Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs) and Bayesian Networks: A Case Study on Maritime Accidents

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Abstract *–Aiming to improve maritime safety, there is a need for a practical method that is capable of identifying the importance weightings for each contributing factor involved in accidents. Hence, Marine Accident Learning with Fuzzy Cognitive Maps (MALFCM) incorporated with Bayesian networks is suggested and applied in this study. MALFCM approach is based on the concept and principles of Fuzzy Cognitive Maps (FCMs) to represent the interrelations amongst accident contributor factors. Hence, in this study, grounding/stranding accidents were investigated with the proposed MALFCM approach. As a result, inadequate leadership and supervision, lack of training and unprofessional behavior were identified as the most probable causes of grounding accident. In addition, in the accident scenario analysis, it was observed that the lack of safety culture contributed most to the system failure based on the posterior to prior failures ratio.*

Keywords: Maritime accidents; Maritime safety; Maritime Accident Learning with Fuzzy Cognitive Maps (MALFCMs); Human factors; Bayesian Networks (BNs).

1. INTRODUCTION

The analysis of historical accident data has revealed that maritime accidents have been traditionally a concern for the shipping industry, as they incur into significant economic consequences, social, and environmental impact (Eliopoulou, Papanikolaou, & Voulgarellis, 2016). Therefore, aiming to reduce the accident rate, maritime organizations are directing efforts into the continuous development and implementation of safety measures, which overall aim to improve maritime safety significantly. Nevertheless, despite all the efforts, maritime accidents are still happening and they remain a major concern when around 90% of world trading is still carried out by shipping companies (Chauvin, Lardjane, Morel, Clostermann, & Langard, 2013).

Moreover, due to inconsistent methods followed during accident investigations, and the additional complexity of identifying all the variables involved into a particular accident scenario, it is extremely challenging to integrate lessons learnt from past accidents into safety assessments. According to Kristiansen (2013) there is no a clear answer to why accidents happen, as they are complex processes, in which there is no a single factor solely responsible for the accident outcome. However, if it is possible to identify and cleverly measure aforementioned accident contributing factors, efforts can be focused on addressing these factors in order to reduce the accidents rate and therefore improve safety.

When analyzing the literature, regardless of the industry in scope, it becomes evident that humans have a significant role into past accidents. For instance, human errors are responsible for at least 66% of the accidents in strategic sectors as nuclear or aerospace. In addition, they count for more than 80% of accidents within the maritime industry (Graziano, Teixeira, & Guedes Soares, 2016; Kurt et al., 2016; Turan et al., 2016).

Hence, this paper aims to identify and weight the importance of each human factor that contributes to the development of past maritime accidents. Thus, this paper applies a new FCM based technique, Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs), and demonstrates it through a case study. By applying aforementioned MALFCM method, it will be possible to weight the individual importance of each human factor by also taking into account its interrelation with each human factor from the system under study. Furthermore, this paper proposes to use the information provided by MALFCM as an input to create a Bayesian Network (BN) model. By creating above-mentioned model, it would be possible to study how the accident probabilities might change by addressing some specific human factors (i.e. it would allow to study the system from a "what-if" perspective).

Under this approach, it will be possible to understand the importance of each human factor in maritime accidents, which would allow researchers to incorporate these factors in risk assessments more effectively. Thus, by studying the model from a what-if perspective, it would be possible to inform risk assessments and predict the effectiveness of risk control options.

This paper is structured as follows: First, a literature review is provided regarding the FCM method, comprising mainly its mathematical representation, main areas of application and its main limitation, which is overcome by applying MALFCM method. Thus, this section also provides a complete review of the BN method. In addition, in Section 2 a detailed description of the methodology is provided. Moreover, in Section 3 the results and discussion are shared. Finally, the conclusions, limitations and recommendations for further work are included in Section 4.

