A FUZZY COGNITIVE MAPS MODEL TO DEVELOP A RISK ANALYSIS MODEL THROUGH THE IDENTIFICATION OF CRITICAL HUMAN FACTORS

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ABSTRACT
Over the past years, technological developments have led to a decrease of accidents due to technical failures through the use of redundancy and protection. However, the *"human factor"* contributes significantly in accident dynamics, both statistically and in terms of severity of consequences. In fact, estimates agree that the errors committed by man are causes over 60% of accidents and for the remaining part the causes are due to technical deficiencies. This paper deals with various aspects of human behavior that can influence operator reliability, considering the environment in which operator is working. The aim of the research is to propose a fuzzy cognitive map capable to represent human knowledge where the relationships are difficult to describe in mathematical terms.

Keywords: human error, risk analysis, fuzzy cognitive maps, cognitive model

1. INTRODUCTION
Nowadays, the analysis of human factors constitute a highly interdisciplinary field of study not yet well defined, therefore, a complete and universally accepted taxonomy of different types of human errors and causes determining them, does not exist. The objective difficulties of governing the human factor and human error have made many experts believe that the conduct of prevention and safety were related to a person's intrinsic characteristics, such as personality traits. (D'Elia *et al.*, 2013).

In the literature, there are different risk-based approaches reported, ranging from the purely qualitative to the quantitative (Bruzzone *et al*., 2014 a). Many authors used probabilistic risk assessment. A vast majority of tools and techniques available for the Human Reliability Analysis (HRA) are meant for high risk sectors like nuclear, petrochemical industries, and so on, applied within the context of probabilistic safety assessment (Cacciabue, 1996). In the literature, some papers proposed the Fuzzy cognitive maps (FCMs) approach in the field of risk analysis.

In fact, human element in risk analysis cannot be structured in a hierarchical way, as it involves interaction and dependence among factors under various heads, like organizational, personal, design related, task related, and so on. However, this can be analyzed with a network structure, like the use of cognitive maps.

FCMs have gained considerable research interest and widely used to analyse complex systems and making decisions. Recently, they found large applicability in diverse domains for decision support and classification tasks. FCM is an efficient knowledge representation and reasoning method, which is based on human knowledge and experience (Kandasamy and Smarandache, 2003).

This paper deals with various aspects of human behavior that can influence operator reliability, considering the environment in which operator is working (Bruzzone *et al.*, 2014 b). The focus is on understanding the nature of human performance variability and eventually, how to describe and analyze it. The proposed fuzzy cognitive map is capable of representing human knowledge where the relationships are difficult to describe in mathematical terms.

The applicability of the methodology is demonstrated through a case study. The paper is organized in the following sections: section 2 presents general features of fuzzy cognitive maps approach; section 3 analyzes human factors in the context of risk analysis; section 4 elaborates a fuzzy cognitive model to evaluate factors influencing human reliability; finally, section 5 presents results and conclusion.

2. FUZZY COGNITIVE MAP APPROACH
Fuzzy Cognitive Maps (FCM) have found favor in a variety of theoretical and applied contexts that span the hard and soft sciences. Given the utility and flexibility of the method, coupled with the broad appeal of FCM to a variety of scientific disciplines, FCM have been appropriated in many different ways and, depending on the academic discipline in which it has been applied, used to draw a range of conclusions about the belief systems of individuals and groups (Groumpos, 2010).

FCM encompasses a wide range of applications including: risk assessment (Hurtado, 2010) work efficiency and performance optimization strategic deterrence and crisis management, scenario/policy assessment (Amer *et al*., 2011) spatial suitability and prediction mapping and environmental modeling and management (Adriaenssens et al., 2004). FCMs are most often employed in participatory planning and management and/or environmental decision-making contexts, and are primarily used to gain an understanding of how stakeholders internally construct their understanding of their world or a particular issue of interest (Kontogianni *et al.*, 2012).

For the above reasons Fuzzy Cognitive Maps (FCMs) constitute an attractive modeling technique for complex systems (Jose, 2010).

The term fuzzy cognitive map (FCM) was coined in (Kosko, 1986) to describe a cognitive map model with two significant characteristics:

- *Causal relationships between nodes are fuzzified*. Instead of only using signs to indicate positive or negative causality, a number is associated with the relationship to express the degree of relationship between two concepts.
- *The system is dynamic involving feedback*, where the effect of change in a concept node affects other nodes, which in turn can affect the node initiating the change. The presence of feedback adds a temporal aspect to the operation of the FCM.

