Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs): A case study on bulk carrier's accident contributors

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Abstract

Maritime transport has strived to reduce accidents and their consequences since its origins, by addressing safety as the priority from the design stage to decommissioning of any vessel. Complex nature of accidents, where numerous factors combine in a complicated structure, in turn, makes accidental learning ineffective. Statistical analysis of past experiences in maritime is good for demonstrating the trends for certain contributing factors in accidents. However, there is a lack of a detailed technique, which is capable of modelling the complex interrelations between these factors. Due to aforementioned complex interrelations between these contributing factors and insufficient information stored in accident databases about these contributors, it was not possible to understand the importance of each factor in maritime accidents, which prevented researchers from considering these factors in risk assessments. Therefore, there is a need for a practical technique, which is capable of estimating the importance of each contributing factor. The results of such a technique can be used to inform risk assessments and predict the effectiveness of risk control options. Thus, in this research study, a new technique for Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs) has been introduced and explained. The novelty of MALFCM is the application of fuzzy cognitive maps (FCMs) to model the relationships of accident contributors by utilizing information directly from an accident database with the ability to combine expert opinion. Hence, as each fuzzy cognitive map will be derived from real occurrences, the results can be considered entirely objective, and MALFCM may overcome the main disadvantage of fuzzy cognitive maps by eliminating or controlling the subjectivity in results. In this paper, FCMs were developed for various accident scenarios and contributing human factors were assessed. For instance, in collision accidents in bulk carriers, situational awareness or inadequate communication were identified as the most critical factors, with a normalised importance weighting of 4.88% and

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4.87% respectively. Similarly, importance weightings for each contributing factor in each accident category were obtained and shared in this paper.

Keywords: maritime accidents; human factors; fuzzy cognitive maps; risk factors; accident prevention; accident investigation

1. Introduction

Shipping accidents in maritime sector have defined and changed maritime industry since its origins by informing regulators, designers and operators about the need for better measures to prevent similar consequences (Eliopoulou, Papanikolaou et al. 2016). As a result, accident reporting is of paramount importance and enforced with laws. However, the complexity of identifying all the variables involved in accidents and inconsistent methods followed during accident investigations, make it extremely difficult to integrate lessons learnt from past accidents into risk assessments. According to Kristiansen (2013), there is not a clear answer to why accidents happen. Accidents are complex processes; therefore, usually there is not a single factor solely responsible for the accident. This situation creates a barrier for enhancing safety as identified risk control options cannot be effectively linked back to contributors.

Without a doubt, humans' role in accidents is more difficult to quantify as the relation between human performance and accident development is even more complicated to model. Regardless of the industry in scope, human factors are often considered as the primary source of accidents (Smith, Veitch et al. 2017). For instance, according to Azadeh and Zarrin (2016), human factors are the primary cause of at least 66% of the accidents and more than 90% of the incidents in nuclear or aerospace industries. Similarly, in the maritime sector, at least 80% of marine casualties are attributed to human factors (Wang, Jiang et al. 2013, Graziano, Teixeira et al. 2016, Kurt, Khalid et al. 2016, Turan, Kurt et al. 2016, Fan, Yan et al. 2017, Antão and Soares 2019, Navas de Maya, Ahn et al. 2019). One of the main challenges of analysing a complex accident scenario lays in the process of classifying the factors involved in it (Wolpert 1992). Many authors have addressed classification methods (Aggarwal 2014) as Bayesian Networks, decision trees or fuzzy cognitive maps (FCMs). However, there is not a representative method that could be selected as the most suitable for all datasets (Fernández-Delgado, Cernadas et al. 2014). Traditional FCMs are a classification method that presents a set of advantages such as modelling causal relationships between accident variables (Kardaras and Karakostas 1999, Khan, Quaddus et al. 2001) and the possibility to represent hazy degrees of causality relations between components (Lee and Han 2000). Also, FCMs can be considered as a

powerful tool for modelling systems that cannot be explained entirely mathematically (Stylios and Groumpos 1999). Furthermore, vector-matrix operations allow an FCM model to become a dynamic system (Kosko 1994, Khan, Quaddus et al. 2001) by allowing the system to evolve with time.

Hence, aiming to identify and weight the importance of each factor that contributes to the development of accidents, this paper introduces a new FCM based technique, Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs), and demonstrates it through a case study on bulk carrier accidents.

2. Literature Review

One of the first appearances of Cognitive Maps (CMs) in literature was in 1948, in a paper entitled "*Cognitive maps in rats and men*" (Tolman 1948), which intended to create a model for the psychology domain. Since that first mention, several authors have represented a collection of nodes linked by arcs. By definition, CMs are signed digraphs characterised by the opinions of experts in a particular area of knowledge (Dodurka, Yesil et al. 2017). A CM is composed of two primary elements known as concepts and causal beliefs. The concepts variables, C_x (x=1, 2, …), are represented as nodes linked by arcs within the CM structure. These concept variables are interrelated through causal beliefs (Rodriguez-Repiso, Setchi et al. 2007). Nevertheless, applicability of CMs was limited as they presented two main limitations (Khan, Quaddus et al. 2001). First, the interrelation above between concepts might be established as positive or negative. However, the strength of the internal relation amongst concepts remains unknown. Second, a CM is not able to represent a dynamic system (the system cannot evolve with time), ignoring that the effect of a change in a node may affect other nodes in the process. Therefore, in order to overcome CMs drawbacks, Kosko (1986) developed FCMs, as extensions of cognitive maps which aims to model complex chains of casual relationships, and weight them with fuzzy numbers. Hence, they have become a potential tool for modelling and analysing dynamic interactions between concepts or systems (Lee, Kim et al. 1996) and have been successfully applied for decision making in the past years (Khan, Quaddus et al. 2001).

Even though FCM is not as well-known as other methods, e.g. Bayesian networks or decision trees (Papakostas, Boutalis et al. 2008, Papakostas, Koulouriotis et al. 2012), it has been proved to be very promising and worthy of further investigation and development (Vergini and Groumpos 2016). Thus, several studies have addressed the application of FCMs as a classification tool in different fields, as summarised on Table 1, certifying that FCMs are widely accepted and validated for their effectiveness.

Table 1. Summary of FCM existing studies

Authors	Static/Dynamic	Data Source	Application Area	Contribution
Andreou, Mateou et al. (2003)	Static/Dynamic	Expert opinion	Politics	Model political and strategic issues to support decision-making process for an imminent crisis
Papageorgiou, Spyridonos et al. (2006)	Dynamic	Expert opinion/Archives	Medicine	Development of brain tumour characterization models
Papageorgiou, Stylios et al. (2006).	Static/Dynamic	Expert opinion	Engineering	Model industrial process control problems
Jetter (2006)	-	-	Engineering and Technology	Review of FCMs theory and concepts
Wei, Lu et al. (2008)	Static/Dynamic	Expert opinion	Business	Modelling and evaluating trust dynamics in the virtual enterprises
Bueno and Salmeron (2008)	Static	Expert opinion	Business	Enterprise Resource Planning (ERP) tool selection
Yaman and Polat (2009)	Dynamic	Expert opinion	Business	Illustrative case for effect/based operations
Luo, Wei et al. (2009)	Static/Dynamic	Expert opinion/Data	Computer design	Design of game-based learning systems
Pajares, Guijarro et al. (2010)	-	-	Computer design	Framework for detection of image change
Carvalho (2010)	Dynamic	Expert opinion	Politics	Simulation of complex economic, social and political systems
Kannappan, Tamilarasi et al. (2011), Papageorgiou and Kannappan (2012)	Dynamic	Expert opinion	Medicine	Prediction and diagnosis of autistic disorders
Papageorgiou, Oikonomou et al. (2012)	Dynamic	Expert opinion	Business	Classification tasks
Nápoles, Grau et al. (2014)	Dynamic	Expert opinion	Medicine	Prediction of the degree of resistance of HIV proteins
Azadeh, Salehi et al. (2014)	Dynamic	Expert opinion	Engineering	Assessment of resilience in a petrochemical plant
Soner, Asan et al. (2015)	Static/Dynamic	Expert opinion	Engineering	Prediction and elimination of the root causes of a fire related deficiency
Jamshidi, Rahimi et al. (2016)	Static	Expert opinion	Engineering	Risk assessment of complex and dynamic systems

