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A Bayesian Network approach to the crew error assessment on board a nuclear-powered submarine

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ABSTRACT

This paper addresses Bayesian Network (BN) to propose a way to assess crew error on board a nuclear-powered submarine. Then it summarizes the diesel-electric submarine crew opinions in of a fire event when the submarine is sailing in depth. Assessment relies on crew opinion for estimating the human error probabilities. In such cases, the crew opinions are used to reflect their knowledge and they are used as input data in BNs.

Considering complex nature of a human action on board a submarine the crew opinions with regarding Routine, Workload and Performance Shaping Factors (PSFs) were used to build BNs and their answers were graphed. Subsequently, the human error probability was analyzed. Questionnaires were answered by two diesel-electric submarine crew and their answers can be useful to emphasize the need to have well-established procedures on board a nuclear-powered submarine.

In general the lessons learned from crew opinions in this study can include helpful information to establish specific recommendations for improving guidance, practice and methods to assess human error on board a nuclear-powered submarine. Subsequently the results will be able to assist in the submarine's overall risk analysis.

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I. INTRODUCTION

Given an accident on board a nuclear-powered submarine the crew intervention is one of the most important factors to mitigate its consequences. The crew plays a crucial role to mitigate the consequences of the events and to meet the safety objective of the ship [1], however, operations on board a nuclear-powered submarine for a long time can be complicated and hazardous because of extreme operating conditions and long submerged periods which the crew is submitted. Therefore, it is essential to estimate the Human Error Probability (HEP) associated with crew actions and decisions in response to accidents on board a nuclear-powered submarine. Nowadays, there are numerous Human Reliability Analysis (HRA) methods available that provide guidance for determining the human error probability and they emphasize combinations of Performance Shaping Factors (PSFs), plant conditions, and situational factors function together as a major determinant of mistakes [2,3]. PSFs are factors that influence human reliability through their effects on performance such as teamwork, skill level, communication demands, procedures, training and environmental conditions [4,5].

On board a nuclear-powered submarine, human error assessment can pose a major challenge since the seriousness of the accident is determined according to the availability of the safety systems of the ship and the impact on the crew's safety. The most common cases of nuclear ship accidents are collisions, problems with the nuclear power plant, groundings, fires and explosions, however, there is in the literature examples of which the reason for the accident was a human error of the crew, including disregard for safety measures, regulations and instructions, physical and psychological overload [6,7,8]. Human error is one of the main causes of accidents in nuclear power plant, as in the cases of TMI and Chernobyl [9]. Thus, predicting and taking necessary precautions are necessary to avoid human error on board a nuclear-powered submarine.

In the last years a lot of research has been conducted to improve HRA methods, among them techniques such as A Technique for Human Event Analysis (ATHEANA), the ATHEANA method makes use of Human Failure Events (HFEs) that represent actions or decisions represented in the Probabilistic Risk Assessment (PRA) event tree, and unsafe acts that are modelled in fault trees [10], Accident Sequence Evaluation Program (ASEP), developed to provide an efficient method for estimation of screening HEPs for pre- and post-accident human actions [11], Cognitive Reliability and Error Analysis Method (CREAM), human performance classification based on error modes and consequences (phenotypes) and causes (genotypes) [12], Human Error Analysis and Reduction Technique (HEART), HRA based on nine generic tasks with individual nominal error rates [13], Technique for Human Error Rate Prediction (THERP), developed to provide representational modelling of human actions (HRA Event Trees) and estimation of HEPs [14], Systematic Human Action Reliability Procedure (SHARP1), addresses pre- and post initiator conditions [15].

Recently Bayesian Network (BN) has been widely used as a HRA technique for many industrial sectors, with different levels of complexity where system safety and reliability assessment relies on historical data or experts opinion. Abrishami et al. [16] proposed a new model, so-called BN-SLIM, for improving the performance of Success Likelihood Index Model (SLIM) using BN. The BN-SLIM was developed by mapping SLIM in BN so that the causal links between PSFs and human errors as well as the dependencies among human errors could be modelled. Taleb-Berrouane et al. [17] introduced the Bayesian Stochastic Petri Nets (BSPN) as an innovative modelling tool that combines the concepts of BN and Stochastic Petri nets (SPN) in an interactive way. Tang et al. [18] compare and analyses how accurately the BN structure can be derived given a large and highly variable dataset. Between methods tested to derive the BN structure with the given data there is a guided method utilising literature and expert knowledge. Akhtar and Utne [19] focus on human fatigue and propose an approach to construct a BN for maritime accidents. Sotiralis et al. [20] proposed an approach based on the development of a BN to incorporate human factor considerations into quantitative risk analysis of ship operation. On the other hand, researches has been done to developing an empirically-based understanding of the performance, strengths, and weaknesses of HRA methods by comparing HRA method predictions against actual operator performance in simulated accident scenarios on nuclear power plant (NPP) simulators [21,22,23].

