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Fuzzy cognitive maps for knowledge-oriented human risk management in industry

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Abstract - This contribution proposes an integrated approach making use of Fuzzy Cognitive Maps (FCMs) to organise in a flexible way human knowledge about decision-making (DM) problems of interest in industry. By modelling human reasoning, FCMs allow to represent real phenomena on the basis of spontaneous human brainstorming on relations between pairs of relevant DM elements. Because of its characteristics, the use of FCMs can be effective to model DM problems such as human risk management, particularly critical in the industrial business sector. After identifying human risks in the existing literature, FCMs will be used to define relations among risks, which will be later prioritised by means of a modified Failure Modes, Effects and Criticality Analysis (FMECA). A case study on the sector of automotive industry is eventually implemented and solved to provide practical insights for risk management.

1 Introduction, objectives, structure

Decision-making (DM) models implemented using some preliminary collection of pairwise comparison judgments are grounded on preference transitivity characterized by ordinal consistency as a fundamental principle [1]. Transitivity has indeed represented a cornerstone of normative decision theory [2], having been considered as an essential aspect for elaborating quality and reliable models. However, this principle has been criticised by several authors in the existing literature, since it somehow forces decision makers to align their opinions to the consistency property [3]. This may lead to artificial decisions aimed at responding to a mathematical principle rather than reflecting the often non-transitive nature of human reasoning.

This paper uses fuzzy cognitive maps (FCMs) as a tool independent on transitivity. The formulation of inconsistent judgments of preference is indeed common when dealing with complex industrial DM problems such as risk management issues. We aim to stimulate a spontaneous brainstorming to naturally evaluate DM elements without the need of checking consistency.

The manuscript is organised as follows. The literature review is developed in section 2. Section 3 describes the proposed approach whereas a real case study on the automotive industrial sector is considered and solved in Section 4. Section 5 outlines conclusions along with a few insights for future research.

2 Literature review

Decision support systems frequently rely on judgments of pairwise comparisons attributed by selected stakeholders/experts in the business field of interest. Such an approach usually represents a useful way to increase the probability that the obtained solutions are actually effective in pursuing process optimisation rather than randomly produced. This is what often happens in practice, where subjects in charge for making decisions, despite occupying management positions, are not properly familiar with practical problems at a technical level. In any case, even when it comes to expert subjects, their capability of being consistent when pairwise comparing elements may flaw, especially in complex situations [4, 5] and when vagueness plagues phenomena [6], something that normally occurs in the business world. In this regard, as highlighted in [3], transitivity of preference judgments is a useful mathematical assumption in decision-making given to the link between consistency of pairwise comparisons and reliability of the obtained priorities, being the latter important for establishing the relative importance of the main elements considered in the problem analysis. However, transitive reasoning may be the result of memory phenomena rather than deduction processes. In [7], the theory of transitive reasoning is discussed by stating that it explains transitivity as information-processing constructs such as encoding, mentally-scanning and retrieval cuing. In this context, the authors underline as an important part of human transitive reasoning process responds to genuinely deductive paradigms, which do not merely tend to access an associative mode capturing transitive generalisations as soon as information is acquired.

The ability to understand and manipulate logical transitive relations by making inferences is certainly fundamental for acquiring and developing many mathematical concepts [8]. Moreover, preferences may be intransitive for a huge amount of practical problems [9] and, in such cases, distorting original expert assessments may not be a desirable solution. This is even truer when one has to deal with DM problems in which many diverse elements to be pairwise compared are considered [10]. This may be likely the case of risk management problems in industry, where several risks can be highlighted depending on the specific industrial sector under analysis. Focusing on this kind of practical problems, this contribution proposes an approach for risk assessment making use of FCMs, which stimulate experts towards a spontaneous brainstorming for effective risk analysis. Relationships among the identified risks are captured and represented without requiring the formal check of consistency for preferences expressed between pairs of elements.

Cognitive Maps (CMs) are directed graphs explicitly representing a set of variables and their causal relationships by means of causal weights, also developed in fuzzy version [11]. The CM tool has been formalised and integrated within the mathematics discipline to flexibly describe general behaviour representation by encoding relationships among elements [12]. CMs have been extensively discussed in the literature as an approach capable to provide structural frameworks for managing complex information [13]. Having underlined the possibility of applying CMs to a wide spectrum of scientific fields, Mourhir [14] develops a review on FCM applications in the sector of environmental assessment promoting integration models assessment. Chen et al. [15] propose a hybrid soft computing approach where a FCM is built to evaluate risks associated to projects on public–private partnership. Azar and Mostafaee Dolatabad [16] integrate FCMs and Bayesian Networks to evaluate operational risks and implement risk management strategies in financial institutions. Being the topic of CMs and FCMs particularly lively in the current literature, we propose a FCM-based application for industrial risk management and, particularly, for human risk modeling and potential hazard propagation identification on the basis of relations highlighted among risks. Furthermore, we propose an *a posteriori* integration with an updated Failure Modes, Effects and Criticality Analysis (FMECA) [17] for eventually proceeding with risk prioritisation. FMECA-based analyses can be indeed particularly beneficial for quantitative risk evaluation purposes by contributing to the general improvement of the performance level for systems and processes [18].

