Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria

Application of fuzzy cognitive maps to investigate the contributors of maritime collision accidents

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Abstract

Maritime transport has been striving to reduce ship accidents since its origins, which results in loss of lives or properties and damage for the environment. Hence, a continuous effort to enhance safety is a crucial requirement for the maritime sector, for which several approaches have been tried for the past years. This paper presents the first results of a study which aim is to assess the factors affecting collision accidents in order to enhance safety and resilience. This aim is achieved by using Fuzzy Cognitive Maps (FCMs) method, which consider and evaluates importance of these factor by calculating and assigning individual weights to them. Moreover, FCM appears to be a suitable approach since it can take into account both, fuzzy data and past accidents experiences. Hence, in this paper with the help of FCM, past accidents from the Marine Accident Investigation Branch (MAIB) database regarding collision are analysed to identify the contributors of collision accidents and their FCM weightings.

Keywords: maritime accidents; maritime safety; collision; fuzzy cognitive maps

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Nomenclature

FCMs Fuzzy Cognitive Maps
MAIB Marine Accident Investigation Branch

1. Introduction

Maritime transport has been characterised by ship accidents since its origins, with significant consequences and impact on society (Eliopoulou et al., 2016). Traditionally, an accident was defined by Kristiansen (2013) as "an undesirable event that results in damage humans, assets and/or the environment". In the last ten years, the shipping industry has implemented different measures designed to improve its safety level. Despite these actions, shipping accidents, and particularly collisions, remain a major concern considering that around 90% of world trading is carried out by the maritime sector according to Chauvin et al. (2013).

Analysing the literature, it becomes evident that humans have played a major role in past accidents (Smith et al., 2017). The statistics indicate that human factors are the major cause of at least 66% of the accidents and more than 90% of the incidents in different industries, i.e. aerospace or nuclear (Azadeh and Zarrin, 2016). For instance, in aviation between 70% and 80% of the accidents are connected with human errors as described by O'Hare et al. (1994). Regarding the maritime sector, Rothblum (2000) indicates that "about 75–96% of marine casualties are caused, at least in part, by some form of human error". Graziano et al. (2016) explain that "human factors … are implicated in 80% of marine casualties" and Turan et al. (2016) identify that "more than 80% of shipping accidents are attributed to Human/organisational Error". Hence, considering how human elements affects accidents, in the last years the maritime sector has developed an increasing interest in the understanding of the importance of the human elements, resulting in more research on board focused on human factors (Kurt et al., 2016).

The aim of this paper is to analyse both human and technical factor contributing to collision accidents. These factors are obtained from analysing a database provided by the MAIB, which investigates marine accidents involving UK vessels worldwide and all vessels operating in UK territorial waters. It provides information for 211 vessels for the period 2000-2011. As it was mentioned before, particularly collisions, remain a major concern when analysing the number of shipping accidents occurred, therefore, this study will be focus in collision accidents. In the next sections of this paper a FCM will be created in order to show both human and technical factors, and their interrelations that contribute to maritime collision accidents.

2. Methodology

With the aim to model an FCM that will represent the relation between human and technical factors within collision accidents the following steps are followed: Firstly, the FCM method is briefly explained. Secondly, the factors that are responsible for collision accidents are defined. It is important to mention that these factors have been established and defined by the MAIB, hence, the nomenclature may vary from other sources in the literature referring human factors. Thirdly, the initial state vector is selected. For this study, two different initial state vectors are considered in order to compare how they will affect the final weight of the collision factors. Then, the required interaction matrix for the FCM is calculated, showing the relation between all the collision factors. Finally, the threshold function is applied obtaining the final weight distribution of factors in collision accidents.

2.1. Fuzzy Cognitive Maps (FCMs)

When an accident occurs, the different factors that leaded to it are interconnected, hence, developing a model for analysing these connections becomes to be a crucial target. Maritime accidents are characterised as complex processes in which there is no a simple solution to prevent them (Kristiansen, 2013), therefore, due to the vagueness and data unavailability regarding accidents, and that this study is based on data collected from past experiences, a method that can deal with both as the FCMs method should be applied (Azadeh et al., 2014).

As defined by Eden (1988), FCMs are extensions of cognitive maps aiming to model complex chains of casual relationships and they have become a potential tool for modelling and analysing dynamic interactions between concepts in the past years (Lee et al., 1996). Cognitive maps were created by Axelrod (1976) in the 1970s, aiming to represent social scientific knowledge. Then, evolving from them Kosko (1986) developed fuzzified cognitive maps, mainly characterised by three components: the characteristics of the system, signed and weighted arcs representing the interrelations within the elements. The main target in a FCM is to define the relations between the concepts represented, understanding the global structure and the dynamics of the system (Azadeh et al., 2014).