1.1 Fuzzy Cognitive Maps (FCMs) Theory

When analyzing a complex accident scenario, one of the main challenges lays in the process of classifying the factors involved in it (Wolpert, 1992). From the extensive list of available classification methods, FCMs present a set of advantages. First, FCMs allow to model causal relationships between accident variables (Kardaras & Karakostas, 1999; M. Khan, Quaddus, & Intrapairot, 2001). Second, an FCM is a suitable technique to represent hazy degrees of causality relations between components (S. Lee & Han, 2000). Third, they are considered traditionally as a powerful tool for modelling systems that cannot be explained entirely mathematically (Stylios & Groumpos, 1999). In addition, vector-matrix operations allow an FCM model to become a dynamic system (M. Khan et al., 2001; B Kosko, 1994) by allowing the system to evolve with time.

By definition FCMs are extension of cognitive maps, in which the main difference with traditional cognitive maps is that the concepts represented in an FCM are weighted (Bart Kosko, 1986). Thus, FCMs aim to model complex chains of casual relationships and they have become a potential tool for modelling and analyzing dynamic interactions between concepts or systems in the past years (K. Lee, Kim, & Sakawa, 1996).

For the construction of an FCM model, experts of a specific area of knowledge develop a model based on their experience in a process composed by three stages. First, key concepts are identified within a determined area. Second, interrelationships are proposed between these concepts, identifying if these relations are positive or negative, while in the last step experts estimate the causal relationship strength (Papageorgiou, 2010; Zare Ravasan & Mansouri, 2016). In terms of decision support, there are two methods to analyze a FCM model. Firstly, a static analysis can be carried out in order to establish the relative importance of concepts and the causal effects between nodes (Axelrod, 1976; M. S. Khan & Quaddus, 2004). Nevertheless, only a dynamic analysis allow to study and explore the impact in the decision process with time (M. S. Khan & Quaddus, 2004).

An FCM is mainly characterized by three elements: the characteristics of the system, and signed and weighted arcs representing the interrelations within the different elements. The main target in an FCM is to define the relationships between the different concepts represented in the map, understanding the global structure and the dynamics of the system (Azadeh, Salehi, Arvan, & Dolatkhah, 2014). Figure 1 shows the structure of a traditional FCM.

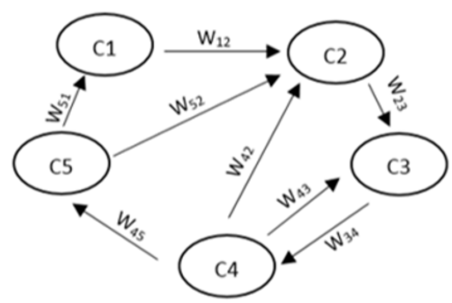

Fig. 1. A simple representation of an FCM (Navas de Maya, Kurt, & Turan, 2018).

Moreover, within an FCM, each of the concepts is represented by a number, A_i, that represents its value within the interval [0,1] (León, Rodriguez, García, Bello, & Vanhoof, 2010). It is possible to identify three types of connections between the concepts described in the FCM that represents the nature of their respective influence (Azadeh et al., 2014; León et al., 2010):

(i) The weights between the concepts C_i and C_j is positive ($W_{ij}>0$), which means that an increase in the first concept will lead to an increase in the second concept and vice versa.

(ii) The weights between the concepts C_i and C_j is negative ($W_{ij}<0$), which means that an increase in the first concept will lead to a decrease in the second concept and vice versa.

(iii) There is no relation between the concepts C_i and C_j ($W_{ij}=0$).

According with (Bart Kosko, 1986), a traditional formula to calculate the values of concepts in an FCM is represented in Fig. 2, in which A_i represents the value of C_i; f is the threshold function; W_{ji} represents the weight between concepts C_i and C_j; and A_j is the value of the concept C_j.

$$A_i^{(t+1)} = f\left(A_i^{(t)} + \sum_{j=1, j\neq i}^{n} W_{ji} A_j^{(t)}\right)$$

Fig. 2. Formula to calculate the values of concepts in an FCM.

