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Risk analysis methodology using STPA-based Bayesian network- applied to remote pilotage operation

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A B S T R A C T

The maritime industry is currently ongoing into a digital transformation to develop cleaner, safer and smarter transport services. Establishing such services requires identifying and assessing new emerging risks such as software and design flaws. Thus, suitable hazard identification and risk analysis methods must be developed and implemented for these complex services. This study aims to develop a novel risk analysis methodology by integrating Systems Theoretic Process Analysis, Bayesian Network, Noisy-OR gates, Parent divorcing technique and Sub-modelling. The effectiveness of the proposed methodology is demonstrated through a case study of Remote pilotage operation. The results show that the methodology can be applied to complex operations to assess the propagation of risks from a single fault or failure in a system to the hazards, accidents and incidents, and ultimately the losses. Furthermore, it is demonstrated how the remote pilotage risk model can support pilots and pilotage companies in real-time decision-making by estimating the likelihood of losses in case of a single fault or failure.

1. Introduction

Maritime stakeholders are exploring the viability of operational transformation using increased automation and digitalisation. One of them is the Remote pilotage operation (RPO), which is currently at the development stage in Europe in several countries (Hadley and Pourzanjani, 2003; Lahtinen et al., 2020; Salonen et al., 2020). In addition to the potential cost reduction (Danish Maritime Authority, 2014), RPO may improve maritime safety by reducing human errors and risks related to pilot embarkation and disembarkation (Lahtinen et al., 2020). However, the increased automation and digitalisation can propagate unrecognised risks due to software flaws, design flaws, and ineffective communication and condition monitoring during pilotage (Bolbot et al., 2019; Hoem et al., 2019; Leveson, 2011; Utne et al., 2017). Thus, it is essential to identify the hazards and analyse these potential emergent risks in RPO.

Given that RPO is in its infancy stage, risk-based design can be considered an appropriate methodology for safe and cost-efficient system design (Leveson, 2011; Utne et al., 2017). However, only a few studies have focused on the risk management of RPO up to this date. Lahtinen et al. (2020) researched remote pilotage configurations and critical risks related to RPO in an intelligent fairway. The authors used expert surveys, interviews and remote pilotage simulation to identify risk-influencing factors associated with RPO, such as situational awareness, human behaviour, ergonomics, data transmission, navigational aids, operational conditions, and cyberattacks. Similarly, Hadley & Pourzanjani (2003) provided vital risk factors related to RPO, including navigational aids, language barrier, operational conditions, crew capabilities, and crew fatigue. Other additional crucial factors have been highlighted in other studies, such as feedback systems for remote pilots (Bruno and Lützhöft, 2009), standardised procedures and communication (Bruno and Lützhöft, 2009), and trust between crew and pilot (Bruno and Lützhöft, 2010). Although these studies provide risk influencing factors in RPO, none of them has applied any hazard

Abbreviations: BN, Bayesian Network; CPT, Conditional Probability Table; E, Event; FMEA, Failure Mode and Effects Analysis; FTA, Fault Tree Analysis; PDT, Parent-Divorcing Technique; UCA, Unsafe Control Action; RP, Remote Pilot; RPO, Remote Pilot Operation; SCF, Scenario Causal Factor; SIA, Safety Investigation Authority; STPA, Systems-Theoretic Process Analysis; VC, Vessel Crew.

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identification and risk analysis techniques. On the other hand, risk analysis is essential for enabling new maritime services from the maritime authority's perspective (IMO, 2018). For example, the Finnish pilotage act, (LVM, 2019), specifies that the pilotage service provider needs to present a detailed risk management strategy for RPO to obtain the permit. Hence, the industry's lack of risk management studies and the explicit requirements from the maritime authorities require a comprehensive hazards identification and risk analysis of RPO.

For identifying hazards in complex socio-technical systems, several studies (Bolbot et al., 2019; Fan et al., 2022; Thieme et al., 2018; Ventikos et al., 2020; Yamada et al., 2022; Zhou et al., 2020) recommended a method based on system theory known as System Theoretic Process Analysis (STPA). Zhou et al. (2020) concluded that the STPA is the most promising hazard identification method for software-intensive systems compared to traditional methods such as Fault Trees Analysis (FTA) and Failure Modes and Effects Analysis (FMEA). While FTA and FMEA focus on component-level failures by dividing the system into components, STPA analyses unsafe scenarios due to system interactions at the component-level as well as the systemic level. However, STPA is limited to hazard identification and does not attempt to estimate and assess the risk levels (Zhou et al., 2020). As a result, some studies have proposed STPA extensions by combining it with risk analysis methods such as FTA (Bensaci et al., 2020; Bolbot et al., 2020), Bow-Tie (Bensaci et al., 2020), Success Likelihood Index method (Ahn et al., 2022) and Bayesian Networks (BN) (Chaal et al., 2022; Johansen and Utne, 2022; Rekabi, 2018; Utne et al., 2020). Among these different options, the BN has been recommended for the risk analysis of complex systems in various studies such as by BahooToroody et al. (2016); Khalaj et al. (2020); Kontovas and Psaraftis (2009); Montewka et al. (2022); Parviainen et al. (2021); Thieme et al. (2018); Ventikos et al. (2022); Zhang and Thai (2016). The advantage of BN compared to FTA include the ability to handle common cause failures and multistate components concisely (Mahboob and Straub, 2011). Hence, the combination of STPA and BN can be considered an adequate method for the hazard identification and risk analysis of remote operation systems due to its novelty and ability to handle complex operations.

The novel combinations of STPA and BN have been explored recently in different studies such as Rekabi (2018), Utne et al. (2020), Johansen and Utne (2022), Xu et al. (2022) and Chaal et al. (2022). The most recent study by Chaal et al. (2022) provided an STPA-BN method for the risk-based design of autonomous ship systems, where BN were used for the identification of critical risk control options. Similarly, Utne et al. (2020), and Johansen and Utne (2022) implemented STPA-BN for online risk modelling for autonomous ships for better decision-making. The authors mentioned that BNs effectively present causal relationships and combine expert knowledge and empirical data as often needed in risk analysis. However, Utne et al. (2020) mentioned that the combination of states grows exponentially with an increased number of parent nodes when developing the BN further, resulting in a necessary trade-off between available resources, model accuracy, and model complexity. Xu et al. (2022) integrated Dempster-Shafer evidence theory into the STPA-BN methodology for improving the accuracy of prior probabilities of BN nodes. However, the BN model developed in the study related to heavy equipment airdrop consisted of only 15 nodes with maximum of 5 parent nodes. An STPA-BN study in a railway domain by Rekabi (2018) also highlighted this limitation and constrained the analysis with the maximum number of parent nodes as 3. Although the above-mentioned STPA-BN studies display great potential with the novel combination, all of these studies are limited to a single system hazard or a specific number of parent nodes.

To address all identified challenges/gaps in implementing the STPA-BN model, this study aims to develop a risk analysis methodology for complex systems and apply it to assess risks in RPO. To this end, an approach that enhances the STPA-BN methods and incorporates Noisy-OR gates, Parent-Divorcing Technique (PDT), and sub-models techniques into the BN development is proposed. For large-scale BN, canonical probabilistic nodes can reduce BN's modelling complexity and computation caused by the high number of parent nodes (BayesFusion, 2020; Pearl, 1988). One of the most popular canonical nodes, Noisy-OR/MAX, has been used in several BN studies (Abaei et al., 2019; Feng et al., 2020; Ji et al., 2022; Sarwar et al., 2018), where the advantages of using the node in BN have been highlighted. Similarly, the Parent-Divorcing Technique (PDT) can also be applied to reduce the number of entries in CPT without reducing the accuracy of the models (Lindley and Blackburn, 2017). As a result, it can improve the model development and simulation time (Barber, 2012; Fenton and Neil, 2019; von Waldow and Röhrbein, 2015). PDT has been demonstrated and recommended for the development of large-scale BN by various studies such as Barber (2012), Fenton and Neil (2019), Lindley and Blackburn (2017), and Neil et al. (2000). In addition to the modelling complexity, large-scale BNs also pose a challenge to the graphical representation of variable dependencies due to the high number of nodes (Neil et al., 2000). The structure and presentation of large-scale BNs can be improved by introducing sub-models (BayesFusion, 2020). Furthermore, the sub-models also facilitate the modularity in large-scale BN and enable the reusability of BN fragments. The usage of the sub-model has been demonstrated by several studies such as Domeh et al. (2021), Barton et al. (2020), Lu et al. (2019), and Valdez Banda et al. (2016). Therefore, the improvement of STPA-BN methodology by integrating these techniques should be explored.

The rest of the article is structured as follows. In Section 2, the related methods are presented. Then in Section 3, an overview of the hazard identification and risk analysis methodology and its steps is provided in detail. Next in Section 4, the results of applying the proposed methodology to the RPO are depicted. The discussions related to the methodology and the results are then provided in Section 4. Finally, in Section 5, the conclusions of this study are presented.

2. Related methods

2.1. System Theoretic Process Analysis (STPA)

STPA is a hazard analysis method based on the System-Theoretic Accident Model and Processes (STAMP), which considers safety a dynamic control problem rather than a failure prevention problem. In addition to component failures, STPA assumes that hazards can also occur due to unsafe interactions of even non-failing components. Hence, the interactions among components are assessed to identify the unsafe scenarios for the system. The STPA methodology consists of the following steps (Leveson and Thomas, 2018):

- Step 1 Define the purpose of the analysis:
  - Step 1.1 The losses that are unacceptable for the stakeholders, which should be mitigated through the analysis are defined first.
  - Step 1.2 Then, the hazards at the system level that can lead to losses are identified.
  - Step 1.3 For each system-level hazard, the constraints that need to be satisfied to prevent these hazards are specified.
- Step 2 Model the control structure: Next, the control structure of the system under assessment is developed. The control structure is a hierarchical model that shows control actions and feedback loops between system components.
- Step 3 Identify Unsafe Control Actions (UCA): Once the control actions of the system components are identified with the control structure, these control actions are then analysed with guidewords to determine the UCA.
- Step 4 Identify loss scenarios: In the last step, the causal factors that can lead to each UCA are then identified.

2.2. Bayesian Networks

Pearl (1988) has provided a detailed description of BN. In brief, BNs are Directed Acyclic Graphs (DAG) used for probabilistic reasoning based on the Bayes theorem. In BN, each node represents a variable with several states, and each arc represents the dependency between the variables (Abaei et al., 2019; BahooToroody et al., 2019; Leoni et al., 2019). The BN graph is directed with an arrow pointing from a parent variable to the child variable. The BN is a distribution with the following form (Neapolitan, 2004):

$$p(x_1, \ldots, x_D) = \prod_{i=1}^{D} p(x_i | pa(x_i)) \tag{1}$$

where $p(x_1, \ldots, x_D)$ is a joint probability distribution and $pa(x_i)$ is the parent set of the variable.

