Marine Accident Learning with Fuzzy Cognitive Maps: A method to model and weight human-related contributing factors into maritime accidents

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'Declarations of interest: none'.

Abstract

Previous statistical maritime accident studies are focused on identifying human factors. However, the previous studies were not capable of modelling the complex interrelations that exist between these factors. As accidents are complex processes, researchers fail to agree on the contribution of each human factor. Therefore, in this research study, a new Fuzzy Cognitive Map (FCM)-based technique known as MALFCMs has been introduced and applied. Its novelty is the application of FCM concepts to model the relationships of accident contributors by combining historic accident data with expert opinion. Our approach is capable of integrating information obtained from real occurrences, therefore, the results can be considered more objective. Thus, in this paper, MALFCMs was applied to grounding/stranding accidents in general-cargo vessels, revealing that “unprofessional behavior”, “lack of training”, and “inadequate leadership and supervision” are the most critical factors, with a normalized importance weighting of 13.25%, 13.24%, and 13.24% respectively.

Keywords: maritime accidents; human factors; marine accident learning with fuzzy cognitive maps; accident investigation.

Introduction

Traditionally, maritime accidents have defined and affected negatively the shipping sector. Thus, the occurrence of a shipping accident usually triggers an automatic response from the maritime authorities; which is often translated into the development and implementation of new safety measures. However, inconsistent methods followed and inaccurate training provided to report accident adequately, and the complexity of identifying all the variables involved into a specific accident make it extremely challenging to integrate lessons learnt from past accidents into risk assessments successfully. In addition, a concise analysis of the literature indicates that human factors (HFs) had been often considered as the primary source of accidents in various industries as nuclear, aerospace (Ali Azadeh & Zarrin, 2016; O'Hare, Wiggins, Batt, & Morrison, 1994) or shipping (Graziano, Teixeira, & Guedes Soares, 2016; Kurt et al., 2016; B. Navas de Maya & Kurt, 2018; Turan et al., 2016).

When modelling and analyzing a complex scenario the classification of the various factors implicated appears to be one of the most challenging aspects (Wolpert, 1992). Various authors have addressed diverse classification techniques. Nevertheless, a representative technique that could be selected as the best method has not yet been identified (Fernández-Delgado, Cernadas, Barro, & Amorim, 2014). One of the most promising solutions for classifying data sets is to apply Fuzzy Cognitive Maps (FCMs), which are extensions of cognitive maps that aim to model complex chains of casual relationships maps (Axelrod, 1976; Eden, 1988; Tolman, 1948). Although FCMs are not as well-known as other methods (Papakostas, Boutalis, Koulouriotis, & Mertzios, 2008; Papakostas, Koulouriotis, Polydoros, & Tourassis, 2012), they have been successfully applied as a classification tool in different fields, e.g. in medicine (Kannappan, Tamilarasi, & Papageorgiou, 2011; Papageorgiou & Kannappan, 2012; Papageorgiou, Oikonomou, & Kannappan, 2012) or information technology (Büyüközkan & Vardaloğlu, 2012). Thus, recent studies have proved that FCMs are very promising and worth of further investigation and development (Vergini & Groumpos, 2016).

In order to build a traditional FCM, experts with a specific background develop a model based on their own 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. Third, the experts estimate the causal relationship strength between each pair of factors (Papageorgiou, 2010; Zare Ravasan & Mansouri, 2016). In order to identify aforementioned strength amongst concepts, various approaches are available. For instance, a common suggestion is to ask each expert to assign a value to the interrelation between two factors within the interval $[0, 1]$. (Dodurka, Yesil, & Urbas, 2017). Nevertheless, it is

extremely challenging for some expert to assign numeric values; hence, an alternative solution is to apply linguistic variables to define the interrelation amongst concepts (Bart Kosko, 1986).

In terms of decision support, there are two methods to analyze an FCM, which represents a given domain. First, a static analysis of the model, which is based on studying the characteristics of the weighted directed graph that represent the model, using graph theory techniques. The most important feature that should be studied on an static analysis is the feedback cycles that exist in the graph (Tsadiras et al., 2001). Second, a dynamic analysis of the model can be performed to explore the impact in the decision process with time. Within this approach, given an interaction matrix and an initial state vector, the final resulting state can provide information regarding any impacts or changes made to the system. Furthermore, by executing a dynamic analysis, it is possible to study the system from a “what-if” perspective (M. S. Khan & Quaddus, 2004).