This paper aims identifying contributions of human error, including crew response times, workload, routine and PSFs, and analysing how a crew would responds to an accident on board a nuclear-powered submarine. From the crew opinion BN has been proposed to achieve this goal.

The paper has been organized as follows: section 2 will provide a brief discussion on Bayesian Network and Conditional Probability Table. The proposed methodology will be discussed in Section 3. Findings will be reflected in Section 4. The general discussion will be summarized in Section 5.

II. BAYESIAN NETWORK (BN)

2.1 BN and Bayes' Theorem

A BN is a probabilistic graphical model representing a set of random variables and their conditional dependencies via a Directed Acyclic Graph (DAG) [24,25,26,27] composed of nodes and arcs. The nodes display random variables with various states, and the arcs represent the cause and effect relationships between the nodes among the participating parameters of an event [28,29]. The node from which an arc is generated is called a parent node, and a child node is a node to which the arc is directed, moreover, no arc can come back from a child to a parent node [30,31].

In mathematical terms a BN can expressed from the Bayes' Theorem. Thus let be P(A) and P(B) the probability of occurrence of event A and B, respectively, and P(B|A) is the probability of event B conditional on event A. The probability of occurrence of a posterior event A given the observed probability of a prior event B is determined by

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{1}$$

In the context of a crew on board a nuclear-powered submarine the events can be in the form of observation of HEP.

2.2 Conditional Probability Table (CPT)

For BN modelling the Netica software is frequently used [32]. The BNs presented in this paper are generated using Netica Version 5.24 [33]. Netica needs three pieces of information to build a Conditional Probability Table (CPT) from an equation for a child node: (1) Assigned state values for each state of the parent

nodes, (2) an equation to be used for the respective child node, and (3) assigned discretization intervals for each state of the child node [34].
CPTs quantify the conditional dependency of a child node given all possible combinations of the states of its parent nodes [16], however, sometimes can be used to refer to the deterministic function table of a node [33,34].

III. METHODOLOGY

3.1 Methodology development

The methodology proposed begun with investigation about crew opinion regarding human intervention on board Brazilian submarines due a fire event. Questionnaires were used to gather information about the crew routines. In total 67 crew members contributed to aim the goal. In a similar way to Bohlin and Olofsson [35], the result shows that many crew members have never experienced a fire on board but they are well familiar with the routines since they regularly have drills on board and they are very well trained.
The proposed methodology is comprised of the four following steps:
Step 1: share questionnaires with the submarine crew. This may help in identify the hazards as well as the most likely human action.
Step 2: Analyze crew answers. This allows a statistical treatment and graphical representation.
Step 3: Construct a BN. In this step must be constructed a BN and, furthermore, build a CPT for each child node to be analyzed.
Step 4: Identify the HEP. This will allows making-decision based on accident situations.

3.1.1 Step 1-Questionnaires

Questionnaires were used to gather information regarding the crew routines, workload, training, fire, and crew action on board a submarine. To validate the survey the questionnaires were distributed among 67 crew members from Brazilian Navy. The goal of the questionnaires was to try the survey on someone with experience from diesel-electric submarines and to understand how their answers could add to assessment human error probability on board a nuclear-powered submarine.

3.1.2 Step 2-Crew opinions

The second step is characterized by graphical representations based on crew answers. The graphics were grouped into four representations to give structure to the survey. The graphics are based on questions and answers regarding background information: workload, routine, PSF and fire fighting time. In the graphics are inputs just the options answered by crew members.
For workload it was proposed four options of classification: below normal, normal, above normal and excessive. However, no crew member has indicated the classification below normal and the crew opinions on this topic is shown in Fig. 1.

