

(1)

The basic element is a frequentist probability \( P_f \), i.e. the fraction of times an event or consequence occurs in principle infinite set of similar situations or scenarios to the one analyzed. \( P_f \) is a thought construct or a model parameter, which is unknown and estimated, say as \( P_f \), which may or may not accurately reflect the “true” frequency \( P \). A subjectivist probability \( P_s \), a degree of belief, is used to describe the uncertainty about the parameters \( P_f \). In combination, the risk description consists of a set of risk curves, which are considered to provide a complete risk description. Importantly, the risk curve representation shows that all uncertainty is quantified and the assessment aims to describe an underlying “true” risk.

An alternative precautionary approach to risk assessment is suggested by Rosqvist and Tuominen (2004). This risk perspective can be schematically summarized as follows, with \( A, C \) and \( P_s \) as above:

\[
\text{Risk} \sim (A, C, P_s, B|BK)
\]  

(2)

Considering a need to consider model bias in terms of optimistic or conservative risk characterizations, a qualitative assessment of the direction of bias \( B \) supplements the quantification of risk using probabilities, conditional to a specific background knowledge. Importantly, in this risk perspective, there is no reference to a “true risk” (Rosqvist, 2010) as the risk model is seen as a reflection of a mental construct by an expert and analyst.

A third uncertainty-based risk perspective is suggested by Flage and Aven (2009) and Aven (2013). The aim of risk assessment under this view is to describe uncertainty about the occurrence of events \( A \) and the consequences \( C \).

\[
\text{Risk} \sim (A, C, P_s, U|BK)
\]  

(3)

A Bayesian network encodes a factorization of the joint probabilistic graphical models, defined as a pair \( \mathcal{A} = (G(X, A), P) \) (Koller and Friedman, 2009; Pearl, 1988), where \( G(X, A) \) is the graphical component and \( P \) the probabilistic component of the model. \( G(X, A) \) is in the form of a directed acyclic graph (DAG), where the nodes \( X \) represent the variables \( X = \{X_1, \ldots, X_n\} \) in the considered problem and the arcs \( A \) represent the probabilistic conditional (in)dependencies between the variables. \( P \) consists of a set of conditional probability tables (CPTs) \( P(X_i|Pa(X_i)) \) for each variable \( X_i, i = 1, \ldots, n \) in the problem. \( Pa(X) \) signifies the set of parents of \( X_i \) in \( G: \text{Pa}(X_i) = \{Y \in X|Y, X_i \in A\} \).

Thus:\[ P = \{P(X_i|Pa(X_i)), i = 1, \ldots, n\}.\]

A Bayesian network encodes a factorization of the joint probability distribution (JDP) over all variables in \( X \):

\[
P(X) = \prod_{i=1}^{n} P(X_i|Pa(X_i))
\]  

(5)

From Eq. (5), it follows that BNs have desirable properties for describing uncertainty about oil spills in ship–ship collisions, conditional to impact scenarios. In particular, when an assessor expresses his uncertainty about the impact scenarios using a set of parent nodes, this uncertainty can be propagated through the model to attain an expression of uncertainty about the possible oil spill sizes.

3. Framework for constructing the Bayesian network model

In this Section, the overall framework for the construction of the Bayesian network is introduced. First, some basic issues concerning Bayesian networks are briefly outlined, showing how BNs can accommodate the adopted risk perspective.

3.1. Bayesian networks

In mathematical terms, Bayesian networks (BNs) represent a class of probabilistic graphical models, defined as a pair \( \mathcal{A} = (G(X, A), P) \) (Koller and Friedman, 2009; Pearl, 1988), where \( G(X, A) \) is the graphical component and \( P \) the probabilistic component of the model. \( G(X, A) \) is in the form of a directed acyclic graph (DAG), where the nodes \( X \) represent the variables \( X = \{X_1, \ldots, X_n\} \) in the considered problem and the arcs \( A \) represent the probabilistic conditional (in)dependencies between the variables. \( P \) consists of a set of conditional probability tables (CPTs) \( P(X_i|Pa(X_i)) \) for each variable \( X_i, i = 1, \ldots, n \) in the problem. \( Pa(X) \) signifies the set of parents of \( X_i \) in \( G: \text{Pa}(X_i) = \{Y \in X|Y, X_i \in A\} \).
To achieve a full assessment of uncertainty and bias in line with the risk perspective of Eq. (4), a qualitative description of $U$ and $B$ supplements the BN.

3.2. Framework for oil outflow modeling in ship–ship collision

As illustrated in Fig. 2, the BN is constructed from an integration of two main elements: a submodel $G_i$ linking the damage extent to ship particulars and oil outflow and a submodel $G_j$ linking the impact scenarios to the damage extent.

First, the resulting oil outflow for product tankers is determined from outflow calculations in a range of damage scenarios using a set of representative product tankers. For these tankers, limited data is available concerning cargo tank number and configuration. The more detailed tank arrangement needed for oil outflow calculations is estimated based on a model presented by Šmailys and Česnauskis (2006). The data obtained from subsequent oil outflow calculations is applied in a Bayesian learning algorithm to construct the first submodel of the BN. This submodel $G_i(X_i, A_i)$ consists of nodes and arcs related to the ship particulars, damage extent and oil outflow. Its construction is elaborated in Section 4.

Second, the impact conditions in terms of ship speeds, masses and other elements of the accident scenario are linked to the damage extent variables by building the conditional probability tables for the damage extent nodes, based on a model presented by van de Wiel and van Dorp (2011). The nodes and arcs linking impact scenario variables to damage extent variables constitutes the second submodel of the BN, denoted $G_j(X_j, A_j)$. Its construction is described in Section 5.

The integration of the two submodels $G_i(X_i, A_i)$ and $G_j(X_j, A_j)$ through the common variables leads to the final BN linking impact scenarios with oil outflow. The presented framework is generic in the sense that other, potentially more accurate, models could be used as underlying building blocks for the BN construction. The discussion on model validity in Section 7 is given as guidance on which parts of the model would benefit most for reducing uncertainties and biases. However, the two main submodels (oil outflow conditional to damage extent and ship particulars and damage extent conditional to impact conditions) will inevitably be present in some form. The following sections show the model construction for a selected set of underlying models and assumptions.