2.1.1. FCMs mathematical representation

Within a FCM, each of the concepts is represented by a number, A_i that represents its value within the interval [0,1]. León et al. (2010) assure that it is possible to identify three types of connections between the concepts described in the FCM that represents the nature of their respective influence:

- The weights between the concepts C_i and C_j would be positive ($W_{ij}>0$). Hence, an increase in the first concept will lead to an increase in the second concept and vice versa.
- The weights between the concepts C_i and C_j would be negative ($W_{ij}<0$). Then, an increase in the first concept will lead to a decrease in the second concept and vice versa.
- As a last case, a zero causality ($W_{ij}=0$) means there is no relation between that two concepts in particular.

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

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

In which $A_i^{(t+1)}$ represents the value of Ci at the step t+1, f is the threshold function which will make sure the concept value is limited within the interval [0,1], W_{ji} represents the weight between both concepts Ci and Cj , and $A_j^{(t)}$ is the value of the concept Cj at step t. Although there are plenty threshold functions available for performing a FCM, three of them are considered significant according to Mohr (1997):

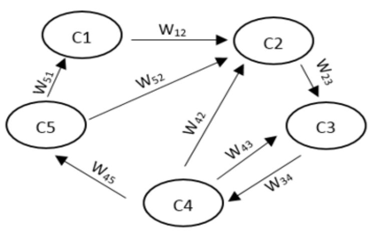
- The bivalent threshold function. The threshold function could adopt two possible values, 0 when there is no relation between two concepts, or 1, when both concepts are linked.
- The trivalent threshold function. It is an extension of the previous function, which could adopt a third value, -1, in order to represent concepts with a negative weight relation.
- The logistic signal function, also known as the Sigmoid function, which provides a truly fuzzy conceptual states giving any possible value within the interval [0,1] and it has been proved by Bueno and Salmeron (2009) that using this function provides greater benefits than the mentioned above. Hence, this function is selected (Equation 2), in which λ is the constant which determines the degree of fuzzification of the function:

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

For representing a FCM there are three main elements which allow to apply the FCM to a set of concepts:

- An interaction matrix with dimension n x n where n indicates the number of concepts involve in the FCM. Fig. 1 shows on the left an example of a simple FCM, while on the right it shows its equivalent transition matrix. Zero elements indicate that a relation does not exist between two particular elements, while non-zero elements show not only that there is a relation but also the strength or weight of that relation.

a)



b)

$$\begin{bmatrix} 0 & w12 & 0 & 0 & 0 \\ 0 & 0 & w23 & 0 & 0 \\ 0 & 0 & 0 & w34 & 0 \\ 0 & w42 & w43 & 0 & w45 \\ w51 & w52 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 1 (a) A simple representation of a FCM; (b) Equivalent transition matrix

- An initial state vector, which shows the initial value of the concepts (during step 0).
- A threshold function with the characteristics and properties described previously.

Once the FCM starts being developed, at each time step (step 1, step 2 etc.) the values of the concepts will be obtained following Equation 1 until the process stop, which could happens in three different scenarios (Kosko, 1994); (Khan et al., 2001); (Xiao et al., 2012):

- The FCM reaches equilibrium. This situation occurs when after two consecutive steps repeating the process both state vectors obtained are identical. In this situation the simulation stop.
- The FCM does not produce a stable state vector. Instead of that, it keeps cycling between a number of values (for example, 0,0.3,0.5,0,0.3,0.5,…,0,0.3,0.5). This situation is known as the 'limit cycle'.
- A last possibility occurs when the FCM does not reach identical values, producing different state vectors for each step. This possibility is defined as 'chaos' and it can appear in complex scenarios.

2.1.2. FCMs application

Despite of the fact that FCM is not as well-known as other methods (Papakostas et al., 2012, Papakostas et al., 2008), it has been proved to be very promising and worth of further investigation and development (Vergini and Groumpos, 2016). Several studies have addressed the application of FCMs as a classification tool in different fields for the past years, proving that FCM is not only a well validated classification tool but also its effectiveness.

FCMs have been mainly used in terms of planning and decision making (Dodurka et al., 2017), nevertheless, the interest from both researcher and industry is increasing and FCMs are specially interested regarding the areas of medicine (Papageorgiou and Froelich, 2012), control (Papageorgiou et al., 2006), business (Glykas, 2013), robotics (Motlagh et al., 2012), environmental science (Kok, 2009), education (Yesil et al., 2013), energy efficiency (Mpelogianni et al., 2015) and information technology (Büyüközkan and Vardaloğlu, 2012).

Finally, in order to demonstrate the potential of FCM for the maritime domain, this method has been applied to the MAIB database, but it could also be applied to a specific case in a company, proving that with the proper data collected it is possible to determine the interrelation between accident factors when an accident takes place.