For example, the joint probability distribution of the variables in Fig. 1 is given by $p(L_1, A_1, A_2, I_1) = p(L_1 | A_1, A_2, I_1)\, p(A_1)\, p(A_2)\, p(I_1)$, where L_1 is dependent on $A_1, A_2,$ and I_1.

2.3. Parent-Divorcing Technique

In a Bayesian Network, if a child node has n parent nodes and all nodes have k states, then the number of CPT entries for the child node increases exponentially with k^{n+1} (Gerssen and Rothkrantz, 2006). A PDT, proposed by Olesen et al. (2007), can be applied to reduce the effects of the combinatorial explosion in CPT entries due to a high number of parent nodes. Several parent nodes are combined in PDT with additional intermediate nodes using suitable idioms. To preserve the accuracy of the model, the PDT should be applied only if the effects of the divorced nodes on child nodes are independent of other non-divorced parent nodes (Cain, 2001). Furthermore, the CPT for the intermediate node should not be specified with uncertainty (the child states should have 100% probability for every combination of parent states) (Cain, 2001).

2.4. Noisy-OR gates

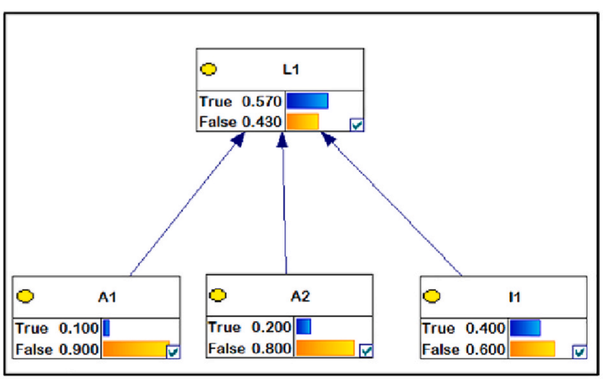
The Noisy-OR gates, proposed by Pearl (1988), can be applied in BNs to reduce the CPT entries. It is a method to determine the conditional probability of Boolean variables, assuming that (i) there is a cause and effect relation between parameters, (ii) parameters are mutually exclusive, and (iii) accountability means that an event can happen if, and only if, at least one cause has occurred (Abaei et al., 2019; Neapolitan, 2004). Once these conditions are satisfied, the CPT can be defined with only n parameters $(p_1, p_2, p_3 \ldots, p_n)$. The parameter p_i denotes the probability that the Y occurs if the cause X_i is present (T), and all other causes are absent (F), which can be denoted as following (Oniśko et al., 2001):

$$p_i = \Pr\left(Y = T \mid x_1 = F, x_2 = F \ldots x_i = T \ldots, x_{\{n-1\}} = F, x_n = F \right) \tag{2}$$

The formula to derive the complete CPT of Y given a subset X_p of the X_is that is present is then provided by the following (Oniśko et al., 2001):

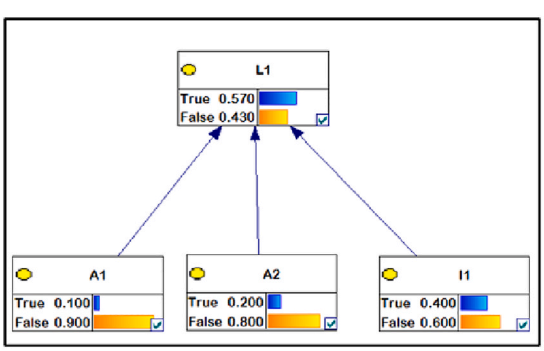
$$\Pr(y | X_p) = 1 - \prod_{i:X_i \epsilon X_p} (1 - p_i) \tag{3}$$

In risk analysis, there can be unidentified causes of effects, i.e., residual risk. To cover the residual risk, a leak factor X_L can be added to the CPT, which denotes the probability that the Y occurs if all the identified causes are absent. The leak probability p_0 can be denoted as following (Oniśko et al., 2001):



A1	True				False			
A2	True		False		True		False	
I1	True	False	True	False	True	False	True	False
True	1	1	1	1	1	1	1	0.005
False	0	0	0	0	0	0	0	0.995

(a)



Parent	A1	A2	I1	LEAK
State	True	True	True	
True	1	1	1	0.005
False	0	0	0	0.995

(b)

Fig. 1. An example of CPT in Bayesian Network (a) without Noisy-OR gate - 16 CPT entries (b) with Noisy-OR gate - 8 CPT entries.

$$p_0 = \Pr\left(Y = T \mid x_1 = F, x_2 = F \dots x_i = F \dots, x_{\{n-1\}} = F, x_n = F \right) \quad (4)$$

Fig. 1 shows an example of the usage of a Noisy-OR gate in a BN network, where the number of CPT entries of a BN is reduced from 16 (Fig. 1a) to 8 CPT entries (Fig. 1b).

2.5. Sub-models

The development and presentation of large-scale BN networks can be improved further by implementing sub-models. Sub-models are nodes or BN fragments that host a section of a BN to improve the BN structure. In addition to the visual improvements, the sub-models facilitate modularity, which enables the reusability of the modules (sub-models) in different BNs if suitable (BayesFusion, 2020).

3. Methodology

Fig. 2 shows the proposed STPA-BN methodology. In Step 1, the STPA is applied to the system. The results of STPA are then used to develop a Bayesian network in Step 2. Next, in Steps 3, 4, and 5, the BN complexity reduction techniques, i.e., PDT, Noisy-OR gate, and sub-models, are implemented, respectively. In Step 6, the resulting BN is then updated by adding the prior probabilities of the root nodes and filling the CPT for the remaining nodes. Finally, the resulting BN model is analysed, and results are inferred in Step 7.

3.1. Step 1: apply STPA to a target system and execute additional steps

The first step is to apply STPA (see Section 2.1) to the investigated system. This study proposes three changes to the standard process defined in the STPA handbook (Leveson and Thomas, 2018). The first change is to add a sub-step to Step 1 of STPA. Instead of identifying system-level hazards directly from the losses (as in the default STPA process), the accidents and incidents that can lead to the losses should be first identified. The definitions of accidents and incidents provided by the Finnish Transport Safety Agency (2014) based on the Maritime Code (674/1994) have been used in this study. The addition of this step can cover the gap between the losses and the further analysis of STPA (Glomsrud and Xie, 2019). Furthermore, this may also ease the process of system-level hazard identification and data gathering for the BN model. Fig. 3 highlights the proposed change in Step 1 of STPA.

The second change is to extend the statements for the Unsafe Control Actions in Step 3 of STPA. In the STPA handbook, the authors recommend including five parts, i.e., Source, Type, Control action, Context, and Link to hazards. In this framework, a modification is proposed to integrate additional parts i.e., the controlled process in the UCA statement. This change may add further clarity to the UCA as the Target (controlled process) is also explicitly specified in the statement. This may ease the generation of scenarios related to the controlled process. Furthermore, it may also simplify the traceability between STPA steps as all of the scenarios can then be linked to the UCA, whereas previously, the scenarios related to the controlled process had to be linked to the hazards instead.

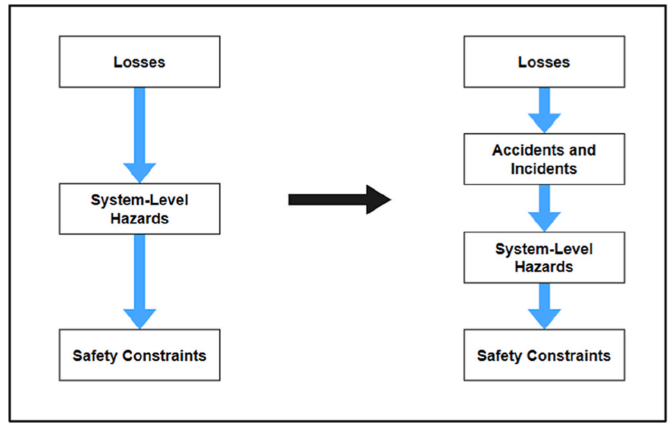


Fig. 3. Addition of a sub-step (Accidents and Incidents) in Step 1 of STPA.

The third and final change is to add another step to STPA, where the identified scenarios should be grouped based on common causal factors. This will reduce the number of nodes in BN as instead of creating a unique node for each STPA scenario in BN, a node for a scenario group will be developed. This is one of the significant advantages of BN compared with counterparts such as FTA, as the common causes in BN can be represented with one node instead of several nodes (events) in FTA (Mahboob and Straub, 2011). The dependencies between nodes in BN are then addressed with links and corresponding Conditional Probability Tables (CPTs) (Mahboob and Straub, 2011).

The steps of STPA in this study with the above-mentioned changes are as follows:

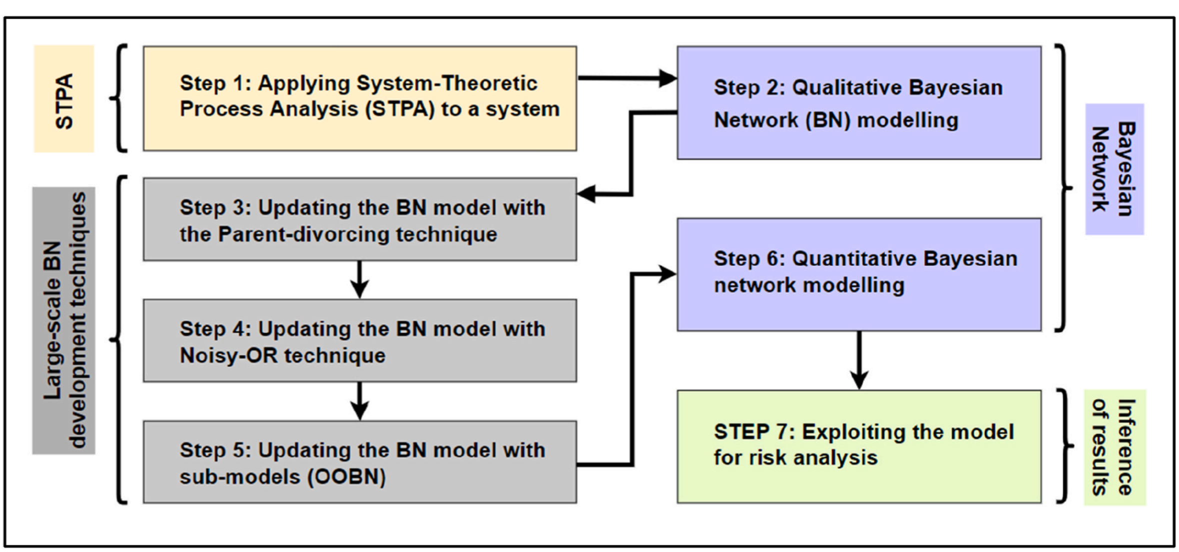


Fig. 2. The steps of the proposed STPA-BN risk management method.