Authors	Static/Dynamic	Data Source	Application Area	Contribution
Navas de Maya and Kurt (2018), Navas de Maya, Kurt et al. (2018), (de Maya, Babaleye et al. 2019)	Dynamic	Expert opinion/Accidental data	Engineering	Identification and weighting of accident contributors in maritime

For the construction of an FCM, experts develop a model based on their experience by following a procedure composed of three stages. First, key factors (henceforth factors) of the model are identified within a specific focus area. Second, interrelationships are proposed between these factors by identifying if these relations are positive or negative. In the last step experts estimate the causal relationship strength for the factors above (Papageorgiou 2010, Zare Ravasan and Mansouri 2016), and therefore, the main limitation of a CM (i.e. lack of ability to define the strength of relationships between factors) is addressed. In order to obtain factors weightings, different approaches have been considered. For instance, one suggestion is to ask experts to assign a value from the interval [0, 1] for each relationship between factors and then calculate the average value (Dodurka, Yesil et al. 2017). However, it is hard for some experts to assign a numerical value when complex relationships occur. Therefore, a second suggestion is to apply linguistic variables, obtaining a linguistic weight which is transformed through the application of a defuzzification method (Papageorgiou 2010). Although FCMs can transcribe experts' opinion, its weaknesses lay on the uncertainty related with each expert's response. Hence, it is possible to weight each expert's opinion in order to increase or reduce the importance of their feedback (Kandasamy and Smarandache 2003).

When it comes to the analysis of an FCM, there are two methods available for researchers. First, a static analysis can be carried out in order to determinate the relative importance of factors and the causal effects between nodes (Axelrod 1976, Khan and Quaddus 2004) in which the relations between nodes can be classified as positive, negative or indeterminate (Axelrod 1976). In most real-world applications, the most common found relation is the indeterminate. Thus, this problem could be solved by creating weights in the casual links, and therefore, it is possible to eliminate the indeterminacy problem (Dodurka, Yesil et al. 2017). Second, dynamic analysis can be conducted to study and explore the impact in the decision-making process in time. Within this approach, given a connection matrix and an initial state vector to create an FCM, the final resulting state vector can provide information regarding any impacts or changes made to the system. Furthermore, with dynamic analysis it would be possible to study the system from a "what-if" perspective (Khan and Quaddus 2004).

2.1 Mathematical representation

An FCM represents the relation between each pair of factors involved in a case with a number W_i that has a value within the interval [0,1] (León, Rodriguez et al. 2010). Moreover, it is possible to define three types of connections between each pair of factors based on the nature of their interrelations (León, Rodriguez et al. 2010, Azadeh, Salehi et al. 2014):

- A positive weighting between factors C_i and C_j ($W_{ij}>0$) which means, an increase in the first factor will lead to an increase in the second factor. At the same time, if the first factor is decreased the second factor will be also decreased.
- A negative value between the weights of factors C_i and C_j ($W_{ij}<0$) which means, an increase in the first factor will lead to a decrease in the second factor. At the same time, if the first factor is decreased the second factor will be increased.
- No causality ($W_{ij}=0$) which means that there is no relation between the two factors.

According with Kosko (1986), a traditional formula to calculate the values of concepts in an FCM is as follows:

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

In which $A_i^{(t+1)}$ represents the weighting for the factor C_i at the step t+1, f is the threshold function which will bound the factor value within the interval [0,1], W_{ji} represents the relation between both factors C_i and C_j, and $A_j^{(t)}$ represents the weighting of the factor C_i at step t.

An FCM requires three components to be created: First, an interaction matrix with dimension *n x n* where n indicates the number of factors analysed in the FCM. The interaction matrix is characterized by having the number of rows and columns equal to the number of factors represented within the FCM. Figure 1, on the left-side, shows an example of a simple FCM for an accident with five factors involved, while on the right-side the equivalent interaction matrix for the same example is demonstrated. Second, an initial state vector, which displays the initial value of the factors in the scenario being modelled at any step interaction. Finally, a threshold function, which purpose is to reduce unbounded inputs to a strict range, aiming to maintain the stability of the qualitative model (Mohr 1997). Although there are plenty threshold functions available (Mohr 1997), the Sigmoid function gives any possible value within the interval [0,1] (Xiao, Chen et al. 2012, Azadeh, Salehi et al. 2014) and it has been

proved by Bueno and Salmeron (2009) that using this function provides greater benefits. Therefore, this function is selected and shown in Equation 2.

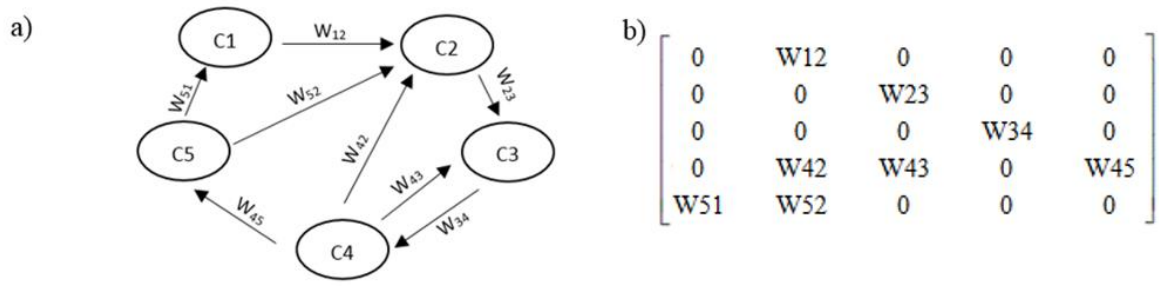

Figure 1. (a) A simple representation of an FCM; (b) Equivalent transition matrix (Navas de Maya, Kurt et al. 2018).

$$A_i^{(t+1)} = \frac{1}{1+e^{-x}} \tag{2}$$

In which $A_i^{(t+1)}$ represents the value of the factor C_i at the step t+1.

2.2 The dynamic FCM models

An FCM is an iterative process in which Equation 1 is repeated for each time step (step 1, step 2 etc.) until the process ends, which could happen in three different scenarios, as shown below (Kosko 1994, Khan, Quaddus et al. 2001, Xiao, Chen et al. 2012):

- **The FCM reaches equilibrium**: After two consecutive iterations, the results are identical. In this case, the simulation stops and the FCM is considered steady.
- **The FCM does not produce a stable result:** The results keep cycling between a set of values without stabilizing. This situation is known as the "limit cycle", and it originates from a particular combination of weight values when applying an FCM, which drive the map away from reaching equilibrium (Wierzchon 1995).
- **None of the previous scenarios:** In complex scenarios with many factors involved, the FCM may not reach identical values, producing different results for each step, case known as 'chaos'.

Thus, the next section in this research study shares the details of the approach adopted, which utilises a new methodology known as Marine Accident Learning with Fuzzy Cognitive Maps.

3 Methodology: Marine Accident Learning with Fuzzy Cognitive Maps (MALFCMs)

As mentioned in previous sections, the main shortcoming of an FCM is the likelihood to restrict the resulting outcome due to experts' lack of knowledge. In order to overcome this problem, a method for Marine Accident

Learning with Fuzzy Cognitive Maps (MALFCMs), which differs from the traditional FCM approach, is proposed with the aim to establish weights for factors involved in 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 can 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 could be described in four main stages (de Maya, Babaleye et al. 2019):

1. First Stage: Historical data analysis
2. Second Stage: Expert opinions analysis
3. Third Stage; Construction of dynamic FCMs
4. Fourth Stage: Consolidation of the results

In the historical data analysis stage, historical data is obtained for accidents in focus (e.g. same vessel category involved or same navigational accident), in order to identify which human and technical factors were involved in the previous similar accidents. Then, each pair of factors is compared to create the interaction matrix. Furthermore, statistical analysis is performed to establish the initial state vector.

In the expert opinion analysis stage, experts are requested to provide their knowledge by comparing each pair of factors involved in accidents. This rating process may be accomplished through numeric values or linguistic values. For linguistic values, a conversion into fuzzy numbers and a defuzzification process are required. Finally, an individual interaction matrix and state vector are created for each expert.

In the construction of dynamic FCMs stage, a threshold function is selected, and two separate FCM processes are performed by following Equation 1. 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 analysed, and the obtained weightings are ranked.

Lastly, in the consolidation of the results stage, final weightings are obtained by combining the results obtained from the historical data and expert opinion stages. Figure 2 displays the overall MALFCM framework. It is important to note that this paper only demonstrates the historical data analysis stage of MALFCM framework for collision, contact and fire/explosion accident categories. In addition, full MALFCM approach is tested on grounding accidents to test how the historical data stage and the expert opinion stage interact, and how the results are affected by aforementioned interaction.

