



Application of Bayesian Belief networks to the human reliability analysis of an oil tanker operation focusing on collision accidents

Marcelo Ramos Martins*, Marcos Coelho Maturana

Naval Architecture and Ocean Engineering Department, University of São Paulo, Av. Prof. Mello Moraes, 2231, Zip-code: 05508-030 São Paulo, Brazil

ARTICLE INFO

Article history:

Received 26 August 2010

Received in revised form

6 June 2012

Accepted 18 September 2012

Available online 9 October 2012

Keywords:

Probabilistic risk assessment (PRA)

Human reliability analysis (HRA)

Bayesian belief networks (BBNs)

Collision

Oil tanker

ABSTRACT

During the last three decades, several techniques have been developed for the quantitative study of human reliability. In the 1980s, techniques were developed to model systems by means of binary trees, which did not allow for the representation of the context in which human actions occur. Thus, these techniques cannot model the representation of individuals, their interrelationships, and the dynamics of a system. These issues make the improvement of methods for Human Reliability Analysis (HRA) a pressing need. To eliminate or at least attenuate these limitations, some authors have proposed modeling systems using Bayesian Belief Networks (BBNs). The application of these tools is expected to address many of the deficiencies in current approaches to modeling human actions with binary trees.

This paper presents a methodology based on BBN for analyzing human reliability and applies this method to the operation of an oil tanker, focusing on the risk of collision accidents. The obtained model was used to determine the most likely sequence of hazardous events and thus isolate critical activities in the operation of the ship to study Internal Factors (IFs), Skills, and Management and Organizational Factors (MOFs) that should receive more attention for risk reduction.

© 2012 Elsevier Ltd. All rights reserved.

1. Introduction

While the evaluation of the operational risks of a system should consider all adverse events that could occur, not all potential events will have the same probability of occurrence. Similarly, certain events would bring disastrous consequences while others would result in secondary losses. Thus, for complex systems, a purely deterministic study of risk events may not be the most appropriate [1]. For these systems it becomes impractical to manipulate all of the hazard factors in operation. Instead, a probabilistic study allows the analyst to classify events in terms of consequences and frequencies, with the selection of limits for these parameters guided by the desired degree of operational safety.

Probabilistic risk studies are generally classified as Probabilistic Risk Assessments (PRAs), or in the case of the nuclear sector, as Probabilistic Safety Assessments (PSAs). For the maritime industry, the International Maritime Organization (IMO) issued the “Guidelines for Formal Safety Assessment (FSA)” [2]. The original intent of this publication was to provide a format for proposals to be submitted to the IMO. However, the FSA has been used by

classification societies as a guide to analyze and enhance maritime security [3].

As with a deterministic analysis, the PRA analyst may encounter difficulties [4]. To ensure the validity of the PRA's results, it is common to adopt ranges instead of fixed values for the manipulated variables [5]. Regardless of these difficulties, a PRA can clearly suggest ways to increase the safety of projects and to improve the operation of complex systems [6].

PRAs can also be used to analyze the human element in integrated systems. During the last three decades, several techniques have been developed for the quantitative study of human reliability. In the 1980s, techniques were developed to model the system by means of binary trees [7]. These techniques do not account for the context in which human actions occur [8], preventing them from modeling individuals, their interrelationships, and the system dynamics, and necessitating further improvement of HRA. Thus, to eliminate or at least attenuate these limitations, several authors have proposed to model systems or system components using BBN [9–12].

Bayesian Networks – also known as opinion networks, causal networks, or graphs of dependency – are graphic reasoning models based on uncertainty that can represent discrete and continuous variables, with arches between nodes representing the direct connection between variables [13]. BBNs use the concept of probability as the analyst's degree of belief [14], allowing for expert judgments to be used as the information to

* Corresponding author. Tel.: +55 11 30915348; fax: +55 11 30915717.
E-mail address: mrmartin@usp.br (M.R. Martins).

fill the Conditional Probability Tables (CPTs). The use of BBNs in FSA was proposed by the IMO in 2006 [15].

Studies applying BBN in risk assessment have been carried out on various ship types including large passenger ships [16], product tankers, oil tankers, bulk carriers [17] and LNG vessels [18], enabling the identification of Risk Control Options (RCOs) for the projects and operations of these ships and allowing for more detailed studies of these RCOs in the obtained models [19–21]. In this context, BBNs are especially useful along with Fault Tree (FT) modeling to model hazard event sequences and quantitatively incorporate Human and Organizational Factors in the study of maritime systems [22]. In a similar approach, a FT can be converted to a BBN, as proposed in [23] and used in [24], enabling the creation of a model that represents the system with a single network. This is possible because any FT can be directly mapped onto a BBN and because basic inference techniques on the latter may be used to obtain classical parameters computed from the former [25].

This paper presents a methodology for HRA, based on a BBN, and applies this method to model the event of a tanker collision along the Brazilian coast. In previous work [26], this event has been studied using the Technique for Human Error Rate Prediction (THERP) [27] – which makes use of binary trees and considers the Performance and Shape Factors (PSFs) in the definition of Human Error Probabilities (HEP) – allowing for the isolation of the tasks and activities that are most relevant to the collision event. Unlike that work, the approach of the actual paper directly considers the PSFs (Internal Factors and Management and Organizational Factors—IFs and MOFs) in the development of the BBN model, allowing for: (1) a representation of the interdependencies between factors relevant to the initiating events for the collision; and (2) a quantitative determination of the influence of the PSFs on the collision event. Thus, the proposed methodology allows for the evaluation of the relative impact of PSFs (IFs and MOFs) on the probability of collision, isolating the human factors with the greatest influence on this event. These factors will represent the most appropriate RCOs to reduce the collision frequency in the studied operation. This approach is justified based on the argument that the most

significant result of the PRA is not the actual computed risk value but rather the determination of elements that considerably impact the system risk [1].

Previous publications have presented an outline of the proposed methodology and some exploratory and preliminary results obtained with this method [4,28]. Hereafter, the methodology is briefly described (Section 2) and the model is discussed with a focus on its application and on the detailed results of the model analysis (Section 3). The hypotheses used to build the conditional probability tables are discussed as well as some of the insights that were gained, including: 1) identification of the most likely sequence of hazardous events leading to a collision; 2) isolation of the critical activities in the vessel operation; 3) identification of the skills and performance factors with the greatest impact on the probability of collision; and 4) determination of the MOFs that should receive the most attention for the effective reduction of the collision probability. Finally, the main conclusions of this work are presented.

2. HRA through Bayesian networks

To achieve the main objective of this study, a methodology covering the key HRA stages was developed. Swain and Guttman [27] presented a methodology covering these stages using THERP, and more recently, Droguett and Menêzes proposed a procedure to integrate BBN (modeling the human factor) into HRA [9]. Combining these procedures and considering the points concerning HRA presented by the IMO [2] resulted in a four-phase methodology to accomplish HRA using Bayesian networks. Fig. 1 describes the phases of the procedure and shows the correlations between the phases of THERP- and BBN-based HRAs.

These correlations lead to the proposed methodology for this work, better visualized in Fig. 2, below. This figure depicts the stages dedicated to qualitative and quantitative modeling. This approach is more similar to THERP than the model proposed by Droguett and Menêzes [9], and it presents a clear division between qualitative and quantitative considerations. This choice

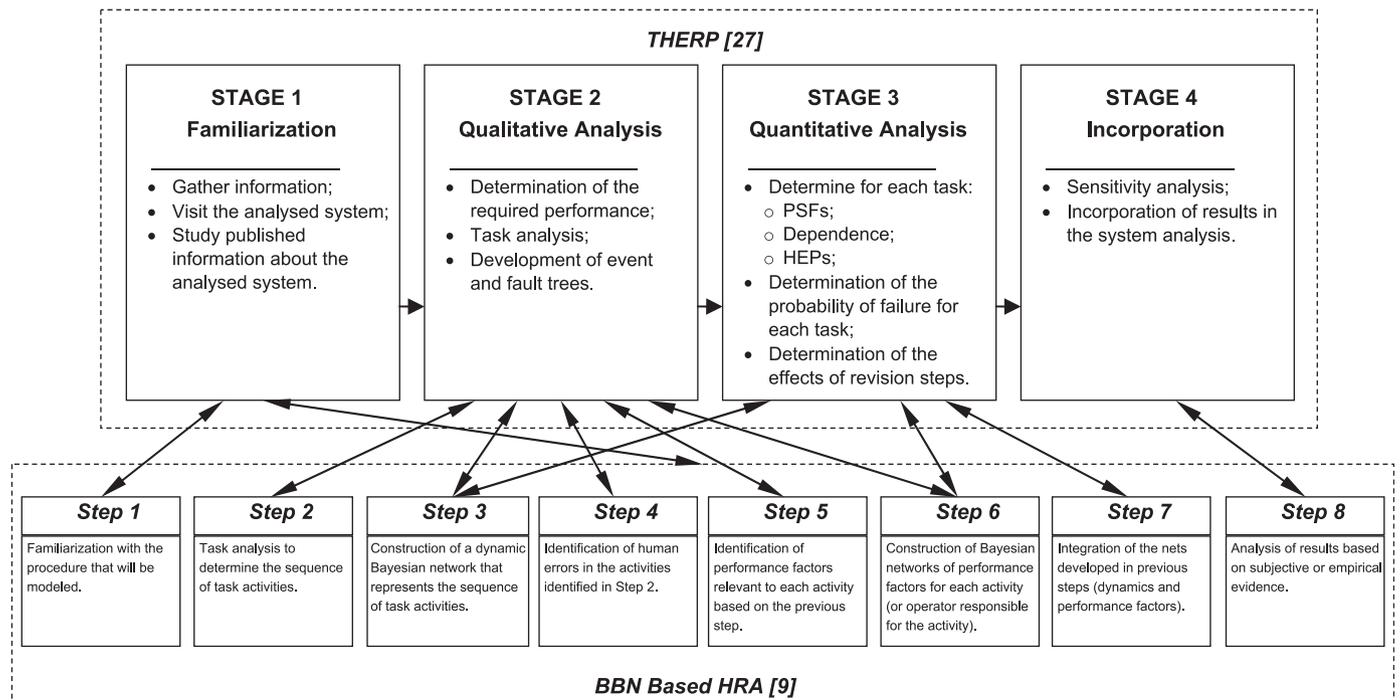


Fig. 1. Correlations between the phases of THERP- and BBN-based HRAs.

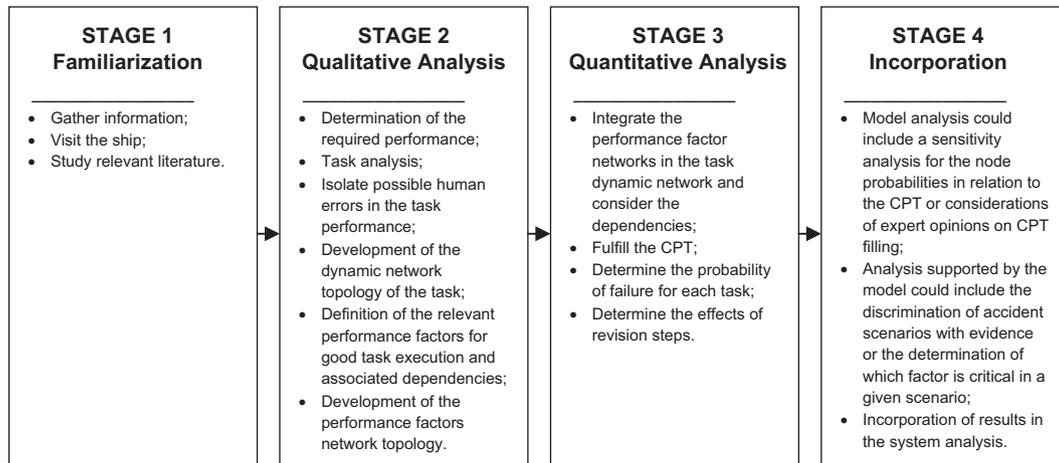


Fig. 2. Methodology for implementing the HRA using Bayesian networks.

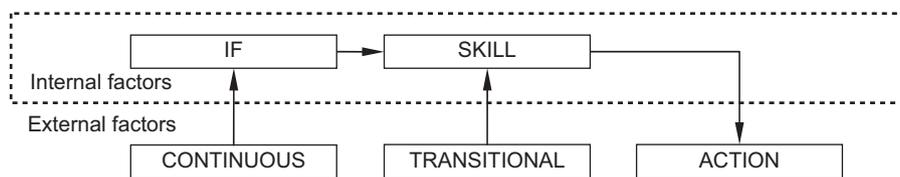


Fig. 3. Simplified dependency model for human factors.

allows for the visualization of the system's behavior even in the qualitative phase, including the number of edges for each MOF, as presented in the last paragraph of Section 4.4, and the influence of the MOFs on the collision probability.

In the procedure proposed in Fig. 2, the first phase involves familiarization with the system under examination and the gathering of information about the system. The recommended activities for this phase include a visit to the ship (for the proposed case, see Section 3) during operation and a review of the published literature on the subject. The second phase is the qualitative analysis of the human factors involved in the system, including task analysis, determination of the PSFs consistently impacting each activity (including its interdependencies; as discussed in next paragraph), and the development of the Bayesian network topology. In the third stage the CPTs are determined and the effects of possible factors should be considered. For example, the influence of adding a revision step on the probability of success in performing the task should be studied when an error can be corrected by the executor or someone else. The last step may consider the incorporation of human factors in the study of the overall system reliability (including machinery), and a sensitivity analysis can be performed to ascertain the impact of changes in the human factors. This step can identify changes to the system that can increase reliability, as supported by the results obtained in the previous phases.