In order to create successfully an FCM, it is necessary to define three main components. First, an interaction matrix with dimension n x n where n indicates the number of concepts modelled within the FCM. Thus, a value of zero in the matrix indicates that a relation does not exist between those two particular elements, while non-zero elements show not only that there is a relation between two elements but also the strength or weight of that relation. Second, an initial state vector, which shows the initial value of the concepts in the scenario being modelled at any point in time (t). Finally, a threshold function to reduce unbounded inputs to a strict range, to maintain the stability of the qualitative model (Mohr, 1997). Although there are plenty threshold functions available, the Sigmoid function gives any possible value within the interval [0,1] (Azadeh et al., 2014; Xiao, Chen, & Li, 2012) and it has been proved that using this function provides greater benefits (Bueno & Salmeron, 2009).

Regarding the dynamic process of an FCM model, once the process starts, the values of the concepts at each time step (i.e. step 1, step 2 etc.) will be obtained by following the equation provided in Fig. 2, until the process stops. The process might stops at any of the following scenarios (M. Khan et al., 2001; B Kosko, 1994; Xiao et al., 2012):

(i) The FCM reaches equilibrium, which occurs when after two consecutive steps repeating the process; both state vectors obtained are identical. In this situation, the simulation stops and the FCM is considered steady.

(ii) The FCM does not produce a stable state vector. as it keeps cycling between a certain number of values, (e.g. 0, 0.3, 0.5, 0, 0.3, 0.5, …, 0, 0.3, 0.5). This situation is known as the “limit cycle”, and it results from a certain combination of weight values when applying an FCM, which drive the map away from reaching equilibrium (Wierzchon, 1995). Nevertheless, an alternative solution to avoid aforementioned limit cycle is to apply an hybrid system comprising both, FCMs and genetic algorithms (Mateou & Andreou, 2006).

(iii) The FCM does not reach identical values, producing different state vectors for each step. This possibility is known as “chaos” and it can appear in complex scenarios, in which a re-definition of the model would be required to overcome a chaos situation.

Despite of the fact that FCM is not as well-known as other methods (Papakostas, Boutalis, Koulouriotis, & Mertzios, 2008; Papakostas, Koulouriotis, Polydoros, & Tourassis, 2012), it has been proved to be very promising and worth of further investigation and development (Vergini & Groumpos, 2016). Several studies have addressed the application of FCMs as a classification tool in different fields for the past years, proving that FCM is not only a well-validated classification tool but also its effectiveness. Thus, FCMs have been widely used in terms of planning and decision making (Dodurka, Yesil, & Urbas, 2017). Moreover, the interest from both researcher and industry is increasing, and FCM has been successfully apply to the areas of medicine (Papageorgiou & Froelich, 2012), control (Papageorgiou, Stylios, & Groumpos, 2006), business (Glykas, 2013), robotics (Motlagh, Tang, Ismail, & Ramli, 2012), environmental science (Kok, 2009), education (Yesil, Ozturk, Dodurka, & Sahin, 2013), energy efficiency (Mpelogianni, Marnetta, & Groumpos, 2015) and information technology (Büyüközkan & Vardaloğlu, 2012).

However, although it has been proved in aforementioned studies that an FCM is an alternative and powerful method to model and analyze dynamic interactions between concepts or systems, it has an important limitation. As FCMs are designed to transcribe experts’ opinion, its weaknesses lay on the uncertainty related with each expert’s response. As a result, an FCM can equally encode the experts’ lack of knowledge. Therefore, the reliability of a traditional FCM is linked to the experts’ knowledge, background and familiarity with the topic that is being addressed. In order to overcome this limitation, a method for Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs), which differs from the traditional FCM approach, is proposed and applied in this paper, with the aim to establish weights for human factors involved in maritime accidents successfully. Within this new method, each FCM is developed through establishing relationships between factors from past accident experiences. Therefore, the results from the technique followed in this paper might be considered more objective, as this new approach overcomes the main disadvantage of fuzzy cognitive maps (i.e. the subjective results and knowledge deficiencies between experts). Thus, MALFCM method will be fully explained in the next section of this paper.

1.3 Bayesian Network (BN)

Bayesian networks (BNs) are directed acyclic graphs that rely on the strength of Bayes’ theorem for assessing accident causations where the causations and their dependencies are all variables of uncertainty. The BNs consist of random variables represented by nodes with causations dependencies depicted by directed arcs linking the nodes. Typically, the BN tend to satisfy the Markov condition where each node is conditionally independent of the collection of all its non-descendant nodes (Du et al., 2015; Neapolitan, 2004). The transformation of any accident model into BN has been covered extensively in the literature (Babaleye and Kurt 2019, Babaleye et al., 2019; Abimbola and Khan, 2019).