2.2. Human and technical factors affecting collision accidents

The factors that are considered within this study are obtained from analysing a database provided by the MAIB for the period 2000-2011, filtered by ships involved in collision, resulting in 872 accidents and 211 different vessels. This database is composed by sixty-eight factors, both human and technical, which are directly responsible of collision accidents. However, creating a FCM with all these elements would result in a complex model which would take a great amount of time and resources. Hence, following the Pareto rule (roughly 80% of the effects come from 20% of the causes), the original sixty-eight factors that were found in collision are analysed in order to determine which of them will be considered for this study, as it is shown in Table 1, from where it is possible to see that twenty-three out of sixty eight factors (33.82% of the causes) have as a result 80.16% of collision accidents.

Table 1. Factors that lead to collision accidents (statistical analysis of MAIB database).

Factor number	Collision accident factors	Total number of accidents (%)	Accumulative percentage (%)	Factor number	Collision accident factors	Total number of accidents (%)	Accumulative percentage (%)
1	Complacency	9.29	9.29	13	Competence	2.18	63.99
2	Procedures inadequate	7.80	17.09	14	Knowledge of regulations/standards inadequate	1.83	65.83
3	Inattention	7.34	24.43	15	Poor decision making/information use	1.83	67.66
4	Situational awareness or communication inadequate	7.34	31.77	16	Understimulation	1.83	69.50
5	Lack of communication or co-ordination	5.96	37.73	17	Inadequate management of physical resources	1.61	71.10

Factor number	Collision accident factors	Total number of accidents (%)	Accumulative percentage (%)	Factor number	Collision accident factors	Total number of accidents (%)	Accumulative percentage (%)
6	Misapplication of regulations policies, procedures or practices	5.73	43.46	18	Other Vessel	1.61	72.71
7	Vigilance	5.05	48.51	19	Perception of risk	1.61	74.31
8	Diminished motivation	3.21	51.72	20	Equipment misuse	1.49	75.80
9	Safety culture	3.10	54.82	21	Fatigue	1.49	77.29
10	Company standing orders inadequate insufficient, conflicting	2.41	57.22	22	Social factors	1.49	78.78
11	Perception abilities	2.29	59.52	23	Current	1.38	80.16
12	Personality	2.29	61.81				

The previous concepts are adapted from a guidance for external user that MAIB as below:

- Factor 1 - Complacency: An organization or individual is dissatisfied with performance.
- Factor 2 - Procedures inadequate: Lack of information in the standing order, open to misunderstanding.
- Factor 3 - Inattention: Loss of attention, including for example failing to monitor displays or forgetting to perform a specific duty. It may also be due to other causes like personal problems, fatigue, etc.
- Factor 4 - Situational awareness or communication inadequate: Incorrect understanding of the situation which can lead to faulty hypothesis. For example, incorrect interpretation of alarms on board.
- Factor 5 - Lack of communication or co-ordination: Not making use of all available information sources to determine current status. For example, poor communication between bridge officers.
- Factor 6 - Misapplication of regulations, policies, procedures or practices: Application of regulations at an incorrect time or circumstances.
- Factor 7 - Vigilance: Ability to keep attention to monitor the vessel adequately.
- Factor 8 - Diminished motivation: Lack of desire to perform well, resulting in a decrease of performance.
- Factor 9 - Safety culture: Characteristics of large-scale bodies (operating companies, industry sectors) that influence the approach taken to safety issues.
- Factor 10 - Company standing orders inadequate, insufficient, and conflicting: The policy, standards, etc. may all contribute to the incident being inadequate or safety procedures may not be operating.
- Factor 11 - Perception abilities: Abilities of the individual in terms of perception i.e. visual, auditory, etc.
- Factor 12 - Personality: Relative enduring characteristics of behavior.
- Factor 13 - Competence: Not competent to carry out the duties assign.
- Factor 14 - Knowledge of regulations/standards inadequate: Lack of knowledge to understand regulations due to lack of experience/training.
- Factor 15 - Poor decision making/information use: Any problem with standards, regulations, etc. may be conflicting, resulting in a poor decision.
- Factor 16 - Understimulation: Degradation of performance due to monotony.
- Factor 17 - Inadequate management of physical resources: Poor management of tools, equipment, etc. needed to perform tasks.
- Factor 18 - Other Vessel: The cause of the accident was other ship.
- Factor 19 - Perception of risk: Abilities of the individual in terms of risk perception.
- Factor 20 - Equipment misuse: Intentional abuse of equipment provided or an over use.
- Factor 21 - Fatigue: Fatigue can result in a variety of factors and is variable amongst individuals. It depends on the watch keeping system and shipboard policies.
- Factor 22 - Social factors: Interactions within small groups or teams.
- Factor 23 - Current: The accident was caused by hazardous natural environment like strong currents.

