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Selecting cost-effective risk control option for advanced maritime operations; Integration of STPA-BN-Influence diagram

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A B S T R A C T

Advanced maritime operations, such as remote pilotage, are vulnerable to new emergent risks due to increased system complexity and a multitude of interactions. Thus, maritime researchers this decade have combined Systems-Theoretic Process Analysis (STPA) and Bayesian Network (BN) to effectively manage these risks. Although these methods are effective in identifying hazards and analyzing risk levels, none of the STPA-BN studies provides a systematic process for selecting a cost-effective combination of risk control measures. Cost-benefit analysis is crucial for organizations to make informed risk-based decisions in allocating available resources for risk mitigation and achieve a balance between risk reduction (benefits) and costs associated with risk control measures. This study offers an innovative method of integrating the STPA-BN-Influence diagram for risk-based decision-making through a cost-benefit analysis. The model automatically evaluates the costs and benefits of all possible risk control options and proposes the optimum cost-effective solution. In the current study, the methodology is illustrated with a case study of remote pilotage operation, where 524,288 different risk control options (combinations of 19 risk control measures) are assessed to select an optimal risk control option. The case study results indicate that the proposed methodology is more significant when the number of risk control measures increases.

1. Introduction

Digital transformation of maritime services continues with remote pilotage operations (RPO) and autonomous ships under development (Mayflower, 2022; Yara, 2022). As enabling these services would require dealing with system complexity and understanding the system interactions, the lack of understanding of the system behavior can lead to new emerging risks (Hollnagel et al., 2015; Leveson, 2016). Therefore, it is crucial to manage the risks of these first-hand technologies as early as possible to ensure the feasibility of their business models. In the maritime domain and regardless of the intelligence level of the operation, the Formal Safety Assessment (FSA), by International Maritime Organization, has been widely used for assessing risks and proposing regulations to improve the safety level. Nevertheless, gaps and inconsistencies have been observed in FSA studies. For instance, FSA studies have been condemned for their failure to demonstrate cause and consequences i.e. chain of events (Psaraftis, 2012). Furthermore, FSA studies thus far are incapable of assessing a greater number of Risk Control Options (RCOs) (Kontovas and Psaraftis, 2009). Therefore, some studies have reviewed FSA (Psaraftis, 2012; Wang, 2001), where the lack of a decision-making tool for the RCO selection is noticed and the integration of Bayesian approaches to make the proposed FSA-based model capable of both probabilistic analysis and decision making for risk management is suggested. To fill the addressed gaps, novel models must be introduced and incorporated into the FSA.

In the past few years, consolidated STPA-BN risk management techniques have been presented by multiple researchers (Basnet et al., 2023; Chaal et al., 2022; Johansen and Utne, 2022; Utne et al., 2020) to identify the hazard and estimate risks in advanced maritime systems. In these methods, the qualitative results of STPA are utilized as input to formulate a quantitative BN risk model. This combination was decided on because of the qualitative capability of STPA to cover a wider range of causal scenarios including software issues, design errors, and control

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Nomenclature

ALU	Additive Linear Utility
BN	Bayesian Network
CPT	Conditional Probability Table
CBA	Cost-Benefit Analysis
ID	Influence Diagram
RCM	Risk Control Measure
RCO	Risk Control Option
RPO	Remote Pilotage Operation
SCF	Scenario Causal Factor
STPA	Systems-Theoretic Process Analysis
UCA	Unsafe Control Action

problems (Thieme et al., 2018; Zhou et al., 2020), and the advanced features of BN for quantitative risk assessment such as efficient handling of common cause failures and multi-state components (Khakzad et al., 2011; Mahboob and Straub, 2011). In the maritime domain, Basnet et al. (2023) outlined a risk analysis methodology for complex systems using an STPA-based BN and verified its capabilities given a case study of remote pilotage operations. Chaal et al. (2022) presented an STPA-BN framework for selecting an RCO for future ships with high autonomy levels. Johansen and Utne (2022) used STPA-BN to develop a supervisory risk controller for better intelligence and decision support for autonomous surface ships. Utne et al. (2020) proposed a framework for online risk modeling for autonomous ships using STPA and BN. Similarly in other domains, Pan et al. (2021) used STPA and BN to identify risk factors in the construction of prefabricated building lifts. Rekabi (2018) explored the application of STPA and BN for the safety analysis of the European railway traffic management system focused on train drivers. All of these studies have shown promising results and suggested further developments toward the combined STPA-BN approach.

Despite great advances in hazard identification (through the STPA part) and risk estimation (using BN models), none of the existing STPA-BN studies provide a decision support tool in their methodology to evaluate the RCOs based on a cost-benefit analysis (CBA). CBA is important for decision-makers in selecting optimum RCOs when trade-offs must be made due to limited resources (IMO, 2018; ISO, 2019). In CBA, the RCOs are compared based on the costs of implementation and the expected benefit due to risk reduction capability, thus facilitating the RCO selection. For assessing different decision alternatives, several methods such as Analytical Hierarchy Process (AHP) (Dos Santos et al., 2019; Konstantinos et al., 2019), Decision Tree (Li et al., 2022a; Romero et al., 2020), and Influence Diagram (ID) (BahooToroody et al., 2019; Villalba et al., 2022; Weflen et al., 2022) have been widely used. For addressing the identified research gap in this paper, a methodology that integrates ID with the STPA-BN method is proposed. ID is selected in the present study for risk-based decision-making on RCO selection due to the following major reasons: a) Unlike AHP, an ID can represent probabilistic relationships among variables for assessing different decision options (Garvey et al., 2020) b) In comparison to Decision Tree, the ID is effective in modeling complex relationships between variables (Howard and Matheson, 2005) c) ID is concise and can include a large number of variables (Fenton and Neil, 2018) d) easier integration with BN due to common foundation (Hall, 2010).

In this study, a methodology extending the STPA-based BN for defining RCMs and selecting cost-effective RCOs, i.e., a combination of RCMs, is proposed. The method employs an ID to estimate and compare the cost and benefits of decisions regarding RCO implementation. This study includes a) A novel methodology for risk-based decision-making on RCO selection b) the Capability to conduct a cost-benefit analysis of numerous RCOs instantaneously c) Integration of STPA, BN, and ID for risk management d) the Selection of RCO for Remote Pilotage. The rest of the article is structured as follows. a brief description of related methods and studies i.e., BN and ID are provided in Section 2. Section 3 is devoted to present the subdivision of methodology followed by Section 4 where the methodology is illustrated with a case study of RPO. The results of the case study and the related discussions are then presented in Section 5 while the conclusion is provided in Section 6.

2. Related methods and studies

2.1. Bayesian Networks

BN is a probabilistic directed acyclic graph (DAG) based on the Bayes theorem representing a set of variables and their conditional interdependencies (Fenton and Neil, 2018). The variables in BN are denoted by chance nodes and the conditional dependence is described qualitatively with arcs and quantitatively with conditional probability tables (CPT) (Barber, 2012; Pearl, 1995). The Bayes theorem and the joint probability distribution of BN variables, $p(x_1, \ldots, x_D)$, are provided in Equations (1) and (2), respectively (Neapolitan, 2004; Pearl, 1995).

$$p(A / B) = \frac{\mathrm{p(B/A)p(A)}}{p(B)} \tag{1}$$

$$p(x_1, \ldots, x_D) = \prod_{i=1}^{D} p(x_i | pa(x_i)) \tag{2}$$

where $pa(x_i)$ is the parent set of variables, x_i .

In the maritime domain, the usage of Bayesian Networks has been demonstrated by various studies for several purposes, such as the evaluation of unattended autonomous machinery plants (Abaei et al., 2022), validation of ship collision risk analysis (Aydin et al., 2021a), risk assessment for asphyxiation in chemical tanker ship (Aydin et al., 2021b), prognostic health management of autonomous ship systems (BahooToroody et al., 2022), maximum roll angle estimation (Montewka et al., 2022), risk management of winter navigation operations (Valdez Banda et al., 2016), monitoring of marine engine lubrication (Ventikos et al., 2022), and uncertainty assessment in maritime accident modeling (Zhang et al., 2018).

2.2. STPA and STPA-based BN

STPA is a hazard analysis method based on System-Theoretic Accident Model and Processes (STAMP), which regards safety as a dynamic control problem rather than a failure prevention problem (Leveson and Thomas, 2018). As a result, it assesses all interactions in the system to identify the components with insufficient controls. In contrast to other hazard analysis methods focusing on component failures, STPA also focuses on identifying hazardous situations due to unsafe interactions between even non-failing components (Leveson and Thomas, 2018). STPA has been demonstrated in the maritime field by different researchers, such as reliability assessment of human interaction systems and emergency shutdown systems (Ahn et al., 2022), safety analysis of cyber-physical systems (Bolbot et al., 2020), and analysis of socio-technical systems in ship allision (Ceylan et al., 2021). The steps to execute STPA are summarized from Leveson and Thomas (2018) as follows.

Step 1: Define the purpose of the analysis: The context and boundaries of the analysis such as losses, system-level hazards, etc to be covered are defined.
Step 2: Model the control structure. The control structure of the system under assessment is developed. The control structure shows a hierarchy of the system components denoting the controllers, control actions, received feedback, and the controlled components.