At this point it is important to emphasize the multitude of factors that influence the execution of tasks in complex systems, complicating or even precluding the inclusion of each factor in a detailed model. To overcome this difficulty, it is necessary to consider a simplified model that includes the factors of interest that have the greatest impact on the study. Therefore, the relationships shown in Fig. 3 are proposed.

This figure (Fig. 3) considers that the quality of execution of the activity under study is directly influenced by the operator's internal factors at the time of the action, with internal factors defined as skills such as concentration, motor control, and creativity (the skills included in the model should be those that

are essential for the proper execution of the activity). The external factors that directly influence the operator's skill states are those present at the moment of execution of the action, with factors that may hinder the execution of the activity such as environmental factors (EFs), individual attitudes, and sabotage observed only at the moment in question as they are transient in nature. Other external factors such as staffing, available physical resources, and organizational culture are more constant and are defined as continuous because they have a low probability of changing during the course of the activity. These factors directly influence other internal factors (IFs that are not skills), such as personality, fatigue, and emotional state, which in turn impact the skill state at the moment of action (in Fig. 3, the internal factors are noted by dotted lines).

The following sections discuss and analyze each step of this methodology in the context of the study of the human factors impacting oil tanker collision accidents.

3. Application to the study of collision probability

To demonstrate the potential of the proposed methodology, it was applied to the operation of an oil tanker (SUEZMAX) traveling between the production unit (Campos Basin/Brazilian coast) and the terminal (São Sebastião) for relief of a FPSO (Floating Production, Storage and Offloading) vessel. The focus of this application was to perform a quantitative analysis of the IFs and MOFs impacting collision scenarios (see Section 3.2.3). A brief description of the developed activities and the results achieved for the three first stages of the methodology are presented below, and the results of the fourth stage are presented in the following section along with the model analysis.

This application was implemented with the support of an initial study conducted in the Naval Architecture and Ocean Engineering Department of the University of São Paulo in 2008 (presented in Martins and Maturana [26]), which implemented HRA through THERP [27] to analyze the same case study.

3.1. Familiarization (1st Stage)

As described in previous work [26], the operation was monitored for a complete cycle, i.e., traveling to the production unit (FPSO) and returning to the terminal. Information was collected on the activities of the crew through interviews (formal with the captain and informal with other officers during their duties), and these data, along with company handbooks and procedures, were compared with the analyses of other authors on tanker collisions [29–33]. All relevant activities were observed in person, particularly those carried out on the Navigational Bridge.

3.2. Qualitative analysis (2nd stage)

In addition to the knowledge gained through analyzing the tasks performed on board and the possible human errors associated with those tasks, the practical results of this stage are the development of a dynamic network topology and the associated shape factor networks. The networks for the tasks of interest (those related to the collision event) were defined through the following sequence: (1) analysis of the tasks of interest through the study of event trees and FTs (extracted from [26]), identifying activities and possible human errors in the task performance (Section 3.2.1), (2) Development of the topologies of the dynamic networks of the task (Section 3.2.2), and (3) Identification and development of the PSF network topology (Section 3.2.3).

3.2.1. Hazard events and the identification of interesting tasks for analysis

A study of event sequences that lead to vessel collision allowed for the preparation of the FT shown in Fig. 4. As described in [26], each basic event presented in this tree is associated with a task performed by the crew, and these tasks were analyzed to develop event trees to determine the probability of each basic event. As an example, Fig. 5 shows the event tree related to the basic Event 5—*Another ship is not detected*. This event is associated with the task of monitoring the traffic during navigation by visual and electronic means. Electronic monitoring (RADAR) has a greater range than visual monitoring, so it was placed first in the chronological ordering of the activities. If the electronic monitoring (RADAR) fails to detect the oncoming ship, the next step is visual detection. If this also fails, the electronic detection equipment has audible alarms to indicate proximity and a collision route (red in Fig. 5 indicates the failure of a task, and green indicates success).

This event tree (Fig. 5) was reviewed in relation to the probabilities presented in Martins and Maturana [26]. More realistic HEPs were assigned to these three activities because of reports that the crew would sometimes leave the Navigational Bridge unmanned due to intentional abandonment by the officer on duty, especially during the night and that the alarm referred to in activity 5-3 *Detect a vessel by alarm* would be turned off in other cases. According to some crew members, the alarm sometimes became activated even in known safe conditions, so the crew would deactivate the alarm and forget to turn it back on. Thus, the probability of failure has increased from $1E-3$ to $6E-1$ for the activity 5-1 *Detect a vessel by RADAR*, from $1E-4$ to $5E-2$ for the activity 5-2 *Detect a vessel visually*, and from $1E-4$ to $2E-1$ for the activity 5-3 *Detect the vessel by alarm*. This results in an increase in the probability shown in Fig. 4 for the basic Event 5 from $1E-11$ to $6E-5$ (little effect on the likelihood of the overall event). These new HEPs were obtained using the same approach presented in [26], i.e., based on the opinion of the crew and the correlation with activities described in [27].

The tasks associated with the basic events shown in Fig. 4 were considered to be of interest, and the event trees associated with these tasks have been used to generate dynamic task network topologies, allowing for the consideration of IFs and MOFs and their interdependence, which was not possible when using THERP, as described in [26], which includes the remaining event trees (beyond the one presented in Fig. 5).

3.2.2. Task dynamic network topology for the tasks of interest

To illustrate the method in action, the task of monitoring the traffic (related to basic Event 5) will be used as an example (see the Appendix for the other tasks). To develop the network, detection failure was considered to mean a failure in the detection by the alarm. It is considered that if the visual detection occurs, the detection by alarm will also occur since the operator's concentration must increase (equipment failures were discarded as a possibility). If detection by RADAR occurs, then visual detection is known for certain. These considerations simplify the dependency relations and allow for simple CPTs (see Section 3.3). The topology of the network is shown in Fig. 6, where node with darker color represent the basic event and the others indicate the activities involved in the task.

The process described above was performed for each of the 15 basic events related to the tasks of the FT (Fig. 4). Two states were defined for each of the 40 activities (considering all tasks). Specifically for the network shown in Fig. 6, the states are reproduced in Table 1.

3.2.3. Relevant PSFs and network topology

Based on the model presented in Fig. 3, the performance factor network topology was established in a generic model that accounts for the performance shape factors of interest in this case study and their major interdependencies, as shown in Fig. 7.

Only the external factors relevant to the case study are considered in this generic model (Fig. 7). Environmental Factors (EFs) are the only transient external factors that are analyzed. The continuous external factors only include factors related to training, organization and management (grouped in MOFs) that have a constant influence over the period of operation.

The performance factors were identified for all activities of each task. As an example, the activities of the monitoring traffic task will be discussed:

- *Activity 5-1 Detect a vessel by RADAR*: Table 2 shows the required skills and the related (most influential) internal performance factors identified. The MOFs associated with the IFs and the EFs related to the required skills are also presented;
- *Activity 5-2 Detect a vessel visually*: The PSFs are very similar to those found for the previous activity. The difference lies in the influence of the EFs. In this case, the influence of visibility is considered, whereas the influences of waves and storms are assumed to be part of the visibility factor, i.e., the visibility factor considers every environmental condition disturbing visual detection (as large wave amplitudes and storm conditions can impair human visual detection or at least delay the time of detection). In the case of the first activity these two factors directly influence the equipment response.
- *Activity 5-3 Detect a vessel by alarm*: The factors that are influential here are also similar to those of the initial activity. However, the influence of environmental factors was not considered here.

With the support of Table 2 and the above descriptions, it was possible to develop the Bayesian network topology for the PSFs influencing the activities involved in monitoring traffic, resulting

5 - Another ship is not detected				
Activity	1 - Detect a vessel by RADAR	2 - Detect a vessel visually	3 - Detect a vessel by alarm	Another ship is not detected
Failure	0.006	0.05	0.2	6.00E-05

Fig. 5. Event tree for basic Event 5. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)



Fig. 6. Dynamic Bayesian network for the task of monitoring the traffic.

Table 1 States for activity nodes presented in Fig. 6.

Detect a vessel by RADAR	Detect a vessel visually	Detect a vessel by alarm
Yes/no	Yes/no	Yes/no

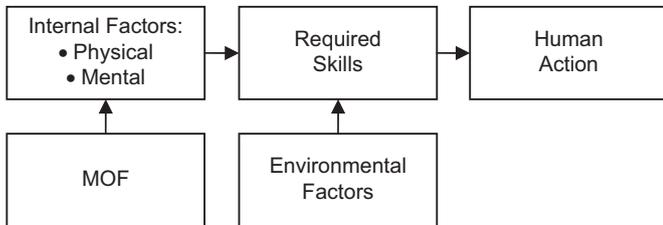


Fig. 7. Generic network for the PSFs.

Table 2 Performance factors for Detect a vessel by RADAR.

Required skills	PSF	MOF	
Concentration	Ifs	Quality of sleep	Work load
		Monotonous work	Working coordination
Perception	Ifs	Distractions	Working coordination
		Quality of sleep	Working coordination
	Efs	Physical condition	Physical resources
		Storm Waves	Work load

Note: The environmental factors that hinder the detection of other ships by radar are assumed to be storms and waves. This is because these phenomena sensitize the instruments, rendering their readings more difficult to interpret.

in structures similar to that presented in Fig. 7 (for each activity). Fig. 8 presents the topology for the activity 5-1 Detect a vessel by RADAR. Similar networks were constructed for each activity and task for each basic event of the FT, and these networks are presented in the Appendix to allow for the reproduction of this work.

After the PSF network topologies were defined, two states were established for each node. For the network shown in Fig. 8, the states are reproduced in Table 3.

3.3. Quantitative analysis (3rd stage)

The third stage of the method is devoted to quantitative analysis of the system under study. Thus, this section integrates the PSF networks with the task dynamic networks considering

their dependencies, allowing for the completion of the CPTs and the generation of a BBN model for each task by quantitatively considering the IFs, EFs and MOFs. This stage also includes the preparation of BBNs representing sequences of hazardous events (modeled on the FT in Fig. 4), which are then used to integrate the networks of all tasks identified as relevant to the collision accident, the focus of this work. Note that the probabilities discussed here refer to the probability of success or failure during one operational cycle, i.e., the period that includes traveling to the production unit (FPSO, Bacia de Campos) and returning to the terminal (São Sebastião). Moreover, all variables were considered discrete, and two states were adopted for each variable (binary variables).

As an example, the case of the traffic monitoring task discussed in the previous stage will be resumed (see the Appendix for the other task obtained model, including the topology and CPTs). For this task the topology of the integrated network is shown in Fig. 9.

As shown in Fig. 9, MOFs and IFs are not repeated for an operator (considering that monitoring traffic is performed by one Nautical Officer). However, for the skill of perception, nodes were created for each specific activity. Although it is classified using the same nomenclature, this skill has a different meaning for each activity, with the first and second activities (Perception and Perception 1, respectively) requiring visual perception, with different interpretation requirements (the first activity requires RADAR assessment, for example), and with the last activity (Perception 2) requiring auditory perception.

Considering that both hard data and expert opinions can be used and mixed to construct the CPTs [34], this study used the network topologies, observations of the phase of familiarization (Section 3.1) and fault data to perform the tasks involved in the basic events of the FT shown in Fig. 4, which was generated by the application of THERP [26].

3.3.1. EF probabilities

First, the prior probabilities for the states of the EF nodes were obtained by eliciting the opinion from the crew during the familiarization phase (see Section 3.1): (1) waves negatively impacting the RADAR reading 20% of the time (state yes), (2) negative influence of storms 10% of the time (state yes), and (3) problems with visibility 5% of the time (state low). These data are shown in Fig. 9, along with the corresponding nodes. Thus, as the nodes are binary, the prior probabilities for the remaining states are already known (Waves—no state: 80%; Storm—no state: 90%; Visibility—high state: 95%).

3.3.2. MOF probabilities

The prior probabilities for the MOF nodes were defined broadly, only taking into account aspects of employee satisfaction (crew members) observed during the trip. The positive and negative states were assigned probabilities of 95% and 5%, as shown in Fig. 9. At this point it is important to note that the

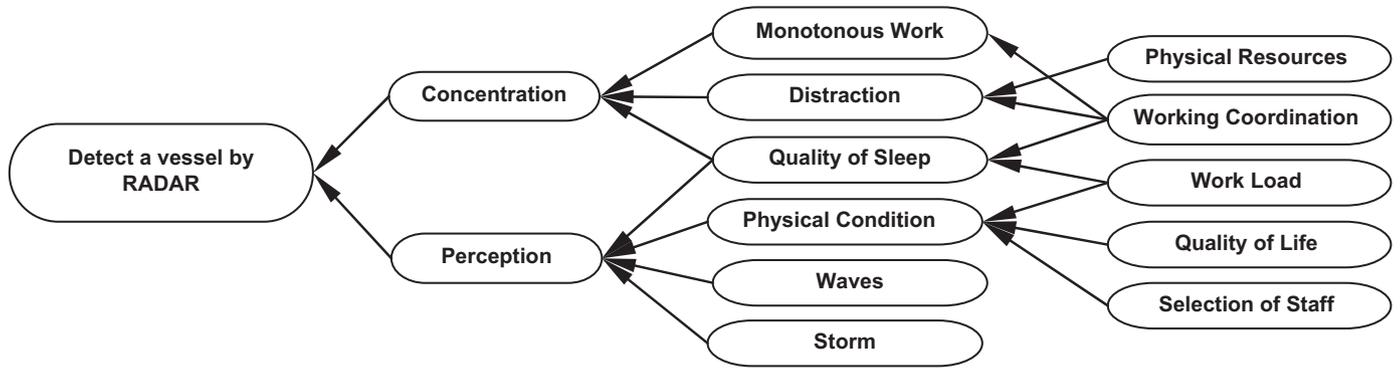


Fig. 8. PSF network topology for the activity 5—1 Detect a vessel by RADAR.