2. METHODOLOGY

2.1 Data Selection

In this study, grounding and stranding accidents involving general cargo vessels between 2011 and 2016 are examined. General cargo vessels, which are usually defined as merchant ships carrying goods and materials from one port to another, were selected for this study due to the higher number of data entries when compared with other vessel categories. The distribution of accidents regarding the vessel type is outlined in Table 1, in which cargo ships shows a higher number of accidents registered. Thus, Table 2 provides a further insight into general cargo accidents' outcome, where grounding and stranding accidents were identified as the most common accident type. Therefore, sixteen accidents were examined and analyzed within this study. Thus, MALFCM method was applied to aforementioned accidents.

Table 1: Total number of accidents per vessel type.

Vessel type	Number of accidents
Cargo ship	50
Fishing vessel	34
Passenger ship	19
Service ship	19
Recreational craft	9
Inland waterway vessel	3
Navy ship	1

Table 2: Total number of accidents' outcome within cargo ships.

Cargo ship	Number of accidents
Grounding/stranding	16
NA	12
Collision	10
Contact	4
Capsizing/Listing	2
Flooding/Foundering	2
Damage to ship or equipment	1
Fire/Explosion	1
Hull failure	1
Loss of control	1

2.2 Maritime Accident Learning with Fuzzy Cognitive Maps (MALFCMs)

MALFCMs method is a Fuzzy Cognitive Map-based technique, which has been designed to combine expert knowledge with lesson learnt from past accident experiences, aiming to provide more reliable weightings as the input for the scenario being modeled are partially obtained from real maritime accidents (i.e. the subjective results and knowledge deficiencies between experts might be overcome within this method). Thus, MALFCM method could be described in four main stages:

(i) Historical data analysis stage
(ii) Expert opinions stage
(iii) FCM stage
(iv) Consolidation of results stage

In the historical data analysis stage, historical data is obtained for the scenario being modelled (e.g. a specific vessel category or an accident outcome), in order to identify which human factors leaded into those accidents. Once all the factors have been identified, each pair of factors is statistically compared to create the interaction matrix described in the previous section. Furthermore, analysis are also performed to establish the initial state vector. To create the interaction matrix for the historical data analysis stage, a comparison between each pair of factors is performed by following two main steps as follows:

(i) First, to determinate the relation between *Factor a* and *Factor b*, the historical accident data is filtered to identify those accidents caused by each of the previous factors. Thus, a second filter is applied to identify those accidents that share both factors as a common accident cause.
(ii) Second, the weight of *Factor a* over *Factor b* is calculated as the relation between the number of accidents with both factors in common, and the number of accidents which have registered *Factor a* as an accident contributing factor. Figure 3 provides a better picture of the process being described.

$$W_{Fa-Fb} = \frac{W_{Fa \cap Fb}}{W_{Fa}}$$

Fig. 3. Formula to calculate the value of each component for the interaction matrix.

Above described steps are repeated in order to obtain the relations and weights of each pair of factors. Moreover, the initial stage vector for each human factor is defined as the relation between the number of accidents which contains that accident contributing factor, and the total number of accidents considered for the case study.

In the expert opinion stage, experts are requested to provide their knowledge by comparing each pair of factors that were identified within the previous stage. This rating process might be accomplished through numeric values. However, as it is extremely challenging for some expert to assign a number value in specific scenarios, an alternative solution is to apply linguistic variables. The seven variables that are used frequently depending on the problem characteristics are: *very very low < very low < low < medium < high < very high < very very high* (Markinos, Papageorgiou, Stylios, & Gemtos, 2007). Aforementioned information is used to define the interaction matrix for the expert opinion stage. Moreover, experts are asked to indicate at which level (within the interval [0,1]) a factor needs to be active in order to have a minimum contribution into an accident. This information allows to define an initial state vector for the expert opinion stage. In addition, as expertise is established with experience, some experts may be more credible. Hence, it is possible to weight each expert's opinion in order to increase or reduce the importance of their feedback (Kandasamy & Smarandache, 2003).