4. Submodel $G_i$: oil outflow given ship size and damage extent

This Section describes the construction of the BN-submodel linking the oil outflow with variables describing the ship size and damage extent. The available data concerning tank configuration, the procedure for determining tank arrangement, the calculation of oil outflow given a damage extent and the algorithm to learn the BN-submodel are described.

4.1. Tank configuration data

The available data set containing tank configuration parameters consists of 219 product tanker designs which operate in the Baltic Sea. These 219 tankers were selected based on their occurrence frequency in the Gulf of Finland: data was obtained from a ship database (IHS Maritime, 2013) for those tankers which enter the area at least twice during the year 2010. It is assumed that these frequently occurring vessels are representative of the entire product tanker fleet in the given area.

The available tanker data is summarized in Fig. 3. The scatterplots above and below the diagonal show the relation between each two pair of variables, whereas the histograms on the diagonal provide insight in the relative number of occurrences of each class within a variable. For example, the histogram of TT shows that the vast majority (93%) of product tankers in the area have tank type 2, much fewer (5%) tank type 3 and only a small number (2%) tank type 1. The broadly linear relationship between $L$ and $B$ and the approximate third power relation between $L$ and Displ are as expected. The relation between $L$ and TT shows that TT2 configurations are found across the range of vessel lengths, whereas TT1 and TT3 are more often found in medium size product tanker...
vessels. The number of side tanks (ST) ranges from 4 to 10, with no apparent relation to the ship length.

4.2. Tank arrangement determination

4.2.1. Methodology

The methodology for determining the tank arrangement is based on the procedure proposed by Smailys and Česnauskis (2006), and is applied for tanker configurations given in the data described in Section 4.1. The main parameters relevant for the determination of the tank volumes and the location of the transverse and longitudinal bulkheads are shown in Fig. 4.

\[ L_T = \frac{L_A - L_L}{n} \]  
\[ B_T = \frac{B - 2w}{m} \]  
\[ D_T = D - h \]

where \( n \) is the number of tanks in the longitudinal direction and \( m \) the number of tanks in the transversal direction. It is thus assumed that all tanks have the same width \( B_T \) and length \( L_T \). Values for \( L_A \) and \( L_L \) are given in Table 1, taken as average values reported by Smailys and Česnauskis (2006). The double bottom height \( h \) and double hull width \( w \) are determined based on the relevant rules for classification of ships (Det Norske Veritas, 2007).

The above information can be used to determine the set of positions of the longitudinal and transversal bulkheads, respectively noted LBH and TBH, as follows:

\[ TBH = \{ L_A + kL_T, \ k = 0 \ldots n \} \]  
\[ LBH = \{ w + kB_T, \ k = 0 \ldots m \} \]

4.2.2. Validation

As the procedure to determine tank arrangement is based on a series of simplifying assumptions, the methodology presented in Section 4.2.1 is validated by comparing the total calculated cargo tank volume with the DWT as available from the data of the 219 tankers, see Fig. 3. Fig. 5 shows a comparison between the DWT as available in the tanker database (DWT D) with the DWT as calculated from the cargo tank volume (DWT C), assuming an oil density of 0.9 tonne/m³. It is seen that the calculation procedure generally overestimates the cargo tonnage. The histogram shows that the cargo tonnage is overestimated by ca. 15% on average, ranging from an underestimate of ca. 20% to a maximum overestimate of ca. 35%. Overall, the procedure thus leads to a conservative estimate for the possible oil outflow.

While important for the evaluation of the oil outflow, it is not possible to validate the methodology in terms of bulkhead locations as the detailed tanker layouts are not available. A limited study by Smailys and Česnauskis (2006) indicates reasonable agreement for this aspect as well.
4.3. Oil outflow calculation for various damage scenarios

4.3.1. Oil outflow for a given damage scenario

The oil outflow in a given damage scenario for a particular tanker size and tank configuration is illustrated in Fig. 6. The collision results in a damage length $y_L$ and damage depth $y_T$, which occurs at a position $l$ relative to the aft of the product tanker. This leads to a hull rupture and, if $y_T$ is sufficiently large, a breach of a number of cargo tanks. The determination of which cargo components are breached is based on a comparison of the penetration depth $y_T$ with the position(s) of the longitudinal bulkhead(s) LBH, respectively the maximum and minimum location of the longitudinal damage extent ($y_{L1}$ and $y_{L2}$, see Section 5.2) with the positions of the transversal bulkheads TBH.

In the presented model, it is assumed that all cargo in the penetrated cargo tanks is spilled, an assumption also made by van de Wiel and van Dorp (2011). In actual collision cases, the damage location can be at a range of vertical positions above or below the waterline. Calculations show that the spilled volume can significantly vary depending on the vertical damage position above or below the waterline (Sergejeva et al., 2013; Tavakoli et al., 2010). However, there is considerable uncertainty regarding the impact location in accident scenarios. None of the available impact scenario models (Goerlandt et al., 2012; Ståhlberg et al., 2013) account for this factor and the vertical damage location will amongst other depend on the striking vessel’s depth, bow shape, loading condition (draft and trim) and on the presence of a bulbous bow. Other factors can be expected to affect the oil outflow, e.g. the damage opening size, the ship stability and wave conditions. However, in risk assessment of maritime transportation, there is considerable uncertainty regarding these factors. While there are reasons to believe that not all oil will be spilled in actual collision accidents, it is reasonable to accept the assumption of a complete loss of cargo oil because this minimizes uncertainty while leading to a conservative estimate.