Mathematical representation of an FCM

Figure 1 illustrates a simple FCM representation, in which each concept is used to represent an entity, a variable, or a characteristic of the system. (Xirogiannis & Glykas, 2004). Within an FCM, each of the concepts is represented by a number, C_i , that represents its value within the interval $[0,1]$ (León, Rodríguez, García, Bello, & Vanhoof, 2010). Thus, it is possible to identify three different connections between the concepts modelled within an FCM (i.e. positive, negative or neutral), which represents the nature of their respective influence (A. Azadeh, Salehi, Arvan, & Dolatkhah, 2014; León et al., 2010).

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

Thus, in order to create successfully a dynamic FCM, it is necessary to establish three components. First, an interaction matrix. Second, an initial state vector, which provides the initial value of the concepts in the scenario being modelled at any point in time (t). Finally, a threshold function, which aims 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 $[0,1]$ (A. Azadeh et al.,

2014; Xiao, Chen, & Li, 2012) and it has been proved that using this function provides greater benefits (Bueno & Salmeron, 2009). In addition, a traditional formula to calculate the values of the concepts in an FCM is provided in Equation 1.

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

Equation 1. Traditional formula to calculate the values of the concepts represented in an FCM over time.

Where $A_i^{(t+1)}$ represents the value of C_i at the step $t+1$, f is the threshold function which assures that the concept's value is limited within the interval $[0, 1]$, W_{ji} represents the weight between both concepts C_i and C_j , and $A_j^{(t)}$ is the value of the concept C_j at step t .

Although 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.

The rest of the paper is structured as follows: First, the methodology, which comprises the proposed FCM-based technique, (i.e. the MALFCMs method), will be further explained. Second, the next sections will address the results and discussions. Finally, conclusions of this study will be summarized.

Methodology

Data selection

For the purpose of this case study, marine accidents involving UK vessels worldwide and all vessels operating in UK territorial waters between 2011 and 2016 were analyzed. In addition, grounding/stranding accidents in general cargo vessels were selected for this study due to the higher number of data entries when compared with other accidents and vessel categories, as highlighted in de Maya, Babaleye, and Kurt (2019).

Marine Accident Learning with Fuzzy Cognitive Maps

Maritime accidents are complex processes in which usually there is more than a HF solely responsible for the accident outcome. Hence, developing a model that considers not only each HF independently but also all interactions between HFs to obtain the final contribution of each HF into accidents comes to importance in this study. Thus, in order to overcome aforementioned limitations of traditional FCMs, a method for Marine Accident

Learning with Fuzzy Cognitive Maps (MALFCMs) is proposed and applied in this paper, with the aim to establish weights for HFs involved in maritime accidents successfully. Within this new method, each FCM is developed through establishing relationships between factors from past accident experiences and, combining the results with expert opinion. 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).

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 results that are more reliable. As the inputs for the scenario being modelled are partially obtained from real maritime accidents, the subjective results and knowledge deficiencies between experts are reduced by applying this method. Thus, MALFCM method could be described in four main stages: 1) Historical data analysis stage. 2) Expert opinions stage. 3) FCM stage and 4) Consolidation of results stage. The MALFCM method developed by the authors has been already introduced in a previous paper (de Maya et al., 2019). The method has been applied and tested for different case studies to finalize the methodology for the historical data analysis stage (de Maya et al., 2019; B. Navas de Maya & Kurt, 2018; Beatriz Navas de Maya et al., 2018)

Thus, this paper is making a significant advancement by reporting the complete MALFCM framework which now includes the expert opinion stage, demonstrates results from a completed case study for the first time and conducts a sensitivity analysis to compare results against results obtained from solely from historical data analysis stage (de Maya et al., 2019). Results of sensitivity analysis are used to decide on the appropriateness of applying different coefficients to FCMs obtained from historical data and expert data stages, in order to reach a mixed weight. Figure 2 shows the procedure followed to calculate the weights of HFs.

Figure 2. Weights of HF's calculation flowchart.

