2021

Fuzzy Cognitive Map-Based Knowledge Representation of Hazardous Industrial Operations

Francesco Longo
University of Calabria

Antonio Padovano
University of Calabria

Letizia Nicoletti
CAL-TEK S.r.l., Rende, Italy

Caterina Fusto
University of Calabria

Mohaiad Elbasheer
University of Calabria

See next page for additional authors

Original Publication Citation
Longo, F., Padovano, A., Nicoletti, L., Fusto, C., Elbasheer, M., & Diaz, R. (2021). Fuzzy cognitive map-based knowledge representation of hazardous industrial operations. *Procedia Computer Science*, *180*, 1042-1048. https://doi.org/10.1016/j.procs.2021.01.351

Authors

Francesco Longo, Antonio Padovano, Letizia Nicoletti, Caterina Fusto, Mohaiad Elbasheer, and Rafael Diaz

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 180 (2021) 1042–1048

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Industry 4.0 and Smart Manufacturing

Fuzzy Cognitive Map-Based Knowledge Representation of Hazardous Industrial Operations

Francesco Longo[a], Antonio Padovano[a], Letizia Nicoletti[b], Caterina Fusto[a], Mohaiad Elbasheer[c], Rafael Diaz[d]

[a]DIMEG, University of Calabria, Ponte Pietro Bucci, Cubo 45C, Third Floor, Arcavacata di Rende (CS), 87036, Italy
[b]CAL-TEK S.r.l., Rende (CS) 87036, Italy
[c]Modeling & Simulation Center – Laboratory of Enterprise Solutions (MSC-LES), University of Calabria, Ponte Pietro Bucci, Arcavacata di Rende (CS), 87036, Italy
[d]Old Dominion University, 5115 Hampton Boulevard Norfolk, VA 23529, United States of America

Abstract

Hazardous industrial operations are highly stochastic, still human-dependent, and risky. Operators working in such an environment must understand the complex interrelation between several factors contributing to safe and effective operations. Therefore, being able to predict the effects of their actions on provoking or mitigating possible accidents is crucial. This study aims to utilize fuzzy cognitive maps (FCM) to model the expert's reasoning about occupational health and safety (OHS) in confined space. This knowledge is used by operators to build their mental models. The developed FCM displays all the possible incidents of a confined space and links these incidents with all their causing and preventing factors. This approach may facilitate the development of simulation-based training solutions and allow operators to act proactively during the operation.

Peer-review under responsibility of the scientific committee of the International Conference on Industry 4.0 and Smart Manufacturing

Keywords: Fuzzy cognitive maps; knowledge representation; hazardous industrial operations; occupational health and safety; confined space

1877-0509
Peer-review under responsibility of the scientific committee of the International Conference on Industry 4.0 and Smart Manufacturing
10.1016/j.procs.2021.01.351

1. Introduction

No matter the scientific area, experts, analysts, and decision-makers often face the inability to effectively and efficiently describe a given problem and thus study its parameters so that they make the proper decisions at the right time. This problem is usually associated with the fact that many intertwined parameters describe the underlying environment [1]. This has substantially contributed to the rise of "knowledge engineering" as one of the most famous grounds for Artificial Intelligence (AI). Knowledge engineering is defined as “the art of engineering the acquired knowledge and then structuring it so that non-experts can utilize it for problem-solving” [2]. The need for developing knowledge-based systems in the field of occupational health and safety (OHS) and emergency management is urgent. Such knowledge systems proved its essence to minimize OHS risks' adverse effects by identifying and providing proper corrective and preventive measures [3]. In particular, using Fuzzy Cognitive Maps (FCM) in OHS-based application is useful in conveying a comprehensive perspective that helps to analyse and understand complexities in this domain. Azadeh et al. [4] utilized FCM to study the effect of resilience engineering factors in the highly hazardous environment of a petrochemical plant. Similarly, Skład [5] used FCM to assess the impact of various processes on an occupational health and safety management system (OHS-MS).