Step 1 Define the purpose of the analysis:
  Sub-step 1 Identify losses.
  Sub-step 2 Identify accidents and incidents (1st change)
  Sub-step 3 Identify system-level hazards
  Sub-step 4 Identify system-level safety constraints
Step 2 Model the control structure.
Step 3 Identify UCAs using the extended statement (2nd change)
Step 4 Identify scenarios leading to UCAs
Step 5 Group scenarios based on common causal factors (3rd change)

3.2. Step 2: qualitative Bayesian Network modelling

Next, the BN model should be developed using most of the outputs from the STPA. Table 1 shows the comparison of outputs from Step 1 and the inputs for BN development. Step 1.2 and Step 5 in Table 2 represent the additional steps to the standard STPA as explained in the previous section. As the table shows, all the outputs except the system-level constraints and control structure diagram are used for the BN development.

For each event identified with STPA such as losses, system-level hazards and UCAs, a BN node must then be created, and the states should be defined. The states of the variable are mainly dependent on the node's type, the scope of the analysis, and data availability. For example, loss of life may have Binary states such as YES and NO, or more than two states such as Single, Multiple, and No fatality. After the variable states are defined, the structure of the BN with variable dependency should be created. Fig. 4 shows the general BN structure of this study. As shown in the figure, the developed BN will have a hierarchy with five layers based on the cause-effect relationship between the STPA outputs. Each layer in the hierarchy corresponds to the type of Output from STPA as specified in Table 1.

Table 1
Comparison of outputs from STPA and inputs for BN development.

Outputs of executing STPA steps	Inputs used for BN
Step 1:	–
Sub-step 1.1 List of losses	List of losses
Sub-step 1.2 List of accidents and incidents	List of accidents and incidents
Sub-step 1.3 List of system-level hazards	List of system-level hazards
Sub-step 1.4 List of system-level constraints	–
Step 2: Control structure diagram	–
Step 3: List of UCAs	List of UCAs
Step 4: List of scenarios leading to UCAs	–
Step 5: List of SCF leading to UCAs	List of SCF leading to UCAs

Table 2
RPO components and functions.

Component	Functions
Applications and Websites (Marine Traffic, Meteorological Institute website, Portnet, etc.)	Provide data related to traffic, weather, ship, etc.
A communication device (PC, tablet, cellphone, VHF, etc.)	Transmit text, audio, and video.
Pilot Plug Unit	Gather and transmit real-time ship data
Ship navigation unit (ECDIS, RADAR, GYRO, GPS, etc.)	Measure and report the ship dynamics data (heading, position, speed, etc.)
Server	Store data
Machine Vision Camera	Detect and Identify objects
Network (4G/5G connectivity)	Enable sharing of data between clients and servers
Display Screens	Display the data
Power unit	Supply necessary power to the hardware
Ship Propulsion Unit (Engine, thrusters, rudders, etc.)	Provide necessary means to propel the ship
Ship control station	Enable controlling and monitoring of propulsion and auxiliary machinery.
Global Maritime Distress and Safety System	Transmit emergency signals to a global network
Ship and fairway safety equipment (Tufone, navigation lights, navigation marks, etc.)	Support safer navigation through visual and audio means.

3.3. Step 3: updating the BN model with the Parent-Divorcing Technique

The nodes that satisfy the conditions of PDT specified previously in Section 0 should be identified and updated with the PDT by adding intermediate nodes. The nodes in the UCA layer in Fig. 4, can be updated with PDT as they satisfy the conditions and usually consist of numerous parent nodes for complex systems.

3.4. Step 4: updating the BN model with Noisy-OR gate

The nodes that satisfy the conditions outlined previously in Section 2.4 should be identified and changed into the Noisy-OR gates. The UCA and the system-level hazards layer in Fig. 4, can be transformed into Noisy-OR gates as these nodes satisfy the conditions and significantly reduce the number of CPT entries. The leak probability of the Noisy-OR gates can then be defined and added to the BN using data or expert opinion (Jianxing et al., 2021; Oniśko et al., 2001).

3.5. Step 5: updating the BN model with sub-models

The BN model should be divided into sub-models as suitable depending on the BN's complexity. First, the nodes that can be grouped should be identified. Then depending on the number of groups, the sub-model nodes should be added. Next, each group of nodes should be placed into a sub-model node.

3.6. Step 6: quantitative Bayesian network modelling

The CPT of BN variables should be updated with the available data. The accident and incident database, simulation studies, or experts' opinions can be used for obtaining the data. This is an iterative process, which means that the model should be updated and assessed accordingly as soon as new data are available. When multiple types of data sources are used, the measure denoted by the data should be made consistent between the sources. This is explained and demonstrated further in the case study in Section 4.2. In the resulting BN model, OR logic can be applied for the propagation of failure from the SCF layer to the UCA layer, and from the UCA layer to the System-level hazard layer. This is because the statements of UCA and hazards in STPA are formulated in such a way that the occurrence of any of the parent nodes in the mentioned layers is certain to trigger the occurrence of the child node.

3.7. Step 7: exploiting the model for risk analysis

The posterior probabilities for the variables can be calculated using the developed model. The model can show the probability of a child node in a particular state from the combination of parent nodes using forward propagation. Since the BN model consists of layers depicting a hierarchy, as shown in Fig. 4, the propagation of risks from one layer to another can also be examined from the model. The analyst can also simulate the potential risk propagation by adding hard evidence to the model. Hard evidence refers to the condition where it is inevitable that a variable is in a specific state (Fenton and Neil, 2019). For example, one can assess the probability of losses or accidents during pilotage when it is certain that one of the ship systems has failed. Thus, the model can be exploited to obtain several inferences depending on the purpose of the analysis.

It is crucial to assess the uncertainty of the BN models. For this purpose, several studies such as Flage and Aven (2009); Marcot (2012); Sahlin et al. (2021) have proposed assessment procedures, metrics and

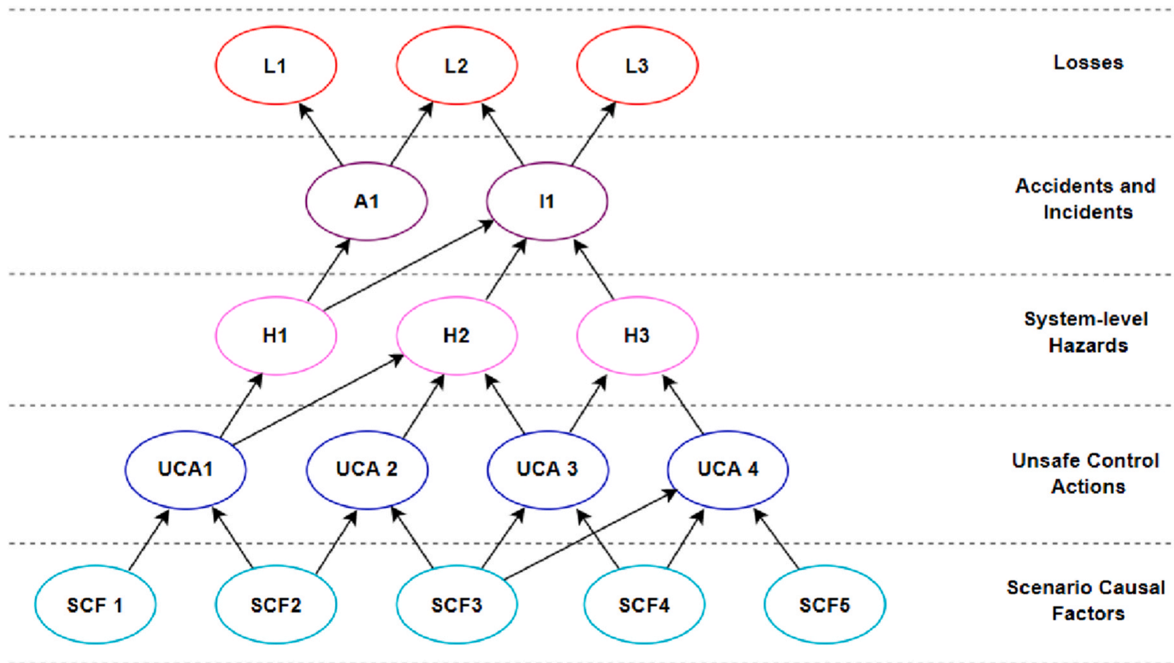


Fig. 4. The hierarchical structure of STPA-based BN in this study.

schemes. Depending on the scope and required accuracy of the model, one of these schemes should be adopted and used for uncertainty assessment. Furthermore, a sensitivity analysis of the model should be conducted to investigate how sensitive a child node is to the changes in the probability in parent nodes (BayesFusion, 2020). This allows analysts to identify highly sensitive parameters in the models, which is critical in assessing the accuracy of the model (BayesFusion, 2020). The sensitivity level of BN nodes can be visualised and evaluated using a widely known “tornado diagram”. Borgonovo and Plischke (2016) provided detailed information about the tornado diagram.

For studies using expert data, the degree of agreement between the experts needs to be demonstrated (IMO, 2018). The level of agreement between experts can be shown by calculating the concordance coefficient (W) as follows (IMO, 2018):

$$W = \frac{12\sum_{i=1}^{i=I}\left[\sum_{j=1}^{j=J} x_{ij} - \frac{1}{2}J(I+1)\right]^2}{J^2\left(I^3 - I\right)} \tag{5}$$

Where i is the number of scenarios, j is the number of experts and x_{ij} is the rating provided by the j^{th} expert for the i^{th} scenario.

The level of agreement between experts is considered good if W is above 0.7, medium if W is between the range of 0.5–0.7, and poor if W is below 0.5 (IMO, 2018).

4. Case study

This section presents the results of applying the proposed methodology to the Remote pilotage operation. The BN shown in this section was developed using the GeNie Modeler tool.

4.1. Remote pilotage operation description

Remote pilotage Operation (RPO), also known as Shore-Based Pilotage Operation, is defined by International Standard for Maritime Pilot Organizations as “an act of pilotage carried out in a designated area by a maritime pilot licensed for that area to conduct the safe navigation of the vessel from a position other than on board the vessel concerned” (ISPO, 2021). In conventional pilotage, the pilot boards the ship to assist the crew in safely navigating the ship in congested areas. However, in RPO, all the relevant information (data and visuals) from the ship and fairway are transferred to the pilot at the shore. Thus, the pilot can assist the crew remotely without boarding the ship.

This case study then aims to identify the hazards and analyse RPO risks in Finnish fairways using the proposed methodology. While RPO involves different components and stakeholders, this analysis focuses on the tasks of the remote pilot, VTS, and Vessel crew.

4.2. Case study data

Table 2 shows the components of RPO and their functions determined through brainstorming sessions with pilots and technology providers. The components list includes (i) hardware/software used by the vessel crew during ship navigation, (ii) the sensors installed on the fairway and ship that generates and transfers data to the remote pilot, and (iii) the hardware/software that the remote pilot may use to develop the situational awareness and to provide navigational advice. The list has been developed using the basis of conventional pilotage and the assumptions from end-users on the required changes to enable remote pilotage. The participants, i.e., end-users of the brainstorming sessions conducted for the case study were pilots, pilotage management staff, researchers, and technology providers. The pilots and the management staff have an experience in pilotage of more than five years. Furthermore, all participants are currently part of an RPO development project in Finland and have demonstrated the RPO recently (ESL Shipping, 2022). The presented components in Table 2 are consistent with the component used during the RPO demonstration.