2.3. Initial state vector

For this study, two different initial state vectors are considered in order to observe if they will affect the weight of the collision factors. For the first case, the initial state vector is defined as the percentage of each factor within the total number of accidents. For example, the first component “complacency” appears in 81 accidents out of 872 which can be translated as a 9.3% of the 872 accidents. However, these factors needs to be normalized to be within the interval [0,1] (Xiao et al., 2012), hence, the value for this component will be 0.093. For the second case, the initial state vector is defined as the percentage of each components within the total number of vessels. Then, “complacency” appears register as a main cause in 13 vessels out of 211 which can be translated as a 6.2% of the total number of vessels. Table 2 shows both initial state vectors for all the collision factors considered.

Table 2. Initial state vectors considering for the FCM.

Factor number	First state vector	Second state vector	Factor number	First state vector	Second state vector	Factor number	First state vector	Second state vector
1	0.09	0.06	9	0.03	0.00	17	0.02	0.03
2	0.08	0.06	10	0.02	0.03	18	0.02	0.04
3	0.07	0.08	11	0.02	0.03	19	0.02	0.03
4	0.07	0.05	12	0.02	0.01	20	0.01	0.01
5	0.06	0.04	13	0.02	0.04	21	0.01	0.02
6	0.06	0.05	14	0.02	0.01	22	0.01	0.01
7	0.05	0.05	15	0.02	0.03	23	0.01	0.02
8	0.03	0.01	16	0.02	0.01			

2.4. Final Interaction matrix

In order to create the interaction matrix, the database is analysed, comparing each pair of accident components. For example, in order to determinate the relation between “complacency” and “procedures inadequate” the database is filtered by the accidents that present “complacency” (81 accidents), and by the accidents that present “procedures inadequate” (68 accidents). Then, the number of accidents is filtered one more time by the accidents from “complacency” that show “procedures inadequate” as a second factor of the accident, resulting in 61 coincidences. Following the same procedure, there are 53 accidents from “procedures inadequate” that also show “complacency” as a second factor. In this way the weight of the component “complacency” over “procedures inadequate” is the relation between the accidents from “complacency” that “show procedures inadequate” as a second factor and all the accidents with “complacency”, resulting in a weight of 0.75. In the same way, the weight of the component “procedures inadequate” over “complacency” is the relation between accidents from “procedures inadequate” that also show “complacency” and the accidents with “procedures inadequate”, resulting in a weight of 0.78. The same process is repeated in order to obtain relations and weights of each pair of components.

Once the initial state vector and the interaction matrix are defined, the threshold function selected (the logistic signal function described before) is applied. For both case studies, the FCM reaches equilibrium after five steps. The results comparison and the discussion are described in the next section of this study.

3. Results and discussion

As it was mentioned before, the MAIB database is used to weight each contributing factors of collision accidents. Table 3 shows the equilibrium for both initial state vectors defined, which is reached at step 5 in both cases. As it can be observed from the table, for both cases the results of applying the FCM method are the same, which allows to conclude that the selection of the initial state vector is not a significant factor affecting the development of a FCM for this study. Fig. 2 shows the evolution of the different components of collision accidents for the time steps of the process until equilibrium is reached at step 5.

Analysing the results, it is clearly shown that there are 15 factors that leads collision accidents with a normalized weight higher than 4.5%. Furthermore, from all the components studied, just two are related with technical factors instead of human factors. These components are “other vessels” and “current”, and their weight are at the bottom of the ranking, just before “perception of risk” and “poor decision making/information use”, which supports the theory regarding human factors as the main cause in maritime accidents (Rothblum, 2000); (Graziano et al., 2016); (Turan et al., 2016) and specially in collision accidents as it was shown in this case study.

