



Critical aspects for collision induced oil spill response and recovery system in ice conditions: A model-based analysis

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ARTICLE INFO

Keywords:

Risk management
COOR system
Mechanical oil recovery
Ice conditions

ABSTRACT

The recovery effectiveness for oil spills in ice conditions depends on a complex system and has not been studied in depth, especially not from a system risk control perspective. This paper aims to identify the critical aspects in the oil spill system to enable effective oil spill recovery. First, a method is developed to identify critical elements in a Bayesian Network model, based on an uncertainty-based risk perspective. The method accounts for sensitivity and the strength of evidence, which are assessed for the different Bayesian Network model features. Then, a Bayesian Network model for the mechanical oil spill recovery system is developed for the Finnish oil spill response fleet, contextualized for representative collision accident scenarios. This model combines information about representative sea ice conditions, ship-ship collisions and their associated oil outflow, the oil dispersion and spreading in the ice conditions, and the oil spill response and recovery of the fleet. Finally, the critical factors are identified by applying the proposed method to the developed oil spill response system model. The identified most critical system factors relates collision aspect: *Forcing Representative Scenario*, *Representative Accident Location*, *Impact Speed*, *Impact Location*, *Impact Angle* and response aspect: *Response Vessel Operability*.

1. Introduction

Oil spill is a risk to the environment, economy and even human life, therefore the research on oil spill risk is an important topic. Recently, the oil spill in ice conditions receives increasing attention in light of the discussions on the potential Northern Sea Route (Bekkers et al., 2018; Theocharis et al., 2019), and with the intense shipping activities in other cold regions, e.g. the Northern Baltic Sea (Goerlandt et al., 2017). Addressing the oil spill risk properly becomes a precondition for the activities in the ice conditions, and is an important aspect of oil spill preparedness and response planning (Laine et al., 2018).

As one of the few areas with dense ship traffic in ice, the Northern Baltic Sea (NBS) is selected as the study region in this paper. In NBS, Goerlandt et al., 2017 and Valdez Banda et al. (2015) find that collision accidents are the main potential accident type leading to spills in ice conditions. Ship collision, as a typical accident, has been studied in many aspects, e.g. from internal mechanics aspect, i.e. focusing on

structure analysis (Pedersen and Zhang, 1998; Ehlers et al., 2008; Haris and Amdahl, 2013; Tabri et al., 2009) and also from probability approach, i.e. focusing on collision probability assessment both in open water (Fujii et al., 1970; Pedersen, 1995; Montewka et al., 2010) and ice conditions (Valdez Banda et al., 2016; Afenyo et al., 2017; Zhang et al., 2019). Meanwhile, there are also diverse research related to oil spills, e.g. some research pays attention to the dynamic features of oil outflow process (Kollo et al., 2017) and also development of support system to help estimate the oil outflow in the grounding case (Tabri et al., 2018). In the research of oil drift, Afenyo et al. (2016) makes state-of-art review and Arneborg et al. (2017) improves the oil drift modelling for ice conditions. In addition, extensive research are conducted to improve the understanding of oil behavior, response and recovery in ice conditions in SINTEF JIP and Arctic Response Technology (ART) JIP (Sørstrøm et al., 2010; ART, 2012; ART, 2017).

However, the process from a collision accident to its oil spill response and recovery actions is an integrated process. How the collision influences the oil spill, response and recovery is actually not well studied.

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<https://doi.org/10.1016/j.jlp.2020.104198>

Received 12 February 2020; Received in revised form 27 May 2020; Accepted 28 May 2020

Available online 22 June 2020

0950-4230/© 2020 The Author(s).

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Nomenclature		MP	Model Parameterization
NBS	Northern Baltic Sea	SA	Sensitivity Analysis
BN	Bayesian Network	ICF	Identified Critical Factors
COOR	Collision-Oil spill-Oil drift-Response and recovery	ED	Data
FRAM	Functional Resonance Accident Method	EM	Model
STPA	Systems Theoretic Process Analysis	EJ	Judgement
FSA	Formal Safety Assessment	EA	Assumption
SoE	Strength of Evidence	C1	The most critical factors
R	Risk	C2	Minor critical factors
C	Consequences of the activity	C3	The least critical factors
Q	Quantified measure of the uncertainties	DAG	Directed Acyclic Graph
BK	Background Knowledge	CPT	Conditional Probability Table
RA	Risk Analysis	RFS	Representative Forcing Scenarios
RC	Risk Control	RAL	Representative Accident Locations
MV	Model Variable	AIS	Automatic Identification System
MS	Model Structure	PADM	Particle Dispersion Model
MD	Model Discretization	IR	Internal Reviews

This requires linkages from the collision to the oil spill outflow, then to the oil drift and oil spill response and recovery, i.e. a system-level analysis. Some research has been dedicated to oil spill and its impact in a system level, modelled by BN models, e.g. [Juntunen et al. \(2005\)](#) and [Aps et al. \(2009\)](#) use BNs to model the oil spill impact on the environment; [Montewka et al. \(2013\)](#) focus on the economic costs of response activities; [Helle et al. \(2011\)](#) and [Lehikoinen et al. \(2013\)](#) model the oil combating effectiveness in open sea conditions. Although the above research considers the system level, they have some common features: 1) the focus is on the environmental or economic impacts of the oil spills, thus they focus more on the response and recovery part and do not include accident/collision features; 2) the existing work does not include dynamic features of oil outflow and oil drift; 3) the existing models for response effectiveness are limited to oil spills in open water.

[Lu et al. \(2019\)](#) proposed a model to calculate the oil recovery effectiveness in ice conditions. However, it focuses on the development of oil spill response and recovery part in ice conditions based on the assumed oil amount and does not include the collision and oil outflow features as how an oil spill happens in an accident. It is unique and useful as it enables the possibility to estimate how much oil can be recovered in the ice conditions. The current work completes the route from the collision stage to oil outflow, oil drift and final response and recovery stage for ice conditions. When these stages are combined with the oil response fleet considered, they form a system, which is here defined as the Collision-Oil spill-Oil drift-Response and recovery (COOR) system. This paper focuses on the analysis of the COOR system.

There are many methods to conduct a risk analysis and management on a system level, e.g. Bowtie, Functional Resonance Accident Method (FRAM), Systems Theoretic Process Analysis (STPA), Fault Tree and Event Tree, Bayesian Networks (BNs), etc. Risk-based methods are widely applied ([Akyuz and Celik, 2016](#); [Bubbico et al., 2009](#); [Fu et al., 2017](#)) and are a significant area of research. Nevertheless, there are only limited options to select the efficient risk control options from a risk analysis model of large-scale systems. [van Dorp and Merrick \(2011\)](#) and [Valdez Banda et al. \(2016\)](#) make prioritization based on probability reduction of the consequence. [Helle et al. \(2015\)](#) apply cost-benefit analysis approach for oil spill management. Some research ranks system components based on sensitivity of the variables ([Hänninen and Kujala, 2012](#)).

Recently, there has been intensified discussion on foundational issues in risk assessment and management, focusing on the treatment of uncertainties ([Aven and Zio, 2014](#); [Goerlandt, 2015](#)). Further research points out that there is limited evidence that quantitative risk analysis for large-scale systems can provide accurate risk estimates ([Rae et al., 2014](#); [Goerlandt et al., 2017](#)). [Kontovas and Psaraftis \(2009\)](#) also point out the uncertainties and weak points in FSA and cost-benefit analysis. Therefore, there seems to be a need to more explicitly consider the importance of uncertainties when identifying the critical aspects in a risk analysis for a large-scale system as a basis for selecting risk control options.

[Goerlandt and Montewka \(2015\)](#) combine both sensitivity and the Strength of Evidence (SoE), which represents how good the evidence underlying the different model aspects is, to rank the important factors in a maritime system. However, the SoE assessment on the system only focuses on the evidence categorizations and do not cover the features of the modelling. In addition, there are academic discussions about the suitability of existing SoE rating schemes recently, see e.g. [Flage and Aven \(2017\)](#), [Goerlandt and Reniers \(2017\)](#) and [Flage and Aven \(2018\)](#). Based on this, this paper aims to improve the development of SoE assessment to deliver a more comprehensive methodology for identifying critical aspects for a large-scale system.

The aim of this paper is to identify the critical aspects for the COOR system so that better risk control options/range can be targeted for oil spill preparedness and planning. This is achieved by first improving the method of identifying critical factors, and then by applying this method to the developed COOR system model.

The scope of this paper is on ship-ship collision accident and mechanical recovery of oil in ice conditions in the NBS area, where only the Finnish fleet is considered as the system in focus. The exclusive focus on the mechanical recovery method stems from regionally agreed requirements covering the NBS area, where the use of chemical agents and other non-mechanical means is restricted by a recommendation adopted by [HELCOM \(2001\)](#). A further scope restriction is the focus on Tier-2 or 3 oil spills (see, e.g., [IMO, 2010](#); [IPIECA and OGP, 2016](#)). If such oil spills occur, existing risk analyses suggest that these result from accidents at open areas ([Valdez Banda et al., 2015](#); [Goerlandt et al., 2017](#)).

The remainder of the paper is organized as follows. Section 2 describes the methodology for identifying the critical aspects in a system

and developing the COOR system. Section 3 presents the model and the identified results. A discussion follows in Section 4. Section 5 presents the conclusions.

2. Methodology

In order to identify the critical system risk aspects of the COOR system in the NBS, the methodology includes two parts: 1) develop a method to identify critical system factors under uncertainty-based risk perspective, and 2) create the COOR system model to apply the developed method. The methodology for identifying critical system risk aspect is introduced firstly in Section 2.1. Then Section 2.2 follows and describes the COOR system model in detail.