Table 3
States for PSF nodes presented in Fig. 8.

Skill	Internal factor	MOF
Concentration	High/low	Physical resources
Perception	High/low	Working Coordination
Environmental factor	Yes/no	Work load
Waves	Yes/no	Quality of life
Storm	Yes/no	Selection of staff

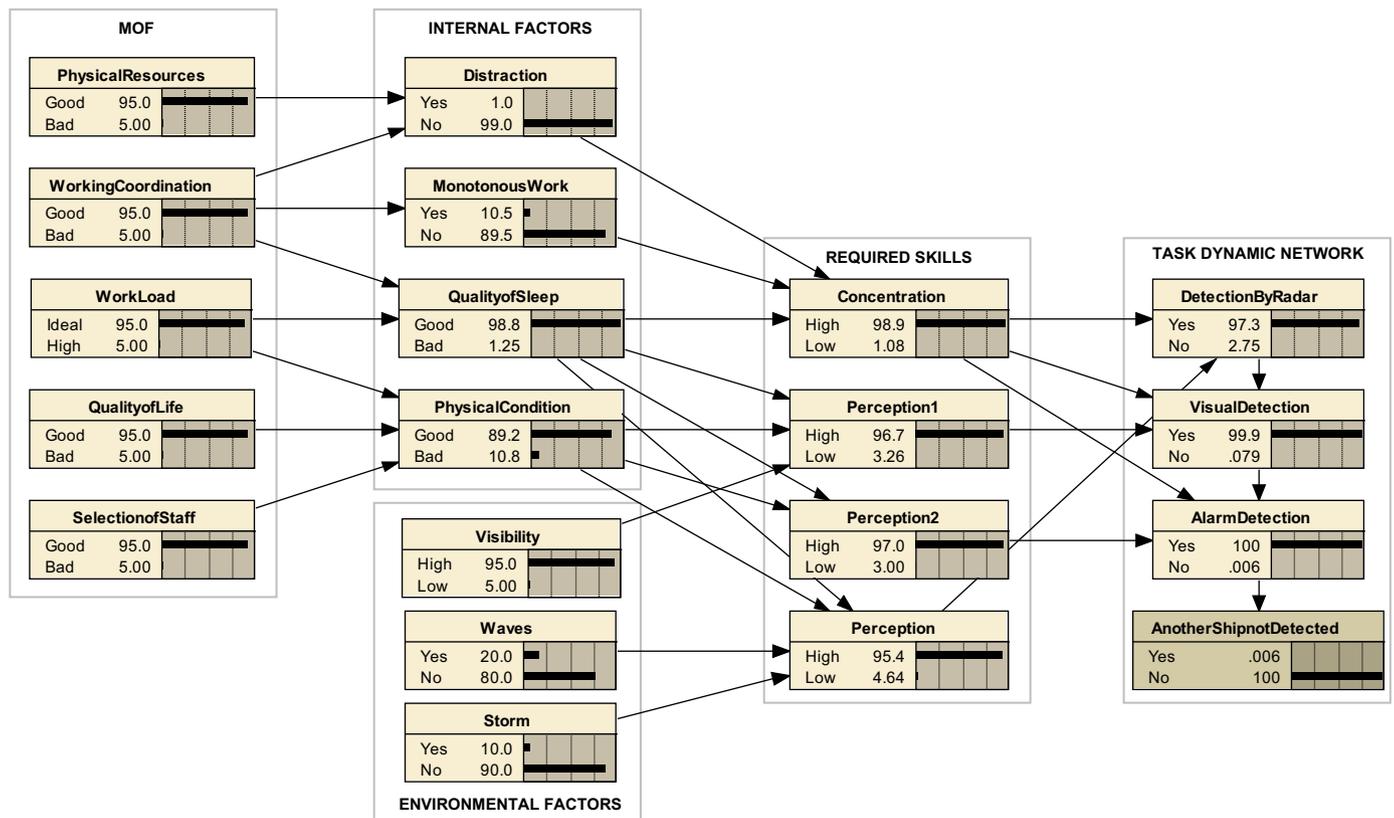


Fig. 9. Network of performance factors for traffic monitoring.

positive states are those associated with a decrease in the probability of failure to perform the task (the negative state exerts an opposite effect on the failure probability).

3.3.3. Activity CPTs

Some of the CPT probabilities for the activities were defined within a network topology, more specifically due to the timing of

the execution of these activities (in the case of the task of monitoring traffic, it is assumed that if the detection by radar occurs, the visual detection will also occur; and, if the visual detection occurs, the detection by alarm will also occur; these associations are independent of skills conditions). The remaining conditional probabilities were defined by linear interpolation according to the number of positive states of parent nodes that represent skills. For example, for the activity 5—3 Detect a vessel by alarm, the CPT is shown in Table 4.

The first two columns in this table refer to the state probabilities, given the parent node states, represented by the next three columns: *Detect a vessel visually*, *Concentration* and *Perception 2*. The last column refers to the number of states that are positive for the skills (per line). In this table, where the state for the parent node *Detect a vessel visually* is *yes*, the conditional probability for the state *yes* of the activity *Detect a vessel by alarm* is 100% (defined by the precedence of the activity *Detect a vessel visually*). For the state *no* of the activity *Detect a vessel visually*, the conditional probabilities were defined according to the number of skills with positive states. In the case of Table 4, two skills have positive states (*Concentration* and *Perception 2*). The conditional probability for the activity state *yes* was assumed to be 100% when all skill were positive and 40% when they were all negative (representing a 60% probability of failure to perform the activity when all the necessary skills are at a negative status). The intermediate conditions were linearly interpolated as mentioned in the previous section. This probability of 40% refers to the worst conditions for the execution of the activity on the ship and is based on the average failure data presented by Martins and Maturana [26] for activities carried out under these conditions, as well as on the information collected during the monitoring of the operation.

3.3.4. IF and Skill CPTs

Considering the lack of data and of expert opinion, the CPTs for the IFs and Skills were joined together, considering the probability of failure to be verified in the task execution. Thus, it was decided that in the absence of evidence, the probability of the state *yes* of the node *Another Ship is not Detected* in Fig. 9 should be similar to that of the basic event of the reference FT (Event 5 in Fig. 4), assuming that these probabilities are representative. This was performed through iterative search and linear interpolation

Table 4
CPT for the activity 5—3 *Detect a vessel by alarm*.

yes	No	Detect a vessel visually	Concentration	Perception 2	Positive states (Skills)
1.00	0.00	Yes	High	High	–
1.00	0.00	Yes	High	Low	–
1.00	0.00	Yes	Low	High	–
1.00	0.00	Yes	Low	Low	–
1.00	0.00	No	High	High	2
0.70	0.3	No	High	Low	1
0.70	0.3	No	Low	High	1
0.40	0.6	No	Low	Low	0

Table 5
CPT for the node *Perception*.

P(high)	P(low)	Sleep quality	Physical condition	Wave	Storm	Positive states	Calculation of P(high)
0.90	0.10	Good	Good	Yes	Yes	2	Min + (Max – Min) * 2/4
0.95	0.05	Good	Good	Yes	No	3	Min + (Max – Min) * 3/4
0.95	0.05	Good	Good	No	Yes	3	Min + (Max – Min) * 3/4
1.00	0.00	Good	Good	No	No	4	Min + (Max – Min) * 4/4
0.85	0.15	Good	Bad	Yes	Yes	1	Min + (Max – Min) * 1/4
0.90	0.10	Good	Bad	Yes	No	2	Min + (Max – Min) * 2/4
0.90	0.10	Good	Bad	No	Yes	2	Min + (Max – Min) * 2/4
0.95	0.05	Good	Bad	No	No	3	Min + (Max – Min) * 3/4
0.85	0.15	Bad	Good	Yes	Yes	1	Min + (Max – Min) * 1/4
0.90	0.10	Bad	Good	Yes	No	2	Min + (Max – Min) * 2/4
0.90	0.10	Bad	Good	No	yes	2	Min + (Max – Min) * 2/4
0.95	0.05	Bad	Good	No	No	3	Min + (Max – Min) * 3/4
0.80	0.20	Bad	Bad	Yes	Yes	0	Min + (Max – Min) * 0/4
0.85	0.15	Bad	Bad	Yes	No	1	Min + (Max – Min) * 1/4
0.85	0.15	Bad	Bad	No	Yes	1	Min + (Max – Min) * 1/4
0.90	0.10	Bad	Bad	No	No	2	Min + (Max – Min) * 2/4

(search for the maximum and minimum values and interpolation of intermediaries) as described below. As an example, the CPT for the node *Perception* in Fig. 9 is shown in Table 5.

The procedure used to generate this CPT was as follows: (1) the network topology shown in Fig. 9 was inserted into a program that addresses BBN (Netica™); (2) the prior probabilities were entered for the EFs, MOFs and activities (already discussed); (3) the probabilities of the CPTs for the nodes of Skills and IFs were parameterized as in the last column of Table 5, depending on the parameters *Max* and *Min*, i.e., $P(high) = Min + (Max - Min) * A/B$, and $P(low) = 1 - P(high)$, where *A* is the number of positive states among parent nodes and *B* is the total number of parent nodes; (4) the parameters *Max* and *Min* were initially both set equal to 100%; (5) The value of *Min* was reduced until the probability of the state *No* in the node *Detect a vessel by alarm* was equal to $6 * 10^{-5}$ (equal to the probability observed for the Event 5 in Fig. 4; Section 3.3.5, i.e., how this node relates to the node *Another Ship is not Detected*, justifies the choice of this node as a reference), which occurred at *Min* equal to approximately 80%. As all nodes for Skills and IFs for the same task were parameterized by *Max* and *Min*, this procedure established all related CPTs.

These principles were followed to fill in the CPTs for the integrated networks of other tasks, and the results are presented in the Appendix together with the network topologies. Importantly, for the task related to Event 10—*Communication Failure*, step 5 shown in the preceding paragraph has not reached its goal of *Max* equal to 100% (as stated in step 4), requiring its reduction to 93% as shown in the CPTs in the Appendix.

3.3.5. Hazardous event BBNs

As mentioned, the events of interest for this work are those related to a collision accident. Thus, the sequences of events to be considered in this study are shown in FT form in Fig. 4. To facilitate the model analysis stage (4th methodology stage, presented in the next section), the FT was converted into a BBN that represents the same domain. For details of how an FT is converted into a BBN, consult Lampis and Andrews [23]. Fig. 10 presents the topology of the BBN obtained by applying those concepts.

This BBN was integrated directly into the task dynamic networks (already integrated into the PSF networks), where the node corresponding to the basic event is directly connected to the node that represents the failure to perform the task. In the task of traffic monitoring, the node of interest is the node for the activity 5-3 *Detect a vessel by alarm*. In this case, the CPT for the node of the basic Event 5—*Another Ship is not Detected* (shown in Fig. 10 as *Another Ship is not Detected*) is shown in Table 6.