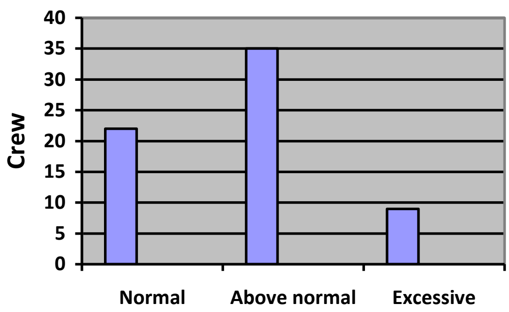

Fig. 1. Workload based on crew opinions.

In a similar way, it was proposed four options of classification for crew routine on board a submarine in a mission beyond 30 days. The options were: normal, little stressful, stressful and very stressful. The Fig. 2 shows the crew opinions on this item.

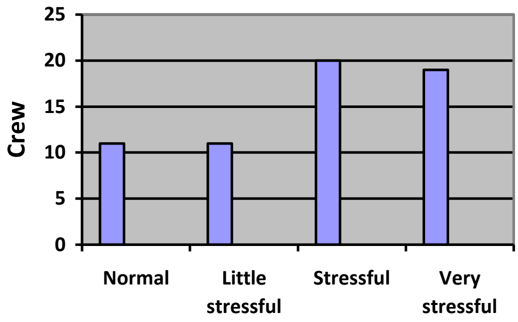

Fig. 2. Routine based on crew opinions.

It is noteworthy to mention that in this case the mission days on board a submarine are upper those on board a diesel-electric submarine thus the crew opinions on this topic can be useful as return of experience to a first on board nuclear-powered submarine crew.

It was asked to crew about the most contributing factors to crew error on board a submarine when it is sailing in depth and a fire occurs. Five options were provided: fatigue, sleepiness, untrained, stress and military hierarchy. The crew answers are shown in Fig. 3.

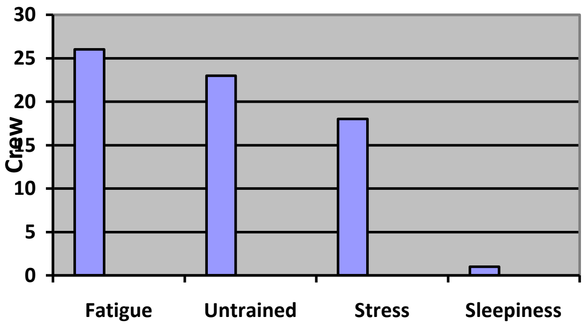

Fig. 3. PSFs based on crew opinions.

The information obtained from crew opinions were used to build the BN and CPT in this work.

3.1.2.1 Questionnaire about fire

The aim of the questionnaires about fire was to understand how the crew is trained to fire fighting on board a diesel-electric submarine and how their answers can be useful for a nuclear-powered submarine crew.

Regarding nuclear-powered submarine opinion some questions were made as detailed following.

Question 1: Crew were asked to rate the fire fighting training level as excellent, very good, good, bad or very poor. No crew member answered the option bad or very poor and the others classified it as excellent, very good or good. Their answers are shown in Fig. 4.

Fig. 4. Fire fighting training level.

Question 2: Regarding fire fighting training two questions were done:

a) What is the fire fighting training frequency on a board diesel-electric submarine?

b) Should the fire fighting training frequency on board diesel-electric submarine be equal on board a nuclear-powered submarine?
The crew answers are shown in Fig. 5.

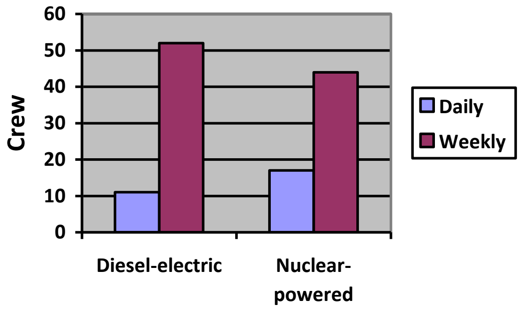

Fig. 5. Fire fighting training frequency on board a submarine.

Question 3: On board a nuclear-powered submarine the fire fighting action should be primarily based on rules / procedures, skills or knowledge?
The crew answers are shown in Fig. 6.

Fig. 6. Fire fighting action.

Question 4: Should the procedures used to fire fighting on board a diesel-electric submarine be the same on board a nuclear-powered submarine?
The crew answers are shown in Fig. 7.