2.1. Methodology for identifying critical system aspect

2.1.1. Risk perspective and framework

Defining an appropriate risk perspective is important in risk analysis and management, which guides how the risk is treated in the analysis and how the results are applied in decision making. Risk is commonly understood as a construct shared by a social group, informed by available evidence (Aven and Renn, 2009; Thompson and Dean, 1996). It is thus not a physical attribute of a system, but a concept attributed to a system in the mind of an assessor (Goerlandt and Montewka, 2015; Solberg and Njå, 2012). In this paper, risk is understood as the occurrence of some specified consequences of the activity and associated uncertainties, in line with state-of-the-art risk research (Aven, 2013; Goerlandt and Reniers, 2016). Correspondingly, the risk perspective can be summarized as follows:

$$R \sim (C, Q, SoE|BK) \quad (1)$$

where C are the consequences of the activity, Q a quantified measure of the uncertainties associated with these consequences, and SoE a qualitative description of the strength of evidence for the quantified uncertainty measure Q. BK is the background knowledge, i.e. the evidence base to which the risk description is conditional. Hence, risk here is described by a quantified measure of the consequences and

uncertainties, along with an indication of the strength of its underlying evidence. All of these aspects of the risk description are conditional to the available background knowledge.

As seen in Fig. 1, under the risk perspective, Risk Analysis (RA) is applied to subsequently reach Risk Control (RC) stage. In RA, BNs are selected as a risk modelling tool, reflecting the events/risk influencing factors leading up to the consequences (C) and its relevant uncertainties (Q). BNs are considered in terms of the four features in model development, i.e. Model Variable (MV), Model Structure (MS), Model Discretization (MD) and Model Parameterization (MP) (Pitchforth and Mengersen, 2012; Goerlandt, 2015). Based on the BN model and its features, Sensitivity Analysis (SA) and Strength of Evidence (SoE) are used as the two main methods to deepen the risk analysis, and in particular identify important system aspects.

SA classifies the variables into three groups: low, medium and high according to the sensitivity results and SoE categorizes into five levels: low, low-medium, medium, medium-high and high. Table 1 shows the principle to classify critical factors when combing the results from the two methods. The variables are grouped into three critical levels C1-C3, as shown in Table 1. In risk management, the method helps to narrow the potential risk control options so that the identified critical factors (ICF) for the system risk control can be found. This coherently links RA with a RC stage where it is clear which system aspects require prioritization. Section 2.1.2 presents a brief overview of BNs as a modeling tool. More details about SA and SoE in Fig. 1 are introduced separately in Section 2.1.3 and 2.1.4.

2.1.2. Bayesian networks

Bayesian Networks (BN) are selected as risk modelling tool in this paper as it has many favorable features. One feature is that it can present relatively complex problems and cope with uncertain and unobserved variables, while also having a graphical dimension. This makes BNs suitable for modeling complex problems, with the additional benefit of being able to incorporate different types of evidence in the model construction. Meanwhile, it also aligns well with the risk perspective. The establishment of the BNs structure is based on a specific background knowledge, and consequences are reflected as quantified measure of the uncertainties by a finite number of mutually exclusive states and corresponding probabilities of occurrence. In addition, the visible graphical structure serves as a useful frame of reference to analyze the strength of evidence, see e.g. Mazaheri et al. (2016). BNs are relatively widely used tools for risk modeling and have been applied many fields (Fenton and Neil, 2012), including maritime risk analysis (Lim et al., 2018; Aps et al., 2009; Hänninen, 2014; Helle et al., 2015).

In mathematical terms, BNs represent a class of probabilistic graphical models, defined as a pair $\Delta = \{G(V,A),P\}$ (Koller and Friedman, 2009), where $G(V,A)$ is the graphical component and P the probabilistic component of the model. $G(V,A)$ is in the form of a directed acyclic graph (DAG), where the nodes represent the variables $V = \{V_1, \dots, V_n\}$ and the arcs (A) represent the conditional (in)dependence relationships between these. P consists of a set of conditional probability tables (CPTs) $P(V_i|Pa(V_i))$ for each variable V_i , $i = 1, \dots, n$ in the network. $Pa(V_i)$ signifies the set of parents of V_i in G: $Pa(V_i) = \{Y \in V|(Y,V_i)\}.$ A

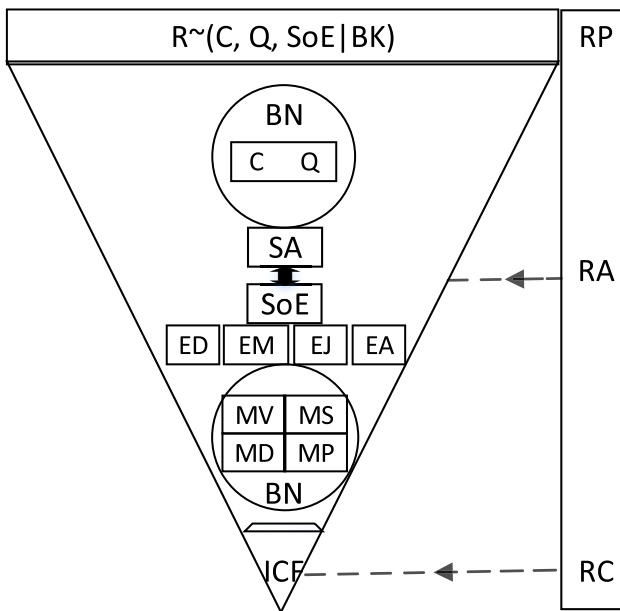


Fig. 1. Risk perspective and framework for identifying critical system risk aspect. ED, EM, EJ and EA are four main evidence aspects, representing data (ED), model (EM), judgement (EJ) and assumption (EA); see more in Section 2.1.4.

Table 1

Classification of critical aspects by combing SoE and sensitivity analysis methods. C1 represents the most critical factors, C2 represents minor critical and C3 represents the least critical ones.

Sensitivity	High	C1	C1	C1	C1	C1
	Medium	C1	C1	C2	C2	C2
	Low	C2	C2	C3	C3	C3
		Low	L-M	Medium	M-H	High
SoE						

BN encodes a factorization of the joint probability distribution (JDP) over all variables in V (Goerlandt and Montewka, 2015):

$$P(V) = \prod_{i=1}^n P(V_i | Pa(V_i)) \quad (2)$$

In a BN model, the variable V is considered as the model variable and $G(V,A)$ compose the model structure. These are the qualitative part of the BN model. In addition to the model variable and structure, the BN modelling also contains the quantitative part, defined as discretization and parameterization (Pitchforth and Mengersen, 2012). Quantitative part converts the various evidence to CPTs and thus complete the BN model.

2.1.3. Sensitivity analysis

Sensitivity analysis concerns investigating the effect of small changes in numerical parameters (i.e., probabilities) on the output parameters (probabilities as quantitative measures of the uncertainty associated with the consequences). Highly sensitive parameters affect the reasoning results more significantly. Identifying them allows for an effective allocation of effort on particular parameters for further risk controls.

The sensitivity analysis in this paper applies the algorithm in GeNIe software, proposed by Kjaerulff and van der Gaag (2000). The algorithm calculates a complete set of derivatives of the posterior probability distributions over the target nodes over each of the numerical parameters of the Bayesian networks. These derivatives give an indication of importance of network numerical parameters for calculating the posterior probabilities of the targets. If the derivative is large for a variable, then a small change in the parameter leads to a large change in the posteriors of the targets. If the derivative is small, then even large changes in the parameter make little difference in the posteriors.

2.1.4. SoE

Strength of Evidence (SoE) is considered as an essential part of a risk analysis in recent risk research, see e.g. Flage et al. (2014) and Goerlandt and Reniers (2016) and it has also been used in oil spill risk analysis related works, e.g. Valdez Banda et al. (2016), as well as in ship accident analysis and modelling (Goerlandt et al., 2017; Mazaheri et al., 2016). The method suggested by Goerlandt and Reniers (2016), i.e. SoE of the BN model is assessed from four main evidence aspects: data (ED), model (EM), judgement (EJ) and assumption (EA), is further developed in this paper.

In the strength of evidence assessment, data is assessed based on the data quality and the amount of data, whereas models are assessed based on their empirical validation and theoretical viability, as shown in Table 2. Goerlandt et al., 2017 describes the criteria for ED, EM, EJ and EA in detail.

It is easy to understand that ED, EM, EJ and EA represent a classification of different sources or manifestations of the evidence. Therefore, the current SoE assessment can be considered to have covered full aspects from the evidence point of view. However, the nature of the model or the features of the modelling is ignored. SoE of a BN model is usually implemented on each variable without clarifying whether the evidence is used for the variable (MV), the structure (MS), the discretization (MD) or the parameterization (MP), i.e. the different components or features of the BNs. This makes the assessment actually incomplete or not

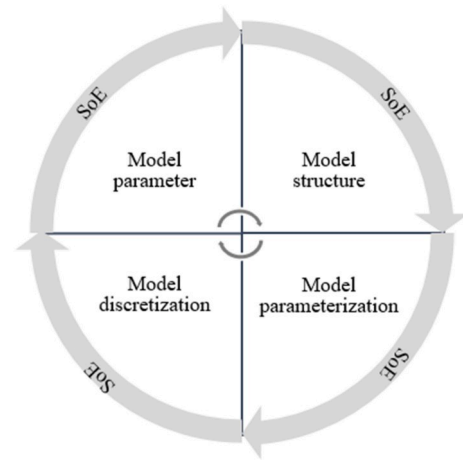


Fig. 2. SoE assessment on the BN model features.

Table 3

The question to be addressed by SoE for each model aspect.