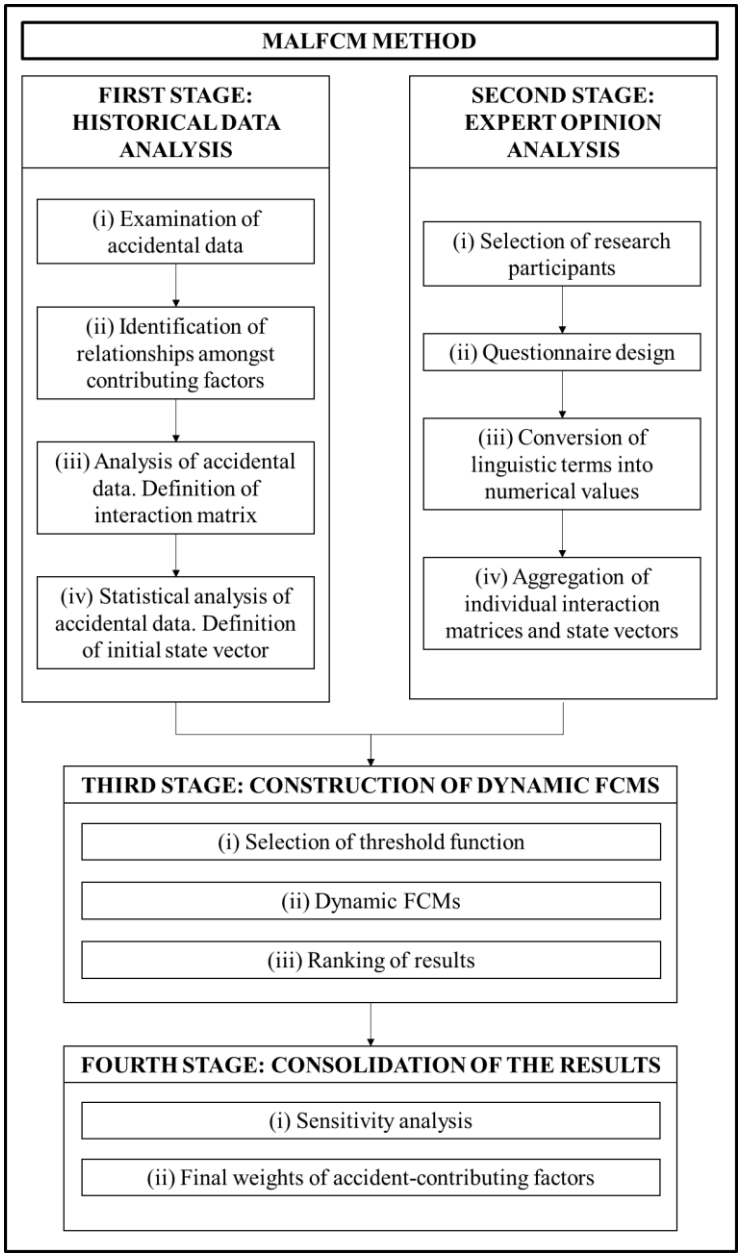

Figure 2. Methodology overview.

3.1 First Stage: Historical data analysis

In this state, historical occurrence data is collected for a predefined case study (e.g. a specific vessel category) in order to identify human and technical factors. Once the previous factors are identified, the interaction matrix and the state vector are created. Within a traditional FCM, experts are requested to provide the strength of the relations amongst each pair of factors. However, the quality of expert's feedback depends on the experience of each expert and the relevance of his/her expertise to this topic (Shankar 2012). Also, often it is not possible to obtain reliable

results due to the unavailability of relevant experts. Thus, by analysing historical data as an additional resource for judgement, it is possible to obtain more objective results as the accidents analysed have already taken place and therefore it is possible to track back the factors were in the root of each accident.

Henceforth, for the interaction matrix construction, each pair of factors are compared. This comparison process is further explained in the case study. Thus, this process is repeated in order to obtain the relations and weights of each pair of factors, creating an interaction matrix n x n, in which n shows the total number of factors being analysed. Moreover, for this case study, the state vector is defined as the statistical occurrence of each factor. Thus, for a factor C_i, the state vector value is defined as the relation of the total number of accidents with C_i involved, and the total number of accidents.

3.2 Second Stage: Expert opinion analysis

The Expert opinion stage comprises expert participation by means of a questionnaire. Through this stage, experts provide their knowledge by comparing each pair of factors C_i and C_j involved in accidents in order to complete the interaction matrix. There are various alternatives for experts to express their beliefs. Nevertheless, given that some experts find it extremely challenging to assign numeric values in specific scenarios, the choices in the questionnaire are presented as linguistic terms.

There are two different types of questions in above-mentioned questionnaire. “Type A” questions enquiry how influential a particular contributing factor would need to be in order to have a minimum contribution into a maritime accident. The choices given are “None or very very low”, “Very low”, “Low”, “Medium”, “High”, “Very high”, and “Very very high” as suggested by Markinos, Papageorgiou et al. (2007). Answers to “Type A” questions will define the state vector for each expert. In addition, “Type B” questions ask, given a change in a particular contributing factor Ci, what would be the level of the effect on the contributing factor Cj. The choices given are “None”, “Very small”, “Small”, “Moderate”, “Big”, “Very big”, and “Very very big”. In addition, answers to “Type B” will define the interaction matrix for each expert.

The next step involves the conversion of each individual interaction matrix and state vector derived at the previous step, expressed in linguistic terms, into numerical terms. As described in the literature, a linguistic weight may be transformed into a numerical value by means of a linguistic-numerical conversion. Therefore, the five linguistic conversion proposed by Tsadiras, Kouskouvelis et al. (2001) is adapted to include the seven linguistic terms used by participants, which are equated to values ranging from a minimum of 0 to a maximum value of 1 as shown in Table 2.

Table 2. Fuzzy conversion measures for the interaction matrix and state vector

Fuzzy linguistic terms	**None**	**Very small** **Very low**	**Small** **Low**	**Moderate** **Medium**	**Big** **High**	**Very big** **Very high**	**Very very big** **Very very high**
Fuzzy numerical weights	0.000	0.165	0.330	0.495	0.660	0.825	1.000

In such a case where experts do not have the same level of knowledge about the case study, the group is considered heterogeneous, and a credibility-weighting coefficient (w_i) is defined for each expert based on his/her knowledge, as shown in Equation 3 (Kosko 1992, Kandasamy and Smarandache 2003).

$$F = \sum w_i F_i \tag{3}$$

Where F_i represents the FCM components for $expert_i$ and w_i is equal to the credibility weight of $expert_i$.

Finally, a generic interaction matrix and state vector are created by combining each interaction matrix and state vector through the credibility-weighting coefficient.

3.3 Third Stage: Construction of dynamic FCMs

In this stage, the threshold function is selected. As it was mentioned previously, although there are plenty threshold functions available (Mohr 1997), it has been proved by (Bueno and Salmeron 2009) that using the Sigmoid function provides greater benefits.

As all elements required for an FCM are already defined, two FCMs are created. The first one is produced with data from the Historical data analysis stage, while the second FCM integrates the findings from the expert opinion analysis stage.

3.4 Fourth Stage: Consolidation of the results

To combine the results obtained from two different data sets, Azadeh, Salehi et al. (2014) propose to apply a sensitivity analysis. Therefore, in the last stage, MALFCM method combines the results obtained from historical occurrence data and expert opinion by means of a sensitivity analysis. As it was mentioned above, full MALFCM approach is only tested on grounding accidents. Therefore, for the remain accident categories considered in this study, the coefficient for expert opinion is zero, and the final weightings are obtained only from the FCM created from the historical occurrence data analysis.

4 Results

For the case study presented in this paper, factors involved in accidents were obtained from MAIB historical accident database for the period 2000-2011. For the aforementioned period, MAIB database includes 2690 entries

related to factors (both human and technical) that contributed to past accidents according to accident investigators' reports. One of the most populated vessel categories in aforementioned database is bulk carriers which is selected for investigation in this paper. There are twelve accident categories linked to bulk carriers, from where four are considered for this study due to the data availability. The accident categories analysed include navigational accidents (i.e. collision, grounding and contact), and fire/explosion accidents. The last accident category is included in order to examine the differences with the results obtained from navigational accidents, as it has been identified in previous studies that fire/explosions are highly responsible of total-loss marine accidents in the world (Chen, Bian et al. 2019). Table 3 indicates both human and technical factors identified in at least one accident in bulk carriers. Even though authors recognize that some factors in Table 3 may be grouped together, in this study in order to be consistent with MAIB nomenclature authors decided to conduct FCM analysis with original factor groupings.