No operational data is available for RPO yet since it is under development. However, RPO has several similarities with conventional pilotage regarding components used and end-user interactions.

Furthermore, the probability of losses if an accident occurs and the probability of accidents if a hazard occurs will be similar regardless of the type of pilotage. Therefore, in this case study, the aforementioned statistics have been extracted from conventional pilotage and have been assumed to be the same for remote pilotage. As a result, the variables used in the RPO BN can be categorised into two categories i) the common variables in conventional pilotage and RPO, and ii) the variables addressing the new factors in RPO. For the first category, the data from the conventional pilotage was used in the BN and for the second category, the expert's opinion was used in this study. As both statistical data and expert opinion are used in this study, all of the data has been formulated so that the probability of occurrence of the unsafe event i.e., the frequentist probability is extracted and used regardless of the data source. For example for root causes using statistics, $\frac{\textit{Number of occurrence of the failure events}}{\textit{Total number of piltoages}}$ is used and for the expert opinion, a frequency level of 2 refers to an occurrence of a failure event per 100 pilotages i.e., $\frac{1}{100}$, and therefore both denote the probability of occurrence and are dimensionless.

The data about the conventional pilotage was extracted from several sources. The first database used was the incidents and accidents reported during a year (from June 10, 2020 to June 10, 2021) of pilotage in Finnish fairways. The data was provided by Finnpilot Pilotage Ltd, a Finnish state-owned company that provides pilotage service in Finnish fairways. This dataset consists of the following information: a) Probability of equipment failure (see Table A2 in Appendix A) b) Probability of hazards leading to accidents (see Table A3 in Appendix A). Secondly, the statistics about the probability of losses occurring due to accidents and incidents were extracted from the reports provided by the Safety Investigation Authority (SIA) of Finland in 13 years (2009–2021). From the extracted statistics from SIA, the pilotage non-relevant data, such as events involving leisure boats, were excluded. Table A4 in Appendix A shows the data extracted from the SIA reports used in the BN model.

To address the new variables due to remote pilotage, the data were collected from the experts i.e. case study participants. An example scale for the probability of frequency provided by the IMO (2018) was modified with suggestions from the experts and was used for the data gathering. Sánchez-Beaskoetxea et al. (2021) reported that around 25% of accidents due to human errors in cargo and passenger ships occurred due to pilot-only errors, which was used in this study to distinguish the error between pilots and vessel crew. Table 3 presents the scale used to collect the expert opinion on this study. Table A5 in Appendix A presents the probability of events occurring in RPO as estimated using expert opinion.

Table 3
The scale used to collect the expert opinion on estimating the frequency of failures related to RPO.

Frequency level	Definition	Corresponding probability [-]
1. Extremely remote	Likely to occur once in 500 remotely piloted ships	0.002
2. Remote	Likely to occur once every 100 remotely piloted ships	0.01
3. Reasonably probable	Likely to occur once every 50 remotely piloted ships	0.02
4. Frequent	Likely to occur once every 10 remotely piloted ships	0.1

4.3. Application of methodology

4.3.1. Step 1: applying STPA to a target system with additional steps

A total of seven losses to be covered in the RPO risk analysis were identified (see Table 4). Next, two accidents that could lead to all the losses and one incident potentially leading to one of the losses, i.e., loss of customer satisfaction were determined (see Table 5). Then in the context of RPO, three system-level hazards potentially leading to all accidents and incidents and the safety constraints to prevent these system-level hazards were identified (see Table 6 and Table 7, respectively).

The control structure of the RPO was then developed using the system information specified in section 4.2 with the inputs from the participants. The control structure includes information about the components (human and equipment) of RPO and interactions between them. Fig. 5 shows the control structure of the RPO. The scope and focus of the analysis are the Remote Pilot (RP), Vessel Crew (VC), and related equipment, as denoted with green boxes in the figure. The control structure shows that the role of the RP in RPO is mostly to monitor the ship dynamics, fairway traffic, weather, etc., and provide navigation suggestions to the Master. The data required by the RPO is gathered and

Table 4
The losses to be covered in the STPA of RPO.

Loss ID	Losses
L1	Loss of life
L2	Injury to people
L3	Loss of ship
L4	Damage to ship
L5	Loss of cargo
L6	Damage to environment
L7	Loss of customer satisfaction

Table 5
The Accidents and Incidents leading to the losses in RPO.

ID	Accidents and Incidents	Related losses
A1	Collision and contact	L1, L2, L3, L4, L5, L6, L7
A2	Grounding	L1, L2, L3, L4, L5, L6, L7
I1	Pilotage delay without accidents	L7

Table 6
Lists of System-level hazards leading to Accidents and Incidents in RPO.

ID	System-level hazards	Related A/I
H1	Ship Violates minimum separation standards or under keel clearance in route	A1, A2, I1
H2	Disruption or loss of ship manoeuvrability during RPO	A1, A2, I1
H3	Lack of requisites for conducting RPO	A1, A2, I1

Table 7
Lists of safety constraints for preventing the system-level hazards in RPO.

ID	System-level safety constraints	Related hazards
SC1	The ship must satisfy the minimum separation standards and the under-keel clearance along the route.	H1
SC2	The manoeuvrability of the ship must not be disrupted or lost throughout the RPO.	H2
SC3	The requisites for conducting pilotage should be available throughout the RPO.	H3

transmitted from the Intelligent fairway and ship.

Table 8 presents an example of the identified Unsafe Control Actions (UCAs) related to the control action - Send pilotage plan and MPX document. In this step, a total of 23 UCAs were identified (see Table A1 in Appendix A). Next, the scenarios (SC) leading to each UCA were identified. For example, Table 9 presents the scenarios leading to UCA 1. A total of 279 scenarios leading to the UCAs in RPO were identified and grouped into 33 Scenario Causal Factors (SCF) based on the common causes (see Table 10).

4.3.2. Step 2: qualitative Bayesian Network modelling

At first, the variables were defined for the STPA outputs. Next for each type of variables, the states were determined. For simplicity, the state's TRUE/FALSE were assigned to all variables. For example, the TRUE state in the Loss of life variable will contain the probability of an accident leading to the loss of life and the FALSE state will hold the probability of an accident not leading to the loss of life. Once the variables and states were defined, the BN was developed with nodes (representing variables) and arcs (denoting the connection between variables). Figure B1, in Appendix B, presents the resulting Bayesian network for RPO.

4.3.3. Step 3: updating the BN model with the parent-divorcing technique

Five intermediate nodes were added to the network in the SCF layer as it consists of numerous nodes and satisfies the PDT conditions specified in Section 0. Table 11 presents the lists of SCFs and corresponding intermediate nodes with PDT. The application of PDT in this BN network reduced the CPT entries of SCF nodes from 2892088 to 2400. Figure B2, in Appendix B, shows the BN with the addition of intermediate nodes through PDT.

4.3.4. Step 4: updating the BN model with Noisy-OR gates

The Noisy-OR gates were applied to all nodes in the BN as they all satisfied the Noisy-OR conditions highlighted in Section 2.4. With this

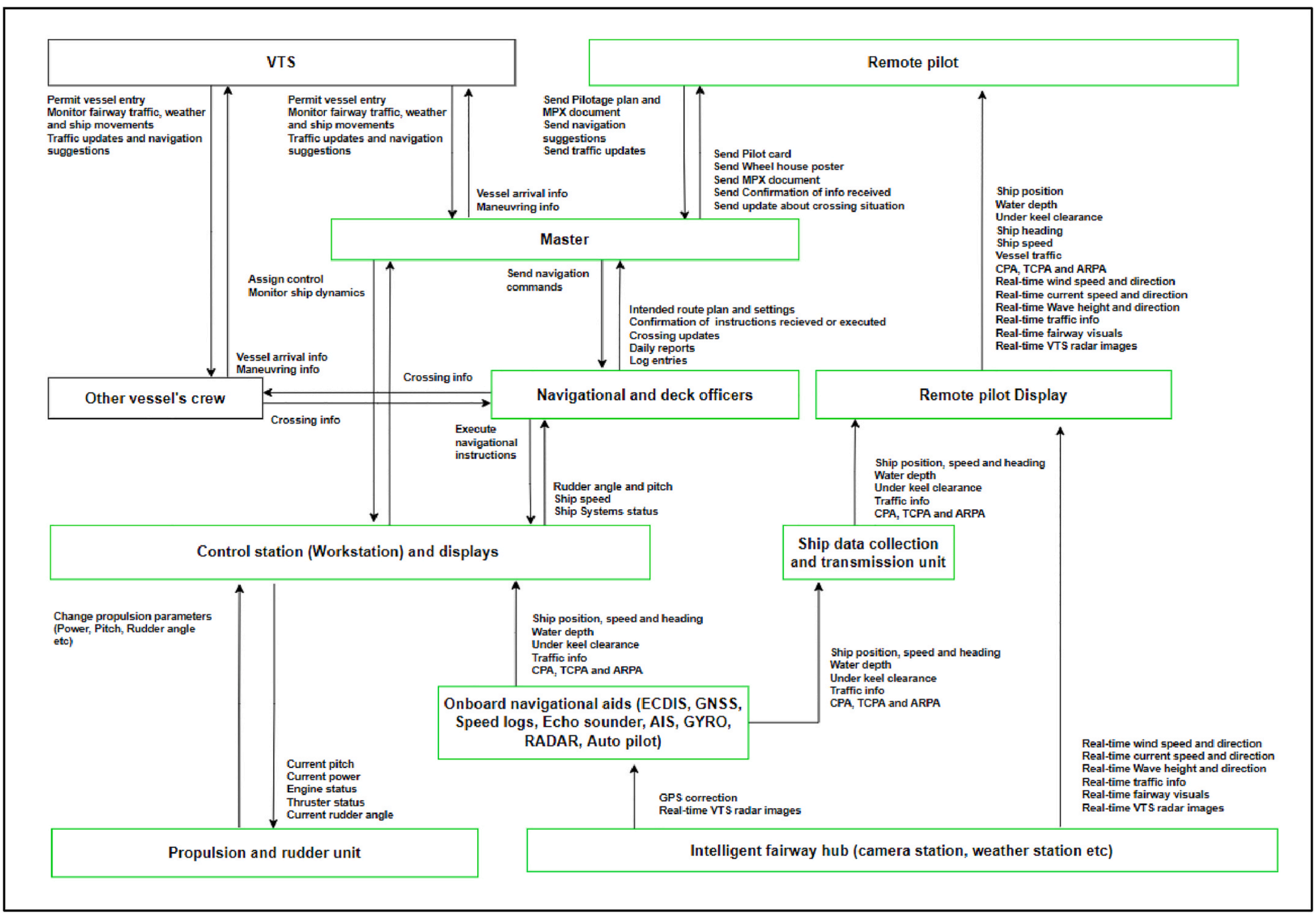


Fig. 5. The control structure of RPO.