Model aspect	The question to be addressed by SoE
MV	What & (How strong) is the evidence to include this variable?
MS	What & (How strong) is the evidence to support the links on the nodes?
MD	What & (How strong) is the evidence to be in favor of the discretized states of the parameter?
MP	What & (How strong) is the evidence to back the CPT of each state?

convincing from the viewpoint of the model.

Based on this, a more comprehensive SoE assessment on each aspect of the model is proposed as shown in Fig. 2. The SoE is assessed for each aspect of the model using SoE classifications in Table 2 and its criteria. However, each aspect of the model has their own features and functions inside the model. It is important to make sure the SoE assessment really addresses the strength of the evidence of each aspect in line with their functionality in the model. Table 3 lists the questions to be addressed by SoE to make the assessment clearly targeted. As listed in Table 3, the assessment criteria will be applied to address the questions listed for different aspects of the model. Thus, even the same evidences used for

Table 4

Example of SoE matrix results. a_{ij} is number 0–4, representing the quantified five-level classifications: low, low-medium, medium, medium-high, high.

	ED	EM	EJ	EA
MV	a_{11}	a_{12}	a_{31}	a_{14}
MS	a_{21}	a_{22}	a_{23}	a_{24}
MD	a_{31}	a_{32}	a_{33}	a_{34}
MP	a_{41}	a_{42}	a_{43}	a_{44}

Table 2

SoE assessment classifications.

Main item	SoE				
	Data		Model	Judgement	Assumption
Sub item	Quality	Amount	Empirical validation	Theoretical viability	–
Classification	Low Low-medium Medium Medium-high High				

the same node in a BN model, they may have different SoE result on each feature (MV, MS, MD, MP). The SoE assessed for the different BN model features is an intermediate step. After these assessments are completed, they are combined to a more explicitly rate for each node and come to an assessment of SoE.

The assessment classifies the SoE of MV, MS, MD, MP into five-category levels: low, low-medium, medium, medium-high, high. In this way, the model will be fully assessed. Thus, the SoE results for each variable in the model are in a 4×4 matrix as shown in Table 4. Expression (3) is applied to obtain the overall SoE for the node, which firstly take the maximum value from each row, i.e. considering the strongest evidence support from the different evidence categories and then take the minimum value from the four BN features, i.e. considering the weakest feature determines the final SoE rate.

$$a = \min_i (\max_j a_{ij}) \quad (3)$$

2.2. COOR system

The COOR system is made up by four main models: accident model, collision damage and oil outflow model, oil drift model and response and recovery model as in Fig. 3. The models are applied to particular contexts, which are included in the system model as representative forcing scenarios (RFS) (including atmosphere, current and ice conditions) and representative accident locations (RAL). There are four representative scenarios and seven representative accident locations, as shown in Fig. 4 in Section 2.2.1. The following sections will describe each model respectively.

2.2.1. Accident model

The accident model here refers to how the two ships collide, which includes information about the ships and the collision scenarios. The ship information is based on the Automatic Identification System (AIS) data in the Northern Baltic Sea, i.e. according to the ship transportation records in this area. Furthermore, representative ships are generated based on the dataset and relevant ship types, see details in Goerlandt et al., 2017. In total, sixteen tanker sizes are generated as representative struck tankers to cover the range of all the operating tankers recorded in

Northern Baltic Sea. Due to the limitation of the software simulation, four tanker sizes are finally selected for the simulations in this paper. Table 5 lists the representative tanker information. The detailed tanker arrangement of the ships can be found in Goerlandt et al., 2017. Meanwhile, two vessels are selected as representative striking ship: icebreaker (6430 DWT) and large cargo ship (28429 DWT), based on an accident analysis by Goerlandt et al., 2017. The collision scenario is also based on this accident analysis, and is here simplified to three striking speeds, two impact locations, and two impact angles. The simulated accident locations (1–7) are shown in the upper-left map in Fig. 4, chosen based on traffic density maps of the winter navigation in the area (Lensu and Goerlandt, 2019). Detailed coordinates can be found in model discretization for parameter Representative Accident Location in Appendix A.

2.2.2. Collision damage and oil outflow model

Assuming the collision accident has happened, the collision damage assessment is a central element for predicting the accidental consequences in terms of an oil spill. In order to evaluate the oil spill dynamics for damaged tankers, it should be identified whether the inner hull of the tanker is breached in a certain scenario. Inner hull damage largely defines the amount of the spilled oil, while the actual dimensions of the damage opening refine this prediction and are important to define the temporal spill dynamics. Here the collision scenarios from section 2.2.1 are used with application of the model by Heinvee and Tabri (2017) to identify the penetration depth and the probability of inner hull breaching. The model is developed for application contexts where only very limited structural data is available for the ships participating in the accident, thus making it suitable for the cases here. A simplification is done for the prediction of damage opening size and it is assumed that the dimensions of the opening follow the dimensions of the intruding structure at its intersection with the hull plating as shown by the dashed line in Fig. 5. It is obvious that this simplification could overestimate the size of the damage opening for some scenarios and thus, would influence the oil spill temporal dynamics while its effect on the amount of the spilled oil is less profound. This size definition is the input for the oil outflow simulations.

The oil outflow model connects different variables, such as tanker

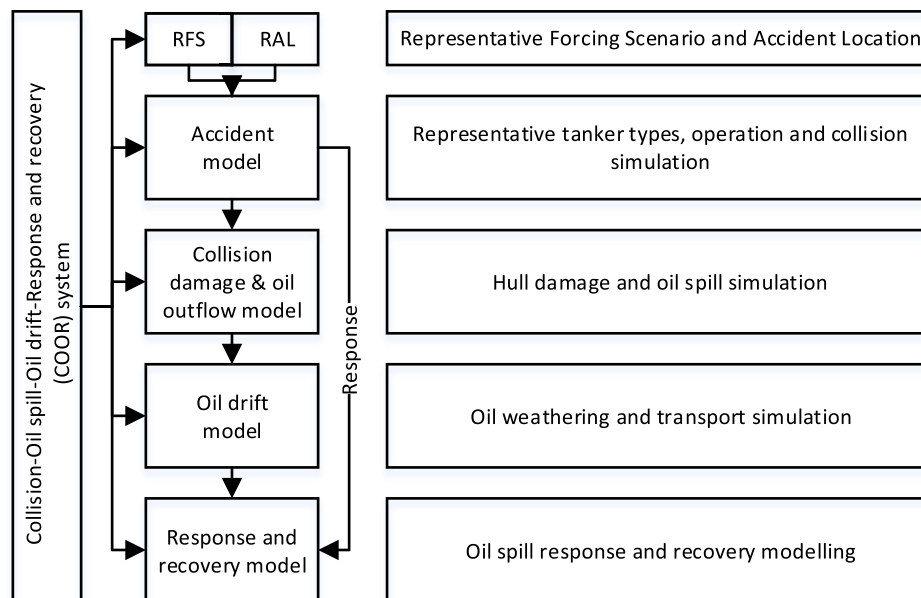


Fig. 3. Composition of the COOR system.

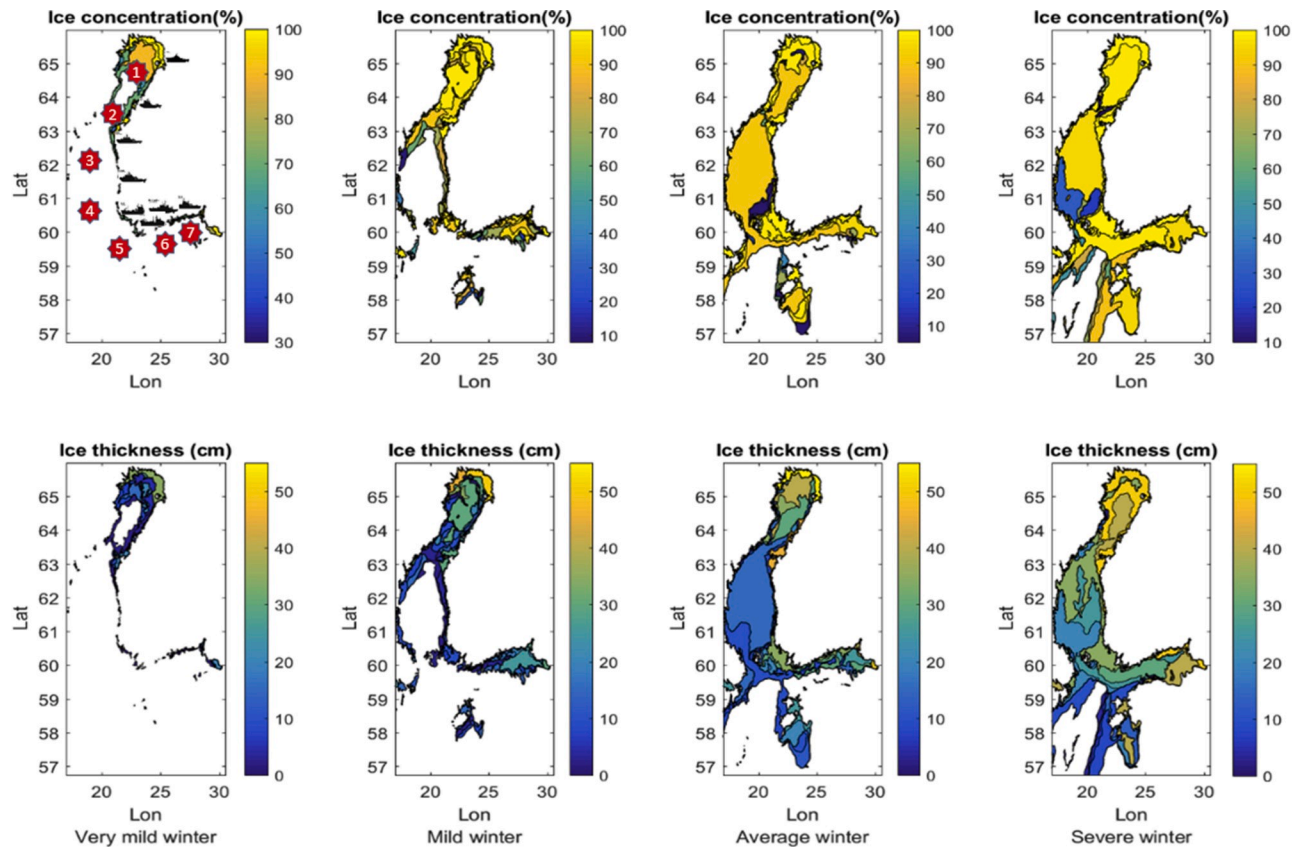


Fig. 4. Representative forcing scenarios and accident locations. Representative accident locations are shown in upper-left map with response vessels locations indicated. Detailed coordinates of accident locations can be found in model discretization for parameter Representative Accident Location in Appendix A. The accident locations are only indicated in one of the map to avoid unnecessary mixture of too much information on all maps. In the analysis, the accidents are simulated in all four winter scenarios.