FCM has its roots in concept and cognitive mapping. Concept maps are graphical representations of organized knowledge that visually illustrate the relationships between elements within a knowledge domain. By connecting concepts (nodes) with semantic or otherwise meaningful directed linkages, the relationships between concepts in a hierarchical structure are logically defined (Novak and Cañas, 2008; Papageorgiou and Salmeron, 2011).

In other words, FCM is a soft computing technique that follows an approach similar to the human reasoning and decision-making process. An FCM consists of nodes which illustrate the different aspects of the system behavior.

These nodes (concepts) interact with each other, illustrating the dynamics of the model. FCM is a complex form of data collection where study participants are asked to develop qualitative static models which are translated into quantitative dynamic models.

A cognitive map can be thought of as a concept map that reflects mental processing, which is comprised of collected information and a series of cognitive abstractions by which individuals filter, code, store, refine and recall information about physical phenomena and experiences.

Fuzzy cognitive map uses two types of elements: concepts, represented by nodes; and causal beliefs, represented by weighted edges connecting the nodes. The graphical representation clearly depicts interaction of concepts and their degree of dependence/ interdependence (Kumar *et al.*, 2013). Figure 1 illustrates an example of an FCM with seven concepts. Concepts characterize the behavior of the system under consideration, and it can be an action, variable, or state, and so on whose values change with time.

The FCM structure can be viewed as a recurrent artificial neural network, where concepts are represented by neurons and causal relationships by weighted links or edges connecting the neurons.

By using Kosko's conventions, the interconnection strength between two nodes C_i and C_j is e_{ij}, with e_{ij}, taking on any value in the range -1 to 1. Values –1 and 1 represent, respectively, full negative and full positive causality, zero denotes no causal effects and all other values correspond to different fuzzy levels of causal effects. In general, an FCM is described by a connection matrix E whose elements are the connection strengths (or weights) e_{ij}. The element in the i^{th} row and j^{th} column of matrix E represents the connection strength of the link directed out of node C_i and into C_j. If the value of this link takes on discrete values in the set {-1, 0, 1}, it is called a simple FCM. The concept values of nodes C1, C2, …, Cn (where n is the number of concepts in the problem domain) together represent the state vector C.

An FCM state vector at any point in time gives a snapshot of events (concepts) in the scenario being modelled.

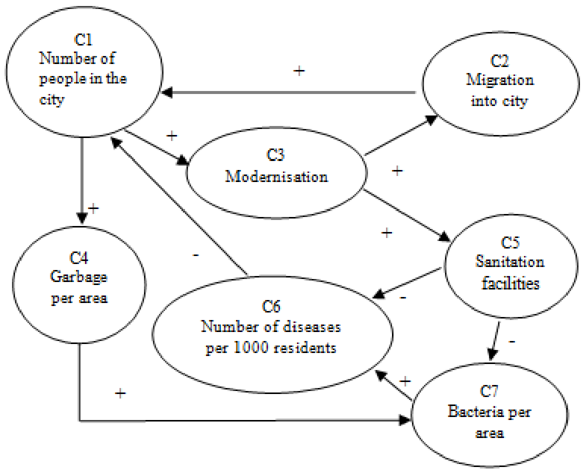


Figure 1: Example of fuzzy cognitive maps

The nodes represent concepts or variables relevant to a given domain. The causal links between these concepts are represented by the edges. The edges are directed to show the direction of influence. Apart from the direction, the other attribute of an edge is its sign, which can be positive (a promoting effect) or negative (an inhibitory effect). Cognitive maps can be pictured as a form of signed directed graph.

The construction of a cognitive map requires the involvement of a knowledge engineer and one or more experts in a given problem domain. In a cognitive map, the effect of a node A on another node B, linked directly or indirectly to it, is given by the number of negative edges forming the path between the two nodes. The effect is positive if the path has an even number of negative edges, and negative otherwise.

3. ROLE OF HUMAN FACTORS IN RISK ANALYSIS

With the development of nuclear power, and the increasing complexity of automated manufacturing processes, the magnitude and significance of accidents have greatly increased. The Chernobyl nuclear power plant disaster in the Ukraine and the Challenger spacecraft explosion are vivid examples.

In order to ensure effective prevention of dangerous events, the role of humans in accident dynamics should be considered during risk assessment processes (D'Elia *et al.*, 2014).