3 Materials and methods

This section presents the description of the proposed approach for human factor risks assessment, illustrated in Figure 1. As already stated, the identified risks are modelled through an FCM aimed at evaluating their effects and, on the basis of these results, a modified FMECA technique is implemented to proceed with risks prioritisation.

Formalisation of risk identification and methodological details about FCM and FMECA approaches are herein provided.

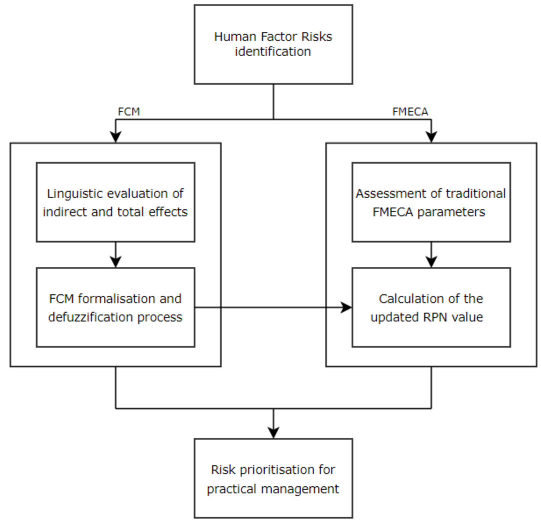

Figure 1. Methodological flowchart for human risk assessment

3.1 Human risks identification

The field of human factor risk is a complex domain [19] where diverse aspects are interconnected. Relationships may create some interference potentially impacting on system performance [20], adding complexity to the risk management process [19]. Aiming at supporting this process, a list synthesising significant human risks in industry has been first drawn up from the literature [21, 19, 22] and shown in Table 1. Next we present the proposed methodological tools.

TABLE 1. Human risks identification

Category	ID Code	Description
Environment	E_1	Noise beyond the normal level [21].
	E_2	Exposition to intense vibration [21].
Work space	WS_1	Unsuitable workplaces organisation [21].
	WS_2	Dangerous disposition of work spaces [21].
	WS_3	Overlapping individual work spaces [21].
	WS_4	Incorrect ergonomics conditions [19].
	WS_5	Personal Protective Equipment (PPE) damaged or improperly used [19].
Machinery and/or tools	MT_1	Inappropriate use and/or management of machines and plants [22].
	MT_2	High variation of tools to be used [21].
	MT_3	Incorrect use of work equipment [19].
Mental load	ML_1	Negative psychological state [22].
	ML_2	Existence of several distraction factors [21].
	ML_3	Bad life habits influencing work [19].

3.2 FCM to model human risks relations

Initially developed by [23] to study social scientific knowledge in decision-making activities focused on international politics, CMs were later extended to FCMs by [11]. FCMs allow to solve two specific problems, namely, modeling complex systems and displaying potential relationships among elements [24]. Concepts and relations are linguistically represented and treated with the support of fuzzy sets. Indirect effects (IE) and total effects (TE) from element C_i to element C_j are described by using such linguistic evaluations e_{ij} as *much*, *some* and *a lot*, which are translated into fuzzy numbers.

Figure 2 shows, as an example, the FCM used by [11] whose connection path network is used here to explain and formalise the next equations.

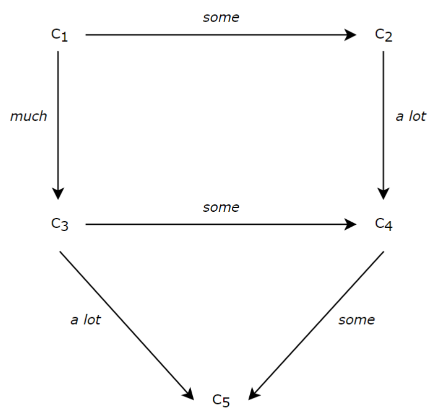

Figure 2. Example of FCM developed by Kosko [11]