Table 3. Human and technical factors involved in accidents to bulk carriers.

Factor No	**Factor Description**	**Factor No**	**Factor Description**
3	Alcohol use	59	Misapplication of regulations, policies, procedures or practices
9	Characteristic defect	61	No compliance
10	Communication	62	Operation Instructions inadequate
12	Company standing orders inadequate, insufficient, conflicting	63	Other vessel
13	Competence	64	Outside operational design limits
14	Complacency	65	Perception abilities
15	Construction defect	66	Perception of Risk
16	Corrosion	68	Personality
17	Culture	69	Personnel unfamiliar with equipment/not trained in use
18	Current	71	Poor decision making/information use
19	Design inadequate	75	Poor regulations, policies or practices
21	Diminished motivation	76	Pressures - organisational
23	Equipment badly maintained	77	Procedures inadequate
25	Equipment not available	80	Safety culture
26	Equipment poorly designed for operational use	81	Seal/gasket
27	Erosion/cavitation damage	83	Ship movement weather conditions
29	Failure to maintain discipline	84	Situational awareness or communication inadequate
30	Fatigue	87	System defect

35	Hazardous natural environment	90	Technical knowledge inadequate
36	Factor 36 - Health: drugs/alcohol	93	Training
37	Health: medical condition	94	Training which itself is inadequate
38	Heavy weather	95	Training, inexperience, knowledge
41	Inadequate management of physical resources	96	Training, skills, knowledge
44	Inadequate resources	98	Ultimate tensile stress exceeded
45	Inattention	100	Uncharted underwater Obstruction
48	Knowledge of regulations/standards inadequate	101	Under stimulation
49	Knowledge of ship operations inadequate	102	Unsafe working practices
50	Lack of communication or co-ordination	104	Vigilance
52	Language problem	107	Visual environment
55	Management and supervision inadequate	110	Worn out

Once the factors involved in accidents in bulk carriers were identified, an FCM was created for each accident category considered in this case study. As mentioned before, an FCM requires three components to be created:

- First, an interaction matrix with dimension n x n where n indicates the number of concepts analysed in the FCM,
- Second, an initial state vector, which displays the initial value of the concepts in the scenario being modelled at any point in time (t)
- And at last, a threshold function.

In the next sections, full procedure for the historical data analysis stage (i.e. creation of the interaction matrix, state vector and FCM representation) is demonstrated for the collision accidents in bulk carriers. Then, results for remaining accident categories where only historical data analysis stage is demonstrated (i.e. contact and fire/explosion) are shared in section 4.4. The results are shared in the form of final weightings for each contributing factor and the FCM graphs demonstrating the iteration process. In addition, section 4.5 includes the full demonstration of MALFCM framework for grounding accidents.

4.1 Interaction matrix

In order to create the interaction matrix, MAIB historical database was analysed by comparing each pair of factors identified in past accidents. For example, in order to determinate the relation between Factor 13 – Competence and Factor 65 – Perception abilities aforementioned in Table 3, the accident database was filtered by the accidents caused by at least one of the previous factors. Moreover, the database was also filtered by the accidents that shared both factors as a common accident cause. Thus, the weight of *Factor 13 – Competence* over *Factor 65 – Perception*

abilities was considered as the relation between the number of accidents with both factors involved and the accidents with *Factor 13 – Competence* but not *Factor 65 – Perception abilities*, as shown in Equation 3. This process is repeated in order to obtain the relations and weights of each pair of factors. Due to the size of the interaction matrix, Table 4 shows a partial representation of the interaction matrix for collisions in bulk carriers for the period 2000-2011. It is important to mention that just the factors from Table 3 linked to collision accidents appear in Table 4 as an example of the process to fulfil an interaction matrix (F10, F12, F13…).

$$W_{F13-F65} = \frac{W_{F13 \cap F65}}{W_{F13 \setminus F65(setsubtraction)}} \tag{3}$$

Table 4. Partial representation of interaction matrix for collision accidents in bulk carriers. Historical data analysis stage. Period 2000-2011.

	F10	**F12**	**F13**	**F14**	**F18**	**F21**	**F41**	**F45**	**F48**	**F49**	**F50**	**F59**	**F61**	**F65**	**…**
F10	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	…
F12	0.000	0.000	0.000	0.500	0.500	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	…
F13	0.333	0.000	0.000	0.000	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.333	…
F14	0.000	0.500	0.000	0.000	0.500	0.500	0.000	0.500	0.000	0.000	0.500	0.000	0.000	0.000	…
F18	0.500	0.500	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	…
F21	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	0.000	…
F41	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	…
F45	0.000	0.500	0.000	0.500	0.000	0.500	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.000	…
F48	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	…
F49	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	…
F50	0.000	0.000	0.000	0.500	0.000	0.500	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	…
F59	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000	…
F61	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	…
F65	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

4.2 State vector

For this case study, the state vector was defined as the statistical occurrence of each factor. For instance, for Factor 13 – Competence, the state vector value was calculated as the relation of the total number of accidents with Factor 13 – Competence involved, and the total number of accidents. Table 5 shows the state vector for collisions in bulk carriers for the period 2000-2011.

Table 5. State vector for collision accidents in bulk carriers. Historical data analysis stage. Period 2000-2011.

F10	F12	F13	F14	F18	F21	F41	F45	F48	F49	F50	F59
0.100	0.200	0.300	0.200	0.200	0.100	0.100	0.200	0.100	0.100	0.200	0.100
F61	**F65**	**F66**	**F68**	**F71**	**F76**	**F77**	**F84**	**F94**	**F95**	**F104**	
0.100	0.100	0.200	0.100	0.100	0.100	0.100	0.400	0.100	0.100	0.100	

4.3 Dynamic FCM from historical data analysis stage

MAIB database utilized in this case study included twelve accident categories (e.g. collision or grounding). In this study, four out of the twelve accident categories were considered for demonstrating proposed MALFCM method. It was identified that 60 factors from MAIB database (listed in Table 3), were a primary cause in at least one out of the twelve accident categories in bulk carriers. Thus, the FCMs were created for each accident category analysed by following Equation 1, until each FCM reached equilibrium. As an example, to illustrate this process, **Error! Reference source not found.** shows the variation in the weightings obtained for both human and technical factors involved in collision for the period 2000-2011, until equilibrium is reached, which occurs before step 6 for this example.

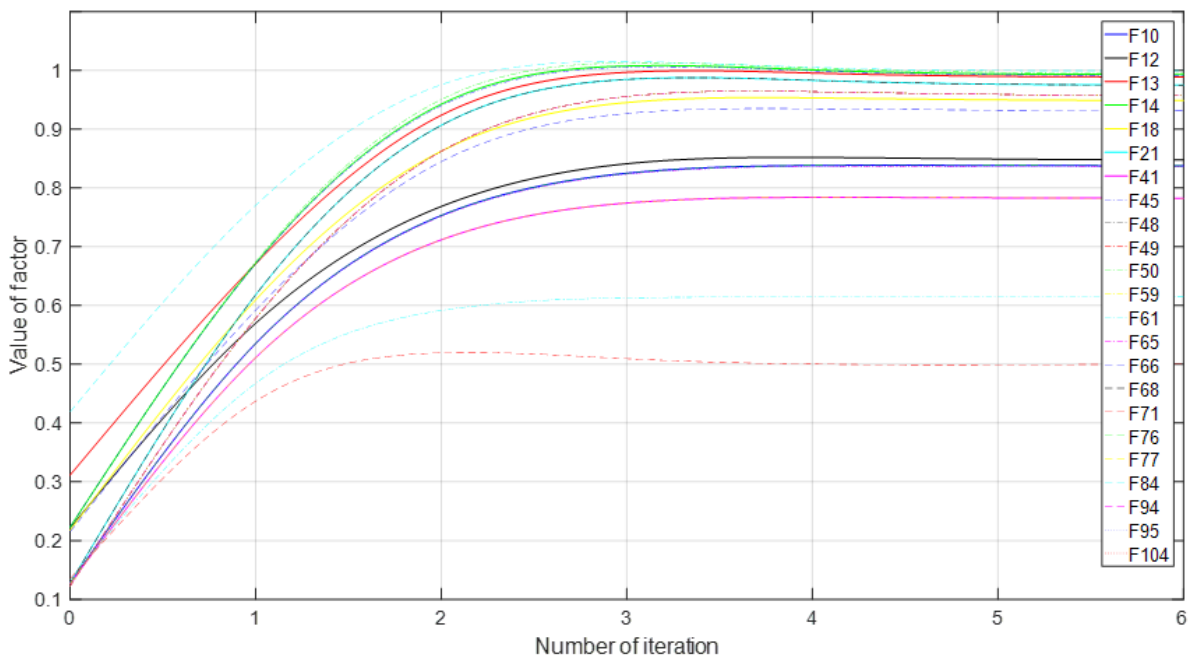

Figure 3. Values of FCM for collision in bulk carriers until equilibrium is reached. Historical data analysis stage. Period 2000-2011