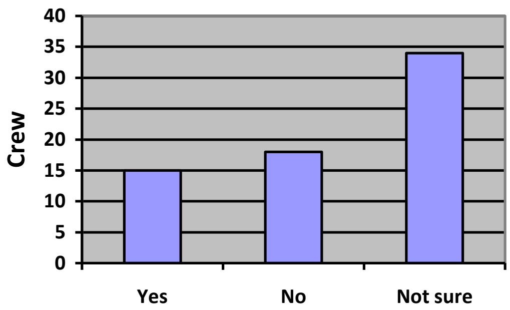

Fig. 7. Crew opinion about the procedures.

Question 5: Suppose an inexperienced crew navigates on board nuclear-powered submarine in a 90-day mission. Under these conditions, given the occurrence of an onboard fire when the submarine is sailing in depth, a question about the most likely crew action were made and their answers are shown in Fig. 8. The options are:

I. The crew has high chance of fire fighting correctly;
II. The crew will fire-fight correctly;
III. The crew has high chance of not following procedures; and
IV. The crew has low chance of following procedures.

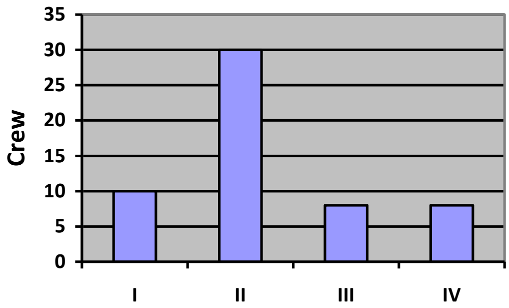

Fig. 8. Fire fighting training level.

It was asked about fire fighting time on board a submarine when it is sailing in depth. The range time proposed was from 0 up to 10 min. The options were: 0 < 1 min, 1 min ≤ t < 2 min, 2 min ≤ t < 5 min, 5 min ≤ t < 10 min and t > 10 min. No crew member answered the option t > 10 min. The crew answers are shown in Fig. 9.

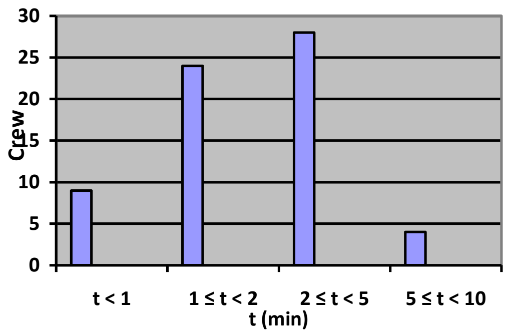

Fig. 9. Fire fighting time based on crew opinions**.**

3.1.3 Step 3-BN and CPT

In the third step was constructed a BN and its CPT was built. The aim of the BN is to assess HEP in situations routine, workload and PSF.

Once obtained the crew response in a way quantitative their answers were converted in percent by using Rule of Three and in following inserted as input data in BN. Table 1 shows the values input in the Bayesian Networks.

Table 1: Input data to BNs.

Node	Value (%)
Routine	
Normal	18
Little stressful	18
Stressful	33
Very stressful	31
Workload	
Normal	33
Above normal	53
Excessive	14
PSF	
Fatigue	38
Untrained	34
Stress	26
Sleepiness	2

In a BN variables can be either continuous or discrete. In many cases discrete variables are described by a limited number of discrete states [34,36].

For each child node a CPT was defined. In a BN, a CPT expresses the probability for the states of a child node, given the states of its parent nodes [34]. In this context, based on crew opinions regarding routine, workload and PSF, a BN, Fig. 10, was built to assess HEP on board a submarine.

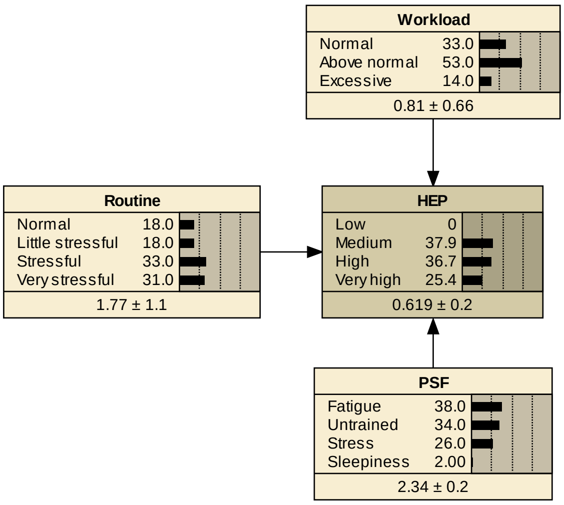

Fig. 10. BN structure based on expert opinions.