Table 8
UCAs and consequences (hazards) related to the control action - Send pilotage plan and MPX document.

Controller	Control actions	UCA			
		Not providing	Providing causing hazard	Providing too early, late, or out of order	Send too soon or applied too long
RP	Send pilotage plan and MPX document	UCA-1 The Pilotage plan and MPX document are not sent from the RP to the master before pilotage (H3).	UCA-2 Wrong, incomplete or unclear pilotage plan and MPX document are sent from the RP to the master and is followed during pilotage in shallow or congested waters (H1)	UCA-3 The pilotage plan and MPX document are sent too late from the RP to the master before pilotage (H3)	NA

Table 9
List of scenarios leading to UCA 1 in RPO.

Scenario ID	Scenarios leading to UCA 1
SC1	The RP doesn't send the pilotage plan and MPX document as he lacks the necessary skills.
SC2	The RP doesn't send the pilotage plan and MPX document due to stress.
SC3	The RP doesn't send the pilotage plan and MPX document due to poor situational awareness.
SC4	The RP doesn't send the pilotage plan and MPX document due to fatigue
SC5	The RP doesn't send the pilotage plan and MPX document due to distraction
SC6	The RP doesn't send the pilotage plan and MPX document due to a lack of professionalism
SC7	The RP doesn't send the pilotage plan and MPX document due to a lack of procedures or checklists
SC8	The RP doesn't send the pilotage plan and MPX document due to a lack of traffic data
SC9	The RP doesn't send the pilotage plan and MPX document due to a lack of weather data
SC10	The RP doesn't send the pilotage plan and MPX document due to a lack of dynamics data
SC11	The RP doesn't send the pilotage plan and MPX document due to a lack of ship systems data
SC12	The RP doesn't send the pilotage plan and MPX document due to a communication device failure at the remote pilotage centre
SC13	The RP doesn't send the pilotage plan and MPX document due to network failure at the remote pilotage centre
SC14	The RP doesn't send the pilotage plan and MPX document due to displays failure at the remote pilotage centre
SC15	Master doesn't receive the pilotage plan and MPX document due to communication device failure onboard the ship
SC16	Master doesn't receive the pilotage plan and MPX document due to network failure at the fairway/ship
SC17	Master doesn't receive the pilotage plan and MPX document due to display failure onboard the ship

Table 10
List of Scenario Causal Factors related to RPO.

SCF ID	Scenario Causal Factors	ID	Scenario causal factors
SCF1	Lack of skills (RP)	SCF18	Lack of professionalism (VC)
SCF2	Stress (RP)	SCF19	Communication device failure
SCF3	Poor situational awareness (RP)	SCF20	Network failure
SCF4	Fatigue (RP)	SCF21	Displays failure
SCF5	Distraction (RP)	SCF22	Language issues
SCF6	Lack of professionalism (RP)	SCF23	Lack of trust
SCF7	Lack of procedures or checklists	SCF24	Thruster unit failure
SCF8	Lack of standard phrases	SCF25	Rudder and helm failure
SCF9	Issues with traffic data	SCF26	Autopilot device failure
SCF10	Issues with weather data	SCF27	ECDIS failure
SCF11	Issues with ship dynamics data	SCF28	GYRO failure
SCF12	Issues with ship systems data	SCF29	RADAR failure
SCF13	Lack of skills (VC)	SCF30	AIS failure
SCF14	Stress (VC)	SCF31	GPS failure
SCF15	Poor situational awareness (VC)	SCF32	Engines failure
SCF16	Fatigue (VC)	SCF33	Control station failure
SCF17	Distraction (VC)		

change, the CPT entries of the BN reduced drastically from 4197444 to 354. For simplicity, the leak probability i.e., residual risk as specified in Section 2.4 wasn't considered for the Noisy-OR gates in this case study and was set to 0.

Table 11
The list of causal factors and corresponding intermediate nodes with parent divorcing.

SCF ID	Causal factors	Corresponding Intermediate node	INT Node ID
SCF1	Lack of skills (RP)	Human errors related to RP	INT1
SCF2	Stress (RP)		
SCF3	Poor situational awareness (RP)		
SCF4	Fatigue (RP)		
SCF5	Distraction (RP)		
SCF6	Lack of professionalism (RP)		
SCF9	Issues with traffic data	Issues with RPO data	INT2
SCF10	Issues with weather data		
SCF11	Issues with ship dynamics data		
SCF12	Issues with ship systems data		
SCF13	Lack of skills (VC)	Human errors related to VC	INT3
SCF14	Stress (VC)		
SCF15	Poor situational awareness (VC)		
SCF16	Fatigue (VC)		
SCF17	Distraction (VC)		
SCF18	Lack of professionalism (VC)		
SCF24	Thruster unit failure	Steering and propulsion unit failure	INT4
SCF25	Rudder and helm failure		
SCF26	Autopilot device failure		
SCF32	Engine failure		
SCF33	Control station failure		
SCF27	ECDIS failure	Navigation unit failure	INT5
SCF28	GYRO failure		
SCF29	RADAR failure		
SCF30	AIS failure		
SCF31	GPS failure		

4.3.5. Step 5: updating the BN model with sub-models

A sub-model was then created for each of the intermediate nodes added during the PDT. Hence five sub-models were added to the network, where each sub-model includes an intermediate node and all its parent nodes. Figure B3 and Figure B4, in Appendix B, show the resulting BN with the addition of the sub-models and the details of each sub-model respectively.

4.3.6. Step 6: quantitative Bayesian Network modelling

Next, the quantitative information related to the variables was provided to the BN model. A combination of data from SIA reports, the Pilotage incident database and expert opinions were added to the BN as explained in Section 4.2. Table A6, in Appendix A, shows an example of CPT of the variable "A1- Collision and contact", where the table corresponds to the variable A1 being True when the Hazards H1, H2 and H3 are true respectively. As mentioned in Section 3, the OR logic was applied for the probability propagation from the SCF layer to the UCA layer, and then from the UCA layer to the System-level hazards layer in the model. Hence, the CPT of all of the variables in the BN was filled and was ready for the inference of results.

4.3.7. Step 7: exploiting the model for risk analysis

A Calculating Posterior Probabilities based on observations

After updating the model with the data, the posterior probabilities of nodes were calculated. With this result, the propagation of risks from the lower layers, i.e., SCF and UCA, to the higher layers, i.e., hazards, accidents, and losses, in the model were assessed. Figure B5 in Appendix B,

Table 12
The posterior occurrence probability of the events (TRUE state) and their ranking with red denoting the critical events.

Type of events	Event (E) ID	The posterior probability of nodes in the TRUE state (p(E))
Losses	L1	0.014
	L2	0.055
	L3	0
	L4	0.172
	L5	0.028
	L6	0.045
	L7	0.327
Accidents and Incidents	A1	0.221
	A2	0.031
	I1	0.218
System-Level Hazards	H1	0.407
	H2	0.004
	H3	0.207
Unsafe Control Actions	UCA1	0.204
	UCA2	0.194
	UCA3	0.204
	UCA4	0.276
	UCA5	0.284
	UCA6	0.284
	UCA7	0.18
	UCA8	0.188
	UCA9	0.188
	UCA10	0.168
	UCA11	0.255
	UCA12	0.193
	UCA13	0.146
	UCA14	0.146
	UCA15	0.146
	UCA16	0.003
	UCA17	0.001
	UCA18	0.003
	UCA19	0.003
	UCA20	0.004
	UCA21	0.004
	UCA22	0.004
	UCA23	0.004

presents the posterior probabilities of nodes in the upper layers of BN i.e., losses, accidents/incidents, and hazards. Furthermore, Table 12 shows the posterior occurrence probabilities (TRUE state) of all the child nodes in the model. These values indicate the posterior probability that these events may occur based on the model and prior observations.

The ranking of events based on occurrence probability in each layer is demonstrated in Table 12 using colours, where the high, medium and low-ranked events are denoted with red, yellow, and green, respectively. For the first layer (losses), the model shows that the most likely losses are loss of customer satisfaction (L7), damage to the ship (L4), injury to people (L2), and damage to the environment (L6) with the posterior probability of 0.327, 0.172, 0.055, and 0.045, respectively. Then for the second layer (accidents and incidents), the contact and collision (A1) and pilotage delay without accidents (I1) are the most likely with a probability of 0.221 and 0.218, respectively than grounding (A2) with a probability of 0.031. Next, in the third layer (hazards), the model indicates that the hazard related to violation of ship separation standards and under keel clearance (H1) has the highest probability of 0.407. Whereas the other hazards, i.e., the lack of requisites for conducting RPO (H3) and the disruption/loss of ship manoeuvrability during RPO, have a probability of 0.207 and 0.004, respectively. In the fourth layer (UCAs), the model shows that the UCAs related to the navigational suggestions from pilot to master, i.e., UCA4, UCA5, and UCA6, are most likely with the occurrence probability of 0.276, 0.284, and 0.284, respectively. This is followed by the UCA11, which is related to navigational commands from master to deck officers and has a probability of 0.255.

B Posterior probabilities analysis based on hard evidence

Next, the probability propagation from lower to upper levels was checked by providing hard evidence in the model. Fig. 6 shows the posterior probabilities of child nodes of H2 when the H2 is provided with hard evidence as $p(H2 = True / ..)$ is 1. This shows the probability of accidents and losses occurring when assumed that the "H2- Ship Violates minimum separation standards or under keel clearance in route" has occurred. For example, the model shows that if the H2 occurs, the probability that the A1 "Collision and contact" occurs increases from 0.221 to 0.544. Similarly, the occurrence probability of L1 increases from 0.014 to 0.034.