We can observe as three possible casual paths connect C_1 to C_5: $P_1(1-2-4-5)$, $P_2(1-3-5)$ and $P_3(1-3-4-5)$. The three indirect effects between C_1 and C_5 associated to these paths (IE_1, IE_2 and IE_3) can be assessed as follows:

$$\begin{aligned} IE_1(C_1, C_5) = \min\{e_{12}, e_{24}, e_{45}\} = \\ \min\{some, a\ lot, some\} = some; \end{aligned} \tag{1}$$

$$\begin{aligned} IE_2(C_1, C_5) = \min\{e_{13}, e_{15}\} = \\ \min\{much, a\ lot\} = much; \end{aligned} \tag{2}$$

$$\begin{aligned} IE_3(C_1, C_5) = \min\{e_{13}, e_{34}, e_{45}\} = \\ \min\{much, some, some\} = some. \end{aligned} \tag{3}$$

Once evaluated indirect effects, the total effect of element C_1 over element C_5 will correspond to the maximum evaluation among them, as follows:

$$\begin{aligned} TE(C_1, C_5) = \max\{IE_1(C_1, C_5), IE_2(C_1, C_5), \\ IE_3(C_1, C_5)\} = \max\{some, much, some\} = much. \end{aligned} \tag{4}$$

This result means that, on the whole, element C_1 imparts *much* causality to element C_5. To be quantitatively manipulated, linguistic evaluations will be translated to fuzzy numbers using the linguistic conversion board of [25]. The conversion to crisp values is performed using the defuzzifying equations of [26].

3.3 Modified FMECA for risks prioritisation

The above presented FCM-based approach is now integrated with the FMECA technique, which we propose in a modified version. FMECA is a systematic procedure aimed at analysing all the potential failure modes that may impact on a system by identifying the related causes and effects. FMECA uses a priority index for each failure mode, the so-called Risk Priority Number (RPN).

The RPN is traditionally calculated by means of the following multiplication:

$$RPN = S \times O \times D; \tag{5}$$

where parameters S, O and D respectively indicate severity (intensity of impact of a given failure mode), occurrence (frequency of occurrence of a given failure mode) and detection (probability of correct failure detection). These parameters are generally ranged within discrete intervals (see [17]).

We proceed with human factor risks prioritisation by integrating the (defuzzified) TE parameter achieved by FCM into the traditional RPN calculation as follows:

$$RPN_{new} = RPN_{old} \times (1 + \phi); \tag{6}$$

ϕ being the defuzzified value of the fuzzy number corresponding to the linguistic evaluation associated to TE. The contribution of causality affecting human risks is considered this way. The scale given in the risk assessment matrix formalised in [19] is used to assess the severity parameter, whereas the scales proposed in [17] are used to evaluate the occurrence and detection parameters for each human risk. To test the applicability of the proposed approach, we show a practical application in next case study section.

4 Case study

Being aware that, in industrial contexts, human resources are exposed to significant risks whose occurrence could easily lead to catastrophic results, we propose a practical application in the sector of the automotive industry. This choice is motivated by the fact that impacts of human risks dramatically increase in the heavy industry, so that risks have to be continuously monitored and kept to a minimum. Connections among human risks identified in the previous section have been evaluated for an automotive company operating in the North of Morocco by involving the responsible of the safety and security system.

Table 2 presents the connection matrix corresponding to the FCM of Figure 3. The matrix collects the linguistic evaluations by the expert. These evaluations have been translated into trapezoidal fuzzy numbers (TrFN) and their defuzzified values have been calculated through the centroid method, as in [25]. The FCM of Figure 3 has been obtained using the Mental Modeler software (http://www.mentalmodeler.org/). The map graphically shows 45 connections identified for its 13 elements (i.e. risks), what corresponds to about 3.46 connections per element. Table 3 shows numerical evaluations for FMECA parameters along with defuzzified values ϕ (for linguistic total effects) to be used in the RPN_{new} calculation. Values of RPN_{old} are also reported for comparisons purposes with traditional FMECA.

We can observe as integrating the ϕ parameter by updating the classical RPN calculation underlines differences in terms of risk prioritisation, which can be significant for management.

TABLE 2. Connection matrix formalising indirect effects for human risks

Risk	E_1	E_2	WS_1	WS_2	WS_3	WS_4	WS_5	MT_1	MT_2	MT_3	ML_1	ML_2	ML_3	IE
E_1	0	0	0	VL	0	0	0	0	0	0	0	VH	L	VL
E_2	VH	0	0	L	0	0	0	0	0	0	0	VH	0	L
WS_1	0	0	0	M	0	L	VL	0	0	0	VL	0	0	VL
WS_2	0	0	0	0	0	0	0	0	0	0	0	0	L	L
WS_3	M	0	0	M	0	0	0	0	L	0	0	VH	0	L
WS_4	0	0	L	H	0	0	L	0	0	0	M	0	0	L
WS_5	VH	VH	0	VH	0	0	0	0	0	0	0	0	0	VH
MT_1	VL	VL	VH	0	0	M	0	0	L	H	0	0	0	VL
MT_2	0	0	M	0	M	0	0	VH	0	0	L	VH	0	L
MT_3	L	L	0	L	0	0	0	H	0	0	0	0	0	L
ML_1	0	0	0	VH	0	0	VH	0	0	0	0	0	0	VH
ML_2	0	0	0	0	0	0	0	0	0	0	L	0	0	L
ML_3	0	0	VH	0	0	0	VH	0	0	VH	L	0	0	L
IE	VL	VL	L	VL	M	L	VL	H	L	H	VL	VH	L	