In Fig. 10 the node HEP has four states to represent its probabilities. Values between 0 and 1 were converted in to conditional probabilities values. The conversion was rated in accord of the number of states for the node HEP. The range rated is depicted in Table 2.

Table 2 Classification interval of node HEP.

HEP	Low (L)	Medium (M)	High (H)	Very High (VH)
Interval	0 – 0.25	0.26 – 0.5	0.56 – 0.75	0.76 – 1

With 0 being the lowest and 1 being the highest permitted value, the ranges are represented by Low (L: 0 – 0.25), Medium (M: 0.26 – 0.50), High (H: 0.56 – 0.75) and Very High (VH: 0.76 – 1.0).
The weighting factors of experts are calculated according to their answers. PSFs' weights were obtained by crew opinions based on weight of the scores proposed in the questionnaires where they have range from 0 up to 4. Table 8 indicates the weights inserted by crew opinions.
Thus, let be F = Fatigue, U = Untrained, S = Stress and Sl = Sleepiness. PSFs' weights in according to crew opinions were obtained using the equation

$$\overline{W} = \frac{\sum PSF_i}{n} \tag{2}$$

Where n is total crew-provided answers and $\overline{W}$ is the average of weight factor of PSF_i. Table 3 shows weight factors of each PSF in according to crew opinions. Rating assumed for weights of the events was adapted from SPAR-H Method Rating [2] and NUREG/CR-6949 [37].To better explain data in Table 3, consider the Sl variable in Table 8, thus Sl = (2+4)/2 = 3 and so on for F, S and U, respectively.

Table 3: Weight factor of PSF_i

Fatigue (F)	Untrained (U)	Stress (S)	Sleepiness (Sl)
2.24	2.19	2.62	3

For parent nodes Routine and Workload the assigned state values for each state are shown in Table 4.

Table 4: Weight factor of parent nodes Routine and Workload

Routine	Weight	Workload	Weight
Normal	0	Normal	0
Little stressful	1	Above normal	1
Stressful	2	Excessive	2
Very stressful	3	---	---

To build the CPT of node HEP, Fig. 10, an equation is entered and expressed by

$$HEP(R,W,PSF) = \frac{(R+W+PSF)}{8} \qquad (3)$$

where R is the Routine and W is the Workload.
To convert each calculated ratio from the Eq. (3) into discrete states, node HEP needs assigned discretization intervals between 0-1 for each state. In Fig. 10, the discretization values between 0 and 1 are shown in Table 2 for node HEP.
In a similar way to [34], this equation divides the sum of the state numbers of each state by the sum of the maximum state numbers. This way, the result lies between 0-1. In the BN, Fig. 10, the sum of the maximum state numbers is 8 (Sleepiness = 3 + Very stressful = 3 + Workload = 2).

3.1.4 Step 4-HEP

In Netica software the CPT is a table that has one probability for every possible combination of parent and child states. Nevertheless function table allows only a single output value for each possible set of parent values as shown in Table 5 for the BN in Fig. 10.

Table 5: Conditional Probability Table (CPT)