In the FCM stage, the selected threshold function is applied to two sets of data, creating two different FCMs. The first FCM is performed by incorporating the results obtained from the historical data stage, while the second FCM integrates the findings from the expert analysis. For both FCMs, the results are analyzed, and the obtained weightings are ranked.

Lastly, in the consolidation of result stage, final weightings for each accident-contributing factor are obtained by performing a sensitivity analysis, which combines the results from both FCMs created in the previous stage.

Although MALFCM is conceptually designed to incorporate together the findings from historical data and expert opinion, it can be perfectly applied exclusively to both, historical data or expert opinion. Therefore, due to the additional difficulty in finding reliable experts with an specific background in human contributing factors into maritime accidents, it was decided that for the purpose of this paper, MALFCM would be only applied to historical accident data. Therefore, expert opinion will not be incorporated into the equation, and the findings from this case study will be purely dependent on the historic data analysis stage.

2.3 Human-contributing Factors into Grounding and Stranding Accident in General Cargo Vessels

As it was indicated previously, within this paper sixteen maritime accidents were scrutinized and analyzed, aiming to identify those human factor that had a contribution into grounding and stranding accidents in general cargo vessels. Thus, nine human factors were identified as shown in Table 3.

Table 3: Human factors involved into grounding/stranding accidents in general cargo vessels.

No	Human factor
HF1	Improper design, installation and working environment
HF2	Inadequate leadership and supervision
HF3	Inadequate safety management system: Inadequate procedures or deviation from Standard Operating Procedure (SOP)
HF4	Inadequate safety management system: Substandard monitoring
HF5	Lack of communication and coordination
HF6	Lack of safety culture
HF7	Lack of training
HF8	Lack of, improper or late maintenance
HF9	Unprofessional behaviour

2.4 Application of MALFCM Method

Once all human-contributing factors were identified, an interaction matrix was created. In order to determine the relation between each pair of factors to fill the interaction matrix, the two steps described in the previous section were followed. For instance, to determinate the relation between HF2 and HF3, the database was first filtered, resulting in five accidents sharing both human factors as a common cause. In addition, eleven accidents recorded HF2, while eight accidents included HF3. Thus, the interrelation between HF2 and HF3 (i.e. $W_{2,3}$ in the interaction matrix) would be calculated as the relation between the number of accidents that recorded both human factors in the same accident (five accidents), and the number of accidents that included HF2 ($W_{2,3}$=0.455). Similarly, the relation between HF3 and HF2 would be calculated as the relation between the number of accidents in common and the number of accidents that included HF3 ($W_{3,2}$=0.625).

Due to the size of the interaction matrix, Table 4 shows only a partial representation of the interaction matrix for grounding/stranding accidents in general cargo vessels for the period 2011-2016.

In addition, for this case study, the state vector was stablished as the statistical occurrence of each factor within the historical accident database. Thus, Table 5 provides a partial representation of the initial state vector (St.0). In addition, Table 5 also provides the dynamic evolution of the FCM until equilibrium is reached, which occurs before step 8 (St.8).

Table 4: Partial interaction matrix for grounding/stranding accidents in general cargo vessels. Period 2011-2016.

	HF1	HF2	HF3…	…	HF8	HF9
HF1	-	0.000	0.000	…	0.500	0.500
HF2	0.000	-	0.455	…	0.000	0.455
HF3	0.000	0.625	-	…	0.000	0.125
…	…	…	…	…	…	…
HF8	1.000	0.000	0.000	…	-	0.000
HF9	0.125	0.625	0.125	…	0.000	-

Table 5: Partial state vector and calculation of steady state for grounding/stranding accidents in general cargo vessels. Period 2011-2016.