Step 3: Identify the Unsafe Control Actions (UCA). The control actions are then assessed individually with guidewords to identify the potentially hazardous situations.
Step 4: Identify the loss scenarios. For each of the UCA, the causal factors are identified. These causes can include component failures, issues with feedback, software error, and human error.

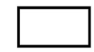
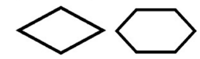
Next in STPA-based BN, the results of STPA hazard analysis i.e., the chain of events leading to the losses, are used as input to create the hierarchical structure of the BN. Each layer in the hierarchy then denotes a type of risk variable such as Unsafe Control actions, system hazards, and losses. BN is then used to estimate the occurrence probability of all risk variables. Fig. 1 presents an example of the hierarchical structure of STPA-based BN. The process of developing BN from STPA outputs is available in several studies such as Basnet et al. (2023), Chaal et al. (2022), and Utne et al. (2020).

2.3. Influence diagrams

An influence diagram is a probabilistic graphical representation in which the uncertain variables, decision options, and probabilistic dependencies are modeled and assessed for decision-making under uncertainty (Kjaerulff and Madsen, 2008). While the BN model consists of chance nodes, the ID extends the BN by adding utility nodes and decision nodes to the model. The decision nodes in the ID then denote the decision alternatives available to the decision-makers and the utility nodes represent the objectives to be maximized. The nodes of an Influence diagram are summarized in Table 1 (Hall, 2010; Pearl, 1988). For combining the utilities, Multi-Attribute Utility nodes such as Additive Linear Utility (ALU), can be added to the ID. These nodes share a common representation with Utility nodes and are used to combine several utility functions. The usage of the ALU node is further detailed in BayesFusion (2020).

ID has been implemented for decision-making in different fields such as automating lead time estimation of agile projects (Weflen et al., 2022), identifying optimal firefighting (Khakzad, 2021), and assessing alternatives for aquaculture and offshore wind farm (Villalba et al., 2022). Furthermore, it has been also applied in risk management studies for several purposes such as pesticide usage decisions (Carriger and Newman, 2012), and failure prognostics of circuit breakers (Velimirovic and Janjic, 2021). In the maritime field, ID has been used for different purposes such as assessing the socioeconomic impacts of oil spills (Afenyo et al., 2022), risk modeling for passenger evacuation and emergency response decision support (Stefanou et al., 2023), ship biofouling management (Luoma et al., 2022), and emergency decision-making of marine oil spill accidents (Li et al., 2022b).

Table 1
The common nodes of an influence diagram.

Node type	Representation	Shapes
Chance nodes	Random and uncertain variables	
Decision nodes	Choices available to decision-makers	
Utility nodes	Objective to be maximized	

3. Methodology

This study uses the terminology of RCM and RCO provided by the International Maritime Organization in the Formal Safety Assessment document. IMO (2018) defines RCM as “A means of controlling a single element of risk”, and RCO as “A combination of risk control measures (RCMs)”. With the consideration of these definitions, Fig. 2 shows the proposed methodology with five steps for integrating CBA into the STPA-BN risk management. The methodology requires an STPA-based BN as the primary input. The process of developing STPA-based BN is beyond the scope of this research and can be found in other studies such as Basnet et al. (2023), Chaal et al. (2022), Johansen and Utne (2022), and Utne et al. (2020). Once the STPA-based BN has been extracted or developed, the first step focuses on defining the risk criteria and identifying the BN variables, such as losses and accidents, requiring risk control. Then in the second step, the RCMs are defined for the BN variables and implemented in the ID model. The model is then assessed to ensure the fulfillment of the risk criteria. If the criteria are not satisfied, new RCMs should be determined and added to the model. Once satisfied, the utilities associated with the nodes i.e., costs of RCM and costs due to losses are added to the ID in the third step. Next in the fourth step, the results inferred from the model are compared and assessed to make the final selection of the RCO. In the last step, the uncertainty in the developed ID model should be assessed.

Step 1: Identify variables requiring risk control based on risk criteria.

In this step, the variables of the STPA-based BN that require risk control should be identified. These variables can differ depending on the method used to develop the STPA-based BN. For example, the BN

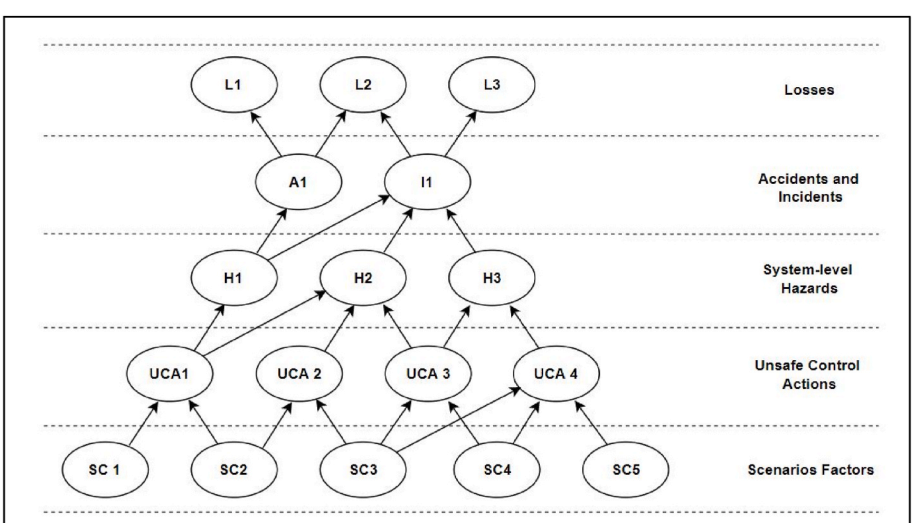


Fig. 1. An example of the hierarchical structure of STPA-based BN (adapted from Basnet et al. (2023)).

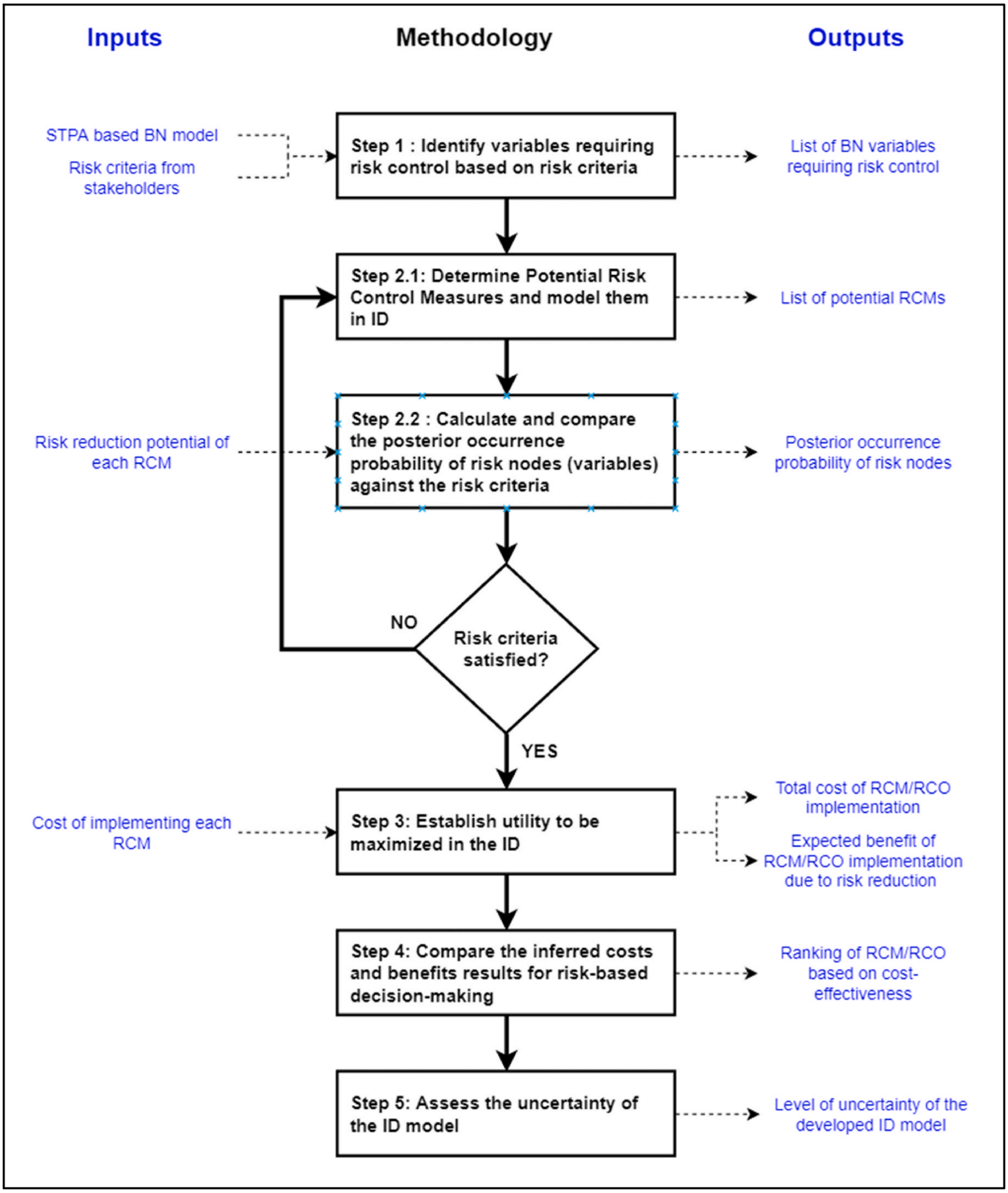


Fig. 2. The sequence of the proposed methodology, the required inputs, and the generated outputs.

developed by Chaal et al. (2022) has causal scenarios in the BN model, whereas Basnet et al. (2023) and Utne et al. (2020) grouped these scenarios based on common causal factors, and added these factors in the BN model. Despite the differences, the suggested methodology can be implemented for all of these BNs, since risk control is still a requirement for all such variables. After identifying the variables requiring risk control in the BN, the stakeholders, owners, or regulatory bodies should then determine the risk acceptance criteria. Next, the occurrence probability of the variables should be estimated using BN and compared against risk criteria to identify the nodes requiring risk control. For estimating the posterior occurrence probability of the variables, the prior probability of the variables is required, which can be calculated using different methods such as statistics, fuzzy logic, and human reliability assessment depending on the availability of the data.