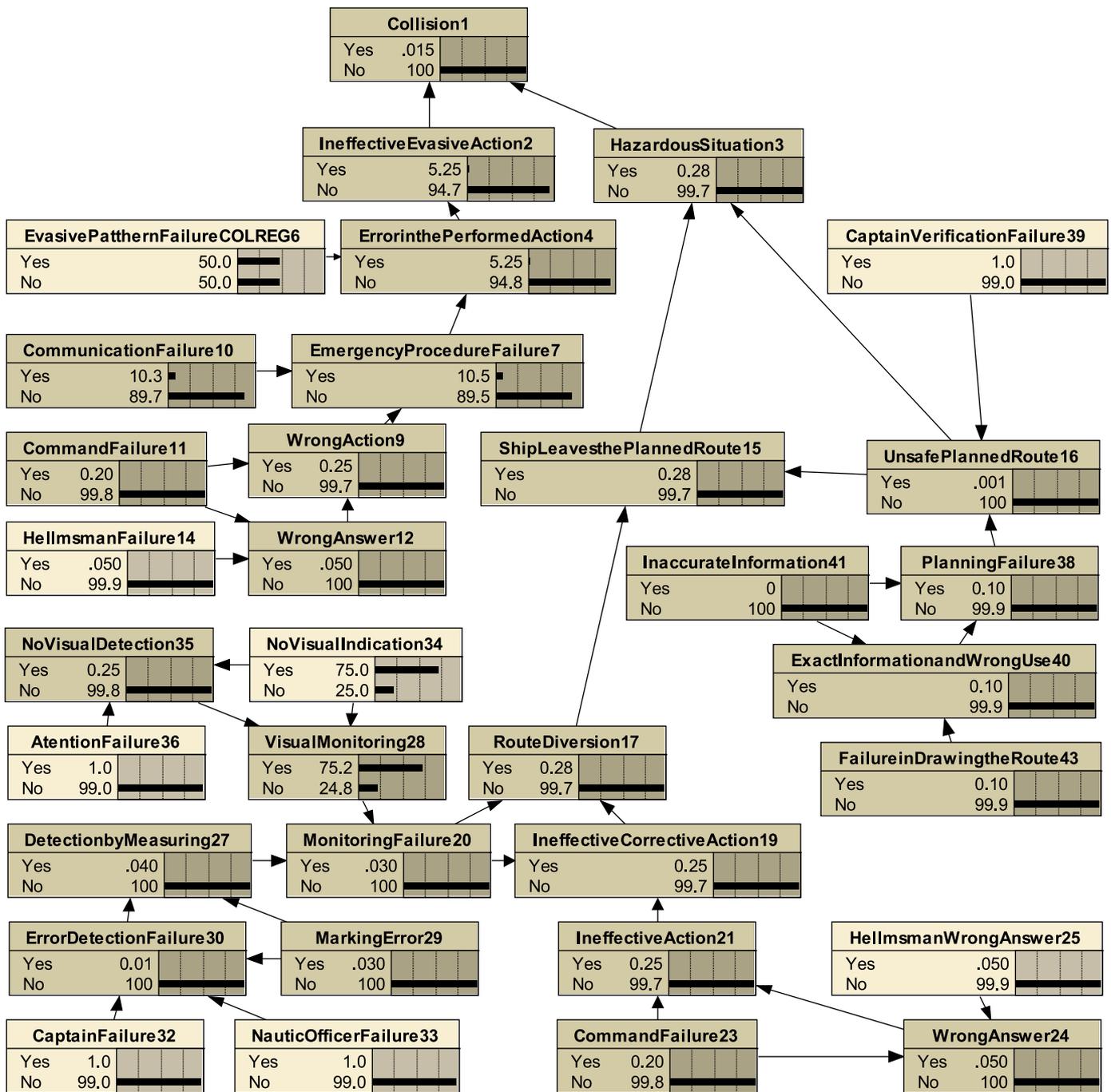


Fig. 10. Bayesian network of hazardous events.

Table 6
CPT for the node *Another Ship is not Detected*.

Detect a vessel by alarm	$P(\text{yes}) \rightarrow \text{failure}$	$P(\text{no}) \rightarrow \text{success}$
Yes	0	1
No	1	0

This approach enabled the development of a model for the system by integrating the FT modeled as a BBN, i.e., a network of hazardous events with dynamic task networks for the performance factors. This concept is illustrated in Fig. 11, where the basic event nodes are the interfaces between the hazardous events network and the dynamic task networks, including shape factors.

4. Model analysis

The focus of this section is to highlight the potential of the proposed methodology and demonstrate the importance of the information that can be extracted from the models developed here. The combination of the hazardous event network, the dynamic task networks and the performance factor networks can be used to make inferences related to all the nodes involved. A node of this integrated network can represent an event, execution of an activity, a skill, an internal PSF (physical or mental), an environmental factor or an MOF. In identifying the points of vessel operation that have critical effects on the probability of a collision, the states of these nodes and their relationships were considered in four steps:

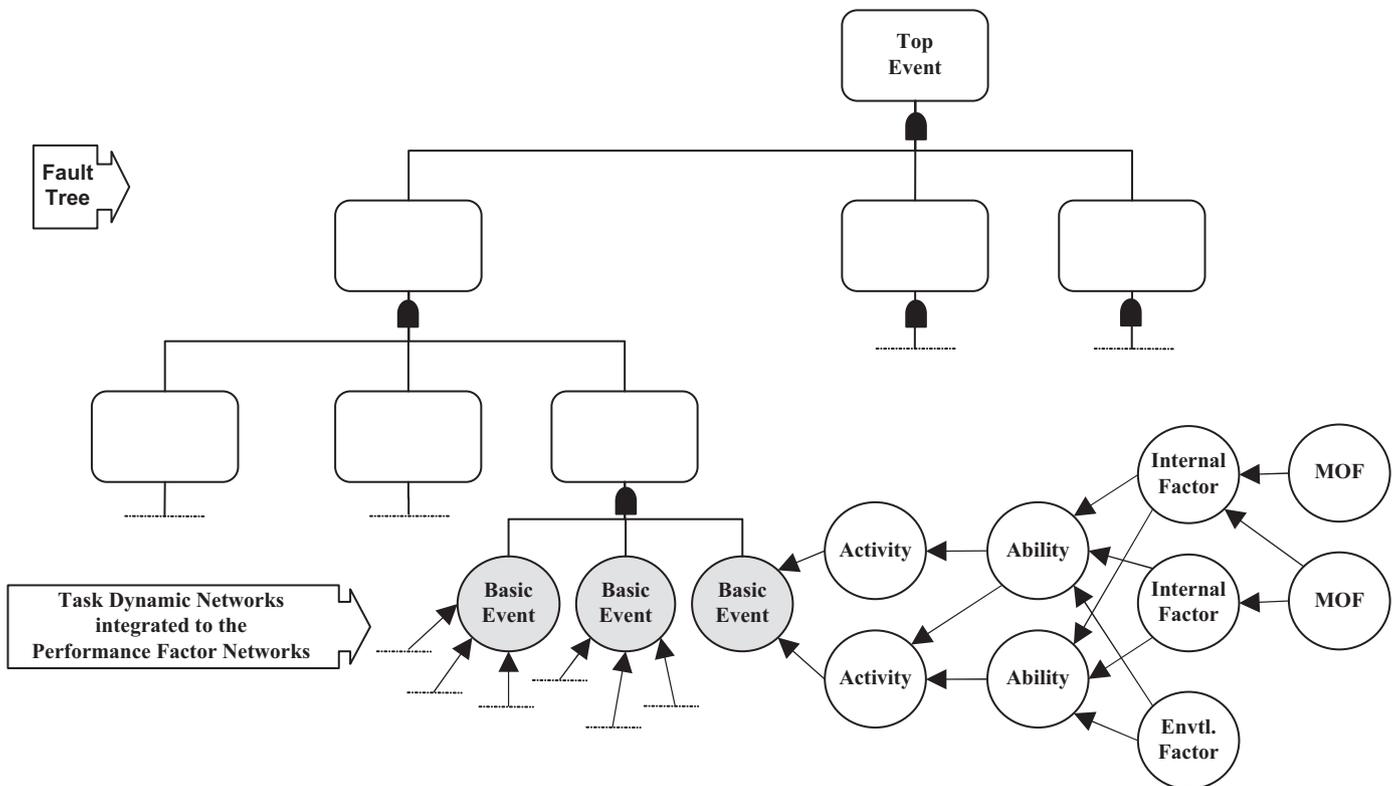


Fig. 11. Integration of fault tree and Bayesian networks.

- *Basic event analysis, given the top event*: Initially, a quantitative analysis of basic events (which generate hazardous events) was carried out in the context of event sequences that can lead to a collision accident;
- *Activity analysis*: Crew activities were considered by isolating them through assumptions about the evidence of the collision event and comparing the results obtained in this way (by means of BBNs) with those presented in the previous work [26];
- *Internal factors and required skills analysis*: This step considered the effects of internal factors and skills on the performance of the activities. Inferences were made about the tasks flagged as critical in the previous steps, such as: (1) determining the probabilities of possible skill states given failure in an activity; (2) determining the chance of the erroneous execution of an activity given that certain conditions were observed by the operator (fatigue, complaints about sleep, etc.); (3) determining the error probability for a repeated task if there an error occurred on the previous attempt;
- *MOF analysis*: This step presented ways to identify MOFs that are important and should be examined more carefully to reduce the chances of an accident.

The results obtained in these four steps are presented below.

4.1. Basic event analysis, given the top event

As pointed out in the system modeling [4], the state probabilities of the FT basic events (Fig. 4) were obtained from a previous work [26]. Initially, the CPTs (for the PSFs in the performance factor network) were adjusted so that the basic event probabilities (represented in the networks) remained the same as the previously obtained values. However, evidence of a collision or “no collision” was not considered. Table 7 outlines the probabilities

associated with the basic event states considering whether there was evidence of a collision or “no collision”.

Based on the collected collision evidence, we obtained new values for the basic event probabilities, which were replaced in the original FT (Fig. 4). The new values generated a probability of 66.58% for the top event, which is associated with the occurrence of one of the event sequences represented by the FT. The remaining 33.42% is associated with no modeled sequences, including equipment failures and human errors that are considered secondary. This result was expected, i.e., 80% of the accidents in the marine industry result from human error [35]. We concluded that secondary events accounted for 13.42% of accidents, while other non-human factors accounted for the remainder. Note that some events that are considered non-human could potentially be classified as human, for example, equipment failure could be classified as a design error or attributed to faulty concepts used in preparation (e.g., poor choice of materials or even the lack of a suitable material for a particular component). However, in this work we only considered errors related to ship operation as human errors.

The calculation of the probability of the top event (collision, as shown in Fig. 4) is performed directly, using the logic gates presented as a function of the basic events. In other words, the top event probability can be calculated according to the probabilities of events that are not basic. Thus, to simplify the following explanation, the collision probability (for the considered tree) can be calculated as a function of the factors presented in Table 8.

In this table, each factor (the first column) represents the probability that the event in the second column will occur (numbered corresponding to the FT shown in Fig. 4); the third column will be explained later. Event 22 was divided into three possibilities: (1) Detection by marking, (2) Detection by marking and visual (both), and (3) Visual detection. This partition helps to understand the event sequence that leads to the top event in the FT.

Table 7
Probabilities associated with basic events.

	Event	State	Collision		Absence of evidence
			Yes	No	
34	No Visual Indication	Yes	7.98E-01	7.50E-01	7.50E-01
6	Evasive pattern Failure (COLREGs)	Yes	9.98E-01	5.07E-01	5.07E-01
10	Communication Failure	Yes	9.53E-01	1.03E-01	1.03E-01
39	Captain Verification Failure	Yes	6.65E-02	1.08E-02	1.08E-02
32	Captain Failure	Yes	1.77E-01	1.08E-02	1.08E-02
33	Nautical Officer Failure	Yes	1.77E-01	1.08E-02	1.08E-02
36	Attention Failure	Yes	3.71E-02	9.81E-03	9.81E-03
23	Command Failure	Yes	6.08E-01	2.03E-03	2.17E-03
11	Command Failure	Yes	3.86E-02	2.16E-03	2.17E-03
43	Failure in Drawing the Route	Yes	2.80E-02	1.22E-03	1.23E-03
25	Helmsman Wrong Answer	Yes	1.65E-01	4.61E-04	4.99E-04
14	Helmsman Failure	Yes	1.28E-02	4.96E-04	4.99E-04
29	Marking Error	Yes	6.64E-02	2.50E-04	2.65E-04
5	Another Ship is not Detected	Yes	4.33E-03	6.19E-05	6.29E-05
41	Inaccurate Information	Yes	0.00E+00	0.00E+00	0.00E+00

Table 8
Correlation between factors and events of the FT.

Factor	Event	Number of possibilities
A	18—Safe planned route	3
B	22—Detection by marking	6
C	22—Detection by marking and visual (both)	3
D	22—Visual detection	2
E	21—Ineffective action	2
F	20—Monitoring failure	4
G	16—Unsafe planned route	2
H	2—Ineffective evasive action	4

Thus, as presented above, the collision probability is calculated by

$$P(\text{Collision}) = A * [(B + C + D) * E + F] + G * H \tag{1}$$

The probabilities of the events presented in Table 8 can be calculated as functions of the basic events. The equations below represent the results obtained in this way.

$$A = (-41 * -43 + -41 * 43 * -39 + 41 * -39) \tag{2}$$

$$B = [-29 * (32 * -33 + -32 * 33 + -32 * -33)] * (-34 * 36 + 34) \tag{3}$$

$$C = (-34 * -36) * (-29 * (32 * -33 + -32 * 33 + -32 * -33)) \tag{4}$$

$$D = (-34 * -36) * (29 * + -29 * 32 * 33) \tag{5}$$

$$E = (25 * -23 + 23) \tag{6}$$

$$F = (-34 * 36 + 34) * (29 * + -29 * 32 * 33) \tag{7}$$

$$G = (-41 * 43 * 39 + 41 * 39) \tag{8}$$

$$H = 5 + -5 * 6 * [10 + -10 * (11 + -11 * 14)] \tag{9}$$

In Eqs. (2)–(9), the bold numbers represent the basic FT events, and the sign “-” is applied to negate the preceding event. In the FT, some events have been defined as the denial of basic events (such as Event 42 in relation to 41, for example) and they are represented in this way in Eqs. (2)–(9) without affecting the proposed calculations.

The above Eqs. (1)–(9) readily show that the probability of the top event can be defined as the sum of several parts (by applying the distributive property of multiplication in relation to the sum). More detailed study of these parts shows that each part represents an event sequence and that the final probability is

the sum of a set of possible sequences that can cause the ship to collide. The third column of Table 8 helps to illustrate the number of ways in which each event can occur, calculated as functions of the number of possible terms in Eqs. (2)–(9) (after applying the distributive property). Thus, Table 8 and Eq. (1) show that in the FT, 320 possible associations determine event sequences that may lead to a collision. These sequences were studied to identify the most probable events given evidence of a collision.