Performing hazardous industrial operations is a complex task that highly depends on the operator's ability to interact with multiple intertwined factors within the working environment. The factors governing work in such industrial settings are naturally indeterministic, complex, and highly interconnected. Therefore, operators face the challenge of predicting a specific event's evolution during the execution of their tasks in a hazardous environment. An adequate understanding of the performed tasks, as their interaction mechanism with the environmental factors, is essential in performing safe and effective operations in a critical environment and to guide the design and development of serious games as part of simulation- and virtual reality-based training systems.

This study suggests the utilization of FCM to model expert's knowledge about working in a hazardous industrial setting, in this case, a confined space. The interaction between technical, environmental, and human factors is mapped and FCM are used to display a cause-effect model of the expert's beliefs. This approach aims to convey knowledge from OHS experts:

- to operators so that they can predict the evolution of accidents and actively analyse their root causes and mitigation possibilities;
- to the serious game designers so they can develop realistic virtual environments and stochastic storyboards in simulation-based training systems.

This paper starts by highlighting the state-of-the-art behind the FCM theory. After that, the methodology and the undertaken case-study are highlighted. The last part of this paper displays the results of the obtained FCM. Finally, a conclusion summarizes the methods and findings of this study.

2. State of the art

2.1 Knowledge representation

Knowledge acquisition (KA) allows the understanding of the elements characterizing various entities and systems to develop knowledge-based systems [6]. KA is concerned with finding and capturing domain experts' knowledge through objects, rules, and frame-based ontologies. The process of the identification of tacit knowledge heavily depends on the approach used for representing and organizing the acquired information through relational databases, texts, images, or man-made system models [7]. Therefore, knowledge representation is central for developing accurate knowledge-based systems, as it is useful to explicate knowledge and brings it forward [8]. However, knowledge representation is described as a multidisciplinary subject that incorporates aspects from ontology, logic, and computation, thus delivering a medium for human expression that provides a computational environment for thinking [9]. One of the most common knowledge representation practices is the use of semantic networks, such that knowledge is represented based on meaning, in a manner that semantically connects concepts that comprise the information elicited from domain experts. Semantic networks use graphical representation to display the relationships between various concepts in the form of nodes and weighted links corresponding to the strength of the relationships between concepts. Cognitive mapping, concept mapping, and mental models are the early tools used to elicit subject knowledge [10]. Fuzzy cognitive maps (FCM) are a natural extension of these knowledge representation approaches. FCM models the imprecise common language into cause-effect maps, thus permitting individuals to express and interpret their environment's complexity and combine knowledge from multiple domains [11].

2.2 Fuzzy cognitive maps

Fuzzy cognitive maps (FCM) are directed graphs of causality [12]. These graphs allow capturing the behaviour of complex systems in states of nodes that represent cognitive knowledge [13]. Like other semantic networks, the basic constructs of the FCMs are nodes (concepts) and directed weighted edges. Therefore, FCM represents the knowledge elicited from domain experts as feedback diagrams of interconnected concepts; these concepts are linked with weighted and signed edges (arrows). Usually, concepts of FCM stand for key-factors of the modelled complex system and represent: goals, inputs, outputs, events, states, trends, and variables [14].
The weighted-signed edges demonstrate the power of the causal relationship between the interconnected concepts. This weight (degree of causality) is a quantitative measure relevant to the strength of other causality interrelations within the FCM [15]. The direction of the edges illustrates the direction and degree of the target concept's causation by showing its influence by the source concepts [14]. This graph structure permits forward and what-if inferencing. FCM feedback paths and cycles allow for complex nonlinear dynamics [1].

3. Materials and methods

This study aims to build an FCM that models expert's conceptualization about the factors that affect the incidents occurring in a critical industrial setting. Therefore, this FCM model represents the effect of each risk factor on provoking possible accidents. Also, the designed FCM aims to display the influence of procedural safety measures on preventing these accidents from occurring. This study undertakes the following steps.