Routine	Workload	PSF	HEP
Normal	Normal	Fatigue	0.28
Normal	Normal	Untrained	0.27375
Normal	Normal	Stress	0.3275
Normal	Normal	Sleepiness	0.375
Normal	Above normal	Fatigue	0.405
Normal	Above normal	Untrained	0.39875
Normal	Above normal	Stress	0.4525
Normal	Above normal	Sleepiness	0.5
Normal	Excessive	Fatigue	0.53
Normal	Excessive	Untrained	0.52375
Normal	Excessive	Stress	0.5775
Normal	Excessive	Sleepiness	0.625
Little stressful	Normal	Fatigue	0.405
Little stressful	Normal	Untrained	0.39875
Little stressful	Normal	Stress	0.4525
Little stressful	Normal	Sleepiness	0.5
Little stressful	Above normal	Fatigue	0.53
Little stressful	Above normal	Untrained	0.52375
Little stressful	Above normal	Stress	0.5775
Little stressful	Above normal	Sleepiness	0.625
Little stressful	Excessive	Fatigue	0.655
Little stressful	Excessive	Untrained	0.64875
Little stressful	Excessive	Stress	0.7025
Little stressful	Excessive	Sleepiness	0.75
Stressful	Normal	Fatigue	0.53
Stressful	Normal	Untrained	0.52375
Stressful	Normal	Stress	0.5775
Stressful	Normal	Sleepiness	0.625
Stressful	Above normal	Fatigue	0.655
Stressful	Above normal	Untrained	0.64875
Stressful	Above normal	Stress	0.7025
Stressful	Above normal	Sleepiness	0.75
Stressful	Excessive	Fatigue	0.78
Stressful	Excessive	Untrained	0.77375
Stressful	Excessive	Stress	0.8275
Stressful	Excessive	Sleepiness	0.875
Very stressful	Normal	Fatigue	0.655
Very stressful	Normal	Untrained	0.64875
Very stressful	Normal	Stress	0.7025
Very stressful	Normal	Sleepiness	0.75
Very stressful	Above normal	Fatigue	0.78
Very stressful	Above normal	Untrained	0.77375
Very stressful	Above normal	Stress	0.8275
Very stressful	Above normal	Sleepiness	0.875
Very stressful	Excessive	Fatigue	0.905
Very stressful	Excessive	Untrained	0.89875
Very stressful	Excessive	Stress	0.9525
Very stressful	Excessive	Sleepiness	1

The SPAR-H method [2,3], calculates HEP using the equation

$$HEP = \frac{NHEP \times PSF_{Composite}}{NHEP \times (PSF_{Composite} - 1) + 1} \qquad (4)$$

where NHEP is the nominal HEP and $PSF_{Composite}$ is the composite PSF. The composite PSF is calculated as the product of the analysts ratings of all PSFs contained on the
SPAR-H worksheet [2].
For purposes of this work suppose that NHEP is equal to HEP from Table 5 and from now called HEP_{CPT}, thus the equation 4 can be rewritten as

$$HEP = \frac{HEP_{CPT} \times PSF_{Composite}}{HEP_{CPT} \times (PSF_{Composite} - 1) + 1} \qquad (5)$$

from Table 3

$PSF_{Composite} = 2.24 \times 2.19 \times 2.62 \times 3 = 38.56$

Considering only HEP values greater than or equal to 0.8, the HEP_{CPT} and HEP are listed in Table 6.

Table 6: Human Error Probability

Routine	Workload	PSF	HEP_{CPT}	HEP
Stressful	Excessive	Stress	0.8275	0.994623
Stressful	Excessive	Sleepiness	0.875	0.996309
Very stressful	Above normal	Stress	0.8275	0.994623
Very stressful	Above normal	Sleepiness	0.875	0.996309
Very stressful	Excessive	Fatigue	0.905	0.997285
Very stressful	Excessive	Untrained	0.89875	0.997087
Very stressful	Excessive	Stress	0.9525	0.998708
Very stressful	Excessive	Sleepiness	1	1

IV. DISCUSSIONS

4.1Crew response

Based on the crew responses graphed in Section 3 of this paper, some questions can be debated as will be seen in this section.

For the workload, four response options were provided, however, the crew members who answered the question did not indicate the below normal option. In addition, as can be seen from Fig. 1, the most crew responded that the workload on board a submarine can be considered as above normal. The above normal item was assigned weight 1 and this value was used to build the BNs shown in this work.

Regarding the onboard routine the crew's responses are shown in Fig. 2. Four options have been proposed and most of the crew rated it stressful. However, situations that increase the risk of error are those situations that are presented in Table 6.

On the other hand, when asked about the factors that contribute to the error on board a submarine five options were proposed among them the military hierarchy option. However, no crew member opted for this response and indicated that sleepiness is the least contributing factor to error as fatigue contributes the most.

Subsequently, the crew was asked about the time required for on board fire fighting when the submarine is sailing in depth and how crew members classify their fire fighting training. Most indicated that the average fire fighting time on board is between 2 min and 5 min as shown in Fig. 9. In this context, based on the graph, it can be concluded that if the fire is not extinguished within 10 min it will cause risk of loss of the submarine and crew. In face of this, for countries that already have or are developing submarines whether diesel-electric or nuclear, it is suggested to implement effective fire fighting measures within a maximum of 5 min, even if the crew has excellent training as shown in Fig. 4.