For evaluating the risks, acceptance criteria such as Frequency-Number (F-N) diagrams and As low as reasonably practicable (ALARP) can be used. Fig. 3 shows the principles of ALARP, where the aim is to define the risk boundaries/thresholds; and reduce the risks of events in the Intolerable region to ALARP. Detailed information about these techniques is provided in ISO (2019) and IMO (2018).

Step 2.1: Determine Potential Risk Control Measures and model them in ID.

For the nodes identified in Step 1, the potential RCMs, and the reduction in risk level should be defined. For this purpose, a

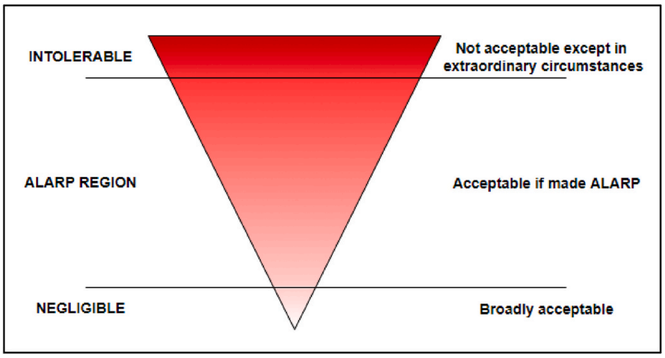


Fig. 3. The ALARP principle (adapted from ISO (2019) and IMO (2018)).

brainstorming session with the stakeholders and end-users should be conducted. As shown in Fig. 4, the RCMs can be defined at any level during the chain of events such as hazards, accidents, and losses. The identified RCMs should then be added to the ID using decision nodes. Furthermore, the states and the risk reduction of each RCM should be also defined and added to the ID. To reduce the uncertainty in expert opinion, a factor of importance can be created if the stakeholders have diverse backgrounds, experiences, etc. The weight factor can be enhanced through several methods such as Chen et al. (2022) and Odu (2019).

Step 2.2: Calculate and compare the occurrence probability of risk nodes (variables) against the risk criteria.

In this step, the model should already be assessed if the implementation of defined RCMs can reduce the occurrence probability of all loss nodes to the tolerable region. For this purpose, the occurrence probability after RCM implementation must be calculated and compared against the risk boundaries/thresholds defined in Step 1. If the defined RCMs are insufficient to reach the tolerable levels, then additional RCMs need to be identified and implemented until the risk criteria are satisfied.

Step 3: Establish utility to be maximized in the ID.

Next, the cost associated with the ID nodes needs to be determined. Depending on the system, the aim of the application, and the available data, these nodes can contain different cost information such as costs of RCM implementation, the costs due to losses, and the costs of system replacement/repair. Furthermore, the costs of RCMs can be defined per operation, per lifetime, per year, initial cost, etc. as required. After determining the costs, these values should then be added to the ID as utility nodes and connected to the associated decision nodes. For combining the cost values, Additive Linear Utility (ALU) nodes can be added to the ID. For example, the utility nodes consisting of the cost information of each RCM can be combined using an ALU node to calculate the total cost of that RCM combination i.e., RCO.

Step 4: Compare the inferred costs and benefits results for risk-based decision-making.

The results are extracted and compared to make the risk-based decision on RCO selection. The ID model is capable of the providing following inferences.

- Occurrence probability: The occurrence probability of the loss nodes before and after an RCM or RCO implementation can be calculated. Even though the RCMs or RCOs can be applied to the different layers in the ID hierarchy (see Fig. 1), the occurrence probability of all affected nodes after RCO implementation can be estimated using forward propagation.
- Prior loss: The total loss before implementing the RCMs can be estimated with the ID model by setting all RCMs to the "Not implemented" state.
- Posterior loss: The total loss after implementing the RCO can be estimated with the ID model. The posterior loss is calculated based on the posterior occurrence probability of loss nodes and the potential costs of the losses. If a decision is made on the ID i.e., some/all RCMs are set to an "Implemented" state, the ID calculates the posterior loss considering the implemented RCOs. However, if the state of the RCMs is not set, then the ID provides the estimated posterior loss for all possible RCOs, i.e. all possible combinations of decisions for RCMs.
- RCO cost: The model can present the total cost of each of the possible RCOs by simply combining the cost of implemented RCMs.

After extracting the inferred results, the Total Expected Benefit (TEB) of each RCO is calculated using Equation (3). The benefit is estimated by subtracting the expected cost of losses before RCO implementation and after RCO implementation. Furthermore, the cost of implementing RCO is also accounted as shown in the equation. The RCOs are then ranked based on the TEB value. The RCOs with the highest TEB (for example top 10) can also be extracted and assessed for the final selection. These RCOs should be compared based on the differences in TEB value, risk reduction, and RCO investment (cost of implementation). In addition, factors such as technical feasibility, environmental feasibility, and time consumption in implementing RCOs can be considered during this final selection. Based on this comparison, the stakeholders can then select a final RCO to be implemented for their system or operation.

$$Total\ Expected\ Benefit = |Prior\ loss| - |Posterior\ loss| - |RCO\ cost| \tag{3}$$

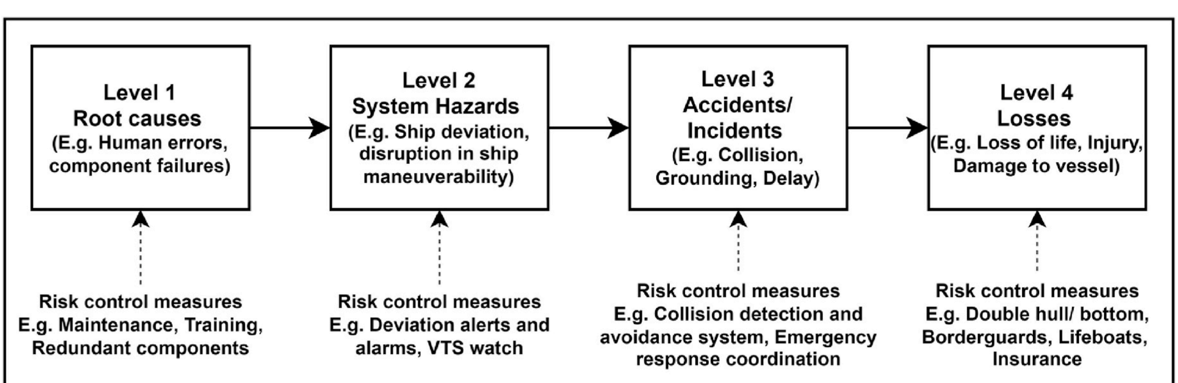


Fig. 4. The chain of risk events during ship navigation and potential risk control measures (adapted from Harrald et al. (1998)).

Step 5: Assess the uncertainty of the ID model

In this step, the uncertainty of the ID model should be assessed. It is important to assess the uncertainty of the ID model since the model results may have severe implications. For this purpose, the existing metrics and schemes for defining the overall uncertainty of the model can be used, which considers several factors such as the data source and assumptions behind the model. Relevant examples of these metrics and schemes are proposed by Flage and Aven (2009), Marcot (2012), and Sahlin et al. (2021). Furthermore, for the studies using expert opinion, the agreement between experts should be assessed (IMO, 2018). The level of agreement between experts can be assessed by calculating the concordance coefficient (W) using Equation (4) (IMO, 2018). 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.

$$W = \frac{12\sum_{i=1}^{i=I}\left[\sum_{j=1}^{j=J} x_{ij} - \frac{1}{2}J(I+1)\right]^2}{J^2\left(I^3 - I\right)} \tag{4}$$

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.

4. Illustrative case study; ship remote pilotage operation

The proposed framework has been demonstrated in this study using a case study of ship RPO. As the STPA-based BN model is required for the demonstration, the RPO BN model developed by Basnet et al. (2023) is extracted and used in this study. Since pilotage is a safety-critical task and RPO is currently under-development in European countries, it is crucial to identify suitable RCOs for reducing risks in RPO from the earliest design phase. Because of the availability of the STPA-based BN model and the necessity of risk management studies, RPO was selected as an illustrative case study for the proposed framework. GeNie software (BayesFusion, 2020) has been used to model the BN and the ID presented in this study. For the visualizations, a package known as Structural Modeling, Inference, and Learning Engine (SMILE) (BayesFusion, 2021) has been used to extract the results from the model in Python.