3.1 Step 1: The case of confined spaces in nuclear facilities

Hazards in confined spaces are difficult to assess and manage due to the complex characteristics of such specific work environments [16]. Confined spaces include vessels, silos, tanks, pipes, or poorly ventilated rooms. Confined spaces in nuclear facilities are particularly dangerous, and the likelihood of accidents is high. In addition to the hazard of radiation that generally presents in such facilities, especially during decommissioning and maintenance activities, operators must deal with several other risks associated with the confined space itself (e.g., asphyxiation, intoxication, and fire). Nevertheless, nuclear plants are extensively piping facilities as an average reactor is associated with 7 miles of pipes. Underground pipes together with buried tanks are generally responsible for water handling, gas handling, and fuel and oil handling systems [17]. However, these pipes and tanks are susceptible to damage, corrosion, and leakages. Therefore, they require continuous monitoring and active maintenance for ensuring ongoing and safe operations. Often, operators are required to intervene when suitable personally inside the pipeline or the tank for carrying out visual checks, applying coating materials, or fixing leakages. In many cases, this involves working in a confined space, hence getting exposed to tremendous danger during task performance [17].

3.2 Step 2: Mapping the causality relations

Building a comprehensive FCM model requires the inclusion of all the factors that provoke accident occurrence (hazards), as well as the ones responsible for prohibiting them. For developing an FCM that models the causality relations of accident occurrence, the division of FCM concepts into three general groups (A, B, and C) is necessary for obtaining practical analysis ability and better visualization for the map. The first group (group A) contains all the possible incidents in confined spaces. The second group (group B) contains all the possible sources of danger (Risk factors) associated with the environment and structure of the confined space. Also, it includes the possible activities . The third group (group C) contains all the factors that can prevent all possible incidents. Hence, this group's concepts' arrows are directed towards (group A) concepts, with negative signs to model the degree of preventing the likelihood of each incident occurrence.

3.3 Step 3: Knowledge elicitation

To estimate the fuzzy weights, it is necessary to capture the opinions of domain experts about the strength of the effects of interconnected factors of the FCM. However, experts can only express their beliefs through linguistic expressions due to the indeterministic nature of the cause-effect relations. Therefore, it is necessary to de-fuzzify experts' linguistic expression into crisp values to display it in the FCM. OHS experts were asked to answer a questionnaire of 34 questions. The questionnaire is divided into 3 parts, each dedicated to a group of concepts (A, B, and C). The first part aims to identify group A (the possible accidents) and estimate the possibilities of each accident occurrence (concepts' activation values). In this part experts are required to choose the closest linguistic expression to their rationale regarding accident possibility (not possible, very low, low, medium, high, very high). The second part of the questionnaire aims to establish the effect relations between the concept of group B and group A. Therefore, experts are asked to identify the effects of each risk factor (hazard) on the possibility of accidents occurring. In this part, experts are required to demine the impact using the linguistic expressions (no effect, very low effect, low effect, medium, high effect, and very high effect). similarly, the third part of the questionnaire establishes the mitigation effect of several proceedable safety measures. However, as previously explained, the causality relation from (group C) concept to (group A) takes a negative sign, contrasting with B and A relations.

3.4 Step 4: Building the FCM

This study uses the Mental Modeler web-based tool (http://www.mentalmodeler.org/) to develop the FCM. The Mental Modeler is used for its simple user interface and its delicate display. Moreover, it allows performing individual analysis for each concept by highlighting only the related concepts. This property provides an excellent approach to knowledge representation.

3.5 Step 5: Calculation of crisp weights

For transforming experts' linguistic expressions into the numerical values (crisp weights) that define the FCM's interrelations, we utilized the modified weighted mean of maximum method [18,19]. The key elements are:

a) Strength of the effect O_i, which corresponds to each membership functions' maximum value;
b) The coefficient $Z_i$which is calculated for each linguistic expression and corresponds to the arithmetic mean of each strength effect O_i of a membership function and the values of the strength effect of the overlapping membership function. Table (2) shows the coefficients Z_i for each membership function.

Eq.(1) calculates the de-fuzzified linguistic expressions.

$$W = \frac{\sum_{i=1}^{N} O_i Z_i}{\sum_{i=1}^{N} O_i}, \tag{1}$$

where W is the crisp weight, and N is the total number of experts participating in the questionnaire.