The crew members who answered the questionnaires are submariners from Brazilian Navy. Regarding how often have their fire training on board a submarine been asked if they think it should be the same as a nuclear-powered submarine. Their responses are shown graphically in Fig. 5 Most of the crew indicated that there is a need for weekly training as is done on the diesel-electric submarine. In addition, they indicated that fire combat actions should be based on rules, Fig. 6. Therefore, fire-fighting manuals and procedures should be clearly established on board a nuclear-powered submarine.

In according to the interview responses the crew are not sure whether the same procedures used on board a diesel-electric submarine should be followed by a nuclear-powered submarine crew, Fig. 7. Besides, based on the crew members who answered the questionnaires, the crew is well trained and even if one crew member is inexperienced when he is on board a nuclear-powered submarine for the first time will have a high chance of following the procedures and fighting the fire in a way correct.

A BN was created to assess the probability of crew error according to crew member opinion. Thus, after building and compiling the BN it was possible to build the CPT and analyze the situations that most contribute to the error on board a submarine. In Table 5 it is possible see that combination of Routine = Very stressful + Workload = Excessive + PSF = Sleepiness = 1 it is the worst situation to lead to the biggest error presented in the table. Therefore, the need for a well-trained crew capable of following the established procedures properly in the time necessary to prevent the propagation of the damage when the submarine is submerged.

4.3 Human Error Probability

The Bayes'rule, Eq. 1, can be used to recalculate all probability distributions after the probability of a state in one node is set to 100% [27,34], Figure 11.

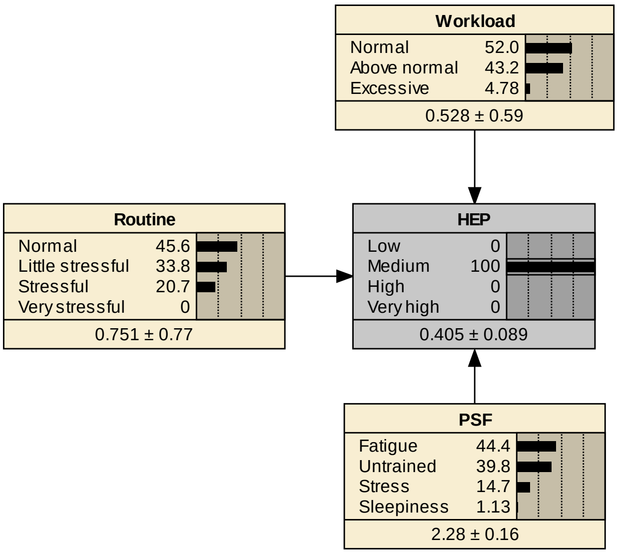

Fig. 11. New evidence in node HEP.

From BN, Fig. 10, it is possible to obtain the updated HEP by observing node HEP as a new evidence. The updated probabilities for the nodes Routine, Workload and PSF are listed in the Table 7.
Therefore recalculation of the nodes Routine, Workload and PSF after an observation has been made for node HEP in according of Bayes' rule.

Table 7: Nodes updated.

	Routine	Workload	PSF
Medium HEP	Normal 0.45579	Normal 0.51973	Fatigue 0.44435
High HEP	Stressful 0.56017	Above normal 0.54986	Stress 0.37717
Very high HEP	Very stressful 0.81804	Above normal 0.64711	Fatigue 0.38

In Fig 10 node HEP is deterministic then the Table 5 provides a value for the child node for each possible configuration of parents values.

In Figure 11 can not enter finding for node HEP, because new finding Low is inconsistent with findings for other nodes, accoding to proposed model. Furthermore the lowest value is a combination among Routine (Normal), Workload (Normal) and PSF (Untrained) for wich HEP = 0.27375.

Therefore, for the proposed model, it is not possible to have HEP = 0 as can see in figure 11 besides in Table 7 there is no value rated as Low.

V. CONCLUSIONS

This paper presents a proposal to evaluate the probability of error of a crew aboard a nuclear-powered submarine from the opinion of submariners experienced on board diesel-electric submarines.

To develop the methodology was used as computational tool Netica software to create the BNs and generate the CPT. The activities started with the distribution of questionnaires for the crew of two diesel-electric submarines of the Brazilian Navy. Given that Brazil is moving towards the construction of its first nuclear-powered submarine, it is expected that from the results presented in this work and based on opinion diesel-electric submarine crew members, be emphasized the need to elaborate appropriate procedures to yours first crew and, subsequently, for other submarines that can be built in around the world.