	HF1	HF2	HF3…	…	HF8	HF9
St.0	0.125	0.688	0.500	…	0.063	0.500
St.1	0.547	0.798	0.679	…	0.516	0.719
St.2	0.663	0.958	0.710	…	0.568	0.939
St.3	0.684	0.968	0.745	…	0.582	0.951
St.4	0.688	0.971	0.747	…	0.585	0.955
St.5	0.688	0.971	0.748	…	0.585	0.955
St.6	0.688	0.971	0.748	…	0.585	0.955
St.7	0.688	0.971	0.748	…	0.585	0.955
St.8	0.688	0.971	0.748	…	0.585	0.955

Once the interaction matrix and the state vector have been defined, the FCM is created by applying the equation represented in Fig. 2, until equilibrium is reached (i.e. before St.8).

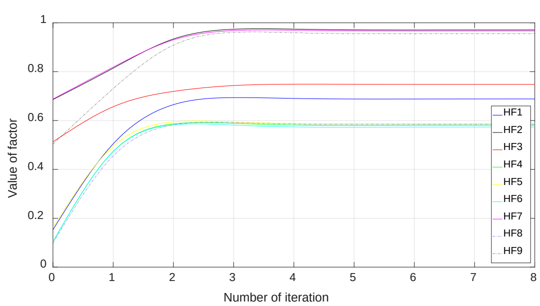

Fig. 4. Values of MALFCM for grounding/stranding accidents in general cargo vessels until equilibrium is reach. Period 2011-2016.

Figure 4 shows the iterative process followed in MALFCM method until equilibrium is reached. In addition, Table 6 shows the final weightings obtained for all human-contributing factors, after the iteration reaches equilibrium and the simulation stops. The weightings provided by MALFCM are constrained to the interval [0,1]. Additionally, these results have been normalized, and the final weightings are also displayed on Table 6, to show the contribution of each human factor into accidents in terms of percentage.

Table 6: Final weight of contributors for grounding accidents in general cargo vessels. Period 2011-2016.

Human factor description	Weight from MALFCM	Weight normalized (%)
HF1: Improper design, installation and working environment	0.688	10.342
HF2: Inadequate leadership and supervision	0.971	14.588
HF3: Inadequate safety management system: Inadequate procedures or deviation from Standard Operating Procedure (SOP)	0.748	11.239
HF4: Inadequate safety management system: Substandard monitoring	0.581	8.730
HF5: Lack of communication and coordination	0.587	8.822
HF6: Lack of safety culture	0.573	8.614
HF7: Lack of training	0.967	14.525
HF8: Lack of, improper or late maintenance	0.585	8.793
HF9: Unprofessional behaviour	0.955	14.348

2.5 Application of Bayesian Networks

Following the estimation of the HF weightings from previous section, the weighted values are fed into the causation nodes of the BN as the prior failure probability. As can be seen from Fig. 5, the wreck and/or stranding occurrence probability can be estimated. In the presence of new evidence, the interactions of the HFs can be ascertained through experiential learning. To do this, a forward or backward propagation of the accident model is performed, such that, the grounding (GND) node is latched at a pre-defined state to obtain posterior probabilities for the causation nodes, in the backward propagation analysis. In addition, any or all the causation nodes may be latched to a given state, say failed state to obtain new information of the GND occurrence probability.

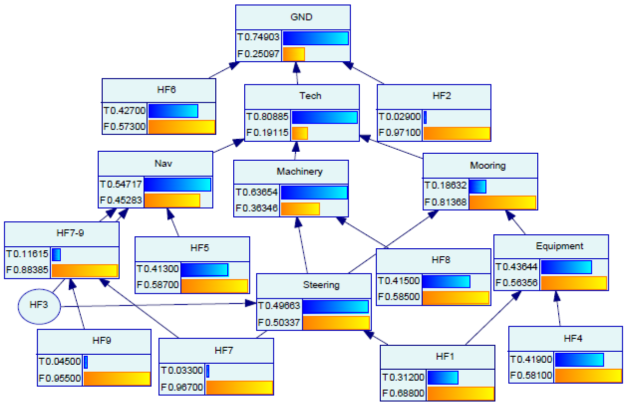

Figure 5. BN model for the wreckage/stranding accident.