Fig. 12 presents a condensed graphical depiction of all sequences modeled by the FT. In this figure, the basic events are represented by circles and the others, added to facilitate understanding, by rectangles. An important point of Fig. 12 is that certain events are linked by two or more paths to success or failure. For Events 32 and 33, for example, there are three paths to failure [identified by failure (1), failure (2) and failure (3)]. The paths failure (1) and failure (3) only occur when there are errors in both tasks (related to Events 32 and 33, linking them to Event 27) because according to the FT, Events 32 and 33 indicate that an error must occur in the analysis of data related to the marking of the nautical chart, and success in one or in both of these will lead to success in evaluating the position error. The path failure (2) occurs when there is a failure in just one of the tasks, with the path going from the task that failed to the one that was successful. There are also some events that only occur when a combination of other events occurs; e.g., Event 20 will only occur if Events 27 and 28 also occur because Event 20 represents the failure to detect the position error, which in turn represents the failure of visual detection and in marking the nautical chart (these are considered to be independent in the FT).

The path in red in Fig. 12 was determined to be the most likely (28.26%) by multiplying the probabilities of the involved events, given evidence of a collision. The events that comprise this path are reproduced in Table 9, along with their associated probabilities.

In this sequence, errors were verified in Tasks 23, 10 and 6. In Basic Event 34 there was also a negative result due to a lack of visual indication (which occurred over 75% of the route according to the original FT; with this evidence the probability increased to 79.8%), but this case is not a crew error. Table 7 shows that errors in these tasks are also among the most likely events given evidence of a collision; they will be studied in more detail in the analysis of performance factors and required skills.

Table 10 shows the sequences with occurrence probabilities greater than 1% given evidence of a collision. In this table, the sequences are represented by their basic events, arranged in columns. The end of each column reports the probability of occurrence of the sequence, given the collision evidence. Note that the sum

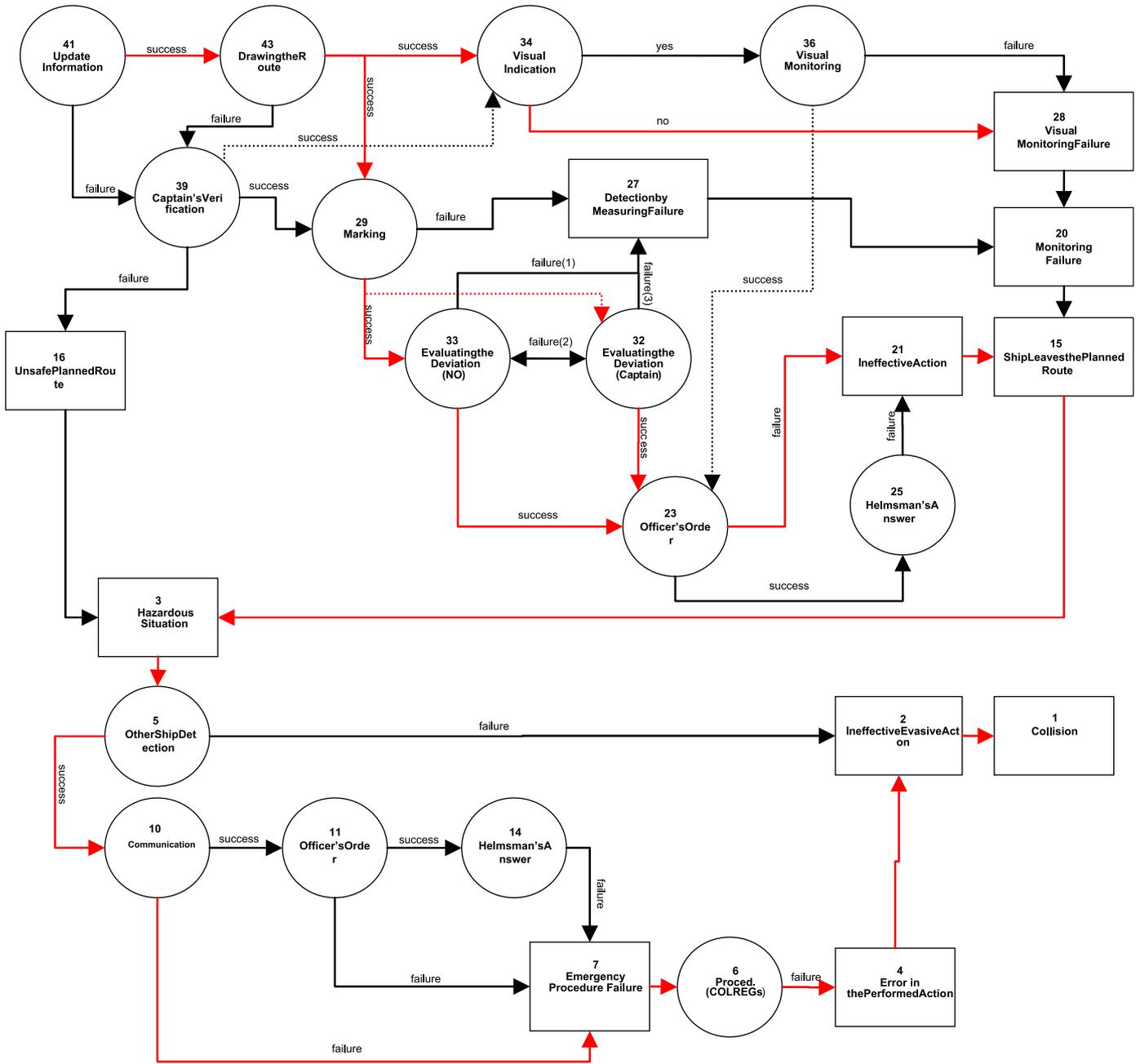


Fig. 12. Diagram for the sequences modeled in the FT. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Table 9
The most likely sequence.

Event/state	41/success	43/success	29/success	33/success	32/success	34/no	23/failure	21	15	3	5/success	10/failure	7	6/failure	4	2	1
Probability	1.00E+00	9.72E-01	9.34E-01	8.23E-01	8.23E-01	7.98E-01	6.08E-01				9.96E-01	9.53E-01	9.98E-01				28.26%

of these probabilities is 31.78%, indicating that these sequences together with the sequence shown in Table 9 represent over 60% of the collision probability given evidence of a collision (the remaining 40% represents other associations, modeled or not).

In Table 10, there are errors in Tasks 6 and 10 for all sequences presented. This was expected for Task 6, as the standard evasive procedure (COLREG: Convention on the International Regulations for Preventing Collisions at Sea) is the last resort in an attempt to avoid an accident. There were errors in Task 23 for most sequences, which supports the choice of these tasks for the analysis of performance

factors and required skills (as will be addressed in the discussion on this subject). The probabilities of the activities involved in these tasks given evidence of a collision are also listed.

4.2. Activity analysis

To begin the quantitative analysis of the activities performed during ship operation that are related to the collision event, Table 11 lists the activity error probabilities with and without collision evidence. Activities were ranked according to the

Table 10
Sequences with occurrence probabilities greater than 1%.

Sequences							
I	II	III	IV	V	VI	VII	VIII
41 success 1.00E+00							
43 success 9.72E-01							
29 failure 6.64E-02	29 success 9.34E-01						
34 no 7.98E-01	33 failure 1.77E-01	33 failure 1.77E-01	33 success 8.23E-01	33 success 8.23E-01	33 failure 1.77E-01	33 success 8.23E-01	33 success 8.23E-01
5 success 9.96E-01	32 failure 1.77E-01	32 success 8.23E-01	32 success 8.23E-01	32 failure 1.77E-01	32 success 8.23E-01	32 success 8.23E-01	32 failure 1.77E-01
10 failure 9.53E-01	34 no 7.98E-01	34 no 7.98E-01	34 no 7.98E-01	34 no 7.98E-01	34 yes 2.02E-01	34 yes 2.02E-01	34 yes 2.02E-01
6 failure 9.98E-01	5 success 9.96E-01	23 failure 6.08E-01	23 success 3.92E-01	23 failure 6.08E-01	36 success 9.63E-01	36 success 9.63E-01	36 success 9.63E-01
	10 failure 9.53E-01	5 success 9.96E-01	25 failure 1.65E-01	5 success 9.96E-01	23 failure 6.08E-01	23 failure 6.08E-01	23 failure 6.08E-01
	6 failure 9.98E-01	10 failure 9.53E-01	5 success 9.96E-01	10 failure 9.53E-01	5 success 9.96E-01	5 success 9.96E-01	5 success 9.96E-01
		6 failure 9.98E-01	10 failure 9.53E-01	6 failure 9.98E-01	10 failure 9.53E-01	10 failure 9.53E-01	10 failure 9.53E-01
			6 failure 9.98E-01		6 failure 9.98E-01	6 failure 9.98E-01	6 failure 9.98E-01
1 yes 4.74%	1 yes 2.08%	1 yes 6.07%	1 yes 3.01%	1 yes 6.07%	1 yes 1.47%	1 yes 6.87%	1 yes 1.47%

observed increase in error probability given evidence of a collision, and the activities that have error probabilities greater than 10% based on the available collision evidence are shown in bold and shaded type.

Table 11 shows that certain activities (*1-Manipulation of rudder* (25), for example, where the number indicates the task that requires the activity) were considered to have low probabilities (4.99×10^{-4}) before evidence of a collision and were assigned a high probability after this evidence was presented (1.65×10^{-1}). Moreover, evidence of a collision reduced the probabilities of some activities (the last five in the table). This reduction can be understood by analyzing the network model; activity *4-Deciding to make contact by other means (visual Morse)* (10) (the last in the table) will be taken as an example. In this activity, the probability of the state *no*, without collision evidence, was 82.8%. The collision evidence changed this probability to 25.9%, representing a 69% reduction in probability. This reduction is justified by the fact that the state *no* also includes the cases when this activity is not performed. Evidence of a collision increases the chance that the activity is performed (with or without error), and the probability of the state *no* is closer to the probability of an error in performing the activity.

The results presented in Table 11 verify that the use of BBNs requires a contextual consideration of the error, i.e., a full consideration of the factors that influence the execution of the activity. This occurs both in the modeling phase and in the model analysis required to understand the results. The activity error probabilities considering the evidence from the node states of the previous activities are presented in Table 12.

Note that the evidence presented here requires the execution of the activities. Therefore, the assumption of no task execution discussed above has less influence on the data presented in this table than on the data in Table 11. The salient point remains that Table 12 presents the error probabilities for the activities, considering the states of the previous activity nodes for the same task, in two conditions: (1) without collision evidence and (2) with collision evidence. Note that this table only shows those activities that are preceded by activity nodes. Moreover, the data shown here represent the activity error probabilities, given that there is a lack of evidence on PSF. In this table, the fifth column (titled *Increase*) refers to the observed error probabilities of the activities if the collision event is observed. The distinct activities (in bold font) refer to activities that had error probabilities greater than 10%, given evidence of a collision.

Given these results, it is possible to determine the critical activities for initial efforts to reduce the probability of a collision (noting that Tasks 10 and 23 have activities that stand out due to higher chances of error, and moreover, that in Table 9 these tasks constitute the most likely sequence given evidence of a collision), define actions to reduce the error frequencies in these activities, mitigate their effects, alleviate the circumstances in which they occur, and/or reduce their consequences. This analysis would lead to a variety of options for risk control: crew training, changes in layout or ergonomics, specification of information that should be made available, and the development of emergency procedures. These activities will be further studied in the next section considering the influence of PSF, which can assist in defining these risk-control options.

Table 11
Activity probabilities.

Task	Activity	State	No collision evidence	Collision evidence	Probability increase (%)
25	1-Manipulation of rudder	failure	4.99E-04	1.65E-01	32,962
5	3-Detect a vessel by alarm	no	6.29E-05	4.33E-03	6777
29	1-Checks of equipment	incomplete	1.00E-03	6.53E-02	6404
23	1-Understand correctly	no	9.81E-03	5.86E-01	5868
23	2-Decision making	failure	1.45E-02	6.22E-01	4202
43	11-Route revision (captain)	failure	1.90E-07	6.85E-06	3511
14	1-Manipulation of rudder	failure	4.99E-04	1.28E-02	2474
5	2-Detect a vessel visually	no	2.18E-04	5.16E-03	2270
43	1-Select publication	failure	1.23E-03	2.80E-02	2184
32	1-Checks	failure	1.08E-02	1.77E-01	1537
33	1-Checks	failure	1.08E-02	1.77E-01	1537
43	2-Reading information	failure	2.21E-03	3.20E-02	1345
43	10-Route revision NO	failure	2.91E-05	3.53E-04	1113
43	3-Establishment of minimum depth	failure	3.05E-03	3.54E-02	1062
43	4-Reading the depth in the nautical charter	failure	3.36E-03	3.66E-02	991
43	5-Identify restricted area	failure	3.48E-03	3.71E-02	967
43	6-Drawing restricted area	failure	4.07E-03	3.96E-02	874
43	7-Drawing successive courses	failure	4.48E-03	4.14E-02	824
43	8-Identify way-points	failure	4.76E-03	4.26E-02	794
10	1-Deciding to make contact by radio	no	7.30E-02	6.21E-01	751
43	9-Choice reference points	failure	5.79E-03	4.59E-02	692
29	3-Respect of the interval to mark	no	1.00E-03	7.40E-03	637
29	4-Reading of position	failure	1.96E-03	1.37E-02	595
29	5-Marking the nautical chart	failure	2.76E-03	1.87E-02	578
39	1-Checks	failure	1.08E-02	6.65E-02	516
10	2- Making contact	no	1.37E-01	7.82E-01	473
11	1-Understand correctly	no	9.81E-03	5.58E-02	469
10	3-Understanding the interlocutor 1	no	1.95E-01	9.60E-01	393
11	2-Decision making	failure	1.45E-02	6.91E-02	377
36	1-Checks	failure	9.81E-03	3.71E-02	278
5	1-Detect a vessel in radar	no	3.93E-03	1.19E-02	203
6	1-Following established procedure	failure	5.07E-01	9.98E-01	97
23	3-Detection of error	no	9.88E-01	9.85E-01	0
29	6-Captain detects the error	no	9.97E-01	9.85E-01	-1
11	3-Detection of error	no	9.88E-01	9.70E-01	-2
10	5-Understanding the interlocutor 2	no	8.55E-01	5.54E-01	-35
10	4-Deciding to make contact by other means (visual Morse)	no	8.28E-01	2.59E-01	-69

4.3. Internal factors and skills analysis

The network formed by the integration of the hazardous events network, dynamic task networks, and performance factor networks has 263 nodes, representing 24 hazardous events (representing the same event sequences modeled in the FT), 40 activities, 12 MOFs and 187 skills and internal and environmental factors (see the Appendix). As a detailed analysis of each network condition (combination of node states) is not feasible, the PSF analysis (except for the MOFs, which will be addressed in the next section) was performed for the activities chosen from among those highlighted in the previous discussion.