Table 5
Oil tanker characterizations.

ID [-]	Length L [m]	Width B [m]	Draught T [m]	Depth D [m]	Deadweight DWT [tonnes]
T1	83.5	13.5	5.3	7	3232
T4	148.0	21.6	8.6	11.2	15000
T6	159.0	27	10.7	15.7	37000
T15	243.6	42.2	15.2	21.8	136000

structure, hydrostatic pressure difference and variable locations of damage opening, into a simulation model. An oil outflow from a tanker occurs when the inside pressure in a cargo-oil tank exceeds the outside pressure at the level of a submerged or semi-submerged damage opening. Excess hydrostatic pressures can result from a relatively high oil level in a tank. As a simplest possible outflow scenario, the unidirectional flow would occur under excess hydrostatic pressure until the pressure inside and outside the tank equalizes. However, especially for double hull tankers, the excess hydrostatic pressure is not necessarily dominating the flow and a bidirectional flow occurs, where oil flows out from a leaking tank and seawater flows in the opposite direction. To complicate the situation further, the mixing of water and oil occurs also inside the double hull. Here, the model proposed by Kollo et al. (2017)

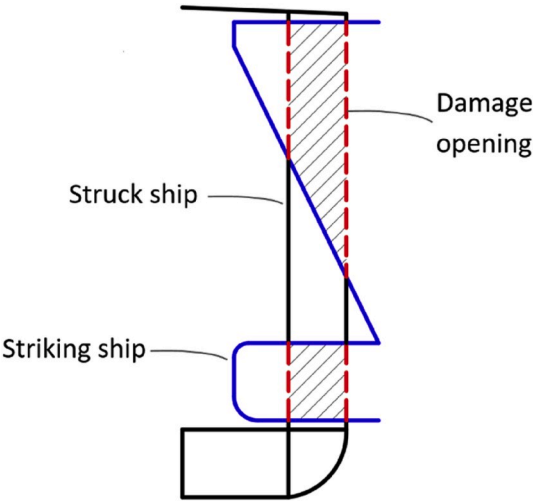


Fig. 5. Collision damage simulation: damage size defined as the intersection of the intruding striking ship and the side structure of the struck ship (indicated by dashed line).

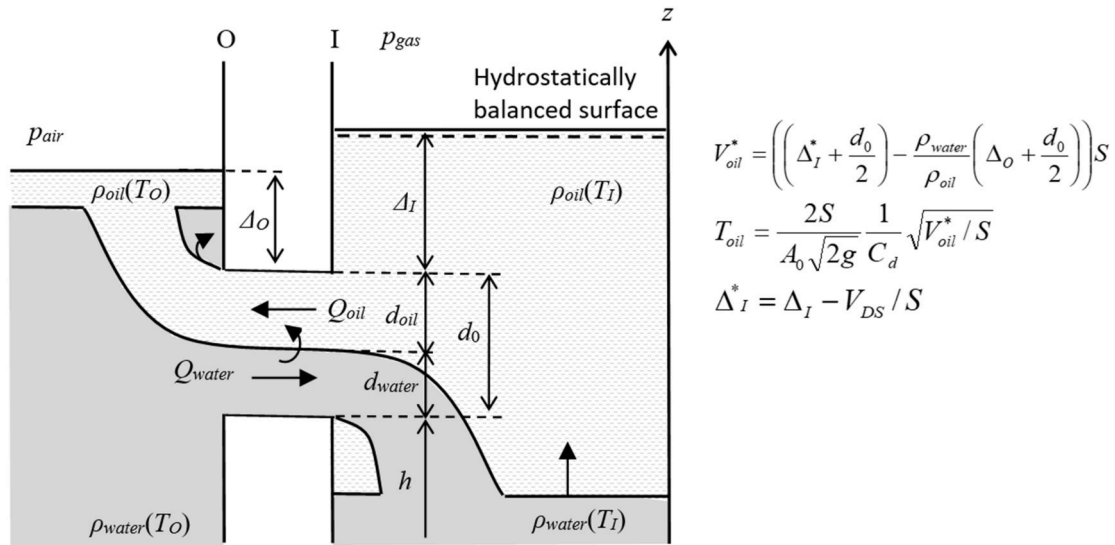


Fig. 6. Oil-spill through side opening in double hull tanker. I represents inside, O means outside, p stands for pressure, ρ is density, T is temperature, Δ represents the pressure difference compared to the water level and air pressure on the sea surface, d means the opening or outflow dimension, Q is the outflow rate, S is the oil-surface area, A_0 is the area of the damage opening, C_d is the discharge coefficient, V_{DS} is the side-ballast volume filled with oil, V_{oil}^* is the spill volume, T_{oil} is spill duration.

based on hydraulic modelling for bidirectional exchange flow through damage opening is used, see Fig. 6.

To evaluate the oil spill dynamics in winter conditions, additional challenges arise from the presence of ice and large temperature differences between the surrounding water and oil. In the case of oil outflow, in addition to the hydrostatic driving pressure and hull-damage characteristics, it is essential to include changes of liquids' physical properties (density and viscosity) due to temperature variations. The hydraulic model of Kollo et al. (2017) was extended in Sergejeva et al. (2017) to account for the effects of heat exchange, which causes the oil temperature variation during outflow. In the current work, the oil spill

models by Kollo et al. (2017) and Sergejeva et al. (2017) are applied to the damage extents resulting from the accident scenarios defined in Section 2.2.1. The combined model predicts the oil-outflow parameters in means of spill volume, duration and temporal variation.

2.2.3. Oil drift model

After the oil has spilled out from the damaged vessel, oil drift in the ice conditions occurs, including oil weathering and transport. The four representative forcing scenarios are as shown in Fig. 4. The simulation of the oil drift is based on the SeaTrack Web model PADM, Particle Dispersion Model (Ambjörn et al., 2014) including the latest

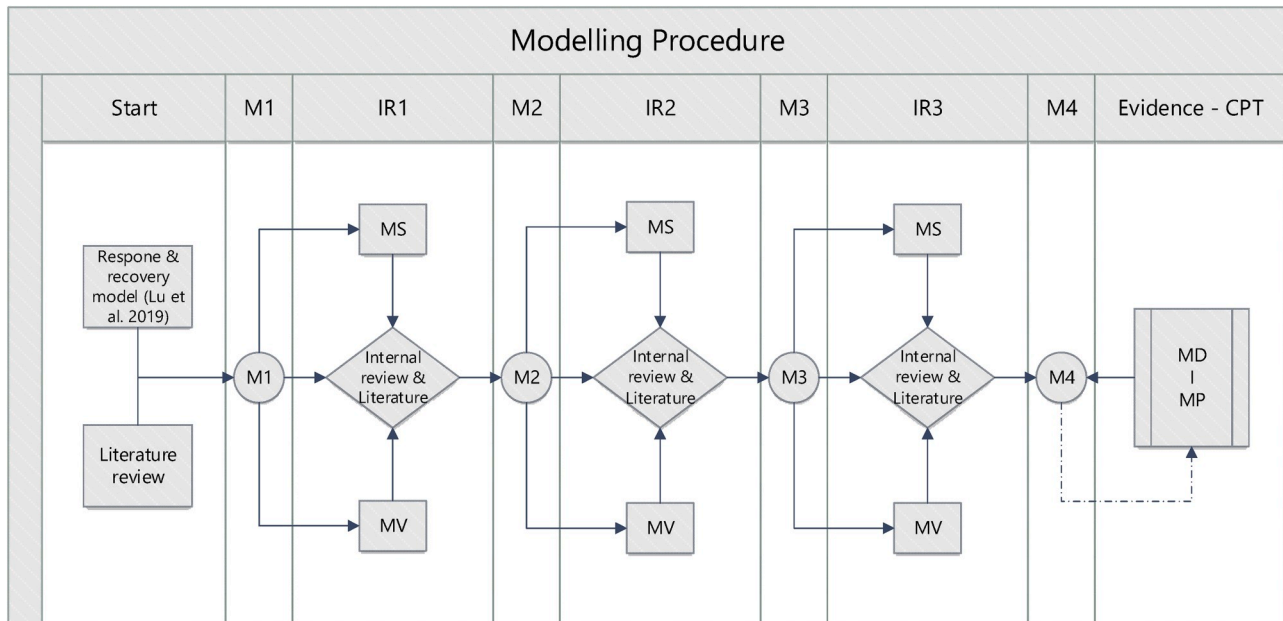


Fig. 7. Detailed BN modeling procedure for COOR system model.