4.4 Final weight of contributors to collision, contact and fire/explosion accidents from historical data analysis stage

Finally, an FCM was created for each accident category considered in this case study by following the process represented in Figure 3 . The weightings obtained from each FCM were restricted to the interval [0,1] due to the threshold function, which aimed to maintain the stability of the qualitative model (Mohr 1997). Thus, the weightings obtained were normalised and ranked in order to show the impact of the identified factors as a percentage. Hence, Table 6 shows the weighting of each accident contributors to collision accidents. It is possible to observe that *Factor 84 - Situational awareness or communication inadequate* has the highest impact on collision accident while *Factor 71 - Poor decision making/information use* is the least influential in this accident category. These results are in line with the findings of Sandhåland, Oltedal et al. (2015), who performed a study on 27 collision accidents that occurred between 2001 and 2011, in which 23 might have been related to the loss of situation awareness (SA). Also, Sætrevik and Hystad (2017) identified that SA has a crucial role since it influences decision-making and performance, hence, a lack of SA might have a significant impact on safety. Moreover, Chauvin, Lardjane et al. (2013) analysed collisions accident using the HFACS method, which identified SA and a deficit of attention as significant elements leading to accidents. Same study also report that inter-ship communication problems have significant impact in collision accidents. In our study we have identified the same factors as the second most important factor as well.

By further analysing the results for collision accidents, it is clearly shown in **Error! Reference source not found.** that there are 23 factors involved in this accident category. From all these factors, just one factor is a technical factor, *Factor 18 - Current*, which reinforces the perception about human element on ships as being the major contributor to maritime accidents (Rothblum 2000, Graziano, Teixeira et al. 2016, Turan, Kurt et al. 2016, Navas de Maya, Kurt et al. 2018); particularly in collision accidents.

Table 6. Final weight of contributors for "Collision" in bulk carriers ranked in order of importance. Historical data analysis stage. Period 2000-2011

Factor number	Factor description	Weight from FCM	Weight normalized (%)
84	Situational awareness or communication inadequate	1.000	4.881
50	Lack of communication or co-ordination	0.997	4.865
14	Complacency	0.994	4.851
45	Inattention	0.992	4.843
13	Competence	0.989	4.829

Factor number	Factor description	Weight from FCM	Weight normalized (%)
21	Diminished motivation	0.976	4.763
68	Personality	0.976	4.763
104	Vigilance	0.976	4.763
48	Knowledge of regulations/standards inadequate	0.958	4.675
49	Knowledge of ship operations inadequate	0.958	4.675
59	Misapplication of regulations, policies, procedures or practices	0.958	4.675
94	Training which itself is inadequate	0.958	4.675
18	Current	0.949	4.633
66	Perception of risk	0.932	4.548
12	Company standing orders inadequate, insufficient, conflicting	0.848	4.138
10	Communication	0.838	4.089
76	Pressures - organisational	0.838	4.089
65	Perception abilities	0.836	4.082
95	Training, inexperience, knowledge	0.836	4.082
41	Inadequate management of physical resources	0.783	3.820
77	Procedures inadequate	0.783	3.820
61	Non compliance	0.614	2.999
71	Poor decision making/information use	0.500	2.441

In addition, Table 7 shows the weightings for contributing factors in contact accidents. According to Table 7, *Factor 83 - Ship movement weather conditions* has the highest influence while *Factor 107 – Visual environment* has the minimum impact for contact. From the ten factors involved in contact accidents, four are technical factors (F19, F38, F63 and F83), representing an average weighting of 44.99% due to technical factors within this accident category. It is noticeable that this is the only navigational accident category that shows a closer distribution between human factors (55.01%) and technical factors (44.99%) weightings.

Table 7. The final weight of contributors for "Contact" in bulk carriers ranked in order of importance. Historical data analysis stage. Period 2000-2011

Factor number	Factor description	Weight from FCM	Weight-normalized (%)
83	Ship movement weather conditions	0.981	12.494
45	Inattention	0.974	12.409
19	Design Inadequate	0.946	12.052
38	Heavy Weather	0.946	12.052
77	Procedures inadequate	0.946	12.052
63	Other Vessel	0.659	8.392

Factor number	Factor description	Weight from FCM	Weight-normalized (%)
94	Training which itself is inadequate	0.659	8.392
55	Management and supervision inadequate	0.620	7.899
84	Situational awareness or communication inadequate	0.619	7.889
107	Visual environment	0.500	6.368

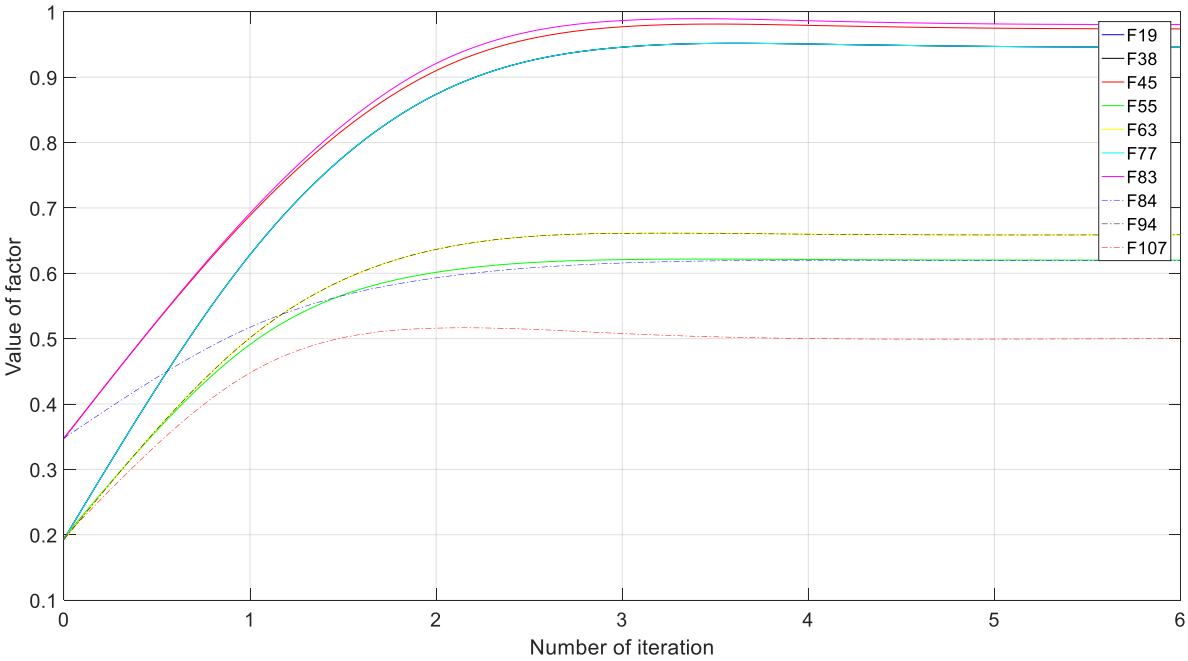

Figure 4. Values of FCM for contact in bulk carriers until equilibrium is reached. Historical data analysis stage. Period 2000-2011

Moreover, the results obtained from fire/explosion accidents are shown in Table 8. It can be observed from the results that, *Factor 77 – Procedures inadequate* has the highest influence while *Factor 59 - Misapplication of regulations, policies, procedures or practices* has the minimum impact on fire/explosion accidents. From the nineteen factors involved in fire/explosion, five are a non-human factor related (F9, F19, F35, F81 and F110), representing a weighting of 27.16%.