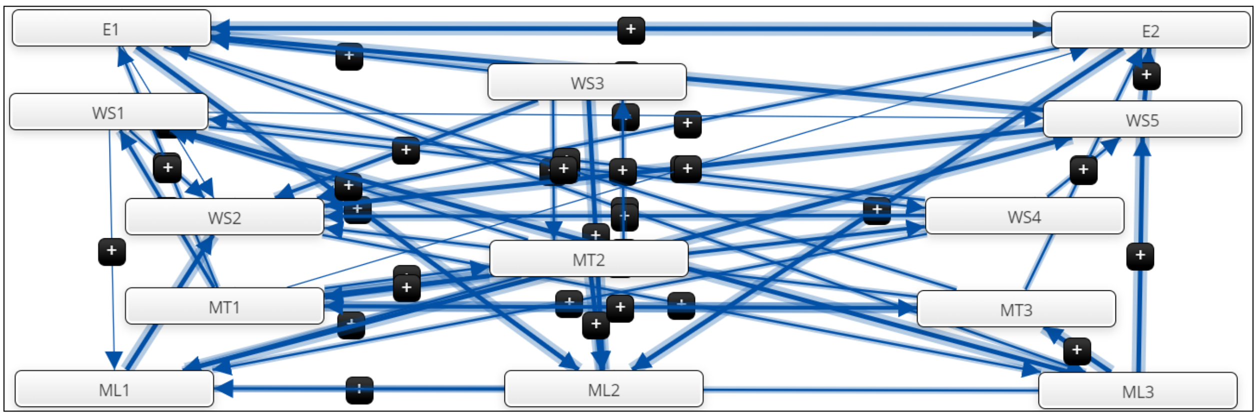

Figure 3. FCM evaluating relationships among the identified human risks

Without considering interaction effects, the most critical risks are, in decreasing order: MT_1, WS_5, and WS_4, with RPN_{old} respectively equal to 32.00, 30.00 and 24.00. Our approach changes the perspective in terms of practical risk management, since the order of risks to be addressed with priority is now WS_5, MT_1 and MT_3, with RPN_{new} respectively equal to 42.00, 41.92 and 31.44. Having associated higher level of causality, aspects related to usage of PPE, management of machines and plants as well as usage of work equipment should be then considered as priorities to enhance safety and security in the automotive industry.

TABLE 3. Output of the combined FCM-FMECA approach

Risk	S	O	D	RPN_{old}	TE	ϕ	RPN_{new}
E_1	1	3	1	3.00	VL	0.4	4.20
E_2	2	3	1	6.00	L	0.14	6.84
WS_1	3	4	1	12.00	L	0.14	13.68
WS_2	5	1	2	10.00	L	0.14	11.40
WS_3	4	2	2	16.00	M	0.23	19.68
WS_4	4	2	3	24.00	L	0.14	27.36
WS_5	5	3	2	30.00	VH	0.40	42.00
MT_1	4	2	4	32.00	H	0.31	41.92
MT_2	2	3	4	24.00	L	0.14	27.36
MT_3	2	3	4	24.00	H	0.31	31.44
ML_1	5	1	4	20.00	VH	0.40	28.00
ML_2	1	4	2	8.00	VH	0.40	11.20
ML_3	2	4	3	24.00	L	0.14	27.36

5 Conclusions and future work

This paper applies a hybrid methodological approach for industrial human risk assessment. We first make use of FCMs to comprehensively organise knowledge and opinions provided by the involved decision maker(s), who are expert(s) in the industrial sector of interest. The FCM-based approach is proposed to model relations among relevant human risks by generating spontaneous brainstorming activities, without being anchored to the need of the *a posteriori* check of consistency of preferences expressed by experts between pairs of risks. After evaluating relations among risks, we propose a modified FMECA for final risk prioritization. The output is a final ranking of risks highlighting those aspects to be improved with priority to globally enhance safety and security, is a fundamental aspect in industry. A case study is implemented to show the applicability of the proposed approach to real industrial contexts. Possible future developments of the present research may refer to the application of FCMs to evaluate the influence of relevant criteria selected to study failure propagation phenomena in complex systems. Moreover, different parameters from those used in traditional FMECA may be considered for the RPN calculation in order to produce more precise assessments oriented to continuous human resource safety improvement.

6 Aknowledgment

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