Results

MALFCM: Historical data analysis stage

MALFCM method can be perfectly applied exclusively to historical data, expert opinion or both. For the purpose of this paper, first, the findings for the historical data analysis that were obtained by de Maya et al. (2019) are used as a starting point and enhanced with including static FCM analysis reported in Figure 3. Then, previous findings are combined with the results from the MALFCM: Expert opinion stage, which is developed in this paper. In de Maya et al. (2019), historical data for maritime accidents involving UK vessels worldwide and all vessels operating in UK territorial waters between 2011 and 2016 was obtained and analyzed. Thus, general cargo vessels were selected due to the higher number of data entries when compared with other vessel categories, and nine HFs were identified as highly contributing into maritime accidents, as shown in Table 1.

Table 1. HFs involved into grounding/stranding accidents in general cargo vessels. Period 2011-2016. (de Maya et al., 2019)

No	HF description
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

Static and dynamic analysis of the FCM

A static analysis of the FCM defined by de Maya et al. (2019) is provided at this stage, in order to observe and analyse the feedback cycles that exist in the FCM graph. Figure 3 provides an insight into the FCM graph, to show the relative importance of concepts and the causal effects between nodes at this time.

Figure 3. Static analysis of FCM for grounding/stranding accidents in general cargo vessels. Historical data analysis stage. Period 2011-2016.

Cycles are formed in the model as a result of direct and indirect relationships. Thus, each cycle within the graph is accompanied by a sign, which is obtained by multiplying the sign of all the arcs that participate in the cycle.

Positive cycles are characterized by amplifying any change that is introduced into the system, while negative cycles counteract any initial change that is introduced into the system (Tsadiras et al., 2001). However, for the system being modelled on this paper, no negative cycles are identified. Table 2 provides the main cycles initiated with HF1, which were identified from the static analysis of the FCM created for the historical data analysis stage. Thus, the model provided on Figure 3 is rich of cycles. At this stage it is not possible to know which cycles will prevail (even for model with less cycles it is difficult to predict). Thus, it is challenging to make scenarios, predictions and draw conclusions by considering all these cycles from the system. For this reason, a dynamic analysis is required.

Thus, a dynamic analysis of the FCM was performed on de Maya et al. (2019) by applying Equation 1 until equilibrium was reached. In addition, Table 13 includes the results from the dynamic analysis that was performed by de Maya et al. (2019), and compares aforementioned results with the findings obtained from this study.

Table 2. Main cycles identified for grounding/stranding accidents in general cargo vessels. Historical data analysis stage. Period 2011-2016.

No	Cycles	No	Cycles
1	HF1-HF7- HF1	14	HF1-HF9-HF1
2	HF1-HF7-HF2-HF3-HF9-HF1	15	HF1-HF9-HF2-HF3-HF7-HF1
3	HF1-HF7-HF3-HF2-HF4-HF9-HF1	16	HF1-HF9-HF2-HF5-HF7-HF1
4	HF1-HF7-HF3-HF2-HF6-HF9-HF1	17	HF1-HF9-HF2-HF6-HF7-HF1
5	HF1-HF7-HF3-HF2-HF9-HF1	18	HF1-HF9-HF2-HF7-HF1
6	HF1-HF7-HF3-HF9-HF1	19	HF1-HF9-HF3-HF2-HF5-HF7-HF1
7	HF1-HF7- HF5-HF2-HF3-HF9-HF1	20	HF1-HF9-HF3-HF2-HF6-HF7-HF1
8	HF1-HF7- HF5-HF2-HF9-HF1	21	HF1-HF9-HF3-HF2-HF7-HF1
9	HF1-HF7-HF6-HF2-HF3-HF9-HF1	22	HF1-HF9-HF3-HF7-HF1
10	HF1-HF7-HF6-HF2-HF9-HF1	23	HF1-HF9-HF6-HF2-HF5-HF7-HF1
11	HF1-HF7-HF6-HF9-HF1	24	HF1-HF9-HF6-HF2-HF7-HF1
12	HF1-HF7-HF9-HF1	25	HF1-HF9-HF6-HF7-HF1
13	HF1-HF8-HF1	26	HF1-HF9-HF7-HF1