Table 1. Membership function and Zi coefficient for each linguistic variable

Linguistic expression	Lower range of the membership function	Higher range of the membership function	Maximum strength of the effect, O_i	Z_i
No effect	0	0	0	0
Very low effect	0	0.2	0.1	0.0175
Low effect	0.15	0.35	0.25	0.068
Medium effect	0.3	0.65	0.475	0.229
High effect	0.6	0.85	0.725	0.51
Very high effect	0.85	1	0.925	0.76

4. Results

As demonstrated in the methodology, the resulting FCM is the aggregation of two FCMs; the first indicates the effects of the different risks factor on the possibility of accidents, while the second demonstrates the safety measures' effects. Experts identified six accidents as the most likely to happen in these confined spaces. Experts' linguistic expressions about these accidents identify their initial activation values. These activation values determine the likelihood of accidents in a confined space of a nuclear facility. Table 2 shows the concepts corresponding to possible accidents and their activation values.

Table 2. possible accidents in the confined space understudy group (A)

Possible accidents	Initial activation value
A1 - Asphyxiation	0.65
A2 - Intoxication	0.65
A3 - Fall/Slip	0.38
A4 - Fire/explosion	0.43
A5 - Radiation	0.79
A6 - Noise	0.18

Risk factors positively participate in the occurrence of different accidents. Positive arrows model the relationship between group (B) and Group (A) from (B) to (A). Table 3 shows the weight matrix of the corresponding FCM.

Table 3. Positive effects of risk factors on accident occurrence.

Concepts of Group B	A1	A2	A3	A4	A5	A6
B1 - Inspection activities	0.64	0.75	0.45	0.38	0.64	0.18
B2 - Water presence check	0.67	0.67	0.38	0.27	0.76	0.18
B3 - Maintenance activities	0.79	0.89	0.66	0.75	0.93	0.18
B4 - Surveying activities	0.56	0.64	0.45	0.27	0.56	0.18
B5 - Structural hazards premises Hight, surface area	0.83	0.83	0.73	0.58	0.28	0
B6 - Presence of Ladder	0	0	0.71	0	0	0
B7 - Presence of electrical equipment	0	0	0	0.26	0	0
B8 - Plants electrical system	0	0	0	0.32	0	0
B9 - Low illumination	0.18	0.65	0.56	0	0	0
B10 - Low oxygen concentration	0.76	0.93	0.73	0.79	0	0
B11 - High humidity	0.61	0.7	0.92	0.61	0.28	0
B12 - The presence of unfavorable gases (CO, CO2, H2S, etc.)	0.93	0.93	0	0.93	0.48	0
B13 - Prolonged operating time	0.93	0.93	0.56	0.18	0.18	0

The safety measure (Group C) negatively affects the possibility of accidents (Group A). Therefore, the weight matrix corresponding to the FCM shows negative weights. Table 4 shows the weight matrix of the relationship between A and C. Figure 1 displays the aggregate FCM that represents the highly probable accidents involved in operations inside confined spaces in nuclear facilities. This FCM includes the risk factors and the safety measures connected to the accidents highlighted by experts. The arrows' signs symbolize the effect of each risk and safety measure on accidents likeliness to happen. The positive signs represent the promoting effect of several hazards on accidents, while the negative signs model the preventive nature of safety measures.

Table 4. Negative effects of safety measures on accident occurrence.

Concepts of group C	A1	A2	A3	A4	A5	A6
C1 - Operators' spatial knowledge	-0.37	-0.37	-0.64	0	0	0
C2 - Using safety helmets	-0.7	-0.7	-0.92	0	-0.58	0
C3 - Using safety shoes	0	0	-0.58	0	0	0
C4 - Using harnesses, a double lanyard, or restrained ropes	0	0	-0.58	0	0	0
C5 - Using of disposable TYVEK suits	0	0	0	0	-0.7	0
C6 - Using protective gloves	0	0	-0.17	0	0	0
C7 - Using protective masks	-0.41	-0.45	0	0	0	0
C8 - Certification of the plant's electrical system	0	0	0	-0.62	0	0
C9 - Measuring gas concentration	-0.925	-0.925	0	-0.79	-0.35	0
C10 - Using supplementary lamps	0	0	-0.67	-0.53	0	0
C11 - Using hearing protectors	0	0	0	0	0	-0.92