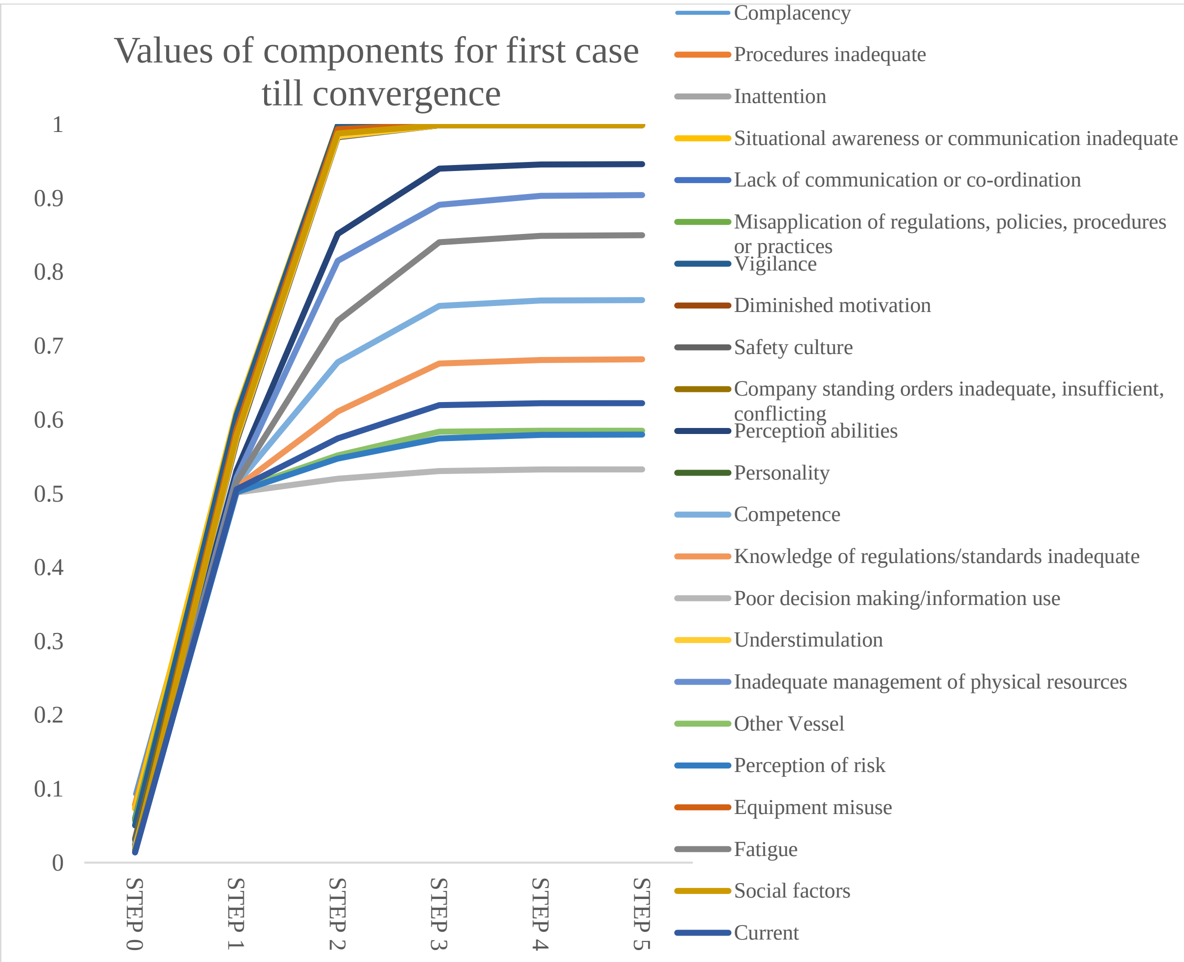


Fig. 2 Values of collision factors for first state vector until convergence is reached

Table 3. Final weight of contributors to maritime collision accidents.

Factor number	Weight from FCM with first state vector	Weight normalized with first state vector (%)	Weight from FCM with second state vector	Weight normalized with Second state vector (%)
1	0.9999	4.89	0.9999	4.89
2	1.0000	4.89	1.0000	4.89
3	1.0000	4.89	1.0000	4.89
4	1.0000	4.89	1.0000	4.89
5	0.9999	4.89	0.9999	4.89
6	1.0000	4.89	1.0000	4.89
7	1.0000	4.89	1.0000	4.89
8	0.9991	4.88	0.9991	4.88
9	0.9990	4.88	0.9990	4.88
10	0.9998	4.89	0.9998	4.89
11	0.9464	4.63	0.9464	4.63
12	0.9993	4.88	0.9993	4.88
13	0.7622	3.73	0.7622	3.73
14	0.6820	3.33	0.6820	3.33

Factor number	Weight from FCM with first state vector	Weight normalized with first state vector (%)	Weight from FCM with second state vector	Weight normalized with Second state vector (%)
15	0.5328	2.60	0.5328	2.60
16	0.9991	4.88	0.9991	4.88
17	0.9045	4.42	0.9045	4.42
18	0.5852	2.86	0.5852	2.86
19	0.5800	2.83	0.5800	2.83
20	0.9998	4.89	0.9998	4.89
21	0.8501	4.15	0.8501	4.15
22	0.9995	4.88	0.9995	4.88
23	0.6225	3.04	0.6224	3.04

Furthermore, comparing the weighted factors obtained through a FCM with the factors obtained from a statistical analysis in Table 1, it is possible to observe from Figure 3 how the importance of the factors vary in both methods. The factors shown in Figure 3 were defined in the previous section, as it can be observed, in some cases the factors differ completely by using one or another method like the factor from the statistical analysis in the twentieth position ("Equipment misuse") which appear in the ninth position by using FCM. This is due to the fact that By using FCMs, the factors that lead to accidents are not only listed and weighted independently but also all the interactions between factors are considered. This method differs from a pure statistical analysis in the sense that an element may appear less times (being less important in a statistical way) but it may be linked with more accident factors leading to a more complex accident (higher weight in a FCM).