### Table 1
Basic information concerning tanker layout, based on (Smailys and Česnauskis, 2006).

<table>
<thead>
<tr>
<th>Layout</th>
<th>Cargo tank $C_i$</th>
<th>10 k–35 k DWT</th>
<th>35 k–50 k DWT</th>
<th>50 k–60 k DWT</th>
</tr>
</thead>
<tbody>
<tr>
<td>TT1</td>
<td>Front</td>
<td>0.7</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Aft</td>
<td>0.91</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>TT2</td>
<td>Front</td>
<td>0.72</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Aft</td>
<td>0.91</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>TT3</td>
<td>Front outer</td>
<td>0.68</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>Front internal</td>
<td>0.84</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>Middle</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Aft internal</td>
<td>0.93</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>Aft outer</td>
<td>0.84</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>$L_A$</td>
<td>0.24 L</td>
<td>0.22 L</td>
<td>0.21 L</td>
</tr>
<tr>
<td></td>
<td>$L_F$</td>
<td>0.06 L</td>
<td>0.055 L</td>
<td>0.055 L</td>
</tr>
</tbody>
</table>

![Fig. 5. Comparison of DWT_C and DWT_D.](image)

![Fig. 6. Definition of oil outflow given a damage extent and collision scenario variables.](image)
4.3.2. Generating damage cases for learning submodel GI

The construction of the BN submodel GI linking the damage extent to ship particulars and oil outflow is based on a Bayesian learning algorithm, see Section 4.4. Such methods require a data set from which the structure and parameters of a BN can be learned. This data set is generated using a Monte Carlo (MC) sampling procedure for each of the 219 product tankers.

First, the tank arrangement is determined for the selected tanker based on the vessel data and tank configuration data as given in Section 4.1, using the procedure outlined in Section 4.2. Subsequently, the oil outflow is calculated for 2300 damage cases according to the rationale in Section 4.3.1. The damage cases are derived from a reasonable estimate of likely impact scenarios in terms of mass \( m_1 \), speeds \( v_1 \) and \( v_2 \), bow shape parameter \( \eta \) and situational parameters \( \phi \) and \( \theta \), as defined and explained in Section 5.2. Through Eqs. (14)–(24), a damage scenario is calculated in terms of \( y_T \), \( y_L \), \( l \) and \( \theta \), which govern which cargo tanks are breached, see Section 4.3.1, and Section 5.2. This procedure is computationally more efficient than direct sampling of variables \( y_T \), \( y_L \), \( l \) and \( \theta \), as these are to some degree correlated because their formulation involves the same impact scenario variables. This way, the generated damage extent and oil outflow calculations are used primarily to learn the parameters in the BBN in realistic areas of the impact scenario space. A direct, uncorrelated sampling of \( y_T \), \( y_L \), \( l \) and \( \theta \) would lead to a large number of cases in unrealistic areas of the impact scenario space, which is unnecessary in actual applications. The ranges for the impact scenario variables in the MC sampling are shown in Table 2.

The resulting data set from which the Bayesian submodel \( G(X, A_i) \) is learned consists of following variables for all damage cases:

- Vessel particulars: length \( L \), width \( B \), displacement Displ, deadweight DWT, tank type TT, number of side tanks ST and number of center tanks CT, see Fig. 3.
- Damage extent parameters: damage length \( y_T \), damage width \( y_L \), relative damage location \( l \), damage direction \( \theta \), see Fig. 6.
- Oil outflow as calculated in Section 4.3.1.

4.4. BN-submodel linking damage extent, ship particulars and oil outflow

4.4.1. Methodology: Bayesian network learning

Learning a Bayesian network from data is a two-step procedure: structure search and parameter fitting, for which a large number of methods have been proposed (Buntine, 1996; Daly et al., 2011). In the presented model, use was made of the greedy thick thinning (GTT) algorithm (Dash and Cooper, 2004) implemented in the GeNIe free modeling software. The GTT is a score + search Bayesian learning method, in which a heuristic search algorithm is applied to explore the space of DAGs along with a score function to evaluate the candidate network structures, guiding the search. The GTT algorithm discovers a Bayesian network structure using a 2-stage procedure, given an initial graph \( G(X, A) \) and a dataset \( T \):

I. Thickening step: while the K2-score function (Eq. (12)) increases:

(i) Find the arc \((X_i, X_j)\) maximizing (Eq. (12)) when deleted in \( G'(X, A') \) where \( A' = A \cup \{ (X_i, X_j) \} \).

(ii) Set \( G \leftarrow G' \).

II. Thinning step: while the K2-score function (Eq. (12)) increases.

![Image](http://dlcl.sis.gtt.edu)

### Table 2: Variable limits for MC sampling for damage case generation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Unit</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_1 )</td>
<td>Striking ship mass</td>
<td>(tonnes)</td>
<td>[0,200 k]</td>
</tr>
<tr>
<td>( v_1 )</td>
<td>Striking ship speed</td>
<td>(kn)</td>
<td>[0.24]</td>
</tr>
<tr>
<td>( v_2 )</td>
<td>Struck ship speed</td>
<td>(kn)</td>
<td>[0.18]</td>
</tr>
<tr>
<td>( \phi )</td>
<td>Impact angle</td>
<td>(°)</td>
<td>[0.180]</td>
</tr>
<tr>
<td>( \eta )</td>
<td>Relative impact location</td>
<td>(°)</td>
<td>[0.1]</td>
</tr>
<tr>
<td>( CDF(1) )</td>
<td>Variable accounting for struck vessel length</td>
<td>(°)</td>
<td>[14,23]</td>
</tr>
<tr>
<td>( CDF(2) )</td>
<td>Variable accounting for struck vessel width</td>
<td>(°)</td>
<td>[0,0]</td>
</tr>
</tbody>
</table>

(i) Find the arc \((X_i, X_j)\) maximizing (Eq. (12)) when deleted in \( G'(X, A') \), \( A' = A \cup \{ (X_i, X_j) \} \).

(ii) Set \( G \leftarrow G' \).

The above algorithm starts with an initial empty graph \( G \), to which iteratively arcs are added which maximize the K2-score function in the thicking step. When adding additional arcs does not lead to increases in K2-score, the thinning step is applied. Here, arcs are iteratively deleted until no arc removal results in a K2-score increase, which is when the algorithm is stopped and the network returned.