4.1. Description

Ship RPO is a service in which a licensed maritime pilot provides support to the ship crew to conduct safe navigation from a location other than onboard the vessel (ISPO, 2021). The pilot, who is an expert on ship navigation in local waters, acts as an advisor to the master of the ship. When pilotage is conducted conventionally, the pilot boards the ship to assist the crew in navigating the ship safely through congested areas. On the other hand, in RPO, all relevant information (data, visuals, and audio) is transmitted from the ship to the pilot at shore via an established connection. As a result, the pilot can assist the crew remotely without having to board the vessel. The primary motivations behind remote pilotage development include enhanced traffic flow, improved safety, reduced cost, and an increasing shortage of pilots (Bruno and Lutzhoft, 2009; Danish Maritime Authority, 2014; Lahtinen et al., 2020).

Basnet et al. (2023) have presented the results of a risk analysis of remote pilotage operation using an STPA-based BN method. To limit the scope, only the BN nodes focusing on the remote pilot are extracted and used in this study. Although RPO is still under development, the current case study aims to establish an ID, which can be used throughout the RPO development for risk management. Therefore, the ID is planned to be used to enforce safety from the earliest system development stage and reduce the costs of design changes in RPO due to safety issues. Fig. 5 and Table 2 present the used BN model and the description of BN nodes respectively. The model consists of four types of losses in the first/top layer denoting loss of life, injury to people, damage to the ship, and loss of cargo. In the second layer of the model, two Accidents/Incidents related to collision and grounding; and two system-level hazards related

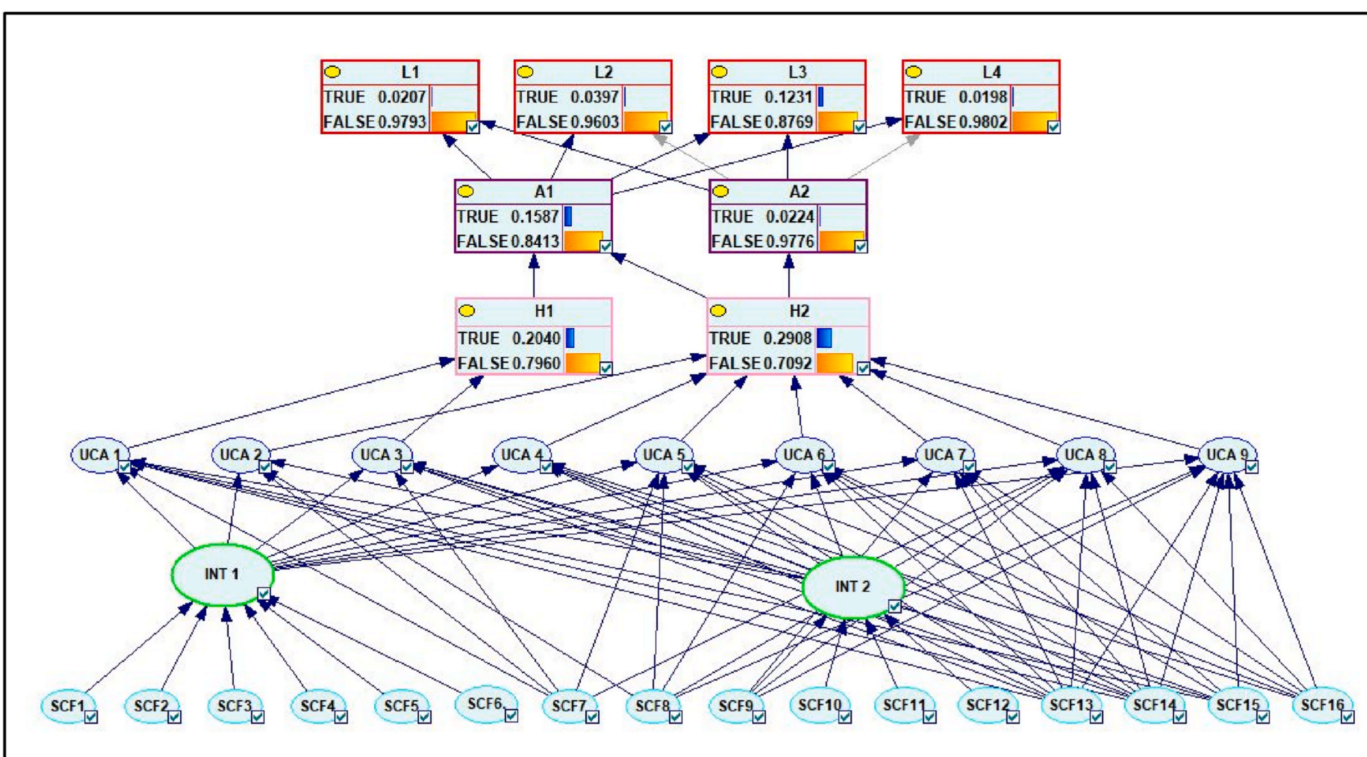


Fig. 5. The BN model applied to RPO extracted from Basnet et al. (2023) (SCF stands for Scenario Causal Factor, INT represents intermediate nodes, UCA stands for Unsafe Control Action, H denotes System-Level Hazard, A denotes Accident/Incident, and L stands for Loss).

Table 2
The description of the nodes of the BN model applied to RPO (extracted from (Basnet et al., 2023)).

Node type	Node ID	Node description
Losses	L1	Loss of life
	L2	Injury to people
	L3	Damage to the ship
	L4	Loss of cargo
Accidents/ Incidents	A1	Collision and contact
	A2	Grounding
System-level	H1	Ship violates minimum separation standards or under keel clearance in route
Hazards	H2	Disruption or loss of ship maneuverability during RPO
Unsafe control actions	UCA1	The Pilotage plan and MPX document are not sent from the remote pilot to the master before initiating the pilotage
	UCA2	Wrong, incomplete, or unclear pilotage plan and MPX document are sent from the remote pilot to the master and is followed during pilotage in shallow or congested waters
	UCA3	The pilotage plan and MPX document are sent too late from the remote pilot to the master before the pilotage
	UCA4	Navigation suggestions are not sent from the remote pilot to the master when required during pilotage in shallow or congested water
	UCA5	Wrong, incomplete, or unclear navigation suggestions are sent from the remote pilot to the master during pilotage in shallow or congested water
	UCA6	Navigational suggestions are sent too late from the remote pilot to the master when required during pilotage in shallow or congested water
	UCA7	Traffic updates are not sent from the remote pilot to the master when required during pilotage in congested water
	UCA8	Wrong or unclear traffic updates are sent from the remote pilot to the master during pilotage in congested water
	UCA9	Traffic updates are sent too late from the remote pilot to the master when required during pilotage in congested water
Scenario causal factors	SCF1	Lack of skills
	SCF2	Stress
	SCF3	Poor situational awareness
	SCF4	Fatigue
	SCF5	Distraction
	SCF6	Lack of professionalism
	SCF7	Lack of procedures or checklists
	SCF8	Lack of standard phrases
	SCF9	Issues with traffic data
	SCF10	Issues with weather data
	SCF11	Issues with ship dynamics data
	SCF12	Issues with ship systems data
	SCF13	Communication device failure
	SCF14	Network failure
	SCF15	Displays failure
	SCF16	Language issues

to violation of ship separation standards, under keel clearance and loss of ship maneuverability are modeled. The model then consists of nine UCAs in the third layer related to the tasks of the remote pilot such as providing a pilotage plan, navigation suggestions, and necessary information. Next, in the last layer, 16 causal factors related to remote pilot human error, issues with data, and equipment failure are modeled, where some of these factors are grouped into two intermediate nodes for reducing the CPT entries. In Basnet et al. (2023), these causal factors were established by identifying the common causal factors of numerous STPA loss scenarios. More details about the STPA analysis, usage of intermediate nodes, the model, and the remote pilotage components are provided in Basnet et al. (2023).

4.2. Case study data source

As ship RPO is still under development, expert opinions have been used to estimate the RCM impact i.e., the potential reduction of occurrence probability. Table 3 presents the 5-point Likert scale (adapted from Valdez Banda et al. (2015)) used in this case study to gather expert opinions. Using this scale, multiple workshops with a group of experts were organized to estimate the RCM impact. The workshop was participated by experts from Finnish Universities with over four years of experience working in the safety engineering field and pilots with more than five years of pilotage experience. All of these experts are currently involved in the RPO development project i.e., Sea4Value in Finland, and have recently demonstrated the RPO in a Finnish fairway (ESL Shipping, 2022). Due to the large similarities between the experts in this study, the weighting factor was disregarded for the expert opinion in this study. Then for the cost related to losses and RCMs, the data is extracted from different literature and company websites as suitable. For the losses related to vessel damage, the cost figures were estimated using the current valuation of the M/S Viikki ship, which has been used in Finland to develop and demonstrate RPO (ESL Shipping, 2022). The cost figures used in this study are later provided in Section 4.3.