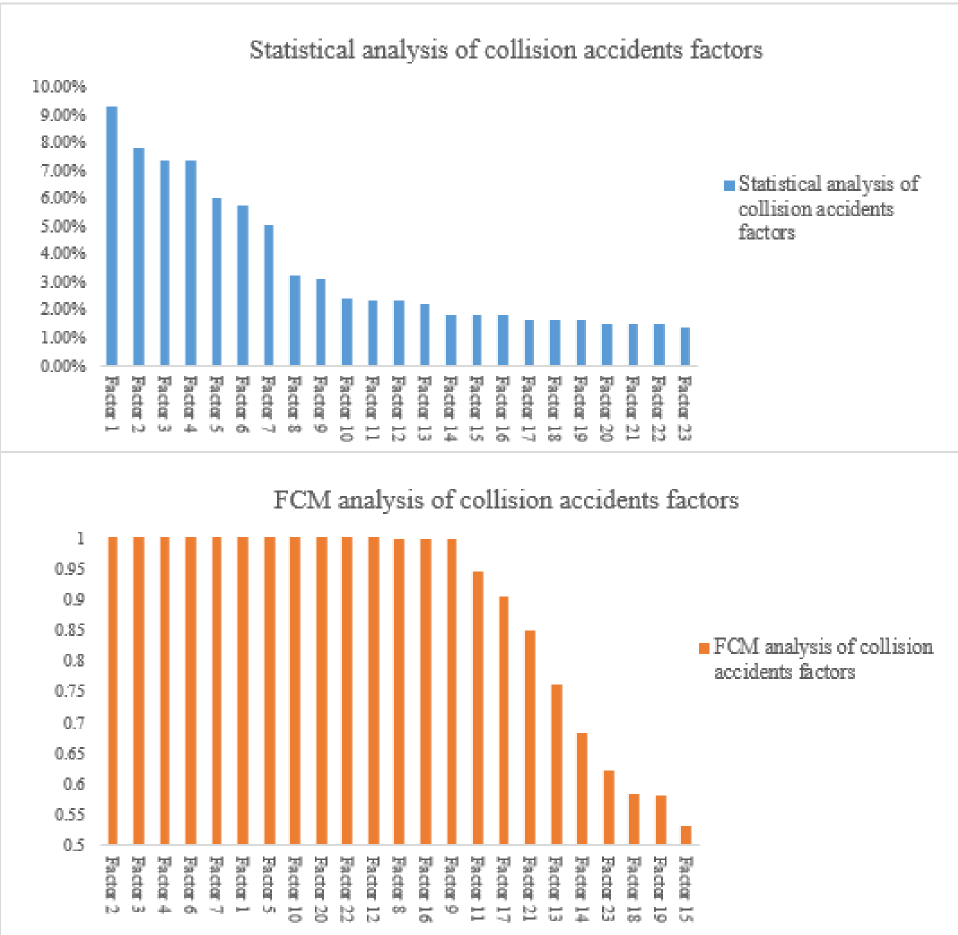


Figure 3. Comparison between accidents factor from FCM and statistical accidents.

Finally, in order to demonstrate the changes in FCM weighting through the years, the period between 2000 and 2011 was divided into three sections (four years each). From the results in Figure 4 it can be observed that the different factors change over time. However, a detailed sensitivity analysis was not conducted to analyse these weight variations. Furthermore, in order to improve visibility, Figure 4 was divided into four smaller graphs.