MALFCM: Expert opinion stage

Data collection

Questionnaires are commonly used to collect expert opinion within the FCM literature (Hossain, 2006; Tsadiras et al., 2001). Thus, in this study each participant completed an online questionnaire, which presented a long list of questions regarding the nine HFs defined on Table 1. With regard to each factor, three type of closed questions were included into the questionnaire. The first type included general questions related with the background of each participant. The second type typically asked how influential a particular factor is to contribute into maritime accidents. A response was selected from the alternatives “None”, “Very low”, “Low”, “Medium”, “High”, “Very high”, and “Very very high”. In addition, the answers to this set of questions would allow defining the state vector for the expert opinion stage. Finally, the last type was designed to allocate strength values to the interrelationship amongst HFs. Hence, this set typically asked, given a change in “Factor a”, what would be the effect on “Factor b”. A response was selected from the alternatives “None”, “Very small”, “Small”, “Moderate”, “Big”, “Very big”, and “Very very big”. Thus, the answers to this set of questions would allow defining the interaction matrix for the expert opinion stage. An extract from the questionnaire, is included in Table 3.

Table 3. Extract from the questionnaire.

No	Questions
Q8	How influential an improper design, installation or working environment is in terms of contributing into maritime accidents?
Q35	Given a change in design, installation or working environment, what would be the effect on leadership and supervision

Participants description and participants answers

For this case study, three selected experts (which are referred to as Participant1, 2 and 3) completed the questionnaire. Skill and experienced participants on the areas of HFs, ship operations and accident investigations were selected in order to have a positive effect on the results. Once the questionnaire was completed, all the answer were collected and analyzed. An interaction matrix was created for each participant, expressed in linguistic terms. Table 4 shows as an example the state vector created by Participant1, which was populated with his/her answers to the second type of questions. In addition, Table 5 provides the interaction matrix created by Participant1, which was populated with his/her answers to the third type of questions, as described above.

Table 4. Initial state vector created by Participant1 by applying linguistic terms.

	HF1	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9
	Low	Medium	Very low	Medium	None	Low	Very low	Very low	High

Table 5. Interaction matrix created by Participant1 by applying linguistic terms.

	HF1	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9
HF1	-	Small	Very small	Small	Very small	Moderate	Very small	Moderate	Big
HF2	None	-	Big	Big	Big	Big	Moderate	Moderate	Very big
HF3	None	Small	-	Small	Small	Moderate	Very small	Very small	Moderate
HF4	None	Small	Small	-	Moderate	Moderate	Very small	Big	Moderate
HF5	None	Big	Moderate	Small	-	Big	Very small	Small	Big
HF6	None	Very big	Moderate	Moderate	Moderate	-	Big	Big	Very big
HF7	None	Very small	Small	Small	Small	Moderate	-	Small	Moderate
HF8	None	None	Very small	Moderate	Very small	Small	None	-	Moderate
HF9	None	Moderate	Very small	Moderate	Moderate	Big	Very small	Moderate	-

Construction of individual FCMs

The next step involved the conversion of the individual FCMs derived at the previous step, expressed in linguistic terms, into numerical expressed FCMs. As described in the literature, a linguistic weight might be transformed into numerical values by means of a linguistic-numerical conversion. Therefore, the five linguistic conversion proposed by Tsadiras et al. (2001) was adapted to include the seven linguistic terms used by participants in this study, which were equated to values ranging from a minimum of 0 to a maximum value of 1. The conversion measures applied are shown in Table 6. Aforementioned conversion measures were applied to transform the participants' FCMs into numerical expressed FCMs.

Table 6. Fuzzy conversion measures for the state vector and the interaction matrix.

Fuzzy linguistic terms used in the questionnaire for the state vector	None	Very low	Low	Medium	High	Very high	Very very high
Fuzzy numerical weights	0.000	0.165	0.330	0.495	0.660	0.825	1.000
Fuzzy linguistic terms used in the questionnaire for the interaction matrix	None	Very small	Small	Moderate	Big	Very big	Very very big
Fuzzy numerical weights	0.000	0.165	0.330	0.495	0.660	0.825	1.000

Analysis of expertise level from experts involved

All the FCMs have been transformed from linguistic into numeric FCMs at this stage. Thus, the individual FCMs needs to be aggregated in order to create a unique FCM, which reflects the knowledge of all participants. In this regard, relevant data is substituted into Equation 2 (Kandasamy & Smarandache, 2003; Bart Kosko, 1992).

$$F = \sum_{i=1}^n w_i F_i$$

Equation 2. Formula to calculate the credibility weight.