The K2-score function is chosen to evaluate the candidate network structures (Cooper and Herskovic, 1992). This method measures the logarithm of the joint probability of the Bayesian network structure \( G \) and the dataset \( T \), as follows:

\[
K2(G, T) = \log(P(G)) + \sum_{i=1}^{n} \sum_{j=1}^{q_i} \log \left( \frac{(r_j - 1)!}{(N_{ij} + r_j - 1)!} \right) + \sum_{k=1}^{r_i} \log(N_{ik})
\]

where \( P(G) \) is the prior probability of the network structure \( G \), \( r_i \) the number of distinct values of \( X_i \), \( q_i \) the number of possible configurations of \( Pd(X_i) \), \( N_{ij} \) the number of instances in the data set \( T \) where the set of parents \( Pd(X_i) \) takes their \( j \)-th configuration, and \( N_{ik} \) is the number of instances where the variables \( X_k \) takes the \( k \)-th value \( x_k \) and \( Pd(X_i) \) takes their \( j \)-th configuration:

\[
N_{ij} = \sum_{k=1}^{r_i} N_{ik}
\]

4.4.2. Application: developing the submodel GI

In the construction of the submodel \( G(X, A_i) \) through Bayesian learning, two preparatory steps are required to transform the oil outflow dataset from Section 4.3.2 in a BN. First, the data is discretized in a number of classes \( r_i \) for each variable \( X_i \), which is done as listed in Table 3.

Second, background knowledge regarding the problem structure is applied to define a set of arcs \((X_i, X_j)_{cd} \), \( cd = 1, \ldots, CD \) representing a priori known conditional dependencies and a set of arcs \((X_i, X_j)_{cd} \), \( s = ci, \ldots, CI \) representing a priori known conditional independencies between variables \( X_i \) and \( X_j \). For instance, from Fig. 3, it is known that there is a relation between \( L \), \( B \) and DWT and Displ, which also follows from general ship design characteristics (van Dokkum, 2006). Likewise, from the formulation of the oil outflow calculations in Section 4.3.1 and the formulas in Section 5.2, it is known that there is a link between \( y_T \), \( y_L \), \( l \), and \( \theta \) and the oil outflow. On the other hand, there is no reason to believe there is a relation between damage scenario conditions \( l \) and \( \theta \) and ship particulars \( L \), \( B \), DWT, Displ, etc.

The results of this submodel \( G(X, A_i) \) are shown in Section 6, where the damage extent variables are linked to the impact scenario parameters, as explained in Section 5.
5. Modeling damage extent conditional to impact scenario

5.1. Ship–ship collision phenomenon and model selection

A ship–ship collision is a complex, highly non-linear phenomenon which can be understood as a coupling of two dynamic processes. First, there is the dynamic process of two ship-shaped bodies coming in contact, resulting in a redistribution of kinetic energy and its conversion into deformation energy. The available deformation energy leads to damage to the hulls of both vessels. This process is commonly referred to as “outer dynamics”. Second, there is the dynamic process of elastic and plastic deformation of the steel structures due to applied contact pressure, referred to as “inner dynamics” (Terndrup Pedersen and Zhang, 1998).

A number of models has been proposed to determine the available deformation energy and the extent of structural damage in a ship–ship collision, see Pedersen (2010) for an extensive review. One of the few methods explicitly accounting for the coupling of outer and inner dynamics is the SIMCOL model reported by Brown and Chen (2002). This model is a three degree of freedom time-domain simulation model where vessel motion and hull deformation are tracked, from which the resulting damage length and depth can be determined. The method has been applied to evaluate the environmental performance of four selected tanker designs: two single hull and two double hull (DH) tankers of various sizes (NRC, 2001), for which a large set of calculation has been performed. The relevant parameters of these damage cases has been transformed in a statistical model based on polynomial logistic regression by van de Wiel and van Dorp (2011), linking the impact scenario variables to the damage extent and the probability of hull rupture.

More advanced collision energy and structural response models exist (Ehlers and Tabri, 2012; Hogström, 2012). However, the model by van de Wiel and van Dorp (2011) is suitable as a basis for our purposes as it is the only method presenting closed-form equations linking impact conditions and damage extent, allowing a simple implementation in the BN, while retaining the underlying physics of the ship–ship collision phenomenon. Moreover, the mentioned models are more oriented towards ship design and also have limitations leading to particular uncertainties and biases. In the model by Ehlers and Tabri (2012), e.g. the bow shape of the striking vessel is simplified to only the bulbous bow, leading to uncertainty and bias in regards to the actual damage extents. In the model by Hogström (2012), the bow geometry is accounted for but the collision damage is calculated assuming a fixed vessel body, which leads to uncertainties related to the redistribution of kinetic energy into deformation energy, particularly for impacts in the bow or stern area (Ehlers and Tabri, 2012). The model by Chen and Brown (2002), which lays at the basis of the model by van de Wiel and van Dorp (2011), is a simpler model in terms of collision energy and structural damage but accounts both for bow shape and external dynamics.

5.2. Formulation of relation between impact scenario and damage extent

The polynomial regression model by van de Wiel and van Dorp (2011) uses a set of predictor variables to link the impact scenario variables to the longitudinal and transversal damage extents. These predictor variables are representative of the impact scenario. An impact scenario can be described through the vessel masses \( m_1 \) and \( m_2 \), the vessel speeds \( v_1 \) and \( v_2 \), the impact angle \( \phi \), the relative damage location \( l \) and the striking ship’s bow half-entrance angle \( \eta \), see Fig. 6. An additional variable is used as a scaling factor between the results of the small and the large tankers given in the set of damage cases (NRC, 2001). This variable is set as the vessel length \( L \) or the vessel width \( B \) depending on whether longitudinal or transversal damage extents are calculated.