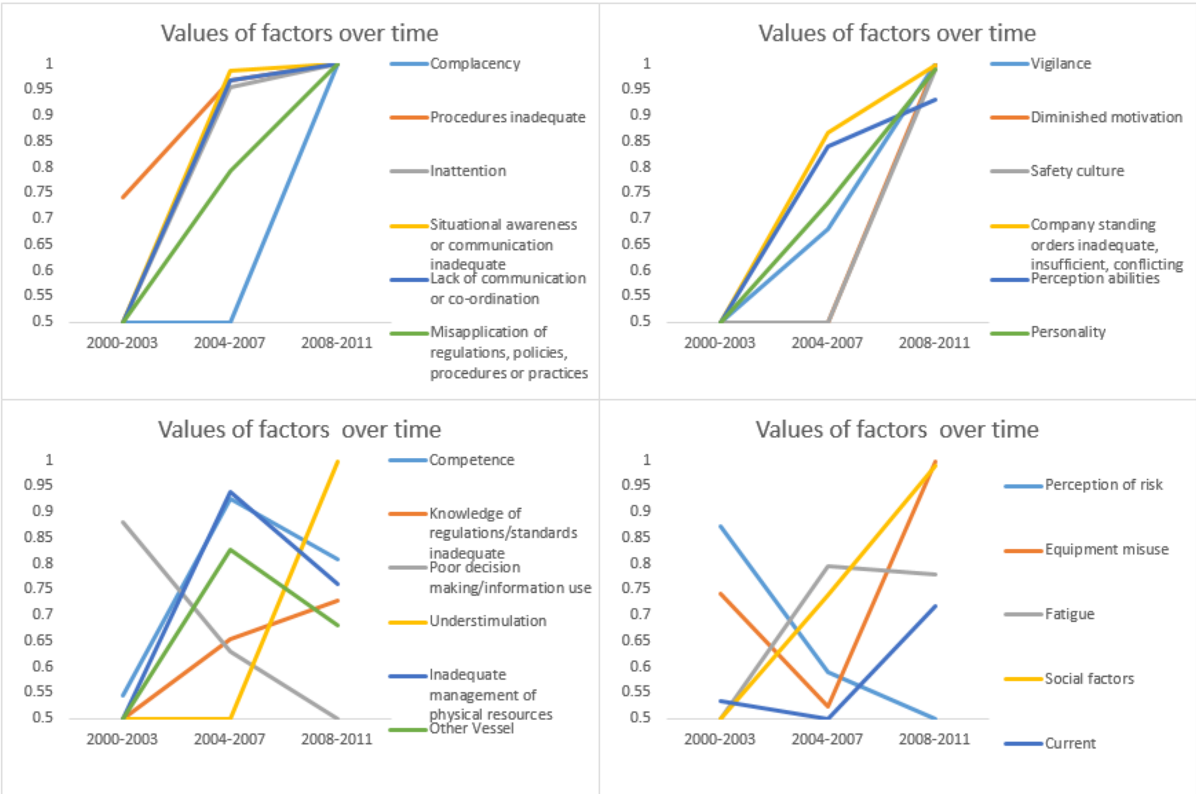


Fig. 4 Accidents factors variation over time through a FCM

4. Conclusion

In this paper, a new modelling and simulation approach based on FCMs was proposed for assessing the factors that lead to collision accidents within the maritime sector. The main target that was aim to achieve was not only to propose a new classification of factors leading to collision accidents based on the MAIB available data but also to propose the use of a tool which allows complex process representation and analysis.

For this study other consideration could have been taken into account, for instance, a further extension of the FCM analysis, considering all the factors that take a part in the process. Furthermore, the data analysed was taken from a database between 2000 and 2011, hence, a more up-to-date database could be analyse to compare if the factors that caused accidents in the past have been addressed thought safety measures or if they are still leading to collision accidents. Moreover, this method could be applied in other sectors, i.e. aviation, in order to compare how human factors causing accidents differ between transport modes. In addition, from the study over time it was observed that the weight of the concepts changes, hence, for further studies the factors could be analysed annually.

This study is conducted as part of a PhD study, in further stages of this PhD study, a similar FCM based on expert opinion will be created to compare how the collision contributors' classification obtained through real data is affected when expert opinion enter in the equation. Finally, a final factor list will be identified considering both FCMs created, in order to develop measures and recommendation for reducing the accidents' rate on the future.

5. References

Axelrod, R. M. 1976. *Structure of Decision: The Cognitive Maps of Political Elites*, Princeton University Press.

Azadeh, A., Salehi, V., Arvan, M. & Dolatkhah, M. 2014. Assessment of resilience engineering factors in high-risk environments by fuzzy cognitive maps: A petrochemical plant. *Safety Science,* 68**,** 99-107.

Azadeh, A. & Zarrin, M. 2016. An intelligent framework for productivity assessment and analysis of human resource from resilience engineering, motivational factors, HSE and ergonomics perspectives. *Safety Science,* 89**,** 55-71.

Bueno, S. & Salmeron, J. L. 2009. Benchmarking main activation functions in fuzzy cognitive maps. *Expert Systems with Applications,* 36**,** 5221-5229.

Büyüközkan, G. & Vardaloğlu, Z. 2012. Analyzing of CPFR success factors using fuzzy cognitive maps in retail industry. *Expert Systems with Applications,* 39**,** 10438-10455.

Chauvin, C., Lardjane, S., Morel, G., Clostermann, J.-P. & Langard, B. 2013. Human and organisational factors in maritime accidents: Analysis of collisions at sea using the HFACS. *Accident Analysis & Prevention,* 59**,** 26-37.

Dodurka, M. F., Yesil, E. & Urbas, L. 2017. Causal effect analysis for fuzzy cognitive maps designed with non-singleton fuzzy numbers. *Neurocomputing,* 232**,** 122-132.

Eden, C. 1988. Cognitive mapping. *European Journal of Operational Research,* 36**,** 1-13.

Eliopoulou, E., Papanikolaou, A. & Voulgarellis, M. 2016. Statistical analysis of ship accidents and review of safety level. *Safety Science,* 85**,** 282-292.

Glykas, M. 2013. Fuzzy cognitive strategic maps in business process performance measurement. *Expert Systems with Applications,* 40**,** 1-14.