CAssessing the sensitivity and uncertainty of the BN model

Fig. 7 presents a tornado diagram of one of the top layer nodes, "L1-Loss of life". The figure demonstrates the ten most sensitive parameters to the posterior probability of L1. Furthermore, the level of sensitivity is illustrated with the bars in the diagram. For example, the figure shows that the "SCF11- Issues with ship dynamics data" is the most sensitive node, followed by "SCF 22- Language issues" and "SCF 13- Lack of skills of vessel crew". The analysis indicates that the 10% increase in the most sensitive parameter (SCF11) can increase the posterior probability of L1 from 0.0138 to 0.0141, which is about a 2% increase. Similarly, the 10%

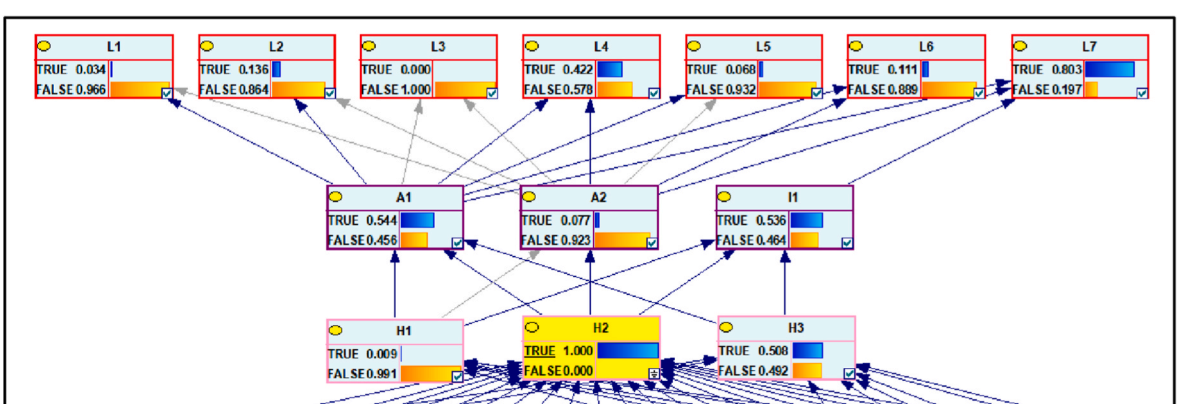


Fig. 6. Posterior probabilities of nodes when H2 (in yellow) is provided with hard evidence as p (H2 = True/.) is 1.

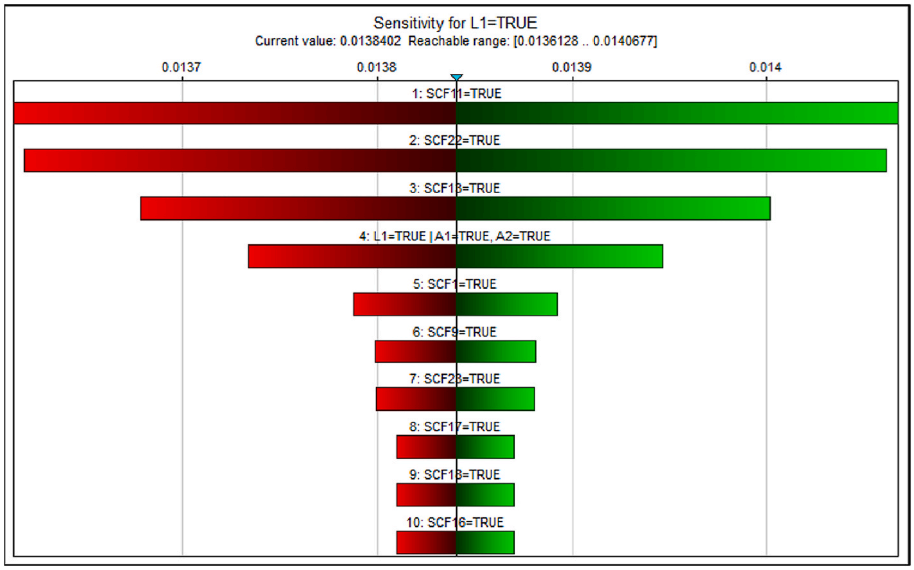


Fig. 7. A tornado diagram presenting the ten most sensitive input parameters (±10% change in probability of occurrence) of the node "L1- Loss of life".

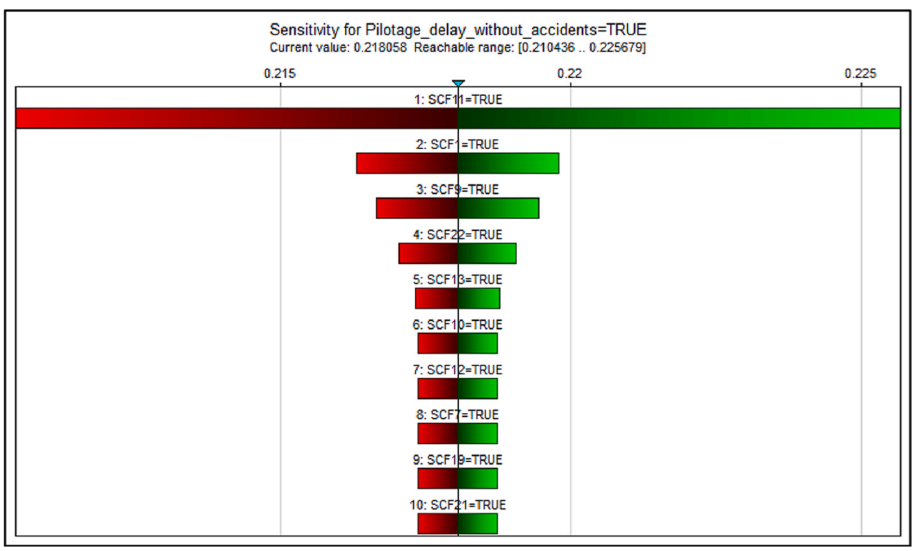


Fig. 8. A tornado diagram presenting the ten most sensitive input parameters (±10% change in probability of occurrence) of the node "L1- Loss of life".

Table 13
Classification scale for assessing the model uncertainty, based on Flage and Aven (2009); Goerlandt and Montewka (2015).

Uncertainty level	Conditions
High uncertainty	One or more of the following conditions are met: - The phenomena involved are not well understood; models are non-existent or known/believed to give poor predictions. - The assumptions made represent strong simplifications - Data are not available or are unreliable - There is a lack of agreement/consensus among experts
Medium uncertainty	Conditions between those characterising high and low uncertainty, e.g.: - The phenomena are well understood, but the models used are considered simple/crude. - Some reliable data are used
Low uncertainty	All the following conditions are met: - The phenomena involved are well understood; the models used are known to give predictions with the required accuracy - The assumptions made are seen as very reasonable - Much reliable data is available - There is broad agreement among experts

decrease in the SCF11 parameter can decrease the posterior probability of L1 from 0.0138 to 0.0136, which is about a 1.5% decrease.

Similarly, Fig. 8 presents a tornado diagram for a second layer node, "I1- Pilotage delay without accidents". The figure shows that the three most sensitive parameters for I1 are "SCF11- Issues with ship dynamics data", "SCF1- Lack of skills of a remote pilot", and "SCF9- Issues with traffic data". The analysis indicates that the change in the most sensitive parameter SCF 11 can alter the posterior probability of I1 from 0.218 to 0.210 with a 10% decrease and to 0.226 with a 10% increase, which is within a ±3.7% variation.

In order to assess the overall uncertainty of the BN results in this study, the scale proposed by Flage and Aven (2009) was used (see Table 13). This scale has been commonly used to assess uncertainty in several risk assessment studies such as Khan et al. (2020); Valdez Banda et al. (2015), and Montewka et al. (2017). As remote pilotage is still under development, many reliable data are not available for the model, which reduces the accuracy of the estimations. However, there are similarities in system components and procedures between conventional pilotage and remote pilotage. Furthermore, the data related to accidents and incidents leading to losses does not vary with the type of pilotage used. Thus, a part of the data used in the model is reliable and accurate. The level of knowledge and experience of the involved experts is considered high as they all have a good understanding and familiarity with conventional pilotage development and operation. Therefore, the assumptions made based on their perception of the remote pilotage operation represent a mixture of strong and reasonable simplifications. Furthermore, the successful demonstration of remote pilotage recently in Finland (ESL Shipping, 2022) shows the level of expertise of the involved participants. Next, the agreement between experts was assessed by calculating the Kendall coefficient of concordance (*W*) using the DescTools R package (Signorell et al., 2018). The coefficient value of 0.956 was obtained with the calculation. Figure A1 in Appendix A presents the R code and the obtained result used to calculate the *W* in this study. As the obtained value is above 0.7, it shows that the experts had a good agreement when providing inputs to the BN model (IMO, 2018). Hence, considering all of these conditions and comparing them with the scale in Table 13, the results of the current remote pilotage BN model was considered to have an overall medium uncertainty level.

5. Discussion

5.1. STPA-BN integration

The STPA method used in the proposed framework identified the losses and their causal factors/sub-factors, such as accidents, hazards, and unsafe scenarios. Moreover, STPA was able to provide vast results as the analysis starts at an abstract level and progresses towards a detailed level covering all system-level hazards and component-level hazards, which is critical in managing the safety of modern complex systems. Then, mapping STPA outputs in BN addressed the gaps in STPA i.e. quantitative risk analysis. The integration process was also resource-efficient as the outputs of STPA were used directly to structure the BN. Using prior observations, the BN model was able to estimate the posterior probability of occurrence of the child nodes i.e. the unsafe events such as hazards, accidents and losses. As the structure of the BN consists of hierarchies, the forward probability propagation from the root causes to the upper layers could be observed from the model.

The additions/modifications proposed in this framework improved the general STPA-BN methodology suggested by previous studies (Rekabi (2018); Utne et al. (2020)). First, adding a sub-step, i.e., identifying the accidents/incidents leading to the losses, filled the gap of a cause-effect relationship between the identification of losses and the identification of hazards. The benefit of this change was realised in the case study as the data about hazards leading to losses were rare compared to the data about hazards leading to accidents/incidents and the accidents/incidents leading to losses. The second upgrade, which is about grouping the loss scenarios based on causal factors, lowered the number of nodes from 279 to 33 in the BN without affecting the result. The viability and benefit of this approach have also been discussed by Utne et al. (2020). The third and final modification of changing the way of formulating the UCA statement added clarity to the UCA itself since it also included the controlled process (Target). Furthermore, the results show that this change allowed the BN structure to have a precise hierarchical level.

5.2. Large-scale BN development techniques

The techniques i.e., Parent-divorcing, Noisy-OR, and Sub-model, integrated into the framework reduced the complexity of developing large-scale BN. The Parent-divorcing and Noisy-OR gate technique reduced the challenges with several parent nodes and corresponding CPT requirements, which were faced by other STPA-BN studies such as Rekabi (2018), Utne et al. (2020) and Chaal et al. (2022). As a result, the compromise of limiting the maximum number of parent nodes or the number of hazards, which limits the size of the BN model is eliminated. The effects of applying these techniques were demonstrated in the case study, where the application of the PDT and Noisy-OR gate reduced the CPT entries significantly. This reduction is substantial for the analysts in developing the large-scale BN as it reduces the required resources. Thus, it increases the feasibility of risk analysis using STPA and BN.

While the sub-model doesn't reduce the CPT entries, it was still beneficial and is highly recommended as it reduced the burden of having one large single BN compared to one main BN accompanied by several sub-models. As the resulting BN from STPA inputs can be huge and disrupted (see Figure B2 in Appendix B), the usage of sub-models improved the visualisation of the BN without changing the results (see Figure B3 in Appendix B). These sub-models can then be used in other similar risk analysis applications. The reusability of sub-models was a benefit previously highlighted by Koller and Pfeffer (1997).