The analysis of the basic events identified the most likely event sequences given evidence of a collision. Specifically, for the most likely sequence, the tasks that failed are (see Table 4):

- 6—Pattern Proceeding (COLREGs);
- 10—Communication;
- 23—Officer’s Order.

As presented in Section 4.2, the activities that make up these tasks can also be identified as the most error-prone. In Tables 11 and 12, these activities were discriminated (in bold) from the activities that have error probabilities greater than 10%, given evidence of a collision. Thus, for Task 6—Pattern Proceeding (COLREGs), we obtained the data presented in Table 13 without considering the collision evidence. In this case, the analysis of other discriminated tasks also disregards the collision evidence. This table presents inferences made for two probability types: (1) task-failure

probability, given the state of the PSF (skill or internal factor) and (2) the likelihood of a negative PSF state given task failure. The table also compares these probabilities with those presented by the nodes without such evidence; the Difference columns synthesize these data. As seen here, these columns present similar results for the same PSF. This similarity can be understood by analyzing the probabilities associated with the nodes in each circumstance and the method of calculating the data presented in the Difference columns. To illustrate, let us first consider

$$P(task|psf) = \frac{P(task|psf)}{P(psf)} \tag{10}$$

where task refers to the failure state of the task node, and psf refers to a negative state for any skill or internal factor node.

The calculation of the difference between the probability with and without PSF evidence was performed according to

$$Difference = \frac{P(task|psf) - P(task)}{P(task)} \tag{11}$$

which, considering Eq. (10), can be manipulated to generate Eq. (12):

$$Difference = \frac{P(task,psf)}{P(task)*P(psf)} - 1 \tag{12}$$

The procedure above can be repeated to check the probability of a negative PSF state given evidence of task failure. For this case, Eq. (13) can be applied, which employs the same variables as

Table 12
Activity probabilities given the previous activities.

Task	Activity	State	No collision evidence	Collision evidence	Increase (%)	Evidences of previous activities			
5	2-Detect a vessel visually	no	5.54E-02	4.34E-01	683	1-Detect a vessel by radar	no		
	3-Detect a vessel by alarm	no	2.89E-01	8.38E-01	190	2-Detect a vessel visually	no	1-Detect a vessel by radar	No
10	2- Making contact	no	6.86E-02	4.25E-01	519	1-Deciding to make contact by radio	yes		
	3-Understanding the interlocutor	no	6.73E-02	8.16E-01	1113	2- Making contact	yes		
	4-Deciding to make contact by other means (visual Morse)	no	6.51E-02	2.45E-01	276	2- Making contact	yes	3-Understanding the interlocutor	No
	5-Understanding the interlocutor	no	1.39E-01	2.25E-01	61	2- Making contact	no		
		no	2.18E-01	9.73E-01	346	2-Making contact	yes	4-Deciding to make contact by other means (visual Morse)	Yes
11	2-Decision making	failure	4.70E-03	1.40E-02	198	1-Understand correctly	yes		
	3-Detection of error	no	1.98E-02	1.40E-01	604	1-Understand correctly	yes	2-Decision making	Failure
		no	2.11E-01	6.59E-01	212	1-Understand correctly	no		
23	2-Decision making	failure	4.70E-03	8.85E-02	1783	1-Understand correctly	yes		
	3-Detection of error	no	1.98E-02	8.51E-01	4191	1-Understand correctly	yes	2-Decision making	Failure
		no	2.11E-01	9.85E-01	366	1-Understand correctly	no		
29	4-Reading of position	failure	9.60E-04	6.30E-03	556	3-Respect of the interval to mark	no		
	5-Marking the nautical chart	failure	7.93E-04	5.10E-03	544	4-Reading of position	success		
	6-Captain detects the error	no	5.23E-03	2.16E-01	4030	5-Marking the nautical chart	failure		
43	2-Reading information	failure	9.89E-04	4.12E-03	316	1-Realizing the publication	success		
	3-Establishment of minimum depth	failure	8.35E-04	3.51E-03	320	2-Reading information	success		
	4-Reading the depth in the nautical charter	failure	3.12E-04	1.30E-03	316	3-Establishment of minimum depth	success		
	5-Identify restricted area	failure	1.25E-04	5.19E-04	316	4-Reading the depth in the nautical charter	success		
	6-Drawing restricted area	failure	5.87E-04	2.58E-03	339	5-Identify restricted area	success		
	7-Drawing successive courses	failure	4.11E-04	1.81E-03	340	6-Drawing restricted area	success		
	8-Identify way-points	failure	2.87E-04	1.27E-03	340	7-Drawing successive courses	success		
	9-Choice reference points	failure	1.04E-03	3.45E-03	233	8-Identify way-points	success		
	10-Route revision NO	failure	5.02E-03	7.70E-03	53	9-Choice reference points	failure		
	11-Route revision (Captain)	failure	6.52E-03	1.94E-02	198	10-Route revision NO	failure		

Table 13
PSF analysis for task 6—Pattern Proceeding (COLREGs).

Task's probability of failure				Indicated state probability		
No evidence about the PSF			5.0722E-01			
With evidence of the indicated PSF state				No evidence of task failure	With evidence of task failure	Difference (%)
PSF	State	Probability	Difference (%)			
<i>Skills</i>				<i>Skills</i>		
Procedural knowledge 1	Poor	5.8089E-01	14.52	4.5888E-01	5.2553E-01	14.52
Perception 6	Low	5.8085E-01	14.52	4.5888E-01	5.2550E-01	14.52
Teamwork and communication 1	Poor	5.8085E-01	14.52	4.5888E-01	5.2549E-01	14.52
<i>Internal factors</i>				<i>Internal factors</i>		
Physical condition 3	Poor	5.2577E-01	3.66	3.4040E-01	3.5285E-01	3.66
Predisposition 1	Incipient	5.2574E-01	3.65	3.4040E-01	3.5283E-01	3.65
Quality of sleep 3	Poor	5.2574E-01	3.65	3.4040E-01	3.5283E-01	3.65
Threats (of failure, loss of job) 1	Demotivating	5.2552E-01	3.61	3.4040E-01	3.5268E-01	3.61
Knowledge of standards 2	Superficial	5.1975E-01	2.47	3.4040E-01	3.4880E-01	2.47
Personality and intelligence 2	Inadequate	5.1964E-01	2.45	3.4040E-01	3.4873E-01	2.45
State of current practice 2	Incipient	5.1959E-01	2.44	3.4040E-01	3.4870E-01	2.44

Note: The numbers accompanying the Internal factor description indicate different nodes in the integrated network (the same PSF can occur for different operators).

Eq. (10):

$$P(psf | task) = \frac{P(task,psf)}{P(task)} \tag{13}$$

The difference between the probability with and without evidence of task failure was calculated according to

$$Difference = \frac{P(psf | task) - P(psf)}{P(psf)} \tag{14}$$

which considering Eq. (13), can again be manipulated to produce the same result shown in Eq. (12).

Hereafter, the above proof will be used to support the assertion that if the calculation of the difference considers the probability of a PSF's state given evidence of a task (or activity) failure, the same result will be found as for the calculation that considers a task (or activity) failure probability given the state of a PSF.

The PSFs with major differences in Table 13 are critical, i.e., their improvement would lead to the largest gains in operational safety. In the case of skills, positive states instead of negative states would decrease the task failure probability by 23.42% for the three cases. In the case of the internal factor *Physical Condition* 3, for example, if the state *good* is observed instead of *poor*, the task failure probability falls by 5.35% to 4.98×10^{-1} . Fig. 13 illustrates the decreases obtained, given this and other internal factors from Table 8.

The data for each activity of Task 10—*Communication* are presented in Tables 14–18 [note that Task 6—*Pattern Proceeding (COLREGs)* consists of only one activity, and therefore needs just one table]. These tables present the inferences for the probability

of negative states of PSFs (skills and internal factors) given errors in activity execution (or the decision not to proceed with the communication). The tables also present a comparison between these probabilities and those derived from the nodes without such evidence; again, the *Difference* columns synthesize these data. In Tables 16 and 18, beyond the cited evidence, the second line of the first column presents further evidence related to the states of the previous activity nodes. This evidence was considered so that the analysis of the PSFs related to a particular activity required the execution of the activity (see Section 4.2).

The results presented in these tables were sorted according to the *Difference* column. Thus, the factors at the top of the table are the most critical in relation to the possibility of an activity-execution error. For example, Table 18 shows that the evidence for the state *poor* for the factor *Quality of sleep 2* is worse than the evidence for the state *poor* for the factor *Physical condition 2* because the probability of a negative state for the first factor increases four times more than that for the second factor based on evidence of an activity error (81.40% and 19.49%, respectively). Based on the considerations presented at the beginning of this

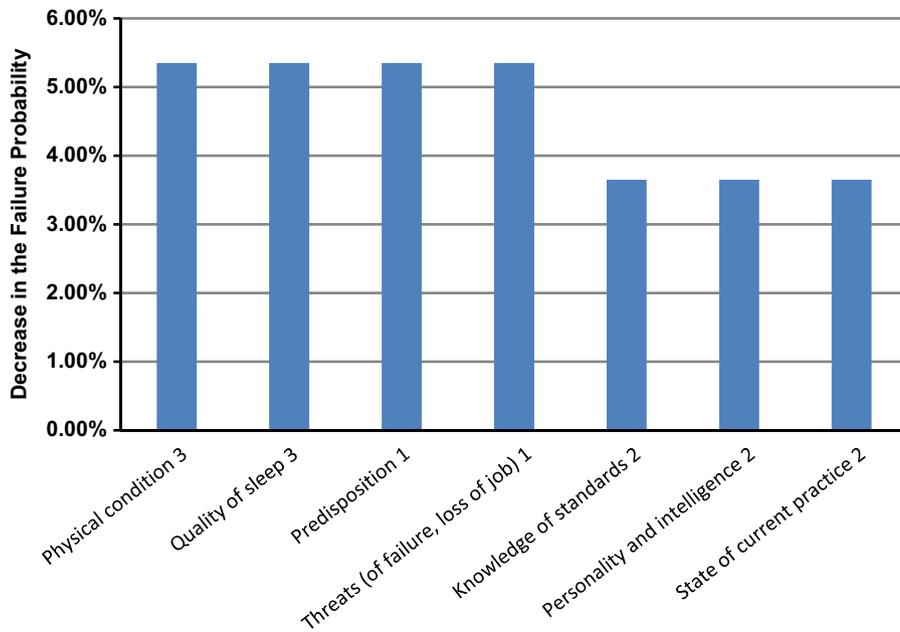


Fig.13. Decrease in failure probability.

Table 14
PSF analysis for activity 1-*Deciding to make contact by radio*.

1- <i>Deciding to make contact by radio</i>		Indicated state probability		
Probability of the state "no" given no evidence about the PSF	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
7.30E-02				
<i>Skills</i>				
Procedural knowledge	Poor	1.22E-01	4.25E-01	248.60
Interpretation	Slow	1.24E-01	4.29E-01	247.08
Teamwork and communication	Poor	1.19E-01	4.09E-01	242.20
<i>Internal factors</i>				
Personality and intelligence	Inadequate	9.80E-02	1.89E-01	93.12
Predisposition	Incipient	8.85E-02	1.54E-01	74.36
Threats (of failure, loss of job)	Demotivating	8.80E-02	1.50E-01	69.97
Knowledge of standards	Superficial	8.80E-02	1.35E-01	53.67
Motivation and attitudes	Low	8.80E-02	1.31E-01	49.15
Fatigue	Yes	9.80E-02	1.45E-01	48.44
State of current practice	Incipient	8.80E-02	1.29E-01	47.06

Table 15
PSF analysis for activity 2-Making contact.