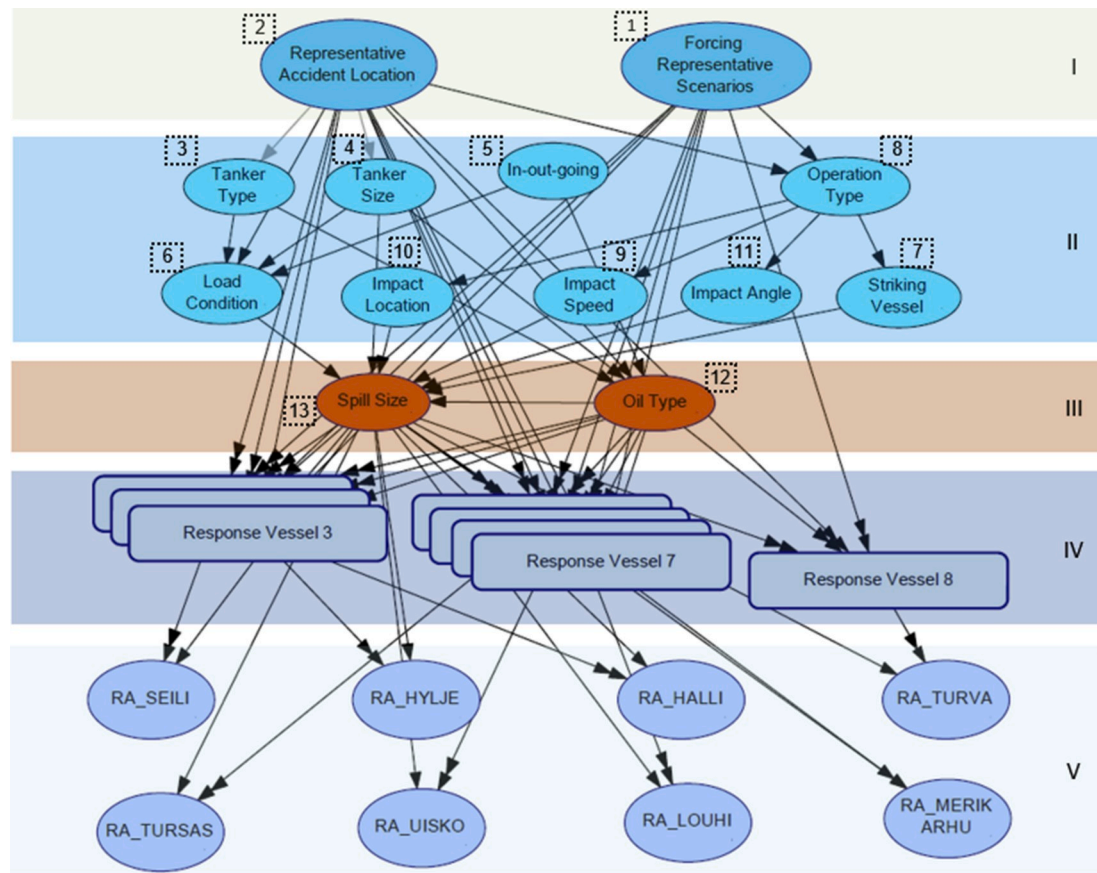


Fig. 8. The Bayesian Network COOR system model; I-RFS and RAL, II-Accident scenario, III-Oil spill, IV-Oil drift, response and recovery, V-Oil recovery.

improvements on the ice parameterization (Arneborg et al., 2017). PADM is a Lagrangian particle tracking model specialized on oil spill modeling. The oil being simulated is represented as a cloud of particles. Each particle represents a quantity of oil with a common set of properties, e.g. mass of oil and weathering status. These properties change over time as oil evaporates, get emulsified, etc. The trajectory of each particle is calculated in three dimensions based on currents, Stokes' drift, buoyancy and other processes relevant for oil spill spreading. PADM is forced by currents, water temperature, water density, ice concentration and ice thickness from a simulation with NEMO-Nordic (Pemberton et al., 2017) where sea surface temperature, ice concentration and ice thickness was assimilated (Axell and Liu, 2016). PADM also uses winds from the atmospheric forcing of NEMO-Nordic, which comes from the EURO4M reanalysis data set (Dahlgren et al., 2016).

2.2.4. Response and recovery model

The response and recovery model includes two parts. First, the oil spill response vessel will start heading to the oil spilled spot already during the oil spill and drift period. Second, the oil recovery procedure will be implemented after arriving. Lu et al. (2019) developed an oil spill response and recovery model for assessing the oil recovery effectiveness in the ice conditions. Therefore, the main part of that model is applied in this paper to construct the COOR system model. Fig. 9 shows the response and recovery model for vessel SEILI as an example. The model includes five parts. Part I relates to the oil condition; part II contains response elements; part III is ice condition and part IV includes atmospheric situation. Part V stands for the recovery process, which calculate the final predicted amount of recovered oil based on the conditions in other parts. The details of the variables are listed in Table 1 in Appendix A. More details of how the model is developed can be referred to Lu et al.

(2019).

3. Model and identified critical factors

3.1. COOR system model

Based on the models described in Section 2.2.1 to 2.2.4 and simulation results, the Bayesian Network COOR system model is created as shown in Fig. 8. The development of the BN model follows a similar process as utilized in Lu et al. (2019). As shown in Fig. 7, it starts from background knowledge establishment and then develops the model variables (MV) and model structure (MS) through multi-stage review process into a qualitative model. Then, model discretization (MD) and parameterization (MP) are conducted to transfer various types of evidence into the qualitative model, forming the final BN model. Compared to Lu et al. (2019), the modelling starts from an established response and recovery model. Thus, the focus is on the parts to be built on top of the existing model, i.e. mainly concerning layer I, II, III in Fig. 8. In the modelling in Layer IV (Lu et al., 2019), expert interviews are used for building the intermedium model. However, internal reviews (as shown in IR1-3 in Fig. 7), focusing on evaluation of model variables and structure, are applied instead in the current work because 1) there are more literature and published networks on ship-ship collision modelling comparing to the response and recovery of oil spill in ice conditions; 2) the BN modelling is to a large extent directly reflects the input-output relations of the models described in Section 2.2.1 to 2.2.4.

The system model is defined under the representative accident location and forcing conditions as in the first layer in the model. The next layer forms the basis of the accident model (Section 2.2.1), which includes the information about the collision scenarios, relating to

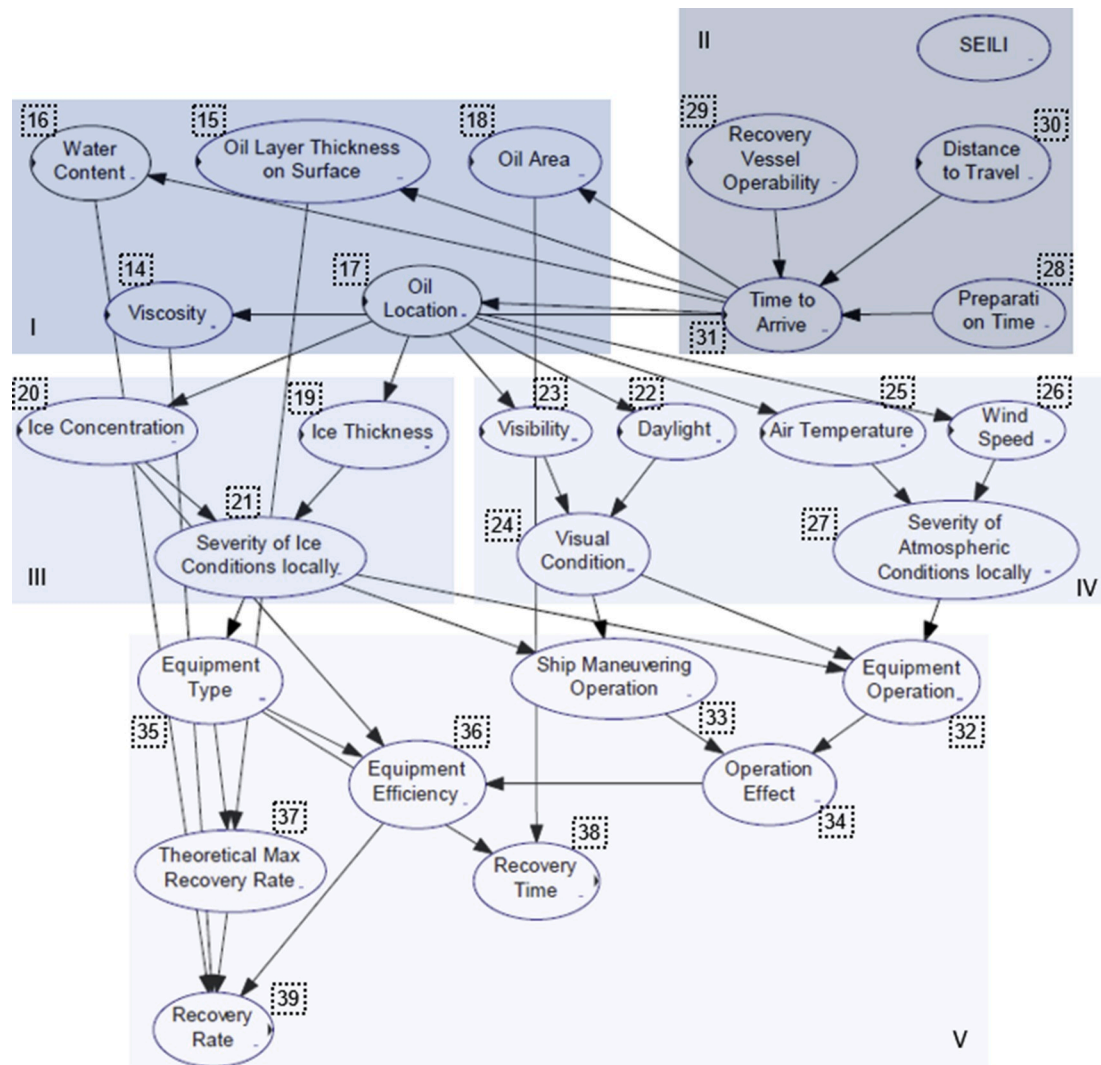


Fig. 9. Response and recovery sub-model for vessel SEILI; I-Oil drift, II-Response, III-Ice condition environment, IV- Atmospheric environment, V-Recovery.