5.3. Case-study: remote pilotage

The case study results show that the proposed framework can be applied to assess the risks in complex socio-technical ecosystems such as RPO. First, the usage of STPA showed that it could identify numerous unsafe scenarios that can lead to hazards, accidents, and ultimately losses. Although the scope of the STPA analysis was limited to the operators (RP and Vessel crew) and related equipment, the scenarios covered numerous factors related to human error, equipment failure, and lack of information (data).

The BN of RPO was able to calculate the posterior probability of all the events identified with STPA i.e., losses, accidents and incidents, hazards, etc. However, it should be noted that modelling risk control options in RPO is not within the scope of this study. The analysis results will then allow the RPO stakeholders to define suitable Risk Control Options (RCOs) to prevent or mitigate the risks to an acceptable level in a future study. Furthermore, if the resources for RPO development are limited, the stakeholders will know the critical scenarios requiring more RCOs. For example, the results showed that the losses such as loss of customer satisfaction, damage to the ship, and injury to people have a higher probability of occurrence than the other losses in RPO. Thus, the stakeholders can invest more resources in these critical losses. However, this doesn't mean that the events with low probability should be ignored as all of the events need to be reduced to an acceptable level. The BN model showed an anomaly with loss of ship where the probability of occurrence is 0. This anomaly is because the data collected and used in the model didn't have a single event where a loss of the ship was observed due to accidents/incidents in Finnish Waters. Regarding the accidents and incidents, the model showed that collision and contact, and pilotage delay have higher occurrences than grounding. Hence, the decision-makers in Finland should prioritise the prevention or mitigation of collision and contact, and pilotage delay.

The BN model also allowed the calculation of the posterior probabilities assuming that an event has occurred using hard evidence. It was observed in the pilotage reports that often when a failure occurs during pilotage, the pilots and crew need to decide to either to continue, halt or abort the pilotage. The usage of hard evidence in the model can support the decision-making for the operators as it can show the change in the probability of occurrence of hazards, accidents and incidents, and losses due to the failure. While a single fault or failure may have been ignored by the operators previously, this model can provide the overall effects at a systemic level which may support operators in making real-time decisions.

The sensitivity analysis of the BN showed that the five most sensitive nodes in the current RPO model are a) SCF11- Issues with ship dynamics data, b) SCF22- Language issues, c) SCF13- Lack of skills of vessel crew, d) Lack of skills of remote pilot e) Issues with traffic data. The results show that the $\pm 10\%$ change in the probability of these nodes can reach a $\pm 3.7\%$ variation in posterior probabilities of accidents and incidents, and losses. To improve the overall model's accuracy, the decision-makers should focus on improving the accuracy of the gathered observations for these sensitive nodes.

5.4. Limitations and future work

The usage of the Noisy-OR gate may slightly reduce the accuracy of the model as specified by Oniśko et al. (2001) and Ji et al. (2022), where a difference of less than ± 3% on the posterior probabilities was reported. Therefore, it should not be used if the accuracy of the model is of uttermost importance. In future, the risk analysis of RPO can be improved further by replacing expert opinions with RPO operational data once available. Furthermore, the methodology should be extended from risk analysis to risk management by introducing risk control options and cost-benefit analysis.

6. Conclusion

The complexity of novel systems requires a systematic and straightforward risk analysis methodology to identify unsafe scenarios, the risk causal factors and to estimate the current risk level. For this purpose, this study presented a novel risk analysis methodology by integrating modified STPA with the BN. The proposed methodology also integrates Noisy-OR gates, Parent-divorcing, and Sub-models to cover the gaps related to limitations with the high number of CPT entries as highlighted by other STPA-BN studies.

The changes proposed to the STPA in this study improved the integration of STPA and BN. The changes improved the data extraction required for the BN model, reduced the number of nodes in the BN, and added clarity to the UCA statements generated during the STPA., The usage of PDT and Noisy-OR then addressed the limitation of STPA-BN methodology resulting from a combinatorial explosion of parent nodes as it reduced the CPT entries in BN from 2892088 to 2400 and from 4197444 to 354, respectively. As a result, it allowed assessing risks in novel operations such as RPO, which suffer from limited data. Furthermore, the usage of sub-models added modularity to the BN and thus improved its visual aspect. The BN model shows that the losses in RPO requiring attention are the loss of customer satisfaction, damage to the ship, injury to people and damage to the environment. The model also shows that the collision and contact and pilotage delay are more likely than grounding in Finnish fairways. These results are critical for decision-makers in determining potential risk control measures for RPO in future. Furthermore, the study shows that the proposed methodology can constitute a valuable tool in the hands of safety engineers as it can be applied to other complex operations in future research.

CRediT authorship contribution statement

Sunil Basnet: Conceptualization, Methodology, Software, Formal analysis, Resources, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ahmad Bahoo-Toroody:** Advisory, Conceptualization, Writing – review & editing, Visualization, Resources. **Meriam Chaal:** Investigation, Writing – review & editing, Visualization. **Janne Lahtinen:** Investigation, Writing – review & editing. **Victor Bolbot:** Writing – review & editing, Visualization. **Osiris A. Valdez Banda:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Data availability

The data is provided in the Appendix. For further information, please contact corresponding author.

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Appendix A

Table A1
UCAs and related consequences (hazards) in RPO.

Controller	Control actions	UCA			
		Not providing	Providing causing hazard	Providing too early, late, or out of order	Sed too soon or applied too long
RP	Send pilotage plan and MPX document	UCA-1 The Pilotage plan and MPX document are not sent from the RP to the master before pilotage (H3).	UCA-2 Wrong, incomplete or unclear pilotage plan and MPX document are sent from the RP to the master and is followed during pilotage in shallow or congested waters (H1)	UCA-3 The pilotage plan and MPX document are sent too late from the RP to the master before pilotage (H3)	NA
RP	Send navigation suggestions	UCA-4 Navigation suggestions are not sent from the RP to the master when required during pilotage in shallow or congested water. (H1)	UCA-5 Wrong or unclear navigation suggestions are sent from the RP to the master during pilotage in shallow or congested water. (H1)	UCA-6 Navigational suggestions are sent too late from the RP to the master when required during pilotage in shallow or congested water. (H1)	NA
RP	Send traffic updates	UCA-7 Traffic updates are not sent from the RP to the master when required during pilotage in congested water (H1)	UCA-8 Wrong or unclear traffic updates are sent from the RP to the master during pilotage in congested water. (H1)	UCA-9 Traffic updates are sent too late from the RP to the master when required during pilotage in congested water (H1)	
Master	Send navigation commands	UCA -10 Navigational instructions are not sent from the master to the deck officers when required during pilotage in congested or shallow water. (H1)	UCA-11 Wrong or unclear navigational instructions are sent from the master to the deck officers during congested or shallow water pilotage. (H1)	UCA-12 Navigational instructions are sent too late from the master to the deck officers when required during pilotage in congested or shallow water. (H1)	NA
					NA

(continued on next page)

Table A1 (*continued*)

Controller	Control actions	UCA			
		Not providing	Providing causing hazard	Providing too early, late, or out of order	Sed too soon or applied too long
Deck officers	Execute navigation commands	UCA-13 Navigation Commands from the master are not executed by the deck officers with the control station during pilotage in congested or shallow water. (H1)	UCA-14 Wrong navigation commands are executed by the deck officers with the control station during pilotage in congested or shallow water. (H1)	UCA-15 Navigation commands from the master are executed too early or too late by the deck officers with the control station during congested or shallow water pilotage. (H1)	
Control station	Turn On/Off	UCA-16 Turn On/Off command is not sent from the control station to the main propulsion unit or side thrusters when requested by the deck officers during RPO. (H1, H2, H3)	UCA-17 The main propulsion unit or side thrusters are turned on without any request from deck officers during maneuvring with tugs in congested or shallow water (H1) UCA-18 The main propulsion unit or side thrusters are turned off without any request from deck officers during critical pilotage manoeuvres in congested or shallow water (H1, H2, H3)	UCA-19 The main propulsion unit or side thrusters are turned On/Off too early or too late when requested by the vessel crew during RPO. (H1, H2, H3)	NA
Control station	Change propulsion parameters (Power, Pitch, Rudder angle etc)	UCA-20 The command to change propulsion parameter is not executed when requested by the deck officers during pilotage in congested or shallow water (H1, H2, H3)	UCA-21 Control station changes to wrong propulsion parameters when requested by the deck officers during pilotage in congested or shallow water. (H1)	UCA-22 Control station changes the propulsion parameters too late or too early than requested by the deck officers during pilotage in congested or shallow water (H1, H2, H3)	UCA-23 Control station changes the propulsion parameters for too long or too short than requested by the deck officers during pilotage in congested or shallow water (H1, H3)

Table A2
Observations related to the ship equipment failure during conventional pilotage in Finish fairways (from June 10, 2020 to June 10, 2021).

Components	Probability [-]
Propulsion and thruster unit failure	0.00098
Rudder and helm failure	0.00028
Autopilot device failure	0.00023
ECDIS failure	0.00023
GYRO failure	0.00093
RADAR failure	0.00047
AIS failure	0.00009
GPS failure	0.00047
Engines failure	0.00219
Control station failure	0.00009

Table A3
Observations on the occurrence of accidents and incidents due to hazards p (A/H) during conventional pilotage in Finish fairways (from June 10, 2020 to June 10, 2021).

Hazards	Accidents and Incidents		
	Collision and Contact	Grounding	Delay without accidents
Lack of requisites for conducting pilotage	0.0227	0	0.8864
Violation of minimum separation standards or under keel clearance in route	0.5385	0.0769	0.1538
Disruption or loss of ship maneuverability	0.0076	0	0.3740

Table A4
Observations related to accidents in Finnish waters leading to losses (p (L/A)) as reported by the Safety Investigation Authority of Finland.

Accidents	Losses					
	Loss of life	Injury to people	Loss of ship	Damage to ship	Loss of cargo	Damage to environment
Collision and contact	0.0625	0.25	0	0.6875	0.125	0.1875
Grounding	0	0	0	1	0	0.1333

Table A5
Probability of events occurring determined using expert opinion

Event	Probability of occurrence p (SC)
Lack of skills (RP)	0.025
Stress (RP)	0.005
Poor situational awareness (RP)	0.005
Fatigue (RP)	0.005
Distraction (RP)	0.005
Lack of professionalism (RP)	0.005
Lack of procedures or checklists	0.01
Lack of standard phrases	0.01
Issues with traffic data	0.02
Issues with weather data	0.01
Issues with ship dynamics data	0.1
Issues with ship systems data	0.01
Lack of skills (VC)	0.075
Stress (VC)	0.015
Poor situational awareness (VC)	0.015
Fatigue (VC)	0.015
Distraction (VC)	0.015
Lack of professionalism (VC)	0.015
Communication device failure	0.01
Network failure	0.002
Displays failure	0.01
Language issues	0.1
Lack of trust	0.02

Table A6
A CPT table of a node "A1- Collision and Contact".