Research conducted in EU funded SEAHORSE Project concluded 20-30% of standard operating procedures are ineffective hence not being followed strictly during operations (Kurt, Arslan et al. 2015, Kurt, Arslan et al. 2016). Our results also present similarities with the study conducted by Barnett (2005), who stated that deficient maintenance is one of the major causes of fire and explosion, which concur with the first factor ranked within this study. Also, Chang and Lin (2006) reviewed 242 accidents for the period 1960-2003, from where fire and explosion accounted for 85% of these accidents and 30% of them were caused by human error, e.g. poor operation

or maintenance. Also in their study Chang and Lin (2006) consider inadequate procedures or inadequate resources, as the top fire/explosion accident contributors.

Table 8. Final weight of contributors for "Fire/explosion" in bulk carriers ranked in order of importance. Historical data analysis stage. Period 2000-2011

Factor number	Factor description	Weight from FCM	Weight normalized (%)
77	Procedures inadequate	1.000	5.595
23	Equipment badly maintained	1.000	5.595
13	Competence	1.000	5.594
44	Inadequate resources	1.000	5.594
14	Complacency	0.998	5.584
25	Equipment not available	0.997	5.575
52	Language problem	0.997	5.575
84	Situational awareness or communication inadequate	0.997	5.575
90	Technical knowledge inadequate	0.997	5.575
110	Worn out	0.997	5.575
9	Characteristic defect	0.978	5.471
19	Design Inadequate	0.978	5.471
35	Hazardous natural environment	0.978	5.471
69	Personnel unfamiliar with equipment/not trained in use	0.925	5.177
81	Seal/gasket	0.925	5.177
104	Vigilance	0.925	5.177
29	Failure to maintain discipline	0.842	4.712
45	Inattention	0.842	4.712
59	Misapplication of regulations, policies, procedures or practices	0.500	2.797

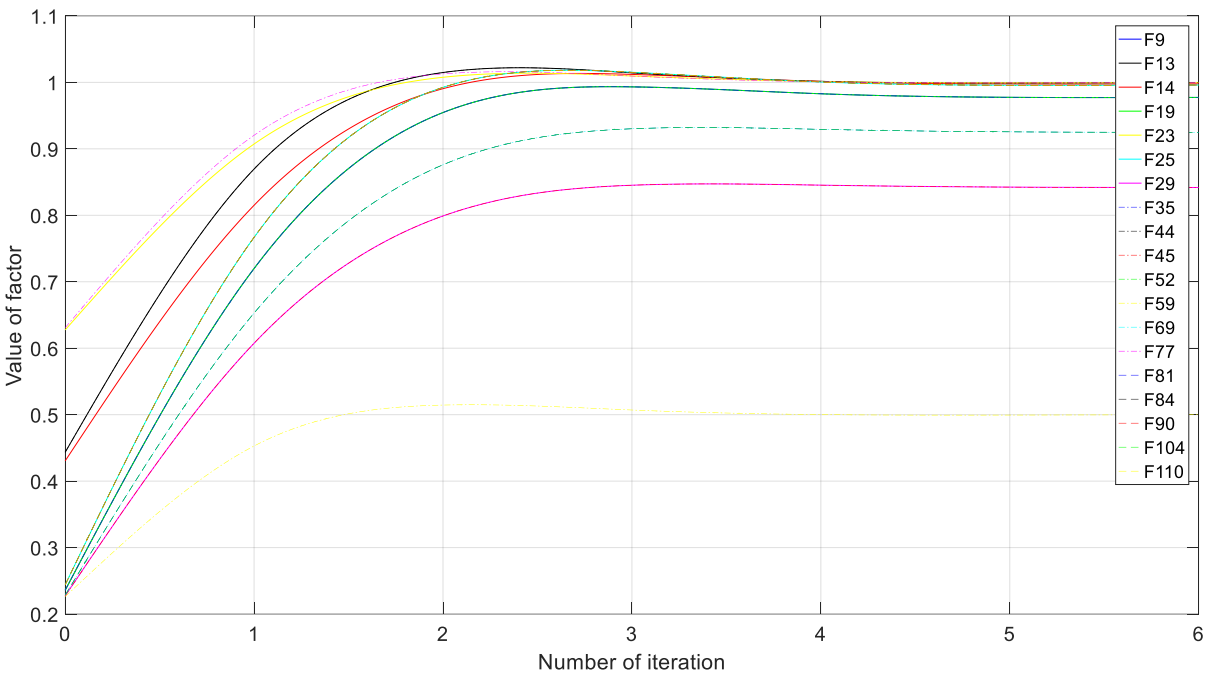

Figure 5. Values of FCM for fire/explosion in bulk carriers until equilibrium is reached. Historical data analysis stage. Period 2000-2011

4.5 Final weight of contributors to grounding accidents from full MALFCM approach

Regarding grounding accidents, full MALFCM approach has been tested to examine the interactions amongst the historical data analysis stage and the expert opinion stage.

First, from the historical data analysis stage, Table 9**Error! Reference source not found.** shows the weights of accident contributors. *Factor 45 – Inattention* is the most relevant contributor for this accident category while *Factor 100 - Uncharted underwater Obstruction* has the least impact in grounding. Moreover, from the eleven factors linked to grounding, just F38 and F100 are related to non-human factors. Similar results were obtained by Yıldırım, Başar et al. (2017), who assessed grounding accidents with HFACS and statistical methods. From their study, the management of resources was identified as the most common accident category, including factors as insufficient communication or lack of procedures, e.g. incorrect passage plan. Moreover, skill-based errors and physical environment follow the management of resources. Furthermore, Barnett (2005) also identified that a lack of situational awareness was a dominant human errors into accidents, as this study highlighted. However, the variation in the factors ranking obtained when comparing this study with other researchers' findings might be influenced by the difference between the accident reports, the expert groups involved, or the accident databases analysed.

Table 9. The final weight of contributors for "Grounding" in bulk carriers ranked in order of importance. Historical data analysis stage. Period 2000-2011.

Factor number	Factor description	Weight from FCM	Weight-normalized (%)
45	Inattention	0.795	12.965
14	Complacency	0.761	12.402
77	Procedures inadequate	0.761	12.402
38	Heavy Weather	0.659	10.741
66	Perception of risk	0.659	10.741
13	Competence	0.500	8.150
50	Lack of communication or coordination	0.500	8.150
71	Poor decision making/information use	0.500	8.150
84	Situational awareness or communication inadequate	0.500	8.150
100	Uncharted underwater Obstruction	0.500	8.150

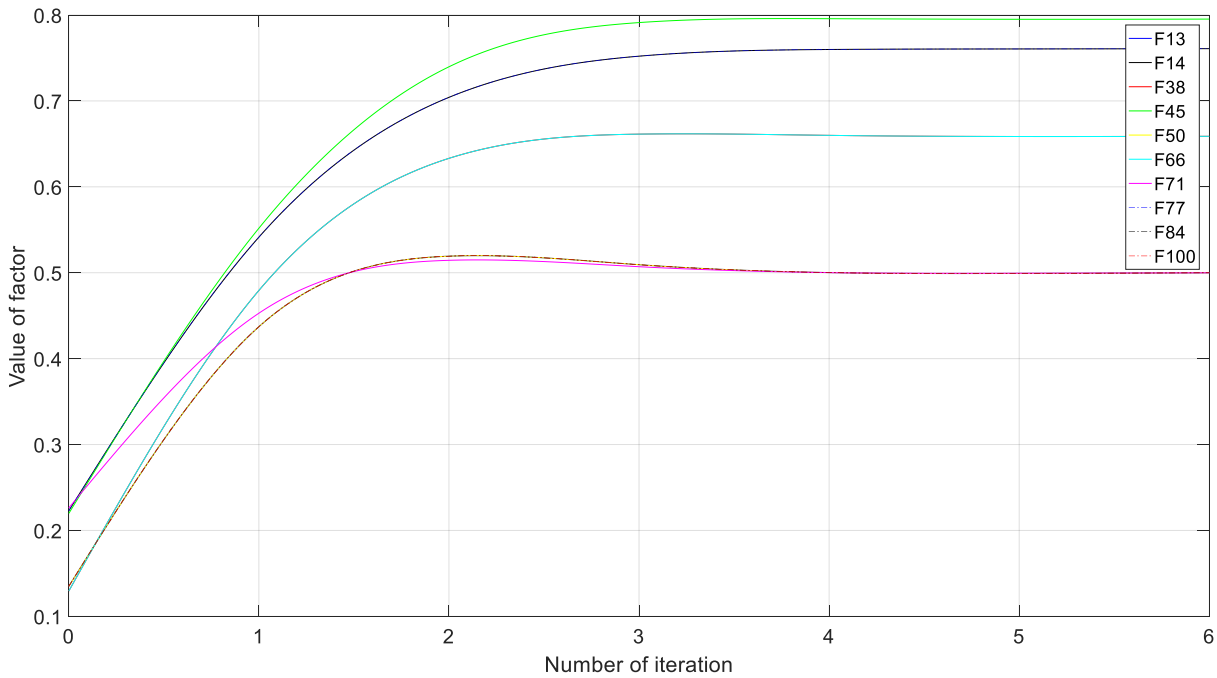

Figure 6. Values of FCM for grounding in bulk carriers until equilibrium is reached. Historical data analysis stage. Period 2000-2011.