For estimating the prior probability of common factors in conventional pilotage and remote pilotage, the study used operational data. For the factors lacking operational data or new in remote pilotage, the expert's opinion was used. Table 4 presents the scale used for the expert opinion for estimating the frequency of failures of RPO risk causal factors. For the factors with operational data, the prior probability is computed using $\frac{Number\ of\ occurrence\ of\ the\ failure\ events}{Total\ number\ of\ piltoages}$ and for 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 Table 5 presents the prior probability of the causal factors extracted from Basnet et al. (2023).

4.3. Application of the methodology and results

Step 1: Identify nodes requiring risk control based on risk criteria.

Based on the discussion with stakeholders, the focus of the case study was determined to reduce the occurrence probability of losses to as low as reasonably practicable i.e., ALARP, where the threshold for unacceptable losses was determined as 0.02. As a result, all losses except L4 were in the intolerable zone (see Fig. 5), which should be reduced to the ALARP region through the risk treatment in this case study. Due to the lack of resources at the early development stage, only the Scenario Causal Factors (SCF) were selected for the risk treatment. The selected model consists of 16 SCFs caused by human errors, equipment failures, and data issues (see Table 2).

Step 2.1: Determine potential RCMs and model them in ID.

At first, the potential RCMs for each SCF were determined through a set of brainstorming sessions with experts. As a result, a total of 19 Unique RCMs were defined. Then for each RCM, the risk reduction potential was estimated. Table 5 presents the list of RCMs and their

Table 3
The Likert scale for estimating the reduction of occurrence probability due to RCM's implementation (adapted from Valdez Banda et al. (2015)).

RCM impact	Potential reduction
very low	10%
low	30%
medium	50%
high	70%
very high	90%

Table 4
The scale for collecting the expert opinion on estimating the frequency of failures of RPO risk causal factors (adapted from IMO (2018)).

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

estimated risk reduction potential. Furthermore, the table shows the SCF's occurrence probability before (Prior PR) and after (Posterior PR) the implementation of each RCM. The list of RCMs included measures such as training, RP requirements, redundancy, and work environment. Moreover, the results show that most of the identified RCMs were concluded to have a high potential to reduce the occurrence probability of the SCFs.

Next, all identified RCMs were added to the ID using decision nodes. For simplicity, the nodes were set to contain two decision alternatives i. e., 1. Implemented 2. Not Implemented. These nodes were then connected to the corresponding SCFs in the ID, and the CPT was filled. The interconnection between SCFs and RCMs can be seen in Table 5. Fig. 6 then presents the resulting ID after the addition of RCMs and the established connection to the SCFs.

Step 2.2: Calculate and compare the posterior occurrence probability of risk nodes (variables) against the risk criteria.

The occurrence probability of loss nodes (L1-4) after RCMs implementation is then calculated and compared with the risk criteria defined in Step 1. Fig. 7 presents the occurrence probability of losses when none, all, and each RCM are implemented. The figure shows that the combination of all RCMs is already sufficient to reduce the occurrence probability of all loss nodes to the tolerable zone, i.e., less than 0.02. For example, for the loss node L3- Damage to Vessel, the occurrence probability reduces from 0.1231 to 0.0126 when all RCMs are implemented. Thus, identified RCMs fulfill the risk criteria and the study can then proceed towards the next stage of reducing the risk levels to ALARP considering the costs and benefits. In addition, the figure shows that the implementations of different RCMs result in different occurrence probability reductions. In comparison to other RCMs, it can be seen that RCMs 14, 18, and 19 provide a higher reduction of occurrence probability.

Step 3: Establish utility to be maximized in the ID.

Then for estimating the cost and benefit of the RCMs, the utility values of the following cost categories were determined.

1. The cost associated with losses: The potential cost if occurred was determined for all four loss types in the ID. Table 6 presents a list of expected costs due to the occurrence of the losses. For the cost related to "L3- Damage to ship", 10% of the current market evaluation of the case study ship was assumed (Liu and Frangopol, 2018).
2. The estimated cost of RCM implementation: The cost of implementing each RCM was extracted from various websites of technology providers in Europe. Table 7 presents the estimated cost associated with each RCM. In this case study, only the initial cost of implementing the RCM for a ship, a remote pilot, or a crew was considered. Furthermore, some of the RCMs related to establishing procedures, requirements, or already existing software (workload planning) are assumed to have no direct cost. n

Table 5
List of Risk Control Measures and corresponding reduction potential of the occurrence probability.

SCF	Prior Probability	Risk Control Measures	Potential reduction	Posterior Probability
SCF1: Lack of skills	0.025	RCM1: Additional remote pilotage training of pilot and master	70%	0.0075
		RCM2: Requirements for RPO such as certification, limitation on minimum crew size etc.	90%	0.0025
SCF2: Stress	0.005	RCM3: Improved situational awareness with the additional ship and fairway cameras	70%	0.0015
		RCM4: Duplex communication for crew and pilot	70%	0.0015
SCF3: Poor situational awareness	0.005	RCM3: Improved situational awareness with the additional ship and fairway cameras	90%	0.0005
SCF4: Fatigue	0.005	RCM5: Workload planning software	70%	0.0015
		RCM2: Requirements for RPO such as certification, limitation on minimum crew size etc	90%	0.0005
SCF5: Distraction	0.005	RCM3: Improved situational awareness with the additional ship and fairway cameras	70%	0.0015
		RCM6: No/Low noise pilot booths	70%	0.0015
SCF6: Lack of professionalism	0.005	RCM7: Monitoring of Pilots (camera + network storage)	70%	0.0015
SCF7: Issues with procedures or checklists	0.01	RCM8: Establish checklists and procedures	70%	0.003
		RCM4: Duplex communication to identify and correct the wrong procedures	90%	0.001
SCF8: Issues with taxonomy	0.01	RCM9: Establish standard phrases for remote pilotage	90%	0.001
SCF9: Issues with traffic data	0.02	RCM10: Multiple websites to gather and compare real-time traffic data	70%	0.006
		RCM11: Additional RADAR, AIS for redundancy	90%	0.002
SCF10: Issues with weather data	0.01	RCM12: Multiple websites to gather and compare real-time weather data	50%	0.005
		RCM13: Weather stations along the fairway	70%	0.003
SCF11: Issues with ship dynamics data	0.1	RCM14: Redundant ship data collection and transmission unit	90%	0.01
SCF12: Issues with ship systems data	0.01	RCM14: Redundant ship data collection and transmission unit	90%	0.001
SCF13: Communication device failure	0.01	RCM15: Redundant communication device	90%	0.001
SCF14: Network failure	0.002	RCM16: Redundant network	90%	0.0002
SCF15: Displays failure	0.01	RCM17: Redundant display	90%	0.001
SCF16: Language issues	0.1	RCM18: Standardized language	70%	0.03
		RCM19: Requirements for RPO (certification)	70%	0.03

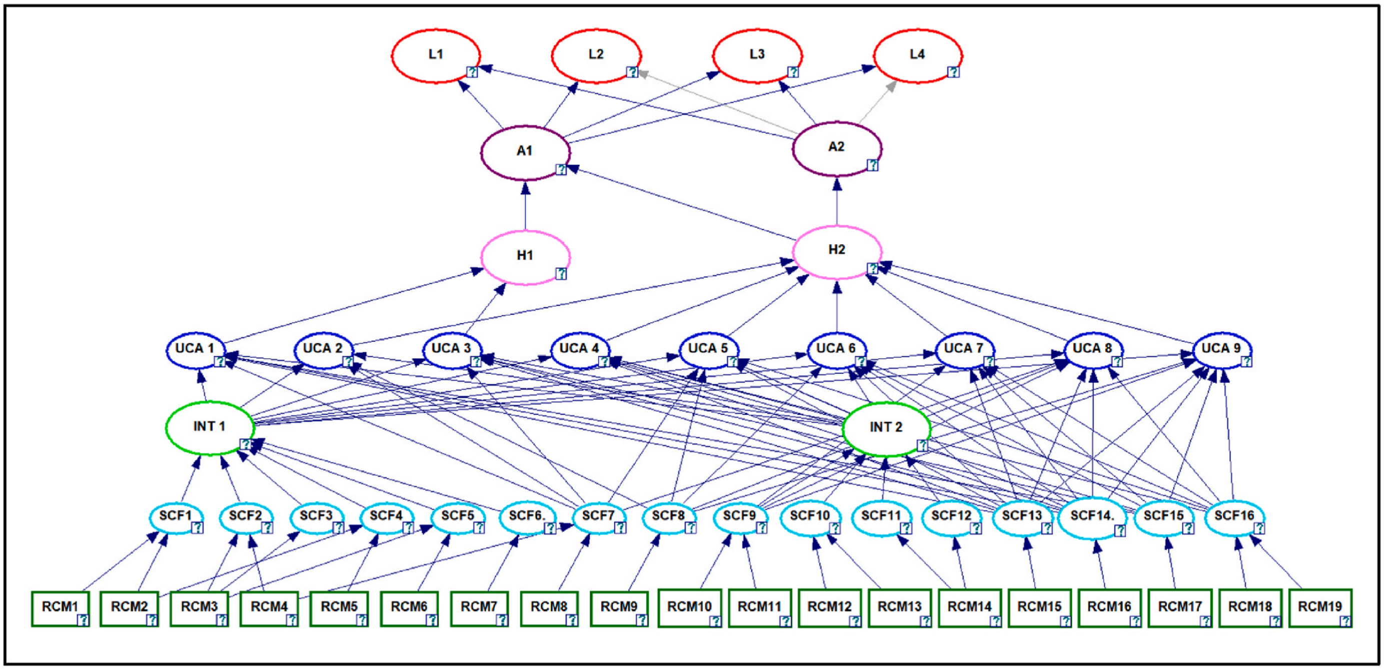


Fig. 6. The ID diagram after the addition of RCMs (bottom layer).