Where F_i represents the FCM matrix for participant i , n is equal to the number of participants, and w_i indicates the credibility weight for participant i .

As some experts may be more credible than others, their contribution is multiplied in this study by a coefficient, w_i , before combining it with other expert opinions, as shown in Equation 2. Many authors in the literature have defended the use of $w_i=1$ (Taber, 1987). Nevertheless, as the participants within this study had various credentials and expertise areas, it was not reasonable to assume the same credibility weight for each participant. Therefore, the credibility weighting for each expert was established by adapting the method developed by (Hossain, 2006). Within this method, numeric values are associated to a person's expertise, in order to provide a relative numeric measure. Each participant's background is drawn to establish if they met each criterion. For each criterion that is successfully met, the associated numeric value to that criterion is assigned to the participant. Thus, all numeric values are totaled resulting in a credibility weigh defined, which is unique for each participant. Hence, credibility weights are substituted into Equation 2, resulting in an FCM matrix. Finally, this process is followed by a normalization step (Tsadiras et al., 2001), as show in Equation 3.

$$F = \frac{\sum_{i=1}^n w_i F_i}{\sum_{i=1}^n w_i}$$

Equation 3. Formula to calculate the interaction matrix resulting from combining all participants' results.

Table 7 shows the criteria that was considered to assign credibility weights for each expert. In addition, Table 8 provides the key to the criteria table, which was adapted from (Hossain, 2006). Finally, Table 9 indicates the credibility value assigned to each participant.

Table 7. Criteria to assign credibility weights. Adapted from (Hossain, 2006)

No	Criteria to be used for participants	Why this criterion is important to determine the credibility of each participant for this specific research?	Numerical value associated with this criteria
1	The participant possesses a solid background on accident investigation	The participant has a low/standard/high level of understanding how maritime accidents are investigated. The participant is able to offer insight and information to this research based on its own expertise/academic level.	2 to 4
2	The participant possesses a solid background on HFs	The participant has a low/standard/high level HFs understanding. The participant is able to offer insight and information to this research based on its own expertise/academic level.	3 to 5
3	The participant possesses a solid background on ship operations	The participant has a low/standard/high level of understanding how ship are operated. The participant is able to offer insight and information to this research based on its own expertise/academic level.	2 to 4

Table 8. Key to criteria table. Adapted from (Hossain, 2006).

Factor assessed	Expert answer	Score for credibility weight
Q1: Knowledge level regarding accident investigation	1 to 2	2
	3	3
	4 to 5	4
Q2: Knowledge level regarding HFs	1 to 2	3
	3	4
	4 to 5	5
Q3: Knowledge level regarding ship operation	1 to 2	2
	3	3
	4 to 5	4

Table 9. Credibility weights assigned to participants.

No Participant	Answer to question			Credibility value
	Q1	Q2	Q3	
Participant1	4	4	4	12
Participant2	4	5	4	13
Participant3	3	5	3	11

Aggregation of expert opinion, establishment of interaction matrix & state vector based on expert opinion

Once the credibility value for each participant was calculated in the previous step, Equation 3 is applied to obtain the interaction matrix and the state vector, which results from combining the answers from all the participants by also taking into account their level of expertise. Table 10 shows the initial state vector (St.0) for the expert opinion stage, while Table 11 represents the interaction matrix obtained.

233 *Table 10. Initial state vector resulting from the aggregation of participants' state vectors.*

	HF1	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9
	0.280	0.536	0.266	0.284	0.110	0.170	0.367	0.115	0.490

234

235 *Table 11. Interaction matrix resulting from the aggregation of participants' interaction matrices.*

	HF1	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9
HF1	-	0.170	0.234	0.289	0.234	0.284	0.445	0.555	0.600
HF2	0.000	-	0.610	0.669	0.619	0.732	0.665	0.463	0.605
HF3	0.000	0.312	-	0.229	0.289	0.403	0.545	0.293	0.385
HF4	0.000	0.422	0.289	-	0.394	0.344	0.234	0.509	0.709
HF5	0.000	0.591	0.344	0.170	-	0.399	0.426	0.289	0.449
HF6	0.000	0.640	0.225	0.385	0.335	-	0.651	0.399	0.706
HF7	0.000	0.486	0.500	0.339	0.449	0.454	-	0.348	0.495
HF8	0.000	0.119	0.055	0.335	0.055	0.339	0.238	-	0.335
HF9	0.000	0.605	0.284	0.385	0.284	0.449	0.435	0.344	-