2-Making contact		Indicated state probability		
Probability of the state “no” given no evidence about the PSF	1.37E–01			
PSF	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Teamwork and communication	Poor	1.19E–01	3.82E–01	220.22
Procedural knowledge 2	Poor	1.22E–01	2.70E–01	121.91
Concentration 2	Low	1.25E–01	2.75E–01	119.97
<i>Internal factors</i>				
Predisposition	Incipient	8.85E–02	1.48E–01	67.76
Threats (of failure, loss of job)	Demotivating	8.80E–02	1.44E–01	63.65
Quality of sleep 2	Poor	9.80E–02	1.37E–01	39.45
Distractions 2	Yes	9.80E–02	1.35E–01	37.61
Knowledge of standards 1	Superficial	8.80E–02	1.16E–01	31.29
Personality and intelligence 1	Inadequate	9.80E–02	1.28E–01	30.59
State of current practice 1	Incipient	8.80E–02	1.13E–01	28.61

Table 16
PSF analysis for activity 4-Deciding to make contact by other means (visual Morse).

4-Deciding to make contact by other means (visual Morse)		Indicated state probability		
Probability of the state “no” given no evidence about the PSF and the state “no” to “2-Making contact”	1.39E–01			
PSF	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Flexibility	Low	1.46E–01	3.43E–01	135.11
Interpretation	Slow	2.76E–01	5.57E–01	101.78
Procedural knowledge	Poor	2.74E–01	5.45E–01	98.92
<i>Internal factors</i>				
Personality and intelligence	Inadequate	1.47E–01	2.66E–01	81.18
Motivation and attitudes	Low	1.11E–01	1.73E–01	55.91
Fatigue	Yes	1.23E–01	1.63E–01	32.72
State of current practice	Incipient	1.13E–01	1.46E–01	28.82
Knowledge of standards	Superficial	1.16E–01	1.48E–01	27.70
Threats (of failure, loss of job)	Demotivating	1.44E–01	1.50E–01	3.81

Table 17
PSF analysis for activity 3-Understanding the interlocutor.

3-Understanding the interlocutor		Indicated state probability		
Probability of the state “no” given no evidence about the PSF	1.95E–01			
PSF	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Concentration 2	Low	1.25E–01	3.52E–01	181.99
Perception 7	Low	1.25E–01	2.85E–01	127.97
<i>Internal factors</i>				
Quality of sleep 2	Poor	9.80E–02	1.84E–01	87.46
Distractions 2	Yes	9.80E–02	1.52E–01	54.95
Physical condition 2	Poor	9.84E–02	1.37E–01	38.98

section, it can also be said that the probability of an activity error will increase by four times more in the first case than in the second, based on the evidence of a negative PSF state.

The procedure presented for Task 10—*Communication* was repeated for Task 23—*Officer Order*, which consists of three activities, and Tables 19–21 shows the results for each task. In this way, it is determined which PSFs have the greatest influence on the initially selected activities.

These results make it possible to outline the actions necessary to reduce the probability of the accident under study (collision). In the context of the steps set out in the HRA, this outline could be the starting point for Step 3—*Risk Control Options* [28].

As an illustration, we take the example of the internal factor *Sleep Quality*; this PSF often appears as the most impactful factor (or as one of the most impactful) in the error probability of the activities analyzed in Tables 13, 15, 17, 18, 19, and 21. Some

Table 18
PSF analysis for activity 5-Understanding the interlocutor.

5-Understanding the interlocutor		Indicated state probability		
Probability of the state "no" given no evidence about the PSF and the state "no" for 4-Deciding to make contact by other means (visual Morse) PSF	1.57E-01			
	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Perception 8	Low	1.60E-01	4.30E-01	169.74
Concentration 2	Low	3.65E-01	8.22E-01	125.12
<i>Environmental and internal factors</i>				
Quality of sleep 2	Poor	1.88E-01	3.40E-01	81.40
Distractions 2	Yes	1.55E-01	2.57E-01	66.36
Visibility 2	Low	1.50E-01	1.96E-01	30.33
Physical condition 2	Poor	1.37E-01	1.64E-01	19.49

Table 19
PSF analysis for activity 1-Understand correctly.

1-Understand correctly		Indicated state probability		
Probability of the state "no" given no evidence about the PSF	9.81E-03			
	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Concentration 5	Low	8.00E-03	2.69E-01	3261.63
Perception 10	Low	2.47E-02	7.80E-01	3055.41
<i>Environmental and internal factors</i>				
Quality of sleep 6	Poor	2.00E-02	2.36E-01	1077.80
Distractions 5	Yes	2.00E-02	1.59E-01	695.40
Physical condition 6	Poor	1.96E-02	1.10E-01	460.24
Visibility 4	Low	1.50E-01	6.58E-01	338.71

Table 20
PSF analysis for activity 2-Decision Making.

2-Decision making		Indicated state probability		
Probability of the state "no" given no evidence about the PSF	1.45E-02			
	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Interpretation 2	Low	7.83E-03	1.35E-01	1621.43
Flexibility 2	Low	7.81E-03	1.33E-01	1599.86
Planning 1	Inadequate	8.00E-03	1.32E-01	1545.38
<i>Internal factors</i>				
Personality and intelligence 4	Inadequate	2.00E-02	1.50E-01	648.80
Motivation and attitudes 2	Low	2.00E-02	1.09E-01	445.50
Fatigue 3	Yes	2.00E-02	7.78E-02	289.21
Predisposition 4	Incipient	2.00E-02	7.37E-02	268.27
Threats (of failure, loss of job) 4	Demotivating	2.00E-02	5.50E-02	174.90

alternatives to mitigate the impact of this factor could include: (1) improving the comfort of the crew accommodations, (2) tightening the rules on the rest period (setting a fixed period of required rest), and (3) developing an awareness program on the importance of sleep. It is noteworthy, however, that isolated actions generally produce isolated results. In the case of the activities examined in Table 21, for example, actions to increase sleep quality that also increase distractions do not have a null effect but only generate a small difference in the probability of an activity error. Thus, it would be best to consider actions to address all PSFs that stood out as potential problems in the analysis.

4.4. MOF analysis

Having established the network as shown in Fig. 11 and completed the CPTs, it was possible to discriminate the MOFs with the greatest influence on the probability of collision. This was accomplished by drawing a graph of the collision probability as a function of the MOFs. A curve was drawn for each MOF of the network to generate the graph in Fig. 14. Some curves in this figure are superimposed on others. The curves for "Performance evaluation" and "Organizational culture" are coincident, and the curves for "Formalization", "Company programs" and "Benefits" are visually coincident in this figure.

Table 21
PSF analysis for activity 3-Detection of error.

3-Detection of error		Indicated state probability		
Probability of the state “no” given no evidence about the PSF, the state “no” for 1-Understand correctly and “failure” for 2-Decision making	1.98E–02			
PSF	State	No evidence of activity failure	With evidence of activity failure	Difference (%)
<i>Skills</i>				
Concentration 5	Low	9.58E–03	1.09E–01	1032.48
Perception 10	Low	2.64E–02	2.86E–01	983.74
Teamwork and communication 4	Poor	6.31E–02	6.52E–01	933.48
<i>Environmental and internal factors</i>				
Quality of sleep 6	Poor	4.64E–02	1.44E–01	209.79
Distractions 5	Yes	1.86E–02	5.02E–02	169.57
Threats (of failure, loss of job) 4	Demotivating	1.29E–01	3.04E–01	136.04
Predisposition 4	Incipient	1.87E–01	4.34E–01	132.45
Visibility 4	Low	1.45E–01	2.65E–01	83.11
Physical condition 6	Poor	8.52E–02	1.31E–01	53.70

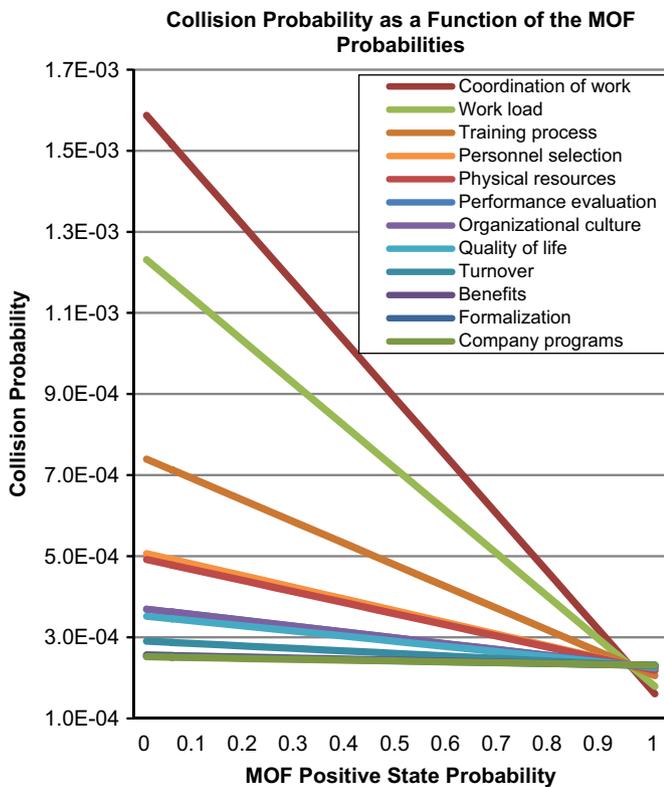


Fig. 14. Likelihood of collision as a function of MOF probability.

To obtain the data presented in this chart, the probabilities associated with the MOF states were varied for each MOF while keeping the probabilities of the remaining MOFs constant (95% for positive states, i.e., those that generate a reduction in the collision likelihood if their probabilities are increased, and 5% for the negative states).

From Fig. 14, Table 22 was created to list the most important MOFs in descending order. The criterion chosen was the probability of collision when the MOF had a low probability of a positive status (for “Performance evaluation” and “Organizational culture” the sorting was alphabetical because the curves were coincident).

The MOFs presented in the first positions are those that lead to the most significant gains in operational safety upon improvement, i.e., those that decrease the probability of collision

Table 22
MOFs ranked by importance.

1st	Coordination of work
2nd	Work load
3rd	Training process
4th	Personnel selection
5th	Physical resources
6th	Performance evaluation
7th	Organizational culture
8th	Quality of life
9th	Turnover
10th	Benefits
11th	Formalization
12th	Company programs

most. If ignored, these MOFs will make significant contributions to an increased collision hazard.

Another way to obtain the above list (Table 22) is to assume evidence of a collision and calculate the probabilities of the MOFs. This was performed with the modeled network and the values obtained are shown in Fig. 15, including the probabilities for both the negative and positive states (as MOFs were defined with only two states, their sum must be 1).

As shown in Fig. 15, the MOFs can be sorted in the same way as in Table 22. The MOFs with lower probabilities of positive states given evidence of a collision are also those that have the greatest effect on the probability of a collision obtained by the previous method (as expected, as the relationship between the probability of collision and the MOFs is linear, and the initial value assumed for each MOF was 95%).

An important finding is that when an MOF is related to a large number of internal factors in the network, due to the direct calculation of the probability of a negative event (a collision event, for example) for a given MOF, a large number of multiplication factors are influenced by the MOF state (due to the many dependencies embedded in the network). Consequently, if the state of the MOF is negative, the probabilities of the internal factors will appear more frequently in the calculation. For the modeled network, considering the order presented in Table 22, Fig. 16 was drawn to show the number of edges leaving each MOF.

Based on this figure, and supported by the discussion in the previous paragraphs, a relationship exists between the number of edges for each MOF and its influence on collision probability. Thus, immediately after the establishment of the network topology, it is already possible to obtain a qualitative idea of the most

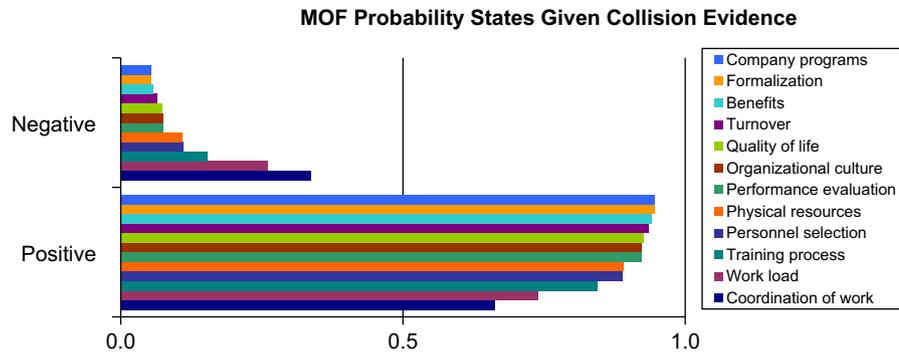


Fig. 15. MOF probability states given collision evidence.