Table 6
Selected Finnish response fleet information.

Vessel	Length [m]	Width [m]	Max speed [kn]	Draught [m]
SEILI	50.5	12.2	12	3.8
MERIKARHU	58	11	16	4.7
HYLJE	64.3	12.5	11	3
HALLI	60.5	12.4	12	3
TURSAS	61.45	10.2	14	4.85
UISKO	61.45	10.2	14	4.85
LOUHI	71.4	14.5	15	5
TURVA	95.9	17.4	18	5.5

striking vessel (*Operation Type* and *Striking Vessel*), struck vessel (*Tanker Type*, *Tanker Size*, *Load Condition* and *In-out-going*) and their collision conditions (*Impact Location*, *Impact Speed* and *Impact Angle*). Basically, the accident model gives the inputs to the collision damage and oil outflow model to predict the oil spill in layer III. The oil drift model uses the forcing defined in *Representative Forcing Scenarios* in layer I in Fig. 8 and the oil spill condition from the oil outflow model. It gives the outputs: *Oil Layer Thickness on Surface*, *Water Content*, *Oil Area*, *Viscosity* and *Oil Locations*, as shown in Fig. 9. When an oil spill happens, the oil response vessels also start their response and recovery actions, which are

described in the response vessel block, i.e. the response and recovery model, illustrated in Fig. 9. Through the response and recovery modelling, the recovered oil amount for each vessel is estimated, as shown in layer V in Fig. 8. All the variables, i.e. nodes in Figs. 8 and 9 are listed in Table 1 in Appendix A with detailed information about the evidence and SoE assessment. The numbers in the dashed box with the nodes in Figs. 8 and 9 are allocated ID number for each variable.

In this system model, the response and recovery model is applied to eight Finnish oil spill response vessels as the other Finnish response vessels are relatively small (less than 35 m) and considered not suitable for ice conditions. Thus, the fleet in the focus of this research includes SEILI, MERIKARHU, HYLJE, HALLI, TURSAS, UISKO, LOUHI and TURVA. The details of the vessels are obtained from HELCOM (2017), listed in Table 6 and the vessels are allocated to the assumed coastal home ports (Kotka, Helsinki, Hanko, Turku, Pori, Vaasa, Kokkola and Oulu) as shown in Fig. 4 to conduct the oil spill response modelling. The normal recovery system of the vessel is not appropriate for ice conditions. Therefore three oil recovery equipment systems suitable for ice conditions are enabled in the modeling for each vessel. They are Equipment A - oil recovery bucket 250, Equipment B - Arctic skimmer 125, Equipment C - Sternmax (Lamor, n.d.); see details of the modelling for the recovery systems in Lu et al. (2019). The available three choices of recovery systems allow the model to be able to include and test the influence from the performance of recovery equipment systems in

Table 7
Variables in combined SoE and sensitivity analysis.

Sensitivity	High		N1, N2, N9, N10, N11			
	Medium		N29	N3, N4, N5, N7, N8, N18, N28, N35, N37, N38	N6, N12	
	Low		N32, N33	N13, N14, N15, N16, N17, N21, N24, N26, N27, N31, N34, N36, N39	N19, N20, N22, N23, N25	N30
		Low	L-M	Medium	M-H	High
		SoE				

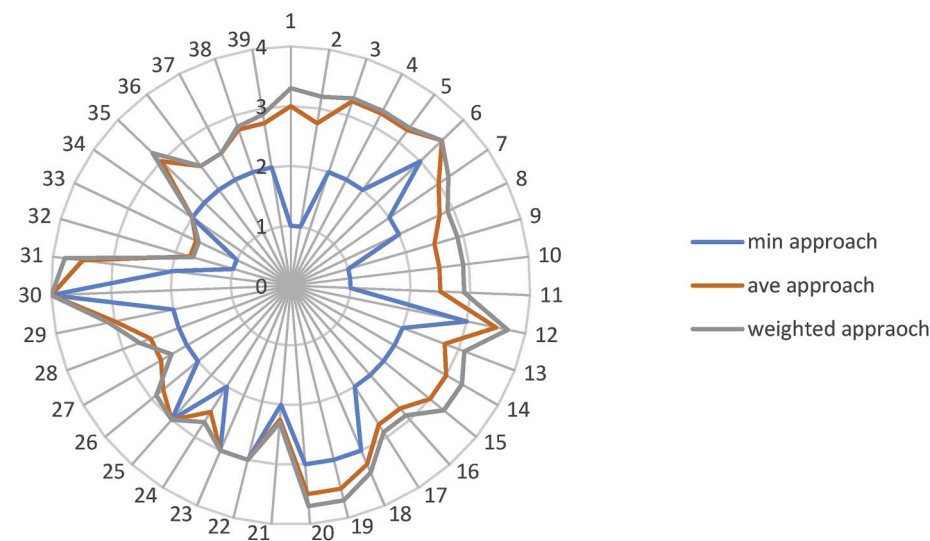


Fig. 10. Comparison of SoE results among different approaches. Number 1–39 means the nodes number, 0–4 represents the low, low-medium, medium, medium-high and high for SoE assessment.

addition to response vessels operability. The oil and environment condition for each response vessel are considered the same and oil area to be combated is assumed to be allocated to each vessel evenly. The disturbance among the ships and oil are not considered.

3.2. Identified critical factors

The critical factors are identified by combining the sensitivity analysis (Section 2.1.3) and SoE assessment (Section 2.1.4). SoE assessment results are listed in Table 1 in Appendix A according to the proposed method in Fig. 2 and Tables 2–4. Corresponding justifications are also included. The sensitivity analysis is conducted by setting the *Recovery Amount* of each the response vessel as the target. The algorithm then calculates the sensitivity of each node over the targeted variable. The results are classified into three levels based on maximum node sensitivity: high sensitivity, medium sensitivity and low sensitivity.

The sensitivity results show that *Impact Location*, *Impact Angle*, *Impact Speed*, *Representative Accident Location* and *Forcing Representative Scenarios* are the most sensitive ones. While *Tanker Type*, *Tanker Size*, *In-out-*

going, *Load Condition*, *Operation Type*, *Striking Vessel*, *Oil Type*, *Oil Area*, *Recovery Vessel Operability*, *Preparation Time*, *Equipment Type*, *Theoretical Max Recovery Rate*, *Recovery Time* are in the medium sensitivity level. The remaining variables are in the low sensitivity category. There are some small differences when setting different target vessels, however, this does not change the classified results in general. Only *Preparation Time* changes from medium sensitivity level to low sensitivity level for some vessels.

In order to combine SoE assessment and the sensitivity analysis results, a matrix of divided categories of SoE and sensitivity level of the variables is created. By locating the variables according to the results from both sensitivity analysis and SoE, Table 7 is obtained to indicate the variable locations in the matrix. Node ID numbers are shown instead of variables.

According to the principle in Table 1, the low or low-medium SoE with medium or high sensitivity area in the matrix in Table 7 are targeted as C1, the most critical aspects for the COOR system. The parameters include *Forcing Representative Scenario*, *Representative Accident Location*, *Impact Speed*, *Impact Location*, *Impact Angle* and *Response Vessel*

Table 8
Variables in combined SoE and sensitivity analysis (average approach).

Sensitivity	High			N2, N9, N10, N11	N1	
	Medium			N8, N18, N28, N29, N37, N38	N3, N4, N5, N6, N7, N12, N35	
	Low		N32, N33	N13, N16, N17, N21, N24, N26, N27, N34, N36, N39	N13, N14, N15, N19, N20, N22, N23, N25, N31	N30
		Low	L-M	Medium	M-H	High
	SoE					

Table 9
Variables in combined SoE and sensitivity analysis (weighted approach).

Sensitivity	High			N9, N10, N11	N1, N2	
	Medium			N8, N18, N28, N29, N37, N38	N3, N4, N5, N6, N7, N12, N35	
	Low		N32, N33	N16, N17, N21, N24, N26, N27, N34, N36, N39	N13, N14, N15, N19, N20, N22, N23, N25, N31	N30
		Low	L-M	Medium	M-H	High
	SoE					

Operability.

4. Discussion

4.1. COOR system

The COOR system is made up by accident, oil outflow, oil drift and oil recovery models. The models have been described from Section 2.2.1 to Section 2.2.4. More discussion on each model can be referred to original model development (Kollo et al., 2017; Sergejeva et al., 2017; Arneborg et al., 2017; Lu et al., 2019). In addition, the evidence and assessment of the integrated system model and parameter are also mentioned in Table 1 of Appendix A when conducting SoE assessment. However, there are also some limitations, which need to be noted.

Firstly, although the COOR system model has integrated representative oil tanker traffic, accident locations and scenarios and oil spill response fleet diversely to facilitate the holistic system model to be able to represent realistic situations. However, the representative winter conditions may still have limitations to represent all possible scenarios for very mild, mild, average and severe winter conditions. Even though the ice conditions in selected RFS show reasonable representativeness, the other forcing, e.g. current and wave applied corresponding with the representative ice conditions in this modelling may be insufficient to represent all typical winter conditions, especially for very mild winter where there is open sea condition. The BN model (Lehikoinen et al., 2013) in open sea conditions, may be more representative for very mild conditions with open water.