Parent	H1- True	H2- True	H3-True
A1- True	0.5385	0.0076	0.0227
A1- False	0.4615	0.9924	0.9773

```
library(DescTools)

RPO <- data.frame(expert1=c(4,3,3,3,3,3,2,2,3,2,4,2,2,1,3,4,3),
                  expert2=c(3,3,3,3,3,3,2,2,3,2,4,2,2,1,2,4,3),
                  expert3=c(4,3,3,3,3,3,2,2,3,2,4,2,1,1,2,4,3))

KendallW(RPO, TRUE)

[1] 0.9562101
```

Fig. A1. R code used in this study to calculate the Kendall coefficient of concordance (W) for assessing the agreement between experts.

Appendix B

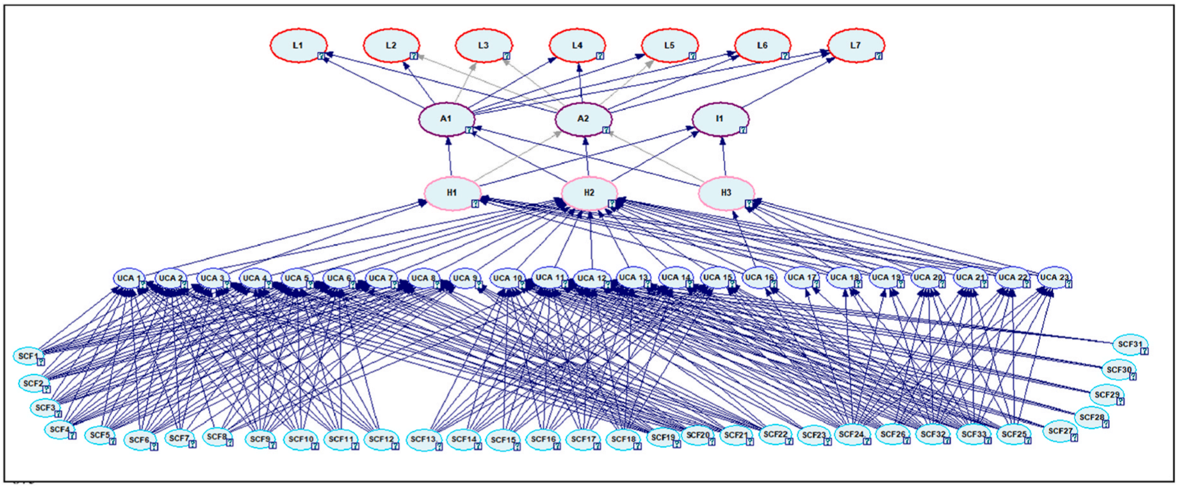

Fig. B1. Large-scale BN of RPO before the implementation of complexity reduction techniques.

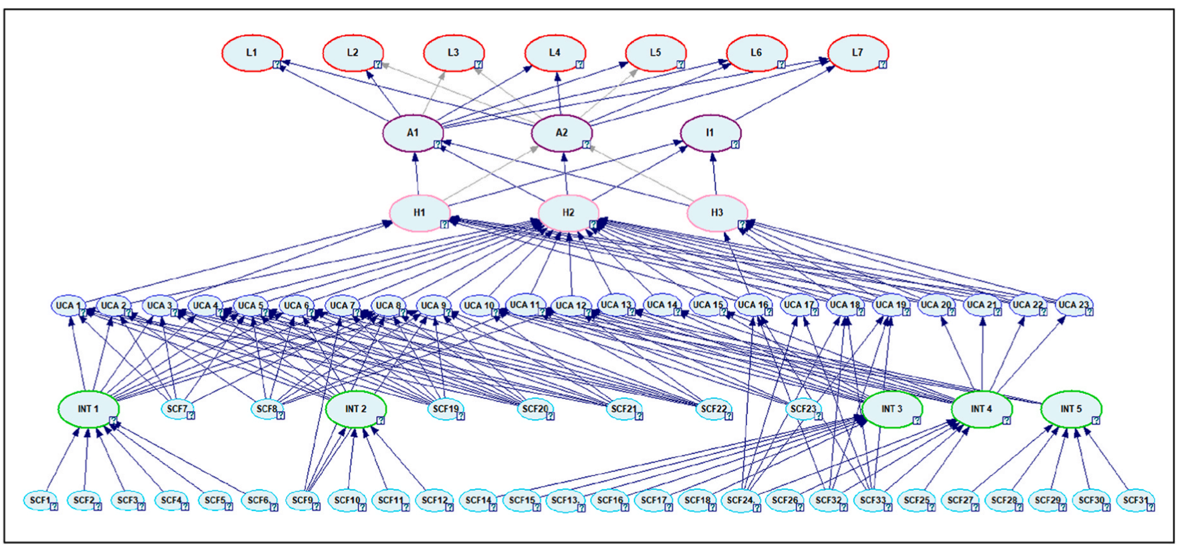

Fig. B2. Large-scale BN of RPO after the addition of five intermediate nodes through Parent-divorcing.

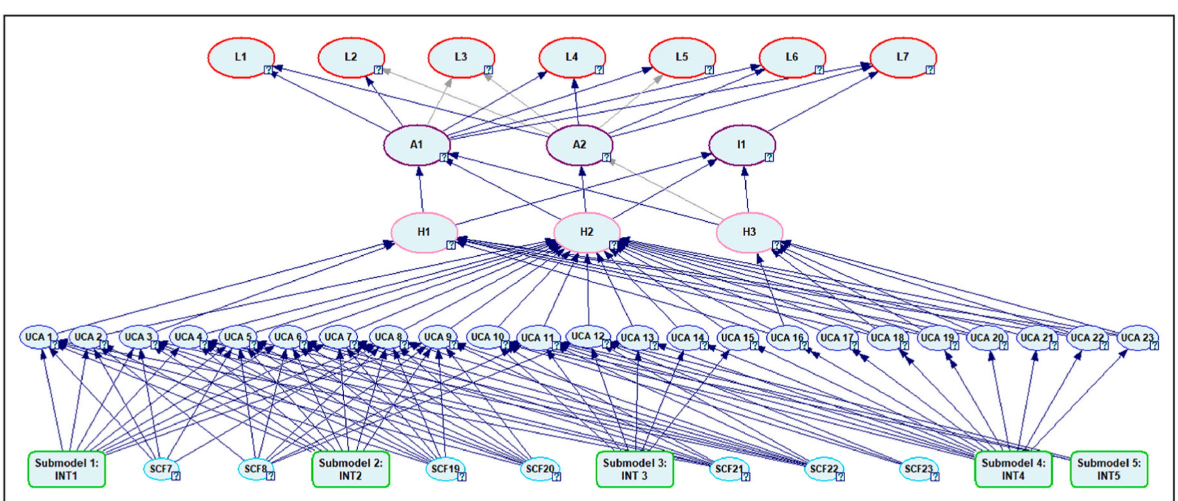

Fig. B3. Large-scale BN of RPO with the addition of five sub-models.

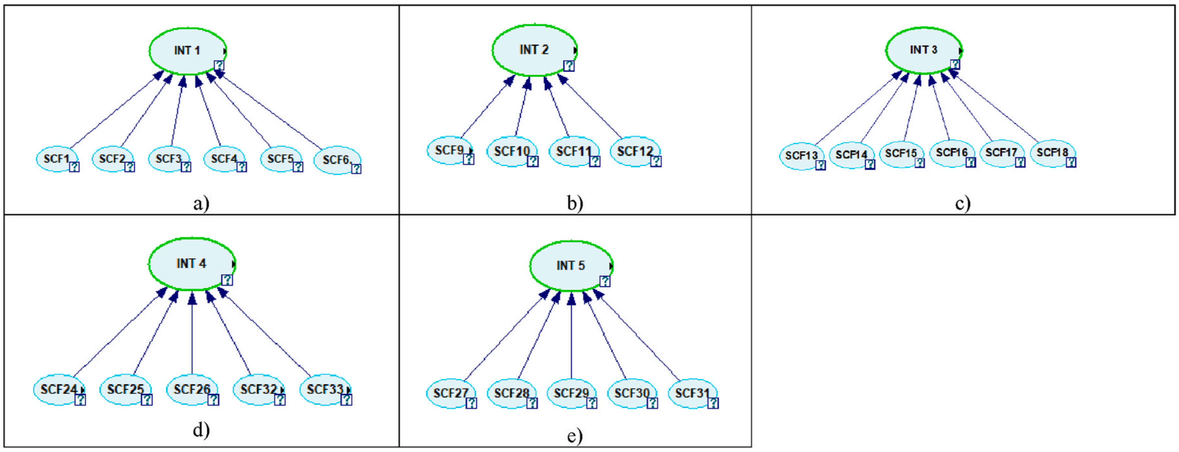

Fig. B4. The five sub-models of the BN - (a) Human errors (RP) (b) Issues with remote pilotage essential data. (c) Human errors (VC) (d) Steering and propulsion unit failure (e) Navigations aid failure.

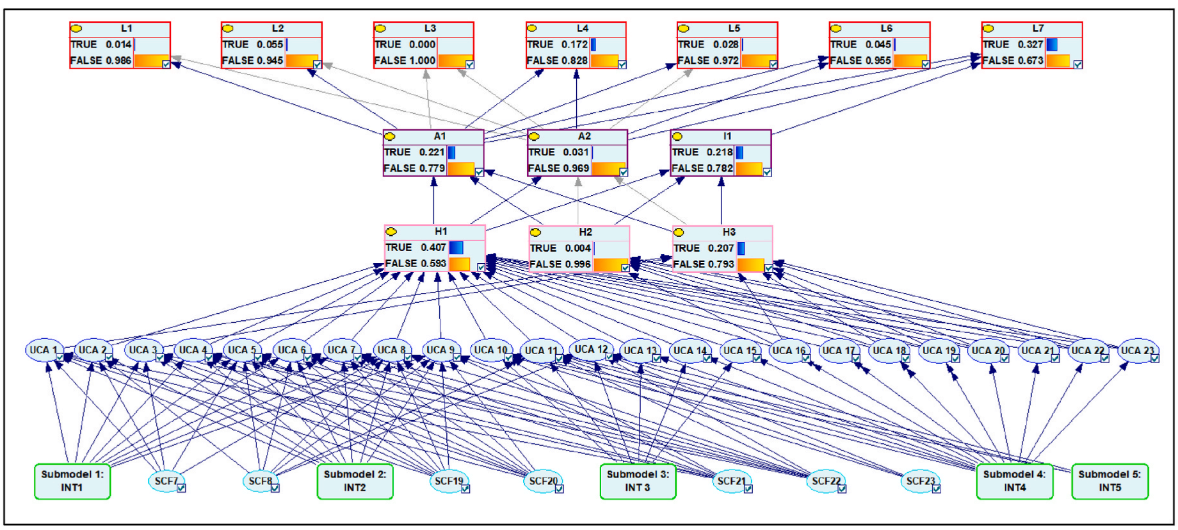

Fig. B5. Large-scale BN of RPO showing the posterior probabilities of nodes in the upper hierarchical level.

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