As predictor variables, dimensionless variables \( x_i \) are applied as follows:

\[
\begin{align*}
    x_1 &= 1 - \exp\left(-\frac{u_1}{C_1}\right)^{C_2} \\
    x_2 &= 1 - \exp\left(-\frac{u_2}{C_3}\right)^{C_4} \\
    x_3 &= \text{Beta}(l^* + \frac{1}{2}[1.25, 1.45]) - \text{Beta}(-l^* + \frac{1}{2}[1.25, 1.45]) \\
    x_4 &= \text{CDF}(\eta) \\
    x_5 &= \text{CDF}(L) \text{ or } \text{CDF}(B)
\end{align*}
\]

where \( e_{k,p} \) and \( e_{k,t} \) are respectively the perpendicular and tangential collision kinetic energy, \( l^* \) the relative impact location with reference to midship and \( u_1, u_2, u_3, a \) and \( p \) parameters of a Weibull distribution for the predictor variables involving respectively the perpendicular and tangential kinetic energy. These are given in Table 4, along with the values for the empirical CDF of the bow half entrance angle \( \eta \) and the empirical CDF(L) and CDF(B). We write:

\[
\Gamma = \left| l^* - \frac{1}{2}\right| (15)
\]

\[
e_{k,p} = \frac{1}{2}(m_1 + m_2)(v_1 \sin(\phi))^2 (16)
\]

\[
e_{k,t} = \frac{1}{2}(m_1 + m_2)(v_1 \cos(\phi))^2 (17)
\]

Using these predictor variables, a polynomial regression model is made for respectively the expected damage length \( y_L \) and penetration depth \( y_T \):

\[
y_L = \exp(h_L(x)[\bar{p}_L]) (18)
\]

\[
y_T = \exp(h_T(x)[\bar{p}_T]) (19)
\]

with:

\[
h_L(x)[\bar{p}_L] = \sum_{i=1}^{5} \bar{p}_{L,i}^* x_i^a (20)
\]

Table 3

Discretization of variables in \( G(X, A) \).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Discretization</th>
<th>Variable</th>
<th>Unit</th>
<th>Discretization</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWT</td>
<td>(tonnes)</td>
<td>7.5-7.5 k:45 k</td>
<td>( y_L )</td>
<td>(m)</td>
<td>0.5-35</td>
</tr>
<tr>
<td>Displ</td>
<td>(tonnes)</td>
<td>10-10:60 k</td>
<td>( y_T )</td>
<td>(m)</td>
<td>0.2-12</td>
</tr>
<tr>
<td>L</td>
<td>(m)</td>
<td>115:15:190</td>
<td>( l^* )</td>
<td>(-)</td>
<td>0:1-5</td>
</tr>
<tr>
<td>B</td>
<td>(m)</td>
<td>17.3:32</td>
<td>( \phi )</td>
<td>(-)</td>
<td>0:1-3</td>
</tr>
<tr>
<td>TT</td>
<td>(-)</td>
<td>1:3</td>
<td>Oil outflow</td>
<td>(tonnes)</td>
<td>(0-4 k, 4-8 k, 8-12 k) &gt;12 k</td>
</tr>
<tr>
<td>CT</td>
<td>(-)</td>
<td>[0,1-5,6,7-8,9-10]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>(-)</td>
<td>(0,1-5,6,7-9,10)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
and as follows:

\[ h_t(x_t^i) = \sum_{l=1}^{5} \bar{b}_l \sum_{j=1}^{5} \bar{b}_l^* p_{ij} \]  

(21)

The regression coefficients for the expressions \( h_t \) and \( h_L \) are given in Table 5.

The determination of the maximum and minimum location of the longitudinal damage extent, respectively \( y_{L1} \) and \( y_{L2} \), depends on the damage length \( y_L \), but also on the relative damage location \( l \), the ship length \( L \) and the damage direction \( \theta \):

\[ y_{L1} = (1 - \theta) y_L + (1 - l) L \]  

(22)

\[ y_{L2} = -\theta y_L + (1 - l) L \]  

(23)

Naturally, \( y_{L1} \) and \( y_{L2} \) cannot exceed the position of the fore or aft perpendicular. The damage direction \( \theta \) accounts for the phenomenon that the longitudinal damage extent will not necessarily be symmetrical around the impact location. In van de Wiel and van Dorp (2011), it is assumed that \( \theta \) depends on the impact angle \( \varphi \) and the relative tangential velocity \( v_r \) as follows:

\[
\theta = \begin{cases} 
0 & \text{if } \varphi = 0 \\
\left(\frac{1}{\varphi} \exp(\mu_{v_r})\right) & \text{if } 0 < \varphi < 90 \\
\left(1 - \frac{1}{\varphi} \exp(\mu_{v_r})\right) & \text{if } 90 < \varphi < 180 \\
1 & \text{if } \varphi = 0
\end{cases}
\]

(24)

where \( v_r = -v_t \cos \varphi - v_b \), \( m = 0.091 \) and \( n = 5.62 \).

The penetration depth \( y_L \) is applied to evaluate which longitudinal bulkheads are breached and hence from which tank compartments in the transverse direction oil can spill. Likewise, the longitudinal limits of the collision damage, \( y_{L1} \) and \( y_{L2} \), are applied to evaluate which transverse bulkheads are breached and hence from which tank compartments in the longitudinal direction oil can spill, see Fig. 6.

In the utilization of the regression model for damage extent conditional to impact conditions, the statistical quality of the regressions based on the damage cases from the NRC (2001) report is important. First, it should be noted that the damage extent model is based on damage calculations of relatively large tankers: the smallest considered struck ship is comparable to the larger ships in the considered class of product tankers. This implies that the damage extents based on the presented model are likely to be overestimated. Second, in terms of the actual regression quality, the statistical fit for the predictor variables \( x_1 \) and \( x_2 \) in Eq. (14) was established by means of probability plots by van de Wiel and van Dorp (2011), which is not replicated here. The agreement is good. Predictor variables \( x_3 \) to \( x_8 \) follow directly from empirical distributions. The regression quality for the models for \( y_L \) and \( y_T \) of Eqs. (18) and (19) is found to be good based on reported \( R^2 \)-values of 70.6% for the \( y_L \)-model and 73.6% for the \( y_T \)-model. The model for the damage direction \( \theta \) under the parameters \( m \) and \( n \) in Eq. (24) is validated by comparing the number of times the application of the model produces the same oil outflow as the NRC-data, given the parameters \( l, y_L, y_T, \varphi \) and \( v_r \). The correspondence is very good with a reported 95.6% correct prediction.