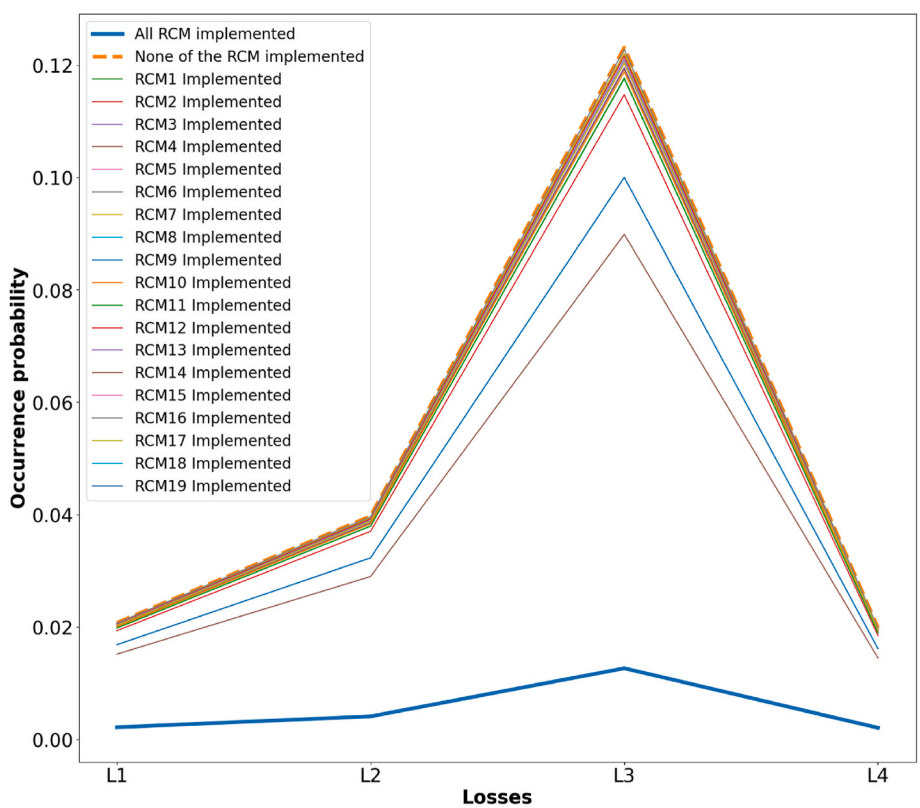


Fig. 7. The occurrence probability of losses after none, all, and each RCM implementation.

The utility values except for the ones with no direct cost (see Table 7) were then added to the ID using utility nodes and connected to the corresponding RCMs. Fig. 8 presents the resulting ID diagram with the addition of utility nodes. In the figure, four utility nodes for the losses are shown at the top (UL1- UL4) and 12 utility nodes for the cost of implementing RCMs are shown at the bottom (URCM1- URCM17). Moreover, four ALU nodes were added to the ID to calculate prior loss, posterior loss, RCO cost, and TEB. Fig. 8 also shows the resulting ID diagram with the addition of ALU nodes denoted with yellow nodes.

Step 4: Compare the inferred costs and benefits results for risk-based decision-making.

The model was then used to assess the cost and benefit of different

Table 6
Estimated costs due to the occurrence of loss events in the ID.

Loss	Estimated Cost
L1: Loss of life	€ 8,000,000 per fatality (Bolbot et al., 2021)
L2: Injury to people	€ 49,200 per injury (Isom et al., 2018)
L3: Damage to ship (10% of ship value)	€ 2,300,000 (Marine Traffic, 2022)
L4: Loss of cargo	€ 122,500 (The Swedish Club, 2018)

Table 7
Estimated cost of implementing each RCM.

RCM	Estimated cost
RCM1: Additional remote pilotage training of pilot and master	€ 5000 (NZ Maritime, 2022)
RCM2: Requirements for RPO (certification, limitation on minimum crew size, etc)	No direct cost
RCM3: Improved situational awareness with additional cameras	€ 1000 (Boe Marine, 2022)
RCM4: Duplex communication for crew and pilot	€ 3000 (Verkkokauppa, 2022a)
RCM5: Workload planning software	No direct cost
RCM6: No/Low noise pilot booths	€ 12,000 (Vicoustic, 2022)
RCM7: Monitoring of Pilots (camera + network storage)	€ 1000 (Verkkokauppa, 2022c)
RCM8: Establish checklists and procedures	No direct cost
RCM9: Establish standard phrases for remote pilotage	No direct cost
RCM10: Multiple websites to gather and compare real-time traffic data	€ 500 (Datalistic, 2022)
RCM11: Additional RADAR, AIS for redundancy	€ 30,000 (Furuno, 2022)
RCM12: Multiple websites to gather and compare real-time weather data	No direct cost
RCM13: Weather stations along the fairway	€ 3000 (Vaisala, 2022)
RCM14: Redundant ship data collection and transmission unit	€ 1250 (Trenz, 2022)
RCM15: Redundant communication device	€ 3000 (Verkkokauppa, 2022a)
RCM16: Redundant network	€ 50 (Elisa, 2022)
RCM17: Redundant display	€ 1000 (Verkkokauppa, 2022b)
RCM18: Standardized language	No direct cost
RCM19: Requirements for RPO (certification)	No direct cost

RCO implementation decisions. At first, the prior loss of € 453,286 was calculated by setting the state of all RCMs to "Not implemented". This value was then stored in the ALU node "Prior loss" in the ID (see Fig. 8). Then, using the ID the implementation cost, posterior loss, and the TEB of each RCO were extracted. With 19 different RCMs, each with two decision options ("Implemented" or "Not implemented"), these values were extracted for 524,288 (2^{19}) unique RCOs. Fig. 9 presents a histogram of the TEB for all possible RCOs. The histogram shows that over 250,000 different RCOs have a low TEB in the range of €100000 - €200000. Furthermore, only around 2500 RCOs have a good TEB of over 350,000€, out of which the highest TEB of €380553 was calculated for the optimum RCO, where all RCMs are implemented except RCM 1,6 and 11. The figure also shows that there are some RCOs (around 1000) leading to negative TEB, which means that the estimated benefit due to risk reduction is lower than the implementing cost of these RCOs. For example, an RCO, where only RCM 6 and 11 are implemented will result in TEB of −17599€.

The 10 RCOs with the highest TEB and satisfying the risk criteria were then extracted for detailed comparison. Fig. 10 presents risk criteria and the occurrence probability after the implementation of the Top 10 RCOs with the highest TEB. As shown in the figure, all 10 RCOs satisfy the risk criteria of 0.02 and are eligible for the final selection. Table 8 presents the 10 RCOs with their corresponding combination of RCMs. These RCOs are then compared in detail using the reduction of occurrence probability of the loss events (also shown in Fig. 10), the total cost of RCO implementation, and the TEB values (see Table 9). As shown in the table, the TEB values between these 10 RCOs range between € 380,553 to € 378,042. Table 9 shows the top 10 RCOs based on TEB and the corresponding reduction in occurrence probability and cost. Furthermore, the rankings of each RCO in each of these measures are shown with color codes where green represents the best ranking and red represents the worst ranking. Based on the strengths of each of these 10 RCOs, the following decision alternatives were considered by the stakeholders.

- Decision 1: Implementing RCO1 with the highest TEB of €380553
- Decision 2: Implementing RCO8 with the TEB of €378274 and lowest implementation cost of €10,800; thus, requiring the lowest initial investment on RCO.
- Decision 3: Implementing RCO9 with the highest risk reduction potential and a TEB of €378195.

After final discussions, Decision 1 i.e., RCO1 was selected, which has the highest TEB of €380553, the second-ranking in reduction of occurrence probability of loss events, and the third-ranking in implementation cost of RCO.

Step 5: Assess the uncertainty of the ID model.

As the results may have several implications for the development of RPO, it is necessary to assess the uncertainty of the ID model presented in this study. For this purpose, a scale proposed by Flage and Aven (2009) as shown in Table 10 was used. This scale has been widely used to assess uncertainty in several risk models such as Khan et al. (2020); Valdez Banda et al. (2016), and Montewka et al. (2017).

Regarding the uncertainty related to the data, RPO still lacks reliable data for RCO effectiveness since the RPO is still under development. However, some of the RCMs defined for RPO such as workload planning software and established standard phrases already exist and can be considered reliable. Furthermore, the cost information is reliable as it was gathered from the official websites of different companies in Finland and Europe. Regarding the assumptions, the experts involved in this study have a good understanding of remote pilotage since all of them are experienced with conventional pilotage, and are involved throughout the development process of RPO in Finland, which has been already demonstrated (ESL Shipping, 2022). Therefore, the assumptions made in this study represent a mixture of strong and reasonable simplifications and relevancy. Regarding the agreement among experts, the concordance coefficient (W) was calculated using Equation (4). For the expert opinions about the effectiveness of the RCMs, the concordance coefficient was calculated to be 0.856, which is above 0.7 and denotes good agreement between the experts. Fig. 11 shows the R code used to calculate the coefficient using the KendallW package (Signorell et al., 2023). Considering the uncertainty related to data, knowledge, assumptions, and expert agreement, the RPO model was determined to have medium uncertainty.