Although the questions were not always answered by all crew members they were important to obtain information that can contribute to crew error on board a submarine and also by using BN it was possible to analyze the probability of crew error in one case simple. The results shown in this paper are preliminary and research that considers the contribution of crew error to the overall risk of the nuclear-powered submarine loss is under development.

The HEP shown in Table 5, Table 6 and Table 7 were obtained from the opinion of crew members experienced in non-nuclear submarines and although they are high they may be considered hypothetical since there is not enough information available come from nuclear-powered submarines that can be used for comparison. The high HEP values may be related to a crew's mission time aboard a nuclear-powered submarine because its mission time may be longer than that of a non-nuclear submarine and so the combination of routine, workload and PSF can contribute significantly to human error, as shown in this paper.

Although the HEP was obtained from the opinion of experienced crew on board non-nuclear submarines, the values found are high and reveal the need for crew training, proper procedures and guidelines to address different types of accidents on board nuclear-powered submarines in different scenarios and depth of navigation.

In addition, the ship must be designed with safety devices that override human error to preserve the submarine and its crew in an emergency. Thus, given the occurrence of a fire aboard a nuclear-powered submarine regardless of its navigational depth, it is important to have devices capable of extinguishing the fire within the predicted time. In this paper according to the opinion of the crew the time should be less than 5 min as shown in Fig. 9.

It is worth mentioning that the Brazil's nuclear-powered submarine is being built with French assistance [38] and, thus, the results obtained in this paper are based on the opinion of non-nuclear submarine crew members of the Brazilian Navy. Countries with nuclear submarines do not disclose their data in open literature for national security reasons. Thus, unfortunately there is no way to compare the results obtained in this work with those of these countries. Nevertheless, the approach adopted in this paper shows the comprehensive how crew opinion can be important to development a way to assess human error on board a nuclear-powered submarine.

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Appendix

Table 8 indicates the weights inserted by crew opinions.

Table 8: Weights inserted in according to crew opinions to the PSFs.

Crew members	Submarine 1				Submarine 2				Other crew			
	Weight				Weight				Weight			
	F	U	S	Sl	F	U	S	Sl	F	U	S	Sl
# 1	2	2	-	-	-	1	-	-	-	-	-	4
# 2	1	3	-	-	-	4	-	-	-	-	1	-
# 3	2	2	-	-	-	0	-	-	-	4	-	-
# 4	2	4	-	-	-	1	-	-	-	4	-	-
# 5	3	2	-	-	-	2	-	-	-	-	-	-
# 6	3	-	-	-	-	4	-	-	-	-	-	-
# 7	2	-	-	-	-	2	-	-	-	-	-	-
# 8	2	-	-	-	-	2	-	-	-	-	-	-
# 9	2	-	-	-	-	2	-	-	-	-	-	-
# 10	4	-	-	-	-	4	-	-	-	-	-	-
# 11	3	-	-	-	-	0	-	-	-	-	-	-

# 12	2	-	-	-	-	3	-	-	-	-	-	-
# 13	2	-	-	-	-	0	-	-	-	-	-	-
# 14	2	-	-	-	-	0	-	-	-	-	-	-
# 15	2	-	-	-	-	-	3	-	-	-	-	-
# 16	4	-	4	-	-	-	3	-	-	-	-	-
# 17	2	-	2	2	2	-	-	-	-	-	-	-
# 18	-	2	-	-	3	-	-	-	-	-	-	-
# 19	-	3	-	-	3	-	-	-	-	-	-	-
# 20	-	2	-	-	1	-	-	-	-	-	-	-
# 21	-	4	-	-	3	-	-	-	-	-	-	-
# 22	-	2	-	-	2	-	-	-	-	-	-	-
# 23	-	-	2	-	0	-	-	-	-	-	-	-
# 24	-	-	3	-	2	-	-	-	-	-	-	-
# 25	-	-	2	-	-	-	-	-	-	-	-	-
# 26	-	-	4	-	-	-	-	-	-	-	-	-
# 27	-	-	2	-	-	-	-	-	-	-	-	-
# 28	-	-	2	-	-	-	-	-	-	-	-	-
# 29	-	-	3	-	-	-	-	-	-	-	-	-
# 30	-	-	3	-	-	-	-	-	-	-	-	-
# 31	-	-	4	-	-	-	-	-	-	-	-	-
# 32	-	-	2	-	-	-	-	-	-	-	-	-
# 33	-	-	2	-	-	-	-	-	-	-	-	-

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