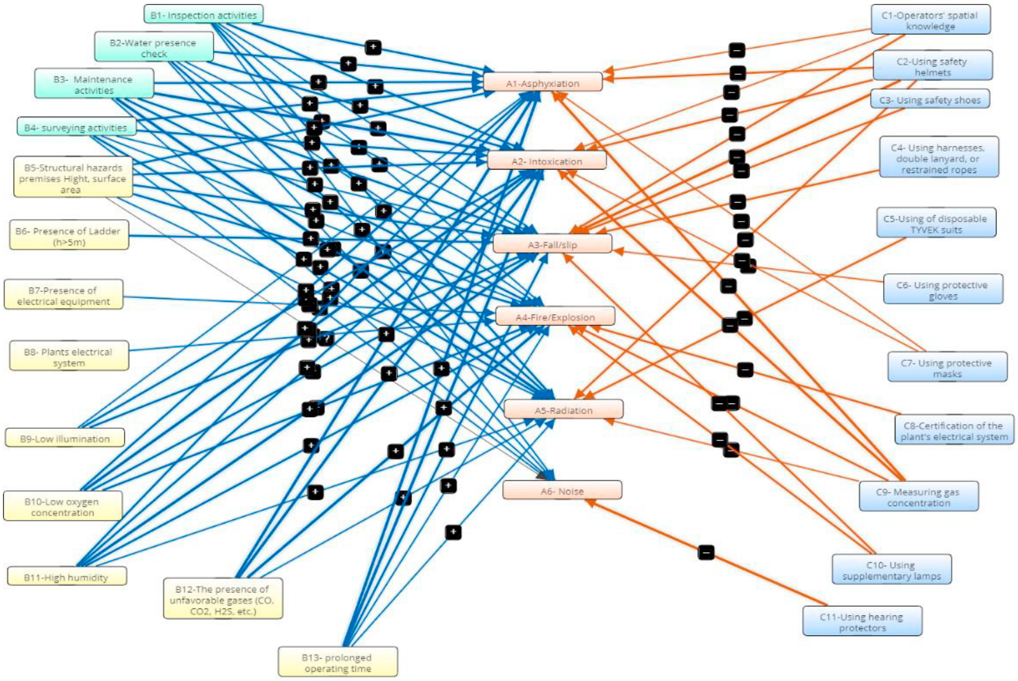

Figure 1. The aggregated FCM

5. Final remarks

This study aims to model experts' conceptualization of work in confined spaces of nuclear facilities using FCM. The obtained FCM is the aggregation of all the identified accidents' causality networks, as every accident is, at least, linked with a causing (promoting) risk and a prohibiting safety measure. The strength of each connection corresponds to experts' linguistic expressions, which are numerized using fuzzy logic. This map benefits from Mental Modeler's ability to display individual concept's interrelationships. Hence, it can individually show each accident causality factors. This property renders the designed FCM a useful tool for knowledge representation. Thus, assisting operators and specialists to better-understanding accident causal relationships and the effect of mitigation for each safety practice. Moreover, this tool is a significant building block for developing dynamic and realistic VR training scenarios that train operators for emergency preparedness and safe operations in nuclear-confined spaces.