5. Discussion

5.1. Risk management using ID and potential FSA improvements

Cost-Benefit assessment is a substantial step for effective risk management. The risk assessment model with the ID can support decision-makers when selecting cost-effective RCOs. Using forward propagation and prior observations, the ID can estimate the effectiveness of RCOs by comparing the occurrence probability of losses before and after the RCO implementation. Since the model is developed using the results of STPA, the ID features a hierarchical structure where each layer represents a specific type of unsafe event. The model presents the risk propagation from a layer consisting of root causes to the layer of hazards, accidents, and ultimately to losses, depicting a clear chain of events. As FSA studies

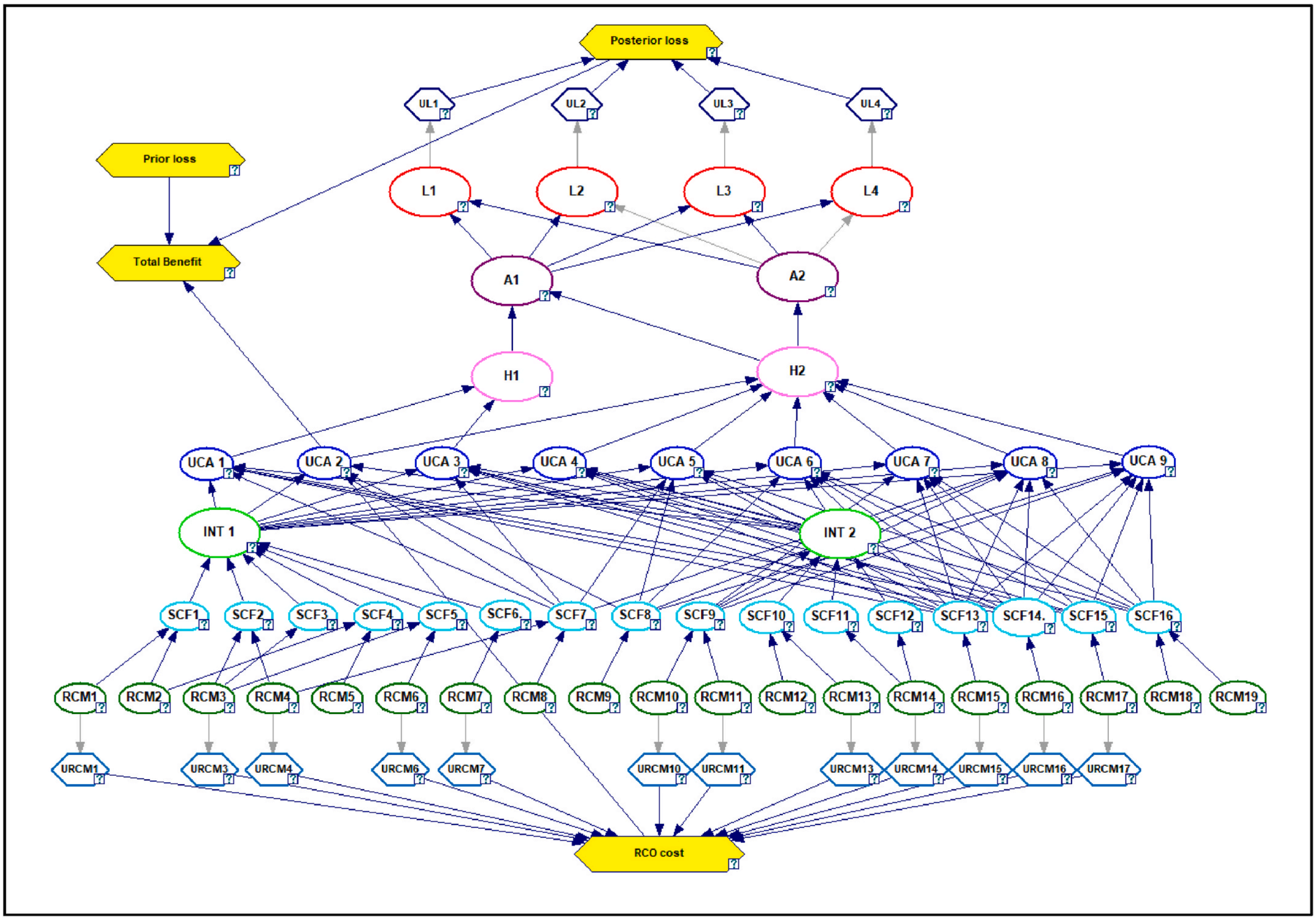


Fig. 8. The ID diagram after the addition of nodes representing the cost associated with losses at the top (UL), the cost associated with RCM implementation at the bottom (URCM), and 4 ALU nodes shown in yellow.

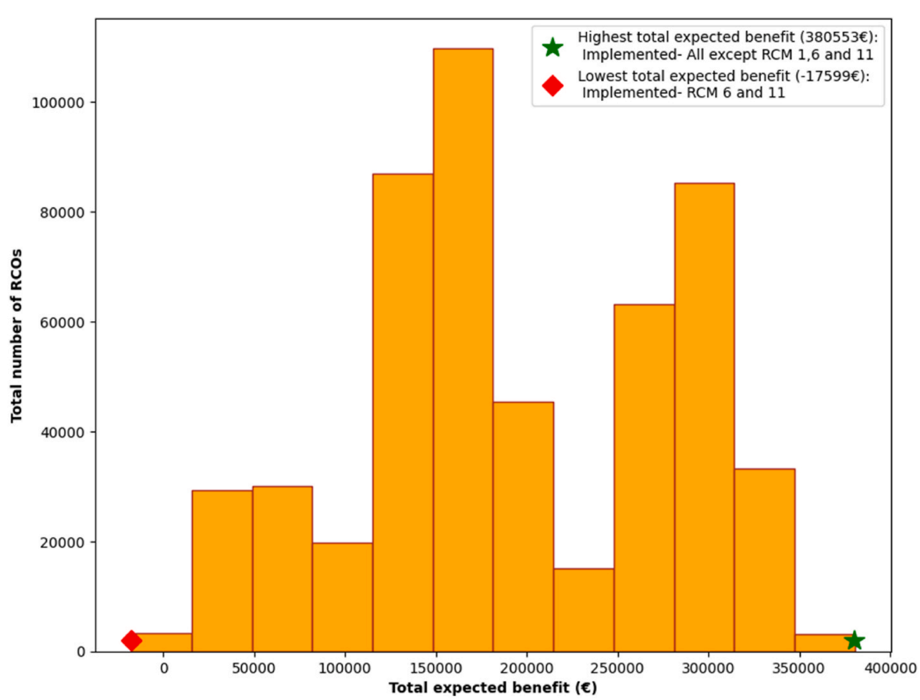


Fig. 9. A histogram of the TEB values for all RCOs with markers denoting the highest and lowest TEB in RPO.

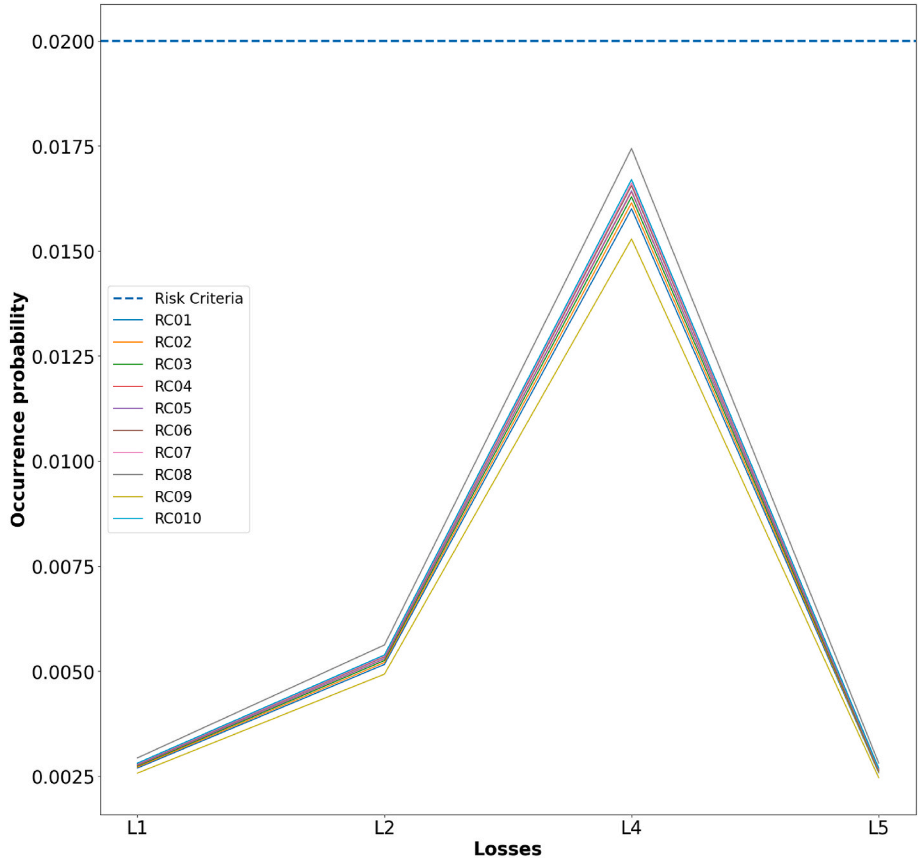


Fig. 10. Posterior occurrence probability of losses with top 10 RCO and the risk criteria.