Secondly, even though the system considers the dynamic changes of the oil spill, the dynamic interactions between the response vessels are not included, which means that each response vessel is considered to operate individually from the response to the recovery stage. The oiled area is divided into eight subareas so that each vessel is assumed to conduct oil recovery in the oiled area without interactions with each other. Thirdly, the port location for the response vessels are assumed so that all the Finnish coastal region can be covered, although the vessels

may not be distributed as such in reality. In addition, the parameterization for the nodes *Response Vessel Operability* and *Preparation Time* for the response fleet are assumed the same, while the arriving time is calculated based on each vessel's performance. The speeds in ice for the fleet are extracted by 1) comparing each vessel's open water performance with the vessel SEIL; 2) estimate each vessel's performance in ice based on SEIL's full scale measurements in various ice conditions.

4.2. SoE and sensitivity

The combination of SoE and sensitivity to assess the system critical factors has been applied in earlier work, e.g. Goerlandt and Montewka (2015), however with the developed theoretical bases in Section 2.1, the improved framework and method more accurately reflects the justification of which aspects of the model are strongly or poorly evidenced. It should be noted that the sensitivity levels are transferred from quantitative sensitivity value to qualitative levels. This process makes the sensitivity lose the accuracy of the parameters. However, the distinction of the sensitivity levels is based on the difference of the magnitude of the sensitivity, i.e. high ($>10^{-2}$), medium (10^{-3} - 10^{-2}) and low ($<10^{-3}$), which is considered sufficient to make a distinction for the parameter importance.

The improved SoE assessment now has assessed each aspect of the BN model, with the different focuses on each aspect in Table 3. This comprehensive assessment makes the SoE subdivided and thus more reliable and clear. However, this also brings a complex result matrix. In this paper, expression (3) is applied to obtain the final SoE result for each parameter, i.e. it takes the best evidence support for each aspect of the BN model and considers the weakest assessment when combining each aspect to final SoE assessment. This approach is subject to further discussion. Here some other approaches are implemented to allow a comparison, in particular an averaged approach and weighted approaches.

The average approach modifies the expression (3) as below, i.e. it takes the average value from the four BN features' individual SoE.

$$a = \text{ave}_i(\max_j a_{ij}) \quad (4)$$

The weighted approach first assigns the relevant weight to each feature according to their importance to the BN model. Usually, it is considered that the model content and structure are the basis for the BN model, thus they more important than the parameterization and discretization. Model content is the basis for the structure, thus content is more important. Meanwhile, parameterization (CPTs) is considered as more important than the discretization (states) as the CPTs determine the final distributions, although states are also very important as they decide the shape of distribution. So the importance in order are MV, MS, MP, MD. The importance of the features in BN is subject to further discussion as well. However, based on the discussion above, assumed weights can be allocated to each aspect. The final SoE can be then calculated by:

$$a = \sum_{i=1}^4 P_i (\max_j a_{ij}) \quad (5)$$

where P_1 to P_4 means the weights for MV, MS, MP, MD. They are set as 0.4, 0.3, 0.2, 0.1 respectively.

Fig. 10 shows the SoE results for different approaches. It can be seen that the min approach is more conservative compared to the other two, but there are differences among the approaches, especially between the min approach and the others. Therefore, although the framework of the SoE assessment is improved in this paper, the approach used for final SoE still needs to be determined carefully and more study and comparisons can be done on this.

Tables 8 and 9 show the results of variable location in the matrix by applying the average approach and weighted approach. They are a bit different from the min approach. However, the overall classification result of the most critical factors based on principle in Table 1 does not vary too much. Only N29, i.e. *Response Vessel Operability* change from C1 to C2 level.

4.3. Future work

Through the analysis, the critical aspects in the COOR system for the Finnish response fleet are identified, which opens a more specific and efficient focus area for further risk control for oil spills in ice conditions. This paper focuses on how to create and assess the system but does not address how to control the oil spill risk in ice condition in detail or in practice, e.g. how to make better preparedness and planning. In other words, the presented work ranks the factors to focus in risk management for oil spill in ice conditions. This is an initial but essential step as no research has done to link the key elements from the accident to the oil recovery effectiveness, i.e. COOR system. It helps to narrow the risk control focus and make it more efficient. However, to make further suggestions to manage the oil spill risk in ice conditions, more research is needed on specific identified aspects. For example, the identified critical factors show that the representative accident location is important. This can lead to further research on the possible accident locations in ice condition: with a more reliable prediction on the locations, more preparedness can be facilitated or planned in advance.

In addition, increasing discussion on the oil spill in the Arctic environments are raised due to the possible increasing ship traffic, e.g. researches on Arctic accident scenario (Afenyo et al., 2017) and oil spill impacts (Nevalainen et al., 2017; Afenyo et al., 2019). Although this study is based on the cases in the Northern Baltic Sea ice conditions, the COOR system can be expected to have large similarity for Arctic cases. Hence, the developed model can be used as a reference for further work on Arctic oil spill response. Moreover, the improved method for SoE assessment in BN model opens more potential for SoE study, as discussed

in Section 4.2.

5. Conclusions

This paper models the general ship-ship collision scenarios, oil outflow, oil dispersion and spreading, oil spill response and recovery and created a COOR system model with Bayesian Network. In addition, the paper improved the method to identify the critical system aspects and applies to the COOR system. The developed framework and method are important for identifying the critical factors and implementing risk controls in general.

When applying the framework and method to COOR system, the most critical system factors are identified: *Forcing Representative Scenario*, *Representative Accident Location*, *Impact Speed*, *Impact Location*, *Impact Angle* and *Response Vessel Operability*. While the other aspects are in the next critical levels, C2-C3. This gives indication that the most efficient risk control options for the COOR system in the Northern Baltic Sea concern the specification of collision scenarios and the response vessel operability. The other aspects, e.g. tanker size, recovery equipment and maneuvering operations (human operation part), etc. can be focused after the most critical ones in the risk management.

In addition, the developed COOR system model is also practically applicable for investigation and development of preparedness and response planning for oil spills in ice conditions by setting relevant variables to assume certain scenarios or oil spill happening. Response authorities can use the model to get an idea of the performance of the fleet in case of an oil spill, which helps contingency planning (Laine et al., 2018). This is practically needed especially in regions like NBS where the seasonal component of ice occurrence is variable.

Author contribution statement

Liangliang Lu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing. **Floris Goerlandt:** Conceptualization, Methodology, Writing - Review & Editing. **Kristjan Tabri:** Software, Writing - Original Draft, Writing - Review & Editing. **Anders Höglund:** Software, Writing - Review & Editing. **Osiris A. Valdez Banda,** Writing - Review & Editing. **Pentti Kujala,** Writing - Review & Editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The work in this paper has been performed as part of the BONUS STORMWINDS project. Funding has been received from BONUS (Art. 185), funded jointly from the European Union's Seventh Programme for research, technological development and demonstration, and from the Academy of Finland, the Estonian Research Council and the Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS). The work is also partially supported by SIMREC project (CBC 2014–2020), funded by the European Union, the Russian Federation and the Republic of Finland. The contributions by the second author were made in context of the project 'Shipping Accident Oil Spill Consequences and Response Effectiveness in Arctic Marine Environments (iSCREAM)', funded through the Marine Observation, Prediction and Response (MEOPAR) Network of Centers of Excellence.

Appendix

Table 1
Variables, discretization and SoE assessment (COWI, 2012; Sunrise and Sunset.).

ID	Model	Content	Data			Model	Ju	As	Justification	SoE
			Q	A	E	T				
1	MV	Forcing Representative Scenario							The variable stems from the input of PADM model experts' judgement (Lu et al., 2019)	
	MS	see Fig. 8							The links are determined by the input and output relationships in PADM model within oil drift model	
	MD	{very mild winter, mild winter, average winter, severe winter}							The states are selected from representatives from NEMO-Nordic dataset, where ice thickness and concentration are assimilated	
	MP	see model CPT							Uniform distribution is assumed for the states	
2	MV	Representative Accident Location							The variable is included as it is one of the inputs for the PADM model as well as accident model, and based on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 8							One part of the links stems from the input and output relationships in PDAM model and the other part relates to the accident features with judgements	
	MD	{L1(64.9, 23.5), L2(63.7, 21.2), L3(62.6, 19.8), L4(60.9, 20), L5(59.6, 21.3), L6(59.85, 25.8), L7(60.07, 27.8)}							The locations are assumed based on region classifications, notation (xx, yy) means xx degrees latitude north, yy degrees longitude east	
	MP	see model CPT							Uniform distribution is assumed for the states	
3	MV	Tanker Type							The parameter is included based on reported ship type classifications from AIS data (COWI, 2012) and authors' internal judgement	
	MS	see Fig. 8							The links are judged based on reported tables and descriptions (COWI, 2012)	
	MD	{oil product tanker, crude oil tanker, other oil carrier}							The states are determined based on data (COWI, 2012)	
	MP	see model CPT							Uniform distribution is assumed	
4	MV	Tanker Size							The parameter is included based on ship data classification (COWI, 2012) and model (Valdez Banda et al., 2016), and authors' internal judgement	
	MS	see Fig. 8							The links are judged based on reported tables and descriptions (COWI, 2012)	
	MD	{T1, T4, T6, T15}							The states are selected as representatives according to classification data (COWI, 2012) and the tanker sizes are based on design models based on AIS data	
	MP	see model CPT							Uniform distribution is assumed	
5	MV	In-out-going							In-out-going is included based on data in report (COWI, 2012) and authors' internal judgement	
	MS	see Fig. 8							The links are from the data in report (COWI, 2012) and authors' internal judgement	