6. Resulting BN and application to example accident scenarios

6.1. Constructing the remaining conditional probability tables

The BN for product tanker cargo oil outflow conditional to impact scenario is constructed based on the integration of the probabilistic link between impact scenario variables masses \( m_1 \) and \( m_2 \), speeds \( v_1 \) and \( v_2 \), bow shape parameter \( \eta \) and situational parameters \( \varphi \) and \( l \), with the submodel which links the damage extent, ship particulars and oil outflow. For this, the conditional probability tables (CPTs) for the variables \( y_L, y_T, \varphi \), as well as the top nodes, are constructed.

Constructing these CPTs requires a discretization of variables \( m_1, m_2, v_1, v_2, \varphi, l, \eta, x_1, x_2, x_3 \) and \( x_4 \), as defined in Section 5, which is done with a resolution as given in Table 6. These are mapped onto the respective discrete classes of the variables \( \eta \), \( y_L \) and \( y_T \), as defined as outlined in Section 4.4.1. This is done by random sampling of 100 cases from the ranges of the parent variables of the probability of the resulting value of the child variable, as calculated through Eqs. (14)-(24), failing in each of its discrete classes.

6.2. Integrated BN model and example application

The resulting BN model for cargo oil outflow of product tankers conditional to given impact scenarios is shown in Fig. 7. The variables describing the impact scenario are \( v_1, v_2, \varphi, l, \eta, x_1, x_2, x_3 \) and \( x_4 \), located in the top and left part of the model. The variables describing the tanker design are grouped in the right part of the model, i.e. variables \( L, B, DWT, \text{Displ}, \text{T}, \text{ST}, \text{CT} \). The central part of the model contains the variables linking the impact scenario with the damage extent and ultimately the oil outflow.

To illustrate the utility and outcome of the model, two realistic scenarios relevant in risk assessment in the Gulf of Finland area are considered. In the first scenario, a fully laden medium-size product tanker sailing at normal operating speed is struck by a RoPax vessel also sailing at normal operating speed. Such a scenario may occur in the TSS area in the crossing area between Helsinki and Tallinn, see Fig. 8. In the second scenario, a fully laden medium-size product tanker sailing at normal operating speed is struck by a fully laden Suezmax tanker also sailing at normal operating speed. Such a scenario may occur in the TSS area off Kilpilahti, where product tankers encounter crude oil tankers sailing on the east–west route, see Fig. 8. With this information, the relevant vessel particulars and impact speeds can be estimated as shown in Table 7. There is however significant uncertainty regarding other impact scenario variables such as the relative impact location \( l \) and impact angle \( \varphi \), as the process from encounter to impact conditions is not well understood (Ståhlberg et al., 2013). To show the effect of these variables, two sets of analyses are shown, where these uncertain variables are systematically varied, see Fig. 9.

---

Table 4

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>( \eta )</th>
<th>CDF (( \eta ))</th>
<th>( L )</th>
<th>CDF (( L ))</th>
<th>( B )</th>
<th>CDF (( B ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>0.4514</td>
<td>( \eta &lt; 17 )</td>
<td>0.224</td>
<td>( L &lt; 190 )</td>
<td>0</td>
<td>( B &lt; 29.1 )</td>
<td>0</td>
</tr>
<tr>
<td>( \beta_p )</td>
<td>589.4</td>
<td>( \eta &lt; 20 )</td>
<td>0.776</td>
<td>( 190 &lt; L \leq 261 )</td>
<td>0.014</td>
<td>( 29.1 &lt; B \leq 50 )</td>
<td>0.048</td>
</tr>
<tr>
<td>( \alpha_r )</td>
<td>0.4378</td>
<td>( \eta &gt; 20 )</td>
<td>1.000</td>
<td>( L &gt; 261 )</td>
<td>1</td>
<td>( L &gt; 50 )</td>
<td>1</td>
</tr>
<tr>
<td>( \beta_r )</td>
<td>709.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

A TSS area is an area where ship traffic is regulated, such that vessels are required to follow certain sea lanes.
7. Discussion

In the preceding sections, the general framework for the BN construction was outlined and the various steps in the construction of the probabilistic oil outflow model were presented in more detail. The validity of the oil outflow model in light of the intended application area and the adopted risk perspective is discussed in more detail in this Section.

While ultimately, the validity a model of a physical phenomenon such as oil outflow from a tanker in a collision could be established by testing the model’s fit with a set of data, this is practically unfeasible for the presented model. There is no data set containing real-world observations for the range of potential scenarios covered by the model, and performing e.g. model tests to generate such a set of experimental data would be very costly and likely still very limited compared to the scope of model scenarios.

Another option, e.g. applied in Montewka et al. (2013c), would be a comparison of the model output with output of other models. The statistical model by Przywarty (2008) or the meta-model be a comparison of the model output with output of other models. Such a set of experimental data would be very costly and likely still very limited compared to the scope of model scenarios.

For these reasons, a more procedural and risk-theoretic approach to validation of the presented model is adopted in this work. The generic framework for this is outlined in the next Section. The evaluation of the presented model in light of this framework is subsequently addressed.

7.1. Framework for validation of risk model BN

Pitchforth and Mengersen (2013) propose a validation framework for Bayesian networks, which contains a range of conceptual elements which can be applied to increase confidence in a BN model. The framework is similar to a framework presented by Trochim and Donnelly (2008) for construct validity in social science research, containing elements as shown in Fig. 10. Translation validity refers to how well the model translates the construct under investigation into an operationalization. Criterion-related validity refers to a number of tests to which the model can be subjected.