Second, from the expert opinion analysis stage, three experts were selected (which are referred to as Participant1, 2 and 3) to complete a questionnaire with included two different types of questions, as indicated in the previous section. Thus, skill and experienced participants with a similar background on the areas of human factors, ship operations and accident investigations were selected.

Once the questionnaire was completed, all the answer were collected, and an interaction matrix and a state vector were created for each participant, expressed in linguistic terms. The next step involved the conversion of each individual set of answers, expressed in linguistic terms, into numerical expressed terms, by following the fuzzy conversion measures displayed on Table 2. After all answers were transformed into numeric values, the individual answers needed to be aggregated in order to create a unique set of answers. Many authors in the literature have defended the use of a credibility weight (w_i) =1 (Taber 1987). Therefore, as participants on this study presented a similar background, it was decided to adopt the same credibility weight for all participants. Table 10 presents the aggregated interaction matrix after incorporating the findings from all participants. Similarly, Table 11 displays the aggregated state vector.

Table 10. Interaction matrix for grounding accidents in bulk carriers. Expert opinion analysis stage. Period 2000-2011

	F13	**F14**	**F38**	**F45**	**F50**	**F66**	**F71**	**F77**	**F84**	**F100**
F13	0.000	0.440	0.110	0.330	0.495	0.220	0.385	0.330	0.440	0.110
F14	0.275	0.000	0.000	0.220	0.330	0.165	0.165	0.275	0.220	0.000
F38	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F45	0.330	0.550	0.055	0.000	0.495	0.055	0.275	0.275	0.495	0.000
F50	0.550	0.385	0.330	0.495	0.000	0.330	0.495	0.440	0.770	0.000
661	0.663	0.550	0.330	0.770	0.715	0.000	0.385	0.385	0.715	0.000
F71	0.605	0.440	0.165	0.715	0.605	0.498	0.000	0.550	0.773	0.275
F77	0.165	0.330	0.000	0.330	0.550	0.165	0.385	0.000	0.275	0.000
F84	0.550	0.440	0.275	0.828	0.660	0.715	0.550	0.275	0.000	0.275
F100	0.220	0.165	0.110	0.605	0.055	0.220	0.055	0.055	0.275	0.000

Table 11. State vector for grounding accidents in bulk carriers. Expert opinion analysis stage. Period 2000-2011

F13	**F14**	**F38**	**F45**	**F50**	**F66**	**F71**	**F77**	**F84**	**F100**
0.495	0.440	0.715	0.883	0.825	0.605	0.825	0.770	0.883	0.605

Third, Equation 1 was applied for each time step (step 1, step 2 etc.) until the process ends, in order to create a dynamic FCM from the expert opinion analysis stage. Figure 7 shows the variation in the weightings obtained for both human and technical factors involved in grounding accidents in bulk carriers for the period 2000-2011, until equilibrium is reached.

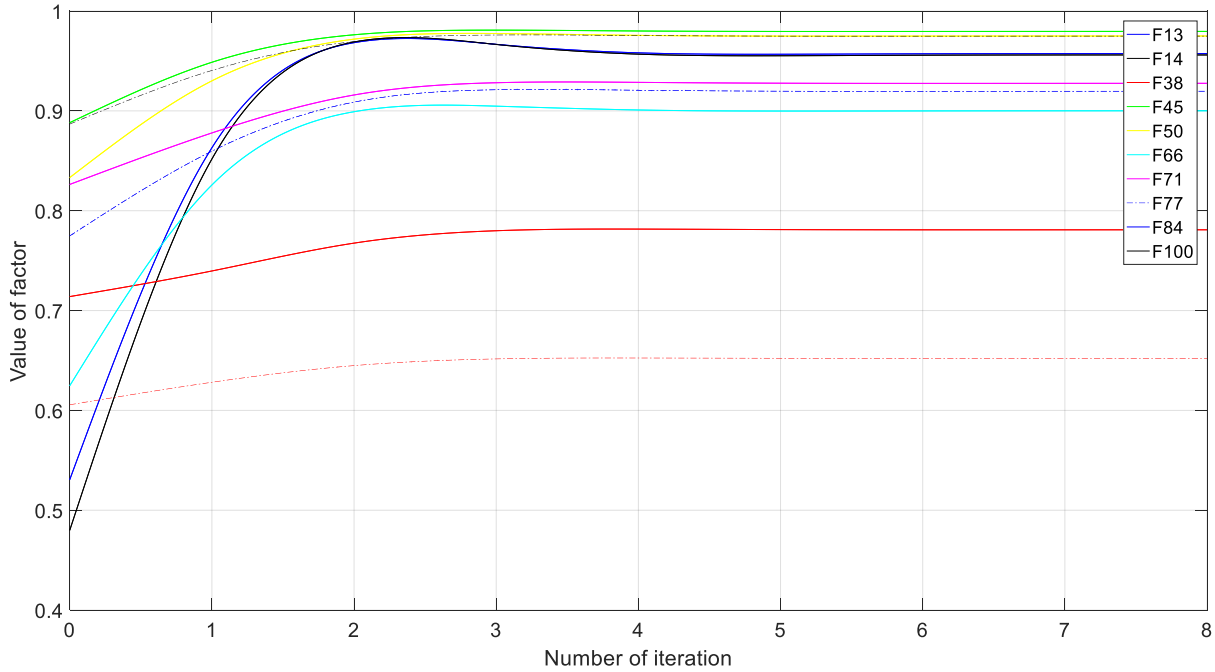

Figure 7. Values of FCM for grounding in bulk carriers until equilibrium is reached. Expert opinion analysis stage. Period 2000-2011

Finally, a sensitivity analysis is proposed to combine the results obtained from the historical data analysis stage and the expert opinion analysis stage. Table 12 includes the weights of each human and technical factor normalized from both, the historical data analysis stage and the expert opinion stage, and the final weights proposed, in which the same importance has been assigned to both sources of data. Thus, Figure 8 represent the sensitivity analysis to provide a better understanding of the process.

Table 12. Sensitivity analysis to combine the results from the historical data analysis stage and the expert opinion stage. Period 2000-2011

No	Normalized historical data results (%)	Normalized experts' results (%)	Final weights (%)
13	8.150	10.610	9.380
14	12.402	10.595	11.498
38	10.741	8.654	9.698
45	12.965	10.856	11.911
50	8.150	10.805	9.478
66	10.741	9.975	10.358
71	8.150	10.280	9.215
77	12.402	10.192	11.297
84	8.150	10.804	9.477
100	8.150	7.228	7.689