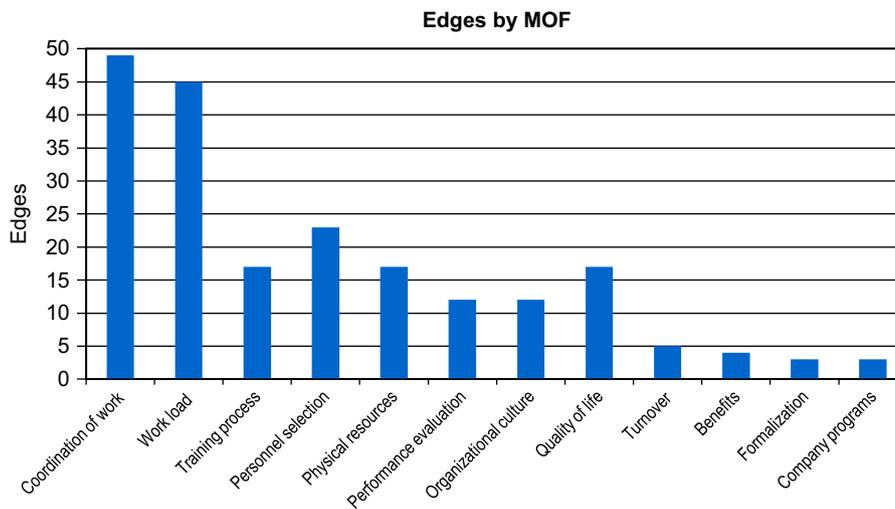


Fig. 16. Number of edges leaving each MOF.

important MOFs discriminated by the quantitative method presented above. These considerations enabled us to determine a group of MOFs with the greatest potential to reduce the probability of collision.

5. Conclusions and recommendations for future work

To explore the potential of BBNs as a tool in HRA, a method (based on existing techniques and on BBN characteristics) was proposed and used to model the human factor, which allowed the investigation of the practicalities involved in working with this tool. The case study was conducted in two stages: modeling of human factors related to the event of a tanker collision and analysis of this model to identify the critical factors for this event. The modeling was performed by applying the aforementioned methodology, considering the results presented in Martins and Maturana [26]. The integrated network obtained in the modeling step underwent a series of assumptions about the states of the factors, resulting in the discrimination of factors that should receive the greatest attention and resources for risk reduction.

Although the use of BBNs in FSAs and maritime applications is not new, the proposed methodology brings an approach that allowed the utilization of previous analysis data – performed by means of FT [26] – for further study of human factors initially considered only superficially. Thus, it enables to account the contribution of internal factors, skills, and MOFs in the collision event for different contexts identifying the most critical ones (see Sections 4.3 and 4.4). The methodology also allows for the

extraction of important information about the behavior of the system even in its qualitative step (e.g. MOFs most impacting the probability of collision).

The critical tasks discriminated by the proposed methodology were similar to those reported in a previous work [26]. However, unlike that work, PSFs (skills, internal and environmental factors) for specific tasks were studied in relation to their impact on the probability of an error. Thus, crew skills and personal characteristics that should be sought or trained for were identified. The tasks considered critical in the analysis included 6—*Pattern Proceeding (COLREGs)*, 10—*Communication*, and 23—*Officer Order*.

Additionally, it was possible to establish the priority with which MOFs must be improved for effective gains in operational safety and to identify MOFs that may be ignored without incurring large increases in the risk of collision. Among the MOFs analyzed, the three considered most critical for increasing the chances of an accident were the following: *Coordination of work*, *Work load* and *Training process*.

Modeling the PSFs in a general way and considering a generic model of relationships between human factors may have contributed to the neglect of important dependencies. Thus, to improve the results, a deeper evaluation of the PSFs should be conducted. Alternatively, the number of PSFs could be increased and the impact of modeling continuous variables as discrete variables could be studied.

Another point of potential improvement in this work is the representation of hazardous event sequences. In the modeling performed using the information provided by a FT, the temporal representation of these events is limited because the order of task

execution is not detected by the FT. Fig. 12 could be used as a starting point for this model.

Proposals for future work include a study of the platform-relief operation (offloading was not considered in this study). This activity may represent an ideal target for modeling because of the human element, the interaction between crews, the proximity of the units involved in the offloading procedure (vessel and platform), and the potential impact of collisions.

Appendix. Task integrated networks

This appendix presents the topology and CPTs of task dynamic networks integrated into the basic event (from the FT in Fig. 4) and performance factor networks.

It is important to emphasize that parents were not assumed for the basic events 34 and 41 in Fig. 4 (*No visual indication* and *Inaccurate information*, respectively). For this analysis, events were not designed tasks, and the values presented in the FT were adopted as prior probabilities associated with the nodes in the integrated model.

The events listed in Table 23 were not repeated in this Appendix. This table also presents reasons for its exclusion.

Table 23
Events not presented.

Event not presented	Similar event
23-Command Failure	Modeling identical to that of Event 11
25-Helmsman Failure	Modeling identical to that of Event 14
33-Nautical Officer Failure	Modeling identical to that of Event 32
39-Captain Verification Failure	Modeling identical to that of Event 32

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at <http://dx.doi.org/10.1016/j.res.2012.09.008>.

References

- [1] Mohadarras M, Kaminsky M, Krivtsov V. Reliability engineering and risk analysis: a practical guide. 2nd ed. CRC Press; 2010.
- [2] International Maritime Organization (IMO). Guidelines for Formal Safety Assessment (FSA) for use in the IMO Rule-Making Process. MEPC/Circ. 392; 2002. <<http://www.safedor.org/resources/1023-MEPC392.pdf>>.
- [3] Martins MR, Goyano F. Preliminary hazard analysis of fire systems of tankers. In: Proceedings of 17th international offshore and polar engineering conference; 2007. p. 3669–76. <<http://www.isope.org/publications/proceedings/ISOPE/ISOPE%202007/papers/I07JSC-202mart.pdf>>.
- [4] Martins MR, Maturana MC. The application of the Bayesian networks in the human reliability analysis. 2009 ASME International Mechanical Engineering Congress and Exposition, IMECE2009, vol. 13, November 13–19; 2009. p. 341–8. 10.1115/IMECE2009-13308.
- [5] International Atomic Energy Agency (IAEA). Procedures for conducting probabilistic safety assessment of nuclear power plants (Level 2): accident progression, containment analysis and estimation of accident source terms. Safety series, no. 50-P-8. Vienna: International Atomic Energy Agency; 1995.
- [6] International Atomic Energy Agency (IAEA). Procedures for conducting probabilistic safety assessment of nuclear power plants (Level 1): a safety practice. Safety series, no. 50-P-4. Vienna: International Atomic Energy Agency; 1992.
- [7] Gertman I, Blackman S. Human reliability analysis and safety analysis data handbook. New York: John Wiley & Sons, Inc.; 1993.
- [8] Hollnagel E. Human reliability assessment in context. Nuclear Engineering and Technology 2005;37(2):159–66.
- [9] Droguett E, Menézes R. Human analysis through Bayesian networks: an application in maintenance of transmission lines. Production 2007;17(1):162–85. <http://dx.doi.org/10.1590/S0103-65132007000100012>.
- [10] Eleye-Datubo A, Wall A, Wang J. Marine and offshore safety assessment by incorporative risk modeling in a Fuzzy-Bayesian network of an induced mass assignment paradigm. Risk Analysis 2008;28(1):95–112. <http://dx.doi.org/10.1111/j.1539-6924.2008.01004.x>.
- [11] Mohaghegh Z, Mosleh A. A causal modeling framework for assessing organizational factors and their impacts on safety performance. In: Proceedings of the eighth international conference PSAM; 2006. <http://dx.doi.org/10.1115/1.802442.paper271>.
- [12] Wang YF, Xie M, Ng KM. An extended quantitative risk analysis model by incorporating human and organizational factors. 2011 IEEE International Conference on Quality and Reliability (ICQR), 12–17 September, 2011; p 361–5. <http://dx.doi.org/10.1109/ICQR.2011.6031742>.
- [13] Charniak E. Bayesian network without tears. AI Magazine, 1991; 12:50–63. <http://dx.doi.org/10.1609/aimag.v12i4.918>.
- [14] Aven T, Kvaløy JT. Implementing the Bayesian paradigm in risk analysis. Reliability Engineering and System Safety 2002;78(2):195–201. [http://dx.doi.org/10.1016/S0951-8320\(02\)00161-8](http://dx.doi.org/10.1016/S0951-8320(02)00161-8).
- [15] International Maritime Organization (IMO). Consideration on utilization of Bayesian network at step 3 of FSA. Submitted by Japan, MSC 81/18/1, February 7, 2006. <http://legacy.sname.org/committees/tech_ops/O44/imo/msc/81-18-1.pdf>.
- [16] International Maritime Organization (IMO). Passenger ship safety: effective voyage planning for passenger ships. FSA – large passenger ships – navigational safety. Submitted by Norway, NAV 51/10; 2005. <<http://research.dnv.com/skj/FSA/PS/NAV51-10.pdf>>.
- [17] International Maritime Organization (IMO). FSA study on ECDIS/ENCs: details on risk assessments and cost benefit assessments. Submitted by Denmark and Norway, MSC 81/24/5; February 6, 2006. <<http://research.dnv.com/skj/fsa-eccis/MS81-24-INF-9-DK-N-ECDIS.pdf>>.
- [18] Vanem E, Antão P, Østvik I, Comas FDC. Analysing the risk of LNG carrier operations. Reliability Engineering and System Safety 2008;93(9):1328–44. <http://dx.doi.org/10.1016/j.res.2007.07.007>.
- [19] Vanem E, Endresen Ø, Skjong R. Cost-effectiveness criteria for marine oil spill preventive measures. Reliability Engineering and System Safety 2008;93(9):1354–68. <http://dx.doi.org/10.1016/j.res.2007.07.008>.
- [20] Vanem E, Gravr G, Eide MS. Effect of ENC coverage on ECDIS risk reduction. DNV Report no. 2007-0304, Det Norske Veritas; 2007. <<http://research.dnv.com/skj/FSA-ENC/ENC.pdf>>.
- [21] Vanem E, Eide MS, Skjong R, Gravr G, Lepsøe A. Worldwide and route-specific coverage of Electronic Navigational Charts. International Journal on Marine Navigation and Safety of Sea Transportation, Transnav 2007;1(2):163–9.
- [22] Trucco P, Cagno E, Ruggeri F, Grande OA. Bayesian belief network modeling of organizational factors in risk analysis: a case study in maritime transportation. Reliability Engineering and System Safety 2008;93(6):845–56. <http://dx.doi.org/10.1016/j.res.2007.03.035>.
- [23] Lampis M, Andrews JD. Bayesian belief networks for system fault diagnostics. Quality and Reliability Engineering International 2008;93(4):409–26. <http://dx.doi.org/10.1002/qre.978>. 10.1002/qre.978.
- [24] Martins MR, Silva DF, Maruyama FM, Loriggio FF, Pedro MF, Varela M. The Bayesian networks applied to a steering gear system fault diagnostics. In: Proceedings of the 29th international conference on Ocean, Offshore and Arctic Engineering, OMAE2010, vol. 2, June 6–11, 2010; p. 639–45. <http://dx.doi.org/10.1115/OMAE2010-20914>.
- [25] Bobbio A, Portinale L, Minichino M, Ciancamerla E. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. Reliability Engineering and System Safety 2001;71:249–60. [http://dx.doi.org/10.1016/S0951-8320\(00\)00077-6](http://dx.doi.org/10.1016/S0951-8320(00)00077-6).
- [26] Martins MR, Maturana MC. Human error contribution in collision and grounding of oil tankers. Risk Analysis 2010;30:674–98. <http://dx.doi.org/10.1111/j.1539-6924.2010.01392.x>.
- [27] Swain A, Guttman H. Handbook of human reliability analysis with emphasis on nuclear power plant applications. Albuquerque: Sandia National Laboratories; 1983 NUREG/CR-1278, USNRC.
- [28] Martins MR, Maturana MC. Application of Bayesian networks in the analysis of human contribution in collision accidents. In: Proceedings of the ASME 28th international conference on Ocean, Offshore and Arctic Engineering, OMAE2009, vol. 2; 2009. p. 321–9. <http://dx.doi.org/10.1115/OMAE2009-79387>.
- [29] Amrozowicz MD, Brown A, Golay M. A probabilistic analysis of tanker groundings. In: Proceedings of the 7th International Offshore and Polar Engineering Conference, ISOPE, vol. 4; 1997. p. 313–20. <<http://www.dept.aoe.vt.edu/~brown/Papers/ISOPE97aPaper.pdf>>.
- [30] Brown A, Amrozowicz M. Tanker environmental risk—putting the pieces together. Joint SNAME/SNAJ conference on designs and methodologies for collision and grounding protection of ships; 1996. <<http://www.dept.aoe.vt.edu/~brown/Papers/C&G1Paper97.pdf>>.
- [31] Brown A, Haugene B. Assessing the impact of management and organizational factors on the risk of tanker grounding. In: Proceedings of the 8th International Offshore and Polar Engineering Conference, ISOPE, vol. IV; 1998. p. 469–76. <<http://www.dept.aoe.vt.edu/~brown/Papers/ISOPE98Paper.pdf>>.
- [32] Bigano A, Sheehan P. Assessing the risk of oil spills in the Mediterranean: the case of the route from the Black Sea to Italy. Fondazione Eni Enrico Mattei, FEEM working paper no. 32.2006; 2006. <http://dx.doi.org/10.2139/ssrn.886715>.
- [33] Rawson C, Crake K, Brown A. Assessing the environmental performance of tankers in accidental grounding and collision. SNAME Transactions 1998;106:41–58.
- [34] Hänninen M, Kujala P. The effects of causation probability on the ship collision statistics in the Gulf of Finland. International Journal on Marine Navigation and Safety of Sea Transportation, Transnav 2010;4(1):79–84.
- [35] Webb RDG, Lamoureux TM. Human reliability and ship stability. Toronto, Canada: Department of National Defense; 2003 July 4.