In the framework, face validity is a subjective, heuristic interpretation of the BN as an appropriate operationalization of the construct. Content validity is a more detailed comparison of the included variables in the BN to those believed or known to be relevant in the real system. Concurrent validity refers to the possibility that a BN or a section of a BN behaves identically to a section of another BN. Predictive validity encompasses both model behavior and model output. In terms of BNs, it consists of behavior sensitivity by determining to which factor and relationships the model is sensitive. The qualitative features analysis compares the behavior of the model output with a qualitative understanding of the expected system response. Convergent and discriminant validity reflect on the relationship of the BN with other models. Convergent validity compares the structure and parameterization of the BN with models which describe a similar system. Discriminant validity refers to the degree to which the BN differs from models that should be describing a different system.

The elements in the framework can be seen as sources for confidence in the model, i.e. in the model’s ability to describe the system. It intends to describe both in terms of the output and in terms of the mechanism by which that output is generated (Pitchforth and Mengersen, 2013). This is in line with the constructivist basis of the adopted risk perspective of Section 2.3, where the elements in the framework serve to assess the strength of the argumentation. Considering what validity means for the adopted risk perspective, important elements in this context are the completeness of the uncertainty assessment (Aven and Heide, 2009) and the completeness of the bias assessment (Rosqvist and Tuominen, 2004). Thus, the validity framework serves not only to assess how well the model describes the system it intends to describe, but also to systemically reflect on uncertainties and biases underlying its construction.

While the various validity concepts can act as sources of model confidence, the extent to which the validity tests fail can be indicated by providing a qualitative uncertainty and bias assessment. This uncertainty and bias assessment highlights which parts of the model would benefit most from a more accurate or comprehensive modeling approach.

7.2. Framework application: discussion on validity concepts

In the framework application, we focus on face, content and predictive validity. Concurrent validity cannot be established as

<table>
<thead>
<tr>
<th>Table 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression coefficients of polynomial expressions for $h_l$ and $h_r$, from (van de Wiel and van Dorp, 2011).</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<th>$i = 3$</th>
<th>$i = 4$</th>
<th>$i = 5$</th>
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<tbody>
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<table>
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<td>$j = 5$</td>
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</table>

<table>
<thead>
<tr>
<th>Table 6</th>
</tr>
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<tr>
<td>Discretization of variables in $G_i(X, A)$.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Discretization</th>
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<td>$m_1$</td>
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<td>$0:10$ and $20$ k</td>
<td>$0.10$ k and $20$ k</td>
<td>$x_1$</td>
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<td>$\theta$</td>
<td>()</td>
<td>$0:1$ and $3:1$</td>
<td>$0.1$ and $3:1$</td>
</tr>
<tr>
<td>$\eta$</td>
<td>()</td>
<td>$0:1:5:1$</td>
<td>$0:1:5:1$</td>
<td>$y_2$</td>
<td>(m)</td>
<td>$0:5$ and $35$</td>
<td>$0:5$ and $35$</td>
</tr>
<tr>
<td>$\eta$</td>
<td>()</td>
<td>$17:3:23$</td>
<td>$17:3:23$</td>
<td>$y_T$</td>
<td>(m)</td>
<td>$0:2:12$</td>
<td>$0:2:12$</td>
</tr>
</tbody>
</table>
no other BN models for accidental oil outflow are known to exist. Convergent and discriminant validity require an in-depth comparison of the BN with models of similar, respectively different systems. These are in-principle options but are considered beyond the scope of the current work.

7.2.1. Face validity

In terms of face validity, the presented BN can be considered an appropriate model for oil outflow in ship–ship collision, conditional to impact conditions. This is clear from its construction, which is based on the tank arrangement model by Smailys and Česnauskis (2006) and the collision damage extent model by van de Wiel and van Dorp (2011). The model by Smailys and Česnauskis (2006) has been validated for a number of cases and the analysis in Section 4.2.2 shows that the model leads to a reasonable, conservative estimate of the ship deadweight. The regression model by van de Wiel and van Dorp (2011) shows a reasonable fit with the cases reported in NRC (2001), see also Section 5.2, and the underlying ship collision mechanics model by Brown and Chen (2002) has been validated for some accident scenarios by Chen (2000). Thus, the BN can be expected to provide reasonable estimates of oil outflows for the intended application in risk assessment for maritime transportation, even when only very limited data about the vessels is available.

7.2.2. Content validity

The oil outflow model includes many, but not all relevant variables for determining the oil outflow. Impact speeds, angle and location and ship masses are important variables in determining the collision damage extent. However, the yaw and sway velocities at the moment of impact also have a certain influence on the collision energy (Ståhlberg, 2010) and damage extent (Wiśniewski and Kolakowski, 2003). Also the specific structural design of the struck ship’s hull is important for the assessment of the collision damage (Högström, 2012; Klanac et al., 2010). It can furthermore be expected that the collision damage may lead to progressive hull failure, which is not accounted for in the model. The spilled oil

Table 7

<table>
<thead>
<tr>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Unit</td>
</tr>
<tr>
<td>$m_1$</td>
<td>tonnes</td>
</tr>
<tr>
<td>$L$</td>
<td>(m)</td>
</tr>
<tr>
<td>$B$</td>
<td>(m)</td>
</tr>
<tr>
<td>$v_1$</td>
<td>(kn)</td>
</tr>
<tr>
<td>$v_2$</td>
<td>(kn)</td>
</tr>
</tbody>
</table>

Fig. 7. Resulting Bayesian network model for accidental oil outflow of product tanker collisions.

Fig. 8. Location of the possible accident scenarios in the Gulf of Finland.
volume depends on the damage opening and position above or below the waterline (Tavakoli et al., 2010), and may be expected to depend on vessel motion in waves, dynamic pressure differences due to wave action and the shape of the opening. Not all these variables are included in the BN, leading to uncertainty regarding the damage extent. The assumption that all oil in all breached tanks is spilled, is conservative, see Section 4.3.1.