References

[1] Christoforou, A., & Andreou, A. S. (2017). A framework for static and dynamic analysis of multi-layer fuzzy cognitive maps. Neurocomputing, 232(May 2016), 133–145. https://doi.org/10.1016/j.neucom.2016.09.115
[2] El Din, H. K. (1989). Knowledge engineering and artificial intelligence a new challenge of engineering education. In Current Advances in Mechanical Design & Production IV (pp. 305-313). Pergamon.
[3] Dabbagh, R., & Yousefi, S. (2019). A hybrid decision-making approach based on FCM and MOORA for occupational health and safety risk analysis. Journal of Safety Research, 71, 111–123. https://doi.org/10.1016/j.jsr.2019.09.021.
[4] 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. https://doi.org/10.1016/j.ssci.2014.03.004.
[5] Skład, A. (2019). Assessing the impact of processes on the Occupational Safety and Health Management System's effectiveness using the fuzzy cognitive maps approach. Safety Science, 117(November 2018), 71–

80. https://doi.org/10.1016/j.ssci.2019.03.021
[6] Leu, G., & Abbass, H. (2016). A multi-disciplinary review of knowledge acquisition methods: From human to autonomous eliciting agents. Knowledge-Based Systems, 105, 1–22. https://doi.org/10.1016/j.knosys.2016.02.012.
[7] Tselykh, A., Tselykh, L., Vasilev, V., & Barkovskii, S. (2018). Knowledge discovery using maximization of the spread of influence in an expert system. Expert Systems, 35(6), 1–19. https://doi.org/10.1111/exsy.12312.
[8] Chandrasegaran, S. K., Ramani, K., Sriram, R. D., Horváth, I., Bernard, A., Harik, R. F., & Gao, W. (2013). The evolution, challenges, and future of knowledge representation in product design systems. CAD Computer Aided Design, 45(2), 204–228. https://doi.org/10.1016/j.cad.2012.08.006.
[9] Cercone, N., & McCalla, G. (1987). What Is Knowledge Representation? The Knowledge Frontier, 14(1), 1–43. https://doi.org/10.1007/978-1-4612-4792-0_1.
[10] Gray, S., & Zanre, E. (2013). Fuzzy Cognitive Map as representation of mental models and group beliefs: theoretical and technical issues. Fuzzy Cognitive Maps for Applied Sciences and Engineering, 54, 29–48. http://www.mentalmodeler.com/articles/Gray et al 2012_FCM_ Mental Models.pdf.
[11] Gray, S. A., Gray, S., Cox, L. J., & Henly-Shepard, S. (2013). Mental Modeler: A fuzzy-logic cognitive mapping modeling tool for adaptive environmental management. Proceedings of the Annual Hawaii International Conference on System Sciences, January, 965–973. https://doi.org/10.1109/HICSS.2013.399.
[12] Kosko, B. (1987). Adaptive Inference in Fuzzy Knowledge Networks. 888–891. https://doi.org/10.1016/b978-1-4832-1450-4.50093-6
[13] Carvalho, J. P., & Tome, J. A. B. (1999). Rule based fuzzy cognitive maps and fuzzy cognitive maps - a comparative study. Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS, September 2014, 115–119. https://doi.org/10.1109/nafips.1999.781665.
[14] Kosko, B. (1986). Fuzzy cognitive maps. International Journal of Man-Machine Studies, 24(1), 65–75. https://doi.org/10.1016/S0020-7373(86)80040-2.
[15] Felix, G., Nápoles, G., Falcon, R., Froelich, W., Vanhoof, K., & Bello, R. (2019). A review on methods and software for fuzzy cognitive maps. Artificial Intelligence Review, 52(3), 1707–1737. https://doi.org/10.1007/s10462-017-9575-1.
[16] Nano, G., & Derudi, M. (2013). A critical analysis of techniques for the reconstruction of workers accidents. Chemical Engineering Transactions, 31(January 2013), 415–420. https://doi.org/10.3303/CET1331070
[17] IAEA. (2018). (NP-T-3.20) Buried and Underground Piping and Tank Ageing Management for Nuclear Power Plant. 35–37. http://www.iaea.org/Publications/index.html
[18] Skład, A. (2019b). Assessing the impact of processes on the Occupational Safety and Health Management System's effectiveness using the fuzzy cognitive maps approach. Safety Science, 117(April), 71–80. https://doi.org/10.1016/j.ssci.2019.03.021.
[19] Peláez, C. E., & Bowles, J. B. (1996). Using fuzzy cognitive maps as a system model for failure modes and effects analysis. Information Sciences, 88(1–4), 177–199. https://doi.org/10.1016/0020-0255(95)00161-1.