	MD	{In, out} see model CPT							The states are quite certain based on the report (COWI, 2012) and authors' internal judgement	
	MP								Uniform distribution is assumed	
6	MV	Load Condition							The parameter is included based on the report data (COWI, 2012)	
	MS	see Fig. 8							The links are based on the reported data categories (COWI, 2012)	
	MD	{Loaded, not loaded}							The states are according to the division in the report (COWI, 2012)	
	MP	see model CPT							CPT combines the reported data tables (COWI, 2012)	
7	MV	Striking Vessel							Striking vessel is considered as a compulsory part of a collision model and bases on authors' internal judgement	
	MS	see Fig. 8							The links base on authors' internal judgement	
	MD	{Icebreaker_DWT_6430, Large cargo vessel_DWT_28420, other}							The states are selected based on striking vessel data analysis (Goerlandt et al., 2017a)	
	MP	see model CPT							Uniform distribution for independent navigation and only icebreaker for other operation	
8	MV	Operation Type							The parameter is included based on analysis (Goerlandt et al., 2017a) and authors' internal judgement	
	MS	see Fig. 8							The links are based on authors' internal judgement	
	MD	{Independent navigation, convoy, cutting loose}							The states are selected based on classification of the ship operations (Goerlandt et al., 2017a)	
	MP	see model CPT							CPT is based on author's judgement	
9	MV	Impact Speed							The parameter is included based on accident models and authors' internal judgement	
	MS	see Fig. 8							The links are referred to the model (Valdez Banda et al., 2016)	
	MD	{3, 6, 9} [kn]							The states refer to data (Goerlandt et al., 2017a)	
	MP	see model CPT							CPT is based on author's judgement	
10	MV	Impact Location							The parameter is included based on accident models and authors' internal judgement	
	MS	see Fig. 8							The links are referred to the model (Valdez Banda et al., 2016)	
	MD	{15% ahead of stern, 50% ahead of stern}							The states refer to data (Goerlandt et al., 2017a)	
	MP	see model CPT							CPT is based on author's judgement	
11	MV	Impact Angle							The parameter is included based on accident models and authors' internal judgement	
	MS	see Fig. 8							The links are referred to the model (Valdez Banda et al., 2016)	
	MD	{90, 150} [°]							The states refer to data (Goerlandt et al., 2017a)	
	MP	see model CPT							CPT is based on author's judgement	
12	MV	Oil Type							The parameter stems from the input of PADM model and experts' judgement (Lu et al., 2019)	

	MS	see Fig. 8							The links are based on structured data (COWI, 2012) and PADM model inputs	
	MD	{gasoline, light diesel fuel, light-medium crude oil, heavy crude oil}							The states are determined based on representative substance (COWI, 2012) and PADM model inputs	
	MP	see model CPT							CPT bases on the structured data (COWI, 2012)	
13	MV	Spill Size							The parameter stems from the input of PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 8							The links are based on accident model and PADM model inputs	
	MD	{0, 0-1k, 1-10k, 10-20k} [m ³]							The states are divided based on the PADM simulation result	
	MP	see model CPT							CPT bases on results from accident model and oil outflow model	
14	MV	Oil Viscosity							The parameter is included as it is one of the outputs from the PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9							The links are based on input and output relationships in PADM model and experts' judgement (Lu et al., 2019)	
	MD	{extreme light (<5), light (5-100), medium (100-7500), high (>7500)} [cSt]							The states base on experts' judgement (Lu et al., 2019)	
	MP	see model CPT							CPT bases on PADM simulation model and results	
15	MV	Oil Layer Thickness on Surface							The parameter is included as it is one of the outputs from the PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9							The links are based on input and output relationships in PADM model and experts' judgement (Lu et al., 2019)	
	MD	{0, 0-1, 1-5, 5-10, 10-50, 50-100, 100-500, 500-1000} [mm]							The states are divided based on the PADM simulation result and author's judgement	
	MP	see model CPT							CPT bases on PADM simulation model and results	
16	MV	Water Content							The parameter is included as it is one of the outputs from the PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9							The links are based on input and output relationships in PADM model and experts' judgement (Lu et al., 2019)	
	MD	{0-30, 30-60, 60-100, 100} [%]							The states are based on author's judgement	
	MP	see model CPT							CPT bases on PADM simulation model and results	
17	MV	Oil Location							The parameter is included as it is one of the outputs from the PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9							The links are based on input and output relationships in PADM model and experts' judgement (Lu et al., 2019)	
	MD	NBS divided into 63 coordinate grids							The states base on author's judgement	
	MP	see model CPT							CPT bases on PADM simulation model and results	

18	MV	Oil Area								The parameter is included as it is one of the outputs from the PADM model and experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links are based on input and output relationships in PADM model and experts' judgement (Lu et al., 2019)	
	MD	{0, 0-1e3, 1e3-5e3, 5e3-1e4, 1e4-5e4, 5e4-1e5, 1e5-1e6, 1e6+} [m ²]								The states base on author's judgement	
	MP	see model CPT								CPT bases on PADM simulation model and results	
19	MV	Ice Thickness								The parameter is included based on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{0-20, 20-40, 40-60} [cm]								The states are determined from NEMO-Nordic ice data	
	MP	see model CPT								CPT bases on NEMO-Nordic ice data	
20	MV	Ice Concentration								The parameter is based on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{0-30, 30-70, 70-100} [%]								The states are determined from the NEMO-Nordic ice data and author's judgement	
	MP	see model CPT								CPT bases on NEMO-Nordic ice data	
21	MV	Severity of Ice Conditions locally								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{light, medium, severe}								The states are divided based on author's judgement	
	MP	see model CPT								CPT is determined based on severity table (Valdez Banda et al., 2016)	
22	MV	Daylight								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{day, day-night, night}								The states are divided based on author's judgement	
	MP	see model CPT								CPT based on sun rise and set data (Sunrise and sunset, 2019)	
23	MV	Visibility								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{poor (<0.2), medium (0.2-0.9), good (>0.9)} [km]								The states base on reported criteria (EPPR, 2017)	
	MP	see model CPT								CPT uses the NEMO-Nordic visibility data	
24	MV	Visual Condition								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{poor, medium, good}								The states are divided based on author's judgement	
	MP	see model CPT								CPT bases on minimum principle (Lu et al., 2019)	
25	MV	Air Temperature								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	

	MD	{(-37)-(-20), {(-20)-(-10), {(-10)-0, 0-10}; [°C]}								The states base on reported criteria (EPPR, 2017)	
	MP	see model CPT								CPT uses the NEMO-Nordic temperature data	
26	MV	Wind Speed								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{0-5, 5-10, 10-15} [m/s]								The states are based on author's judgement	
	MP	see model CPT								CPT uses the NEMO-Nordic wind data	
27	MV	Severity of Atmospheric Conditions locally								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{light ((-13)-0), medium ((-33)-(-13)), severe ((-50)-(-33))}								The states base on reported criteria (EPPR, 2017)	
	MP	see model CPT								CPT Apply formulated criteria with air and wind temperature (EPPR, 2017)	
28	MV	Preparation Time								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{0-2, 2-4, 4-8} [h]								The states are divided based on author's judgement	
	MP	see model CPT								CPT is based on onboard interviews (Lu et al., 2019)	
29	MV	Response Vessel Operability								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{Yes, No}								The states are divided based on author's judgement	
	MP	see model CPT								CPT bases on ice trial data (Lu et al., 2019) and author's judgement	
30	MV	Distance								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{65, 100, 350, 500, 690, 810, 980} [km]								The states are divided based on measured distance data on google map	
	MP	see model CPT								CPT bases on measured distance data on google map	
31	MV	Time of Arrival								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019) and t=s/v model	
	MD	{0-3, 3-6, 6-12, 12-24, 24-48, 48-72, 72-120, 120-168} [h]								The states are divided based on author's judgement	
	MP	see model CPT								CPT bases on measured distance and ice trial speed data with t=s/v model	
32	MV	Equipment Operation								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{poor, medium, good}								The states are divided based on author's judgement	
	MP	see model CPT								CPT bases on minimum principle (Lu et al., 2019)	
33	MV	Ship Maneuvering Operation								The parameter bases on experts' judgement (Lu et al., 2019)	
	MS	see Fig. 9								The links base on experts' judgement (Lu et al., 2019)	
	MD	{poor, medium, good}								The states are divided based on author's judgement	
	MP	see model CPT								CPT bases on minimum principle (Lu et al., 2019)	

34	MV	Operation Effect see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on author's judgement	
	MP								CPT bases on minimum principle (Lu et al., 2019)	
35	MV	Equipment Type see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on available equipment types (Lamor, 2018)	
	MP								CPT bases on expert judgement (Lu et al., 2019)	
36	MV	Equipment Efficiency see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on author's judgement	
	MP								CPT bases on formulated expressions (Lu et al., 2019)	
37	MV	Theoretical Max Recovery Rate see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on author's judgement	
	MP								CPT bases on results from PADM and reported equipment capabilities (Lu et al., 2019)	
38	MV	Recovery Rate see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on author's judgement	
	MP								CPT bases on formulated expressions (Lu et al., 2019)	
39	MV	Recovery Time see Fig. 9							The parameter bases on experts' judgement (Lu et al., 2019)	
	MS								The links base on experts' judgement (Lu et al., 2019)	
	MD								The states are divided based on author's judgement	
	MP								CPT is based on formulated expression and simulated oil area (Lu et al., 2019)	
Not Relevant		Low	Low - Medium		Medium		Medium - High		High	

Note: Q - Quality, A - Amount, E - Empirical validation, T - Theoretical viability, Ju - Judgement, As - Assumption

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