7.2.3. Predictive validity

One aspect of predictive validity concerns a behavior sensitivity test. In particular, the parameter sensitivity of the model output in terms of oil outflow is determined for each node of the presented BN, using the sensitivity function as proposed by Chan and Darwiche (2002):

$$f(z) = \frac{(c_1 z + c_2)}{(c_3 z + c_4)}$$  \hspace{1cm} (25)

Here, $f(z)$ is the output probability of interest given parameter variables $z$, which have the following form:

$$z = p(Y = y_i | x_i)$$  \hspace{1cm} (26)
where $y_i$ is one state of a network variable $Y$, and $\pi$ a combination of states for $Y$'s parent nodes. The constants $c_i$, $i = 1 \ldots 4$ are computed based on the model. The sensitivity value is determined based on the first derivative of the sensitivity function. Table 8 shows the maximum absolute sensitivity values of the ten most sensitive BN nodes, with variable “Oil Outflow” as output. This indicates that the oil outflow is very sensitive to the impact location, the speed of the striking ship, the struck ship mass and the impact angle. Interestingly, the presented BN model shows only very limited sensitivity to the tank arrangement.

A qualitative features analysis can be made based on the accident scenarios of Table 7 and Fig. 9. Considering e.g. scenario 1, it is seen that an impact outside the cargo area (1: [0–0.2]) almost certainly leads to no oil outflow under an oblique impact angle. If a perpendicular impact is considered, the model leads to more probable bigger spills if the impact happens near the aft cargo bulkhead. If the impact occurs in the midship area (1: [0.4–0.6]), there is a non-zero probability of no spill under oblique impact angles, but when impact angles are close to perpendicular there always is a spill. Such behavior can qualitatively be expected as under oblique angles, it is possible that the double hull is not breached whereas for the same available deformation energy under perpendicular impacts, the double hull will be breached. Similar behaviors can be derived from the considered cases of scenario 2, where it is also seen that the probabilities for larger spill volumes are larger than for scenario 1. This can also be expected as scenario 2 considers a larger product tanker than scenario 2. Such a qualitative evaluation of model behavior is not very informative in terms of the accuracy of the probabilities for various scenarios, but the qualitative agreement between the model behavior and a qualitative understanding of the real system does increase confidence in the model.

### Table 8

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sensitivity value (-)</th>
<th>Variable</th>
<th>Sensitivity value (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>0.62</td>
<td>$r$</td>
<td>0.07</td>
</tr>
<tr>
<td>$r_1$</td>
<td>0.43</td>
<td>$\eta$</td>
<td>0.06</td>
</tr>
<tr>
<td>$m_2$</td>
<td>0.23</td>
<td>DWT</td>
<td>0.06</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>0.18</td>
<td>$L$</td>
<td>0.06</td>
</tr>
<tr>
<td>$m_1$</td>
<td>0.12</td>
<td>B</td>
<td>0.04</td>
</tr>
</tbody>
</table>

### 7.3. Framework application: uncertainty and bias assessment

While the Bayesian network validation framework shows that the oil outflow probabilities can be expected to be reasonable, there are several uncertainties and biases present in the underlying models. Systematically assessing these is important in terms of the adopted risk perspective, see Section 2.3 and also Oreskes, 1998 stresses the need to acknowledge weaknesses in policy-oriented models.

The uncertainty and bias assessment presented in Table 9 is performed qualitatively and can be considered to moderate the strength of the argument put forward by the probabilistic oil outflow quantification. Some relevant evidential and outcome uncertainties and biases are listed and scored using a simple 5-point scale, followed by a brief justification why the model element involves uncertainty or bias.

Overall, while the underlying models used for the construction of the BN can be taken to provide reasonable approximations of the involved phenomena as discussed above, the presented BN provides a rather conservative estimate of potential oil outflows, conditional to medium evidential uncertainty.

The assessment of Table 9 is useful for reflecting which parts of the model to improve using better underlying models to decrease uncertainty and bias. It is seen that improvements to decrease uncertainty are desirable mainly in relation to the applied damage

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extent model. Considering bias, a more elaborate model for oil spill volume conditional to an inner hull breach could reduce the conservativeness of the model. This shows that the framework presented in Section 3.2 can be applied again as more accurate damage extent and oil outflow models become available.

It should however also be appreciated that under the adopted risk perspective of Eq. (4), the whole aim of risk assessment is to express uncertainty about the possible occurrence of oil spills, being aware of uncertainties and biases related to the model construction. As also other state-of-the-art damage extent models for ship–ship collision involve uncertainties and biases as mentioned in Section 5.1, the presented model can be considered adequate for assessing oil spill risk under the adopted risk perspective.

8. Conclusion

In this paper, a Bayesian network model for the evaluation of accidental cargo oil outflow in ship–ship collisions involving a product tanker has been presented. The main focus of the paper is the presented framework for the construction of this model and assessment of the underlying uncertainties and biases in line with the intended adopted risk perspective in risk assessment of maritime transportation.

The probabilistic oil outflow model integrates a damage extent model conditional to impact scenarios with a model for evaluating the oil outflow based on an estimated tank arrangement. Based on a large set of damage cases in a set of representative tanker designs, a network linking ship design variables, damage scenarios and oil outflow is constructed using a Bayesian learning algorithm. The impact scenario model is subsequently linked to the damage extent variables.

The model provides a platform to assess the uncertainty about the possible oil outflows in maritime traffic scenarios when only very limited data regarding the ship design is available, as is typical in risk assessment of maritime transportation. It also enables insight in the probabilistic nature of possible oil outflows conditional to the impact conditions, which has been illustrated in two example accident scenarios.

The model can be expected to provide a reasonable estimate of possible oil outflows under various scenarios, which mainly follows from the reported validity of the underlying models for collision damage and tank arrangement. The issue of validation of the Bayesian network model was discussed using various validity concepts aimed to increase confidence in the model in absence of data to which the model output can be compared.

A systematic analysis of uncertainties and biases in the underlying models and assumptions shows that while the presented model allows a quantification of uncertainty regarding oil outflows, some reservations need to be made regarding the accuracy of the results. In particular, some evidential uncertainties are present in the damage extent model and the assumptions made regarding the oil outflow calculations lead to an overestimation of the oil outflow. This assessment allows a reflection on those elements in the model which would benefit most from a more detailed modeling approach, if further accuracy is desired in the assessment of possible oil outflows.

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