Table 8
Top 10 RCOs in RPO ID based on TEB values.

RCO	Combination of RCMs
RCO1	RCMs: 2,3,4,5,7,8,9,10,12,13,14,15,16,17,18,19
RCO2	RCMs: 2,3,4,7,8,9,10,12,13,14,15,16,17,18,19
RCO3	RCMs: 2,3,4,5,7,9,10,12,13,14,15,16,17,18,19
RCO4	RCMs: 2,3,4,5,7,8,9,10,12,13,14,15,17,18,19
RCO5	RCMs: 2,3,4,7,9,10,12,13,14,15,16,17,18,19
RCO6	RCMs: 2,3,4,7,8,9,10,12,13,14,15,17,18,19
RCO7	RCMs: 2,3,4,5,7,8,9,10,13,14,15,16,17,18,19
RCO8	RCMs: 2,3,4,5,7,8,9,10,12,14,15,16,17,18,19
RCO9	RCMs: 1,2,3,4,5,7,8,9,10,12,13,14,15,16,17,18,19
RCO10	RCMs: 2,3,4,5,7,9,10,12,13,14,15,17,18,19

Table 9
Top 10 RCOs based on TEB, the corresponding reduction in occurrence probability of loss events, and cost of implementation.

RCO	Reduction of occurrence probability				RCO cost (€)	TEB (€)
	L1	L2	L3	L4		
RCO1	0.01803	0.03452	0.10709	0.01726	13,800	380,553
RCO2	0.01801	0.03447	0.10695	0.01724	13,800	380,026
RCO3	0.01798	0.03443	0.1068	0.01721	13,800	379,498
RCO4	0.01796	0.03439	0.10668	0.01719	13,750	379,095
RCO5	0.01796	0.03438	0.10666	0.01719	13,800	378,972
RCO6	0.01794	0.03434	0.10654	0.01717	13,750	378,569
RCO7	0.01793	0.03432	0.10648	0.01716	13,800	378,291
RCO8	0.01779	0.03406	0.10566	0.01703	10,800	378,274
RCO9	0.01815	0.03475	0.10781	0.01738	18,800	378,195
RCO10	0.01791	0.0343	0.10639	0.01715	13,750	378,042

Table 10
Model uncertainty assessment scheme, based on Flage and Aven (2009); Goerlandt and Montewka (2015).

Uncertainty level	Conditions
High	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	Conditions between those characterizing 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	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.

```
library(DescTools)

RPO <- data.frame(expert1,expert2,expert3)

KendallW(RPO, TRUE)

[1] 0.855964
```

Fig. 11. R code to calculate the concordance coefficient (W) for assessing the level of agreement between experts.

have been criticized for having a confusing chain of events (Psaraftis, 2012), the usage of ID with a hierarchical structure proposed in this study can be considered an improvement to the FSA framework. The hierarchical structure and the traceability feature of STPA results have also been discussed by previous studies such as Basnet et al. (2023), Chaal et al. (2022), Utne et al. (2020), and Leveson and Thomas (2018). Moreover, the usage of STPA allows the analyst to include a wider range of losses for the CBA, such as cargo loss, loss of customer satisfaction, and loss of sensitive information. As a result, it can increase the scope of risk management studies to other operations where these types of losses can be crucial. In addition, the ID also considers a single RCM affecting multiple causal factors and multiple RCMs affecting the same causal factor during the inference. These features are important in CBA as the effectiveness of an RCM decreases if another RCM has been already implemented to prevent the same cause.

In the proposed methodology, RCMs are modeled using decision nodes with states such as “Implemented” or “Not Implemented” denoting available decisions. The usage of decision nodes in this study enabled the model to automatically calculate the Posterior occurrence probability and the costs of all possible RCOs. In contrast to this usage, modeling the RCMs with chance nodes in Chaal et al. (2022) required a manual selection and assessment of the RCOs. The usage of decision nodes in this study is a major improvement in risk management as it reduces the analysis time significantly since the number of possible RCOs increases exponentially to the number of defined RCMs. For example, defining 10 RCMs with two decision options (states) for a system will result in 1024 (2^{10}) RCOs to be analyzed, which is not resource efficient as it requires experts to manually select and assess each RCO at a time. This is also associated with one of the shortcomings of existing FSA studies as the cost-benefit analysis using FSA has been observed to be limited in evaluating either each RCM separately (Lois et al., 2004), or assessing few RCOs (Kontovas and Psaraftis, 2009; Purba et al., 2020; Wang et al., 2020) or completely omitting CBA as future work (Görçün and Burak, 2015; Zhang et al., 2013). The ID model developed using the proposed methodology in this study fulfills this gap since it can provide the estimations for all possible RCOs automatically within a short time depending on the available computational resources. The analysts can then extract these values from the model to compare all possible RCOs.

The researchers and industry experts working with BNs in the risk management field could benefit from the presented methodology. While previously the cost-benefit analysis was limited to analyzing a few RCOs due to time and resource limitations, the ID model developed by following the methodology allows analysts to conduct a cost-benefit analysis of numerous RCOs instantaneously. While the study focuses on STPA-based BN, the methodology can be adapted to all BN risk models that are developed using cause-and-consequence relationships between the nodes. When applying the proposed methodology, the authors recommend the usage of programming languages such as Python to gather inferences from the model. The usage of a Python package called SMILE (BayesFusion, 2021), considerably reduced the time and resources required to extract and assess the RCOs in terms of benefits and costs. Moreover, the usage of Python also supported decision-makers by providing visualizations/plots of the results. While this case study focused on just satisfying the risk criteria, it was realized that the analyst could easily enforce additional constraints. For example, if the available budget for RCO implementation for a company is €5000, then the comparison of RCOs could be done simply by extracting all the RCOs that are under the available budget.

5.2. Case study results

The results of the case study demonstrate the capability of the proposed methodology in supporting the decision-makers with the selection of RCO, i.e., the RCMs combination. With 19 RCMs, the ID model was able to assess the cost and benefit of all possible RCOs i.e., 524,288 for the RPO. The model then provided the top ten RCOs based on TEB values. Then from these ten RCOs, 3 RCOs each with unique strengths, i.e. highest TEB value, highest potential reduction of losses, and lowest implementation cost, were proposed for the final selection. The RCO1 was then finally selected, which consists of all RCMs except 1, 6, and 11. The model shows that the RCM 1 (Additional remote pilotage training of pilot and master) at € 5000 applied to SCF 1 (Lack of skills), is not cost-effective when compared to the expected benefit acquired with the risk reduction. In addition to the high cost, it is also because of RCM 2 (Requirements for RPO such as certification, limitation on minimum crew size, etc), which at no initial cost has already a significant reduction of the occurrence probability of SCF 1. Similarly, RCM 6 (No/Low noise pilot booths) and RCM 11 (Additional RADAR, AIS for redundancy) are omitted by the ID due to the high implementation cost (see Table 7) and more cost-effective RCMs (see Fig. 8) affecting the same causal factor.

6. Conclusion

CBA allows decision-makers to select a suitable RCO by assessing the associated costs and expected benefits due to risk reduction. In this study, a methodology to conduct CBA using the ID was proposed. The study used the foundation provided by the STPA-BN method, which identified the chain of events leading to losses and estimated the associated risks. The proposed ID model is capable of estimating the potential benefit and costs associated with all possible RCOs defined for the system or operation. These results can then be used by decision-makers to specify the optimum RCO. The proposed methodology was then demonstrated using a case study of RPO and the results were provided.

The number of RCOs increases exponentially relative to the defined number of RCMs. As a result, the existing FSA studies are limited to assessing either each RCM at a time or only including a few RCOs. Therefore, the methodology proposed in this study strengthens the FSA by providing a risk management model that can automatically select all possible RCOs and assess their risk reduction, TEB, and implementation cost. Furthermore, the method improves another shortcoming of FSA studies related to the confusing chains of events. The developed ID model follows a hierarchical structure depicting a chain of events where each layer denotes a specific type of unsafe event such as root causes, hazards, accidents, and losses. Hence, this model offers clear and systematic traceability of the event's chain.

The proposed methodology can be of great importance when there are several RCMs defined, which was demonstrated in the case study. The current RPO model provides a basis for managing risks in RPO, which can be used to incorporate safety from the earliest design phase. As a direction for future study, it would be beneficial to expand the scope of this study by adding other risk factors associated with other pilotage stakeholders such as management, agent, and tug crew. Furthermore, the accuracy of the model can be improved by replacing the expert opinion with operational data once available.

CRediT authorship contribution statement

Sunil Basnet: Conceptualization, Methodology, Software, Formal analysis, Resources, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ahmad Bahootoroody:** Advisory, Conceptualization, Writing – review & editing, Resources. **Jakub Montewka:** Advisory, Conceptualization, Writing – review & editing. **Meriam Chaal:** 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 has been already presented in the manuscript

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