Graziano, A., Teixeira, A. P. & Guedes Soares, C. 2016. Classification of human errors in grounding and collision accidents using the TRACEr taxonomy. *Safety Science,* 86**,** 245-257.

Khan, M., Quaddus, M. & Intrapairot, A. Application of a Fuzzy Cognitive Map for Analysing Data Warehouse Diffusion. Applied informatics-proceedings, 2001. 32-37.

Kok, K. 2009. The potential of Fuzzy Cognitive Maps for semi-quantitative scenario development, with an example from Brazil. *Global Environmental Change,* 19**,** 122-133.

Kosko, B. 1986. Fuzzy cognitive maps. *International journal of man-machine studies,* 24**,** 65-75.

Kosko, B. 1994. The new science of fuzzy logic: fuzzy thinking. *HarperCollins, LondonLane DC, Oliva R (1998) The greater whole: towards a synthesis of the system dynamics and soft system methodology. Eur J Oper Res,* 107**,** 214235Lee.

Kristiansen, S. 2013. *Maritime Transportation: Safety Management and Risk Analysis*, Taylor & Francis.

Kurt, R. E., Khalid, H., Turan, O., Houben, M., Bos, J. & Helvacioglu, I. H. 2016. Towards human-oriented norms: Considering the effects of noise exposure on board ships. *Ocean Engineering,* 120**,** 101-107.

Lee, K., Kim, S. & Sakawa, M. 1996. On-line fault diagnosis by using fuzzy cognitive map. *IEICE transactions on fundamentals of electronics, communications and computer sciences,* 79**,** 921-927.

León, M., Rodriguez, C., García, M. M., Bello, R. & Vanhoof, K. Fuzzy cognitive maps for modeling complex systems. Mexican International Conference on Artificial Intelligence, 2010. Springer, 166-174.

Mohr, S. 1997. Software design for a fuzzy cognitive map modeling tool. *Tensselaer Polytechnic Institute*.

Motlagh, O., Tang, S. H., Ismail, N. & Ramli, A. R. 2012. An expert fuzzy cognitive map for reactive navigation of mobile robots. *Fuzzy Sets and Systems,* 201**,** 105-121.

Mpelogianni, V., Marnetta, P. & Groumpos, P. P. 2015. Fuzzy Cognitive Maps in the Service of Energy Efficiency. *IFAC-PapersOnLine,* 48**,** 1-6.

O'Hare, D., Wiggins, M., Batt, R. & Morrison, D. 1994. Cognitive failure analysis for aircraft accident investigation. *Ergonomics,* 37**,** 1855-1869.

Papageorgiou, E. I. & Froelich, W. 2012. Multi-step prediction of pulmonary infection with the use of evolutionary fuzzy cognitive maps. *Neurocomputing,* 92**,** 28-35.

Papageorgiou, E. I., Stylios, C. & Groumpos, P. P. 2006. Unsupervised learning techniques for fine-tuning fuzzy cognitive map causal links. *International Journal of Human-Computer Studies,* 64**,** 727-743.

Papakostas, G. A., Boutalis, Y. S., Koulouriotis, D. E. & Mertzios, B. G. 2008. Fuzzy cognitive maps for pattern recognition applications. *International Journal of Pattern Recognition and Artificial Intelligence,* 22**,** 1461-1486.

Papakostas, G. A., Koulouriotis, D. E., Polydoros, A. S. & Tourassis, V. D. 2012. Towards Hebbian learning of fuzzy cognitive maps in pattern classification problems. *Expert Systems with Applications,* 39**,** 10620-10629.

Rothblum, A. M. Human error and marine safety. National Safety Council Congress and Expo, Orlando, FL, 2000.

Smith, D., Veitch, B., Khan, F. & Taylor, R. 2017. Understanding industrial safety: Comparing Fault tree, Bayesian network, and FRAM approaches. *Journal of Loss Prevention in the Process Industries,* 45**,** 88-101.

Turan, O., Kurt, R. E., Arslan, V., Silvagni, S., Ducci, M., Liston, P., Schraagen, J. M., Fang, I. & Papadakis, G. 2016. Can We Learn from Aviation: Safety Enhancements in Transport by Achieving Human Orientated Resilient Shipping Environment. *Transportation Research Procedia,* 14**,** 1669-1678.

Vergini, E. S. & Groumpos, P. P. 2016. A new conception on the Fuzzy Cognitive Maps method. *IFAC-PapersOnLine,* 49**,** 300-304.

Xiao, Z., Chen, W. & Li, L. 2012. An integrated FCM and fuzzy soft set for supplier selection problem based on risk evaluation. *Applied Mathematical Modelling,* 36**,** 1444-1454.

Yesil, E., Ozturk, C., Dodurka, M. F. & Sahin, A. Control engineering education critical success factors modeling via Fuzzy Cognitive Maps. Information Technology Based Higher Education and Training (ITHET), 2013 International Conference on, 2013. IEEE, 1-8.