Through backward propagation analysis, a new evidence, 'failed state' is set for the grounding (GND) occurrence to obtain new information for the causations. These occurrence probabilities are the posterior failure for the causation events. Table 7 shares the posteriors occurrence probabilities obtained.

Table 7: Posterior occurrence probabilities for grounding accidents in general cargo vessels.

Human factors	**Prior Probability**	**Posterior Probability**	**Importance Measure (P_f/P_i)**
HF1	0.688	0.709	1.03
HF2	0.971	0.991	1.02
HF3	0.748	0.792	1.06
HF4	0.581	0.578*	0.99
HF5	0.587	0.655	1.12
HF6	0.573	0.834	1.46
HF7	0.967	0.971	1.00
HF8	0.585	0.655	1.12
HF9	0.955	0.958	1.00

3. RESULTS AND DISCUSSION

For the case study presented in this paper, human-contributing factors involved in grounding and stranding accidents in general cargo vessels were identified and weighted, aiming to use them as an input for the BN model. The data that was utilized within the MALFCM method was obtained from an historical accident database for the period 2011-2016. Within this period, sixteen accidents were selected and further analyzed, as they reported human factors that lead into those accidents.

After applying MALFCM method, an "inadequate leadership and supervision" was identified as the most critical factor. An inadequate supervision has been extensively identify in the literature as highly related with maritime accidents. For instance, B. M. Batalden and Sydnes (2017) applied a modified Human Factor Analysis and Classification System (HFACS) framework, identifying that the main causal factors leading to very serious accidents are found in the higher levels of organization, that is organizational influence and unsafe supervision. Thus, B.-M. Batalden and Sydnes (2014) also performed a study to investigate casualties and incidents, revealing that unsafe supervision emerges as the biggest challenge, and it is a causal factor leading to very serious accidents (34.7% of analyzed cases), to serious accidents (23.1%), and to less serious accidents (42.1%). Furthermore, a study conducted by Macrae and Management (2009) on grounding and collision accidents revealed that a lack of supervision and team communication were reported as important contributing factors in the study of grounded vessels.

Moreover, also a "Lack of training" was identified as an important human factor leading into maritime accidents. This observation is in line with previous studies. For example, a study performed by Puisa, Lin, Bolbot, and Vassalos (2018) revealed that an inadequate training was observable in numerous past accidents, and it was a frequent causal factor across all reports analyzed within aforementioned study. In addition, Graziano et al. (2016) applied the Technique for Retrospective and Predictive Analysis of Cognitive Errors (TRACEr), finding that most of the failures were associated with factors like fatigue or inadequate training/instruction. Thus, a study performed by Kum and Sahin (2015) on arctic regions revealed that maritime accidents on those regions were mainly associated with inadequate quality and extension of training.

Finally, an "Unprofessional behavior" was identified as the third main contributing factor within this case study. Inadequate behaviors have been previously linked to maritime accident in the literature. For example, a study performed by Antão, Almeida, Jacinto, and Guedes Soares (2008) highlighted that inadequate behaviors are identified within particular tasks, leading into occupational accidents.

4. CONCLUSIONS

This study investigates the human factors contribution to global maritime accidents, with emphasis on stranding and/or grounding of ship structures. A new methodology is introduced for modelling the potential causations of maritime accidents using Marine Accident Learning with Fuzzy Cognitive Maps (MALFCM) incorporated with Bayesian networks. The weightings of the accident contributors are estimated based on the application of MALFCM method. These weightings are then fed into the causal nodes of the Bayesian network to systematically evaluate the stranding/grounding occurrence probability.

The Bayesian network model is used as a tool to update the occurrence failure probabilities for each human factor contribution, given that a new evidence become available about the grounding/stranding accident. The developed framework was applied to a case study on grounding/stranding accidents in general cargo vessels. In the accident scenario analysis, it was observed that the lack of safety culture (HF6) contributed most to the system failure based on the posterior to prior failures ratio. Based upon the prior failure probabilities obtained from the MALFCM model analysis, it was seen that Inadequate leadership and supervision (HF2), lack of training (HF7) and unprofessional behavior (HF9) are the most probable causes of stranding and/or grounding accident.

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