236

237 Dynamic FCM to Obtain the Weights of Accident Contributing HFs Obtained from Expert Opinion

238 A dynamic analysis of the FCM is performed by applying Equation 1. Table 12 provides the initial state vector

239 (St.0) and the dynamic evolution of the FCM until equilibrium is reached, which occurs before step 8 (St.8). In

240 addition, Figure 4 shows the iterative process followed until equilibrium is reached.

241 *Table 12. Calculation of steady states for grounding/stranding accidents in general cargo vessels. Expert opinion stage.*

242 *Period 2011-2016.*

	HF1	HF2	HF3	HF4	HF5	HF6	HF7	HF8	HF9
St.0	0.280	0.536	0.266	0.284	0.110	0.170	0.367	0.115	0.490
St.1	0.500	0.713	0.707	0.718	0.722	0.759	0.748	0.735	0.766
St.2	0.500	0.919	0.859	0.880	0.869	0.918	0.928	0.902	0.952
St.3	0.500	0.951	0.902	0.920	0.911	0.951	0.957	0.935	0.974
St.4	0.500	0.955	0.908	0.926	0.917	0.956	0.961	0.940	0.977
St.5	0.500	0.956	0.909	0.926	0.918	0.956	0.962	0.941	0.977
St.6	0.500	0.956	0.910	0.926	0.918	0.956	0.962	0.941	0.977
St.7	0.500	0.956	0.910	0.927	0.918	0.956	0.962	0.941	0.977
St.8	0.500	0.956	0.910	0.927	0.918	0.956	0.962	0.941	0.977

244

245 *Figure 4. Dynamic FCM for grounding/stranding accidents in general cargo vessels until equilibrium is reached. Expert*
246 *opinion stage. Period 2011-2016.*

247 **Sensitivity Analysis**

248 In addition, to combine the results obtained from both data sources (i.e. historical data and expert judgement), a
249 sensitivity analysis is conducted in the fourth stage of the MALFCMS method. The purpose of a sensitivity
250 analysis is to understand how the uncertainty in the output of a mathematical model or system can be divided and
251 allocated to different sources of uncertainty in its inputs. Hence, as the aim of this stage is to combine the outputs
252 from the historical data and expert opinion analyses, a sensitivity analysis seems adequate to perform this task.
253 Thus, sensitivity analyses have been already applied in the literature to merge the outputs from expert analysis
254 and questionnaires (A. Azadeh et al., 2014). Hence, in order to combine the finding from the historical data
255 analysis stage obtained by de Maya et al. (2019) and the expert opinion stage developed on this study, a sensitivity
256 analysis is performed in this section. Table 13 includes the weights of each HF normalized from both, the historical
257 data analysis stage and the expert opinion stage, and the final weights proposed, in which the same importance
258 has been assigned to both sources of data. In addition, Figure 5 represent the sensitivity analysis to provide a better
259 understanding of the process.

260 *Table 13. Sensitivity analysis to combine the results from the historical data analysis stage and the expert opinion stage.*

HF	Normalized historical data results (%) (de Maya et al., 2019)	Normalized experts' results (%)	Final weights (%)
HF1	10.342	6.213	8.2775
HF2	14.588	11.882	13.235
HF3	11.239	11.302	11.2705
HF4	8.73	11.513	10.1215
HF5	8.822	11.409	10.1155
HF6	8.614	11.884	10.249
HF7	14.524	11.955	13.2395
HF8	8.792	11.697	10.2445
HF9	14.348	12.144	13.246

261
262 *Figure 5. Sensitivity analysis to combine the results from the expert opinion stage and the historical data analysis stage.*