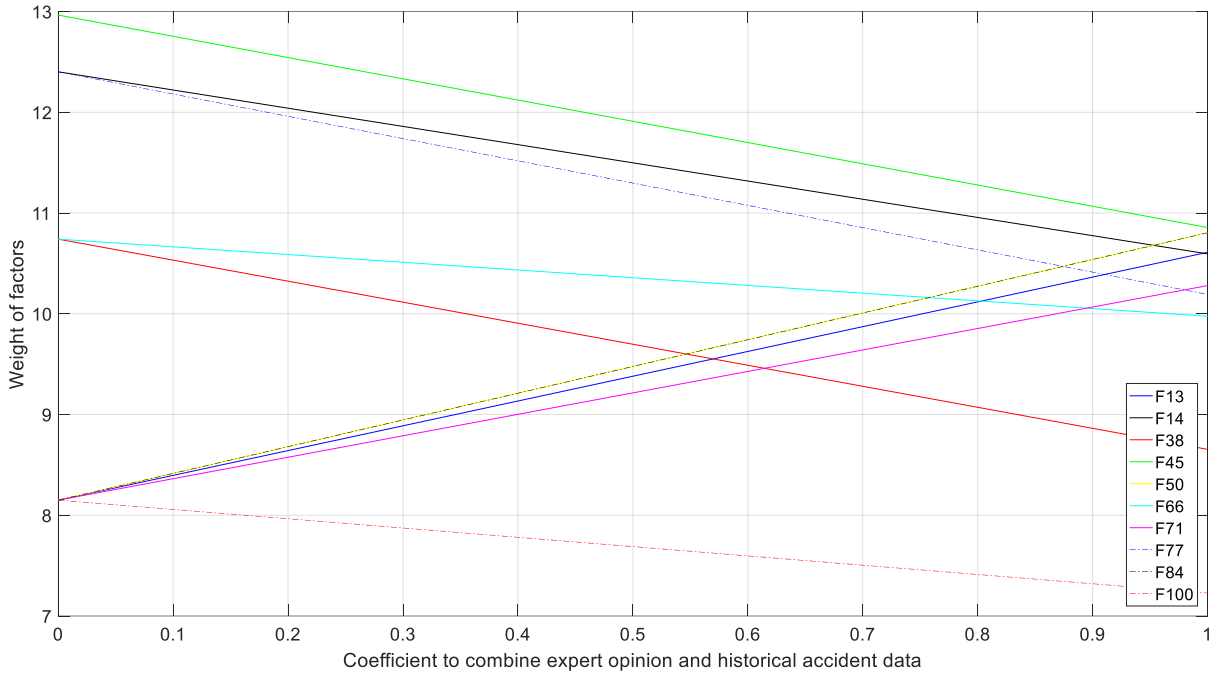

Figure 8. Sensitivity analysis to combine the results from the expert opinion stage and the historical data analysis stage. Period 2000-2011

5 Discussion

Although traditional FCMs are a suitable technique for modelling causal relationships between variables as indicated in the literature, they present an important limitation. As traditional FCM are designed to transcribe experts' opinion, its weaknesses lay on the uncertainty related with each expert's response (i.e. 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 this new approach, authors have developed a framework that considers historical accident data when building FCMs which can be considered as a strength to make FCMs more realistic. The develop method (MALFCM) applies FCMs to model the relationships of accident contributors by utilizing information directly from an accident database with the ability to combine expert opinion. Hence, as each fuzzy cognitive map is derived from historical data, the results could be considered entirely objective, and MALFCM may overcome the main disadvantage of FCMs by eliminating or controlling the subjectivity in results.

According to our analysis, for collision accidents, the top five accident contributors identified are "*situational awareness or communication inadequate", "lack of communication or co-ordination", "complacency", "inattention"*, and *"competence",* with a normalised importance weighting of 4.88%, 4.87%, 4.85%, 4.84%, and 4.83% respectively. Findings of MALFCM for collision accidents appear to agree with current challenges identified by field experts in the area of collision avoidance. As collision accidents happen generally due to skills based and competence related shortcomings, it is not a surprise to observe that factors like situational awareness and communications problems were ranked as leading contributors to collision accidents. Hence, MALFCM results can be considered to represent the reality of the collision accidents well. Furthermore, the maritime sector already recognises the high contribution of skill based factors such as "*competence*" into maritime accidents. Hence, training and competence issues are addressed and controlled by regulations (e.g. STCW) or. However, more research is needed in order to measure the effectiveness of current safety regime in terms of addressing aforementioned accident contributors.

In addition, for contact accidents, the same contributors were ranked as *"ship movement weather conditions",* "*inattention", "design inadequate"*, "*heavy weather*", and *"procedures inadequate",* with a normalised importance weighting of 12.49%, 12.41%, 12.05%, 12.05%, and 12.05% respectively. Moreover, this navigational accident reached a closer distribution between human factors (55.01%) and technical factors (44.99%) weightings. It can be seen from the results that heavy weather and ship movement due to weather conditions play an important role in contact accidents which makes ship handling more difficult especially during tricky manoeuvres. The results look realistic as it is common to have contact accidents in adverse weather conditions.

Regarding fire/explosion accidents, the top five accident contributors were "*procedures inadequate", "equipment badly maintained", "competence", "inadequate resources*", and *"complacency",* with a normalised importance weighting of 5.60%, 5.60%, 5.59%, 5.59%, and 5.58% respectively. Outcomes of MALFCM study for fire/explosion accidents demonstrate that on board operational procedures play a significant role in this type of accident together with badly maintained equipment, which is logical. There are studies that support the fact that deficient maintenance is one of the major causes of fire and explosion accidents (Barnett 2005). Furthermore, inadequate procedures is one of the challenging topics in shipping that is requiring urgent attention to raise the standards of safety. EU funded research project SEAHORSE concluded that significant amount of standard operating procedures are not followed by crew members on board due to the fact that they do not represent operational realities. This situation encourages crew members to conduct workarounds, which carry additional safety shortcomings. (Kurt, Arslan et al. 2016).

Finally, regarding grounding accidents, the top five accident contributors from applying full MALFCM framework were identified as *"inattention", "complacency", "procedures inadequate", "perception of risk",* and *"heavy weather",* with a normalised importance weighting of 11.91%, 11.50%, 11.30%, 10.36%, and 9.70% respectively. These outcomes are in line with factors identified by other researcher and experts. Since navigational accidents mainly happen due to the in correct attitude and skill gaps that exist on-board a ship, it is expected to see that "lack of attention" or the "use of inadequate procedures" are listed as critical by MALFCM. Moreover, findings from this study reveal that contributing factors responsible for grounding accidents are more related to individual actions or behaviour (e.g. perception of risk or inattention), while in collision accidents factors related to working as team also plays an important role (e.g. lack of communication). In addition, the two set of weights obtained for grounding accidents were mixed together to reach more reliable weights for each accident contributing factors. 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, as shown in Figure 8.

As it can be observed from aforementioned importance weightings, navigational accidents (i.e. collision, grounding and contact) present similar accident contributing factors between each other (e.g. "*inattention"* was identified in all the cases, while *"procedures inadequate", "complacency",* and *"heavy* weather" were identified in at least two of these accident categories). The identification of common accident contributing factors might be related with the characteristics of aforementioned accident categories, since they are all part of navigational accidents, and therefore, they present some similarities. However, when comparing fire/explosion accidents with navigational accidents, it was observed that there was less commonality between the factors involved in these accidents. This difference is expected since navigational accidents are mostly influenced by a lack of specific skills and situational awareness, while fire and explosion are generally due to poor maintenance or a lack of adequate procedures on board.

6 Conclusion

In this paper, a new modelling and simulation approach, MALFCMs, was proposed and applied to a case study on bulk carriers. The aim of this paper was to obtain the weighting of each human and technical factor that lead to accidents with MALFCM. Therefore, FCMs were developed for various accident scenarios (i.e. a number of navigational accidents and fire/explosion accidents) and contributing factors were analysed and presented in the previous sections.

Once the weighting for all accident contributing factors are obtained, they can be used by decision makers in order to identify primary areas where safety can be increased, and therefore accidents could be better addressed and overall safety might be improved. Moreover, it is possible to apply MALFCM technique to other accident categories or vessel categories or to study a more specific scenario. As seen from this study, the proposed model rank accident contributing factors effectively and quickly and the results obtained are in line with those from similar studies. In addition, MALFCM has the potential to be applied to other sectors in which historical accident databases are available (e.g. aviation sector) in order to identify which human and technical factors are responsible for accidents in aforementioned sectors. Besides, this study was performed with accident data from 2011 onwards, therefore, an updated database could be analysed to compare if the factors that caused accidents in the past have been adequately addressed thought safety measures, or if they are still leading to accidents nowadays. Furthermore, the importance weightings obtained from MALFCM could be utilised to identify appropriate training by safety managers, i.e. the top contributing factors could be addresses by developing a suitable training program, and therefore enhance overall safety. Finally, these weightings can be linked to risk assessment studies in order to consider human factor contributions to accidents. Overall, authors of this study believe that MALFCM or similar FCM based techniques have great potential to address safety assessment of complex systems and scenarios by appropriately integrating existing data and expert opinion.

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700