263 **Discussion**

264 In this section, data is used to weight each HF involved into grounding/stranding accidents in cargo vessels. Two
265 sources of data are employed to calculate final weights for each HF. The first source is an historical accident
266 database, while the second source is the data collected from questionnaires.
267 According to results of the dynamic analysis of the FCM created within the historical data analysis stage, “HF2:
268 Inadequate leadership and supervision”, “HF7: Lack of training” and “HF9: Unprofessional behavior” were

identified as the main contributing factor (de Maya et al., 2019). In addition, the dynamic analysis of the FCM created within this study (i.e. the FCM obtained from the expert opinion stage) revealed similar results. Based on the participants' answers, "HF9: Unprofessional behavior" was identified as the main human-contributing factor, followed by "HF7: Lack of training", "HF6: Lack of safety culture", and "HF2: Inadequate leadership and supervision". Thus, these results are in line with the findings from the historical accident database. Nevertheless, the main disagreement between both FCM created occurs for "HF1: Improper design, installation and working environment", which was identified by participants as the less influential factor into maritime accidents, while it has a medium importance according with de Maya et al. (2019). In addition, similar situation occurs for "HF6: Lack of safety culture", which has the lowest contribution based on the database analysis, but it was ranked third place by experts.

Finally, the two set of weights obtained are mixed together to reach more reliable weights for each HF. It should be noticed that equal coefficients (i.e. both coefficients are 0.5) are used for the weights derived from historical data and participants' views). Nevertheless, a sensitivity analysis has been further proposed to examine how important are the coefficients used to reach a mixed weight. Figure 5 shows the changes on final weights by changing the coefficient from 0.1 to 0.9, which has been used to combine both FCMs results. It is possible to observe that "HF1: Improper design, installation and working environment" is the most sensitive factor to changing the coefficients "expert opinion-historical accident data", as there is a 4.129% difference between the maximum and the minimum value of this factor. In addition, the least sensitive factor to changes in its value is "HF3: Inadequate safety management system: Inadequate procedures or deviation from SOP", which remains almost insensitive to changing the coefficients' distribution. Thus, this insensitivity is a good indicator of the ability to compare together historical accident data and expert opinion.

Clearly, the mixed solution proposed (i.e. both coefficients having the same importance) is in line with the previous results obtained, as "HF9: Unprofessional behavior", "HF7: Lack of training" and "HF2: Inadequate leadership and supervision" remains the top three human-contributing factors into grounding/stranding accidents in cargo vessels.

Conclusions

In this study, a FCM-based technique, Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs) is proposed and applied for the calculation of the weights for HFs involved into grounding/stranding accidents in cargo vessels. The aim of this paper was to apply the full MALFCM approach to obtain the weight of each HF

from two different sources (i.e. historical accident data (de Maya et al., 2019) and expert opinion) to overcome the main disadvantage of traditional FCMs. Thus, human-contributing factors obtained from both sources were analyzed and presented in the previous sections.

Based on the previous results, MALFCM method can be considered to represent the reality of accidents within the maritime sector well, as the maritime sector already recognizes the high contribution of skill-based factors such as “supervision”, “training”, or “behavior” into maritime accidents. Finally, the sensitivity analysis performed in this paper revealed that both results may be combined together, and equal coefficients are proposed for both historical data and expert opinion. Thus, the mixed weights obtained as a result of this combination reflect satisfactory the weights obtained separately for each stage (i.e. “HF9: Unprofessional behavior”, “HF7: Lack of training” and “HF2: Inadequate leadership and supervision” remains the top three human-contributing factors).

As seen from this study, the proposed model rank accident contributing factors effectively and the results are in line with similar studies from the literature. In addition, MALFCM has the potential to be applied to other sectors in which historical accident databases are available (e.g. aviation sector). Finally, as the weights obtained from MALFCM are ranked, efforts must be focused on identifying appropriate strategies to address the top contributing factors, and therefore enhance overall safety. Thus, the results from MALFCM method can be linked to risk assessment, to address the human contribution into accident in a more effective way. Overall, MALFCM has a great potential to address safety assessment of complex models by appropriately integrating existing data and expert opinion.

Finally, in a future study, the developed MALFCMs methodology can be applied to additional accident databases and taxonomies not only in the maritime sector but also in other sector in which human factors have a high contribution into accidents (e.g. aviation, nuclear, etc.). Thus, the proposed MALFCMs approach can be also applied to different vessels (e.g. passenger vessels, fishing vessels, etc.) and accident categories (e.g. contact, fire and explosion, etc.).

Acknowledgements

The authors of this paper would like to acknowledge the support of the Marine Accident Investigation Branch (MAIB) who provided the required data for performing this study.

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426

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