The researchers' great efforts to propose models of human behavior (French *et al.*, 2008) favoring numerical values of error probability in order to predict and prevent unsafe conduct are clearly evident.

Analysis of human reliability is a multidisciplinary problem, calling for knowledge and expertise from probabilistic safety analysis, plant design and operations, decision science, and the behavioral sciences (Hollnagel, 2002). Human Reliability Analysis (HRA) grew up in the 1960s, with the intention of modeling the likelihood and consequences of human errors (Sharit, 2012).

Human reliability is a crucial element in ensuring plant performance, and it is critical to situations or activities where the operator interacts directly with the system the stress factors include physiological and psychological stressors like fear, monotonous workload, overload, and so on. There are not many studies dedicated to the assessment of performance shaping factors (PSFs) on human reliability.

Human reliability cannot be analyzed in the same manner as that of equipment/component. The main issue with human reliability analysis (HRA) is the uncertainty of the data concerning human factors, together with the difficulty in modeling the human behavior (Hollnagel, 2005).

Risk assessment is a systematic process for assessing the impact, occurrence and the outcome of human activities involving products or systems with hazardous characteristics. Three questions need to be answered: *''What can go wrong?''*; *''How likely is it that this will happen?''*; *''If it does happen, what are the consequences?''* (Kaplan and Garrick, 1981).

Risk identification usually involves specifying one or more scenarios of risks. A risk scenario describes an interaction between a person and a system or product that possesses hazardous characteristics. It describes the activity of the person(s) involved, the hazard(s), the external factors of the situation and the potential injury.

Methods for risk assessment need to be as univocal and precise as possible to differentiate the risk level of various activities. In this light, we need to reduce the uncertainty in measurement of qualitative attributes such as "severity" and "likelihood" (Carter, 2003).

The focus is on understanding the nature of human performance. The likelihood of human errors in a specific condition depends upon the combined effects.

4. IMPLEMENTATION OF A FUZZY COGNITIVE MODEL TO EVALUATE HUMAN INFLUENCE IN RISK ANALYSIS

Given the basic outline of risk assessment, this paper explores the factors and parameters that need to be considered in order to design a good quality risk assessment.

It is important to realise that perceived risks and benefits are important, and that these may differ from person to person.

The proposed model deals with various aspects of human behavior that can influence his/her reliability, considering the environment in which he/she is working and the nature of task.

The main objective of building a cognitive map around a problem is to be able to predict the outcome by letting the relevant issues interact with one another. These predictions can be used for finding out whether a decision made by someone is consistent with the whole collection of stated causal assertions.

In the proposed research Mental Modeler software is used. Mental Modeler is a fuzzy-logic cognitive mapping software (http://www.mentalmodeler.org/), allows you to build Fuzzy-logic Cognitive Maps easily and intuitively (Gray *et al.,* 2013). Once models are built, increasing or decreasing the components included in the model allows you to examine different scenarios of change. Because of their flexibility, FCM have been used in a range of scientific disciplines, from political science to economics to ecology.

Based in Fuzzy-logic Cognitive Mapping (FCM), users can easily develop semi-quantitative models of environmental issues, social concerns or social-ecological systems in Mental Modeler by:

- Defining the important components of a system
- Defining the relationships between these components
- Running "what if" scenarios to determine how the system might react under a range of possible changes

Here below case study framework is presented.

Step #1: Problem description.

In the present case study a chemical company is evaluated. The data collection phase followed the normative literature for conducting fieldwork in risk management. The authors drew upon their own extensive industrial experience to inform and guide the design of an interview protocol that defined the scope of the necessary data to explore.

Semi-structured interviews were conducted with the Managing Director (MD), Production Director (PD), and Production Manager (PM) in order to:

- determine or describe the context;
- describe the possible error modes;
- describe the probable causes;
- perform a more detailed analysis of main task steps.

Step#2: Factors influencing human performance.
Based on the literature review and personal experience, the human error in risk analysis is highly dependent on state and condition of the personnel engaged in the work. Major factors, which characterize the behavior of the personnel are the following:

- Emotional stability C1
- Knowledge and skill C2
- Attention and alertness C3
- Perception and memory C4
- Motivation C5
- Workplace environment C6
- Clarity of instructions C7
- Communication C8
- Time pressure C9

The above factors formed our fuzzy cognitive map.

Step#3: Fuzzy cognitive map model development
The factors that influence others, along with their linguistic degree of causation are determined as shown in Figure 2. While in Figure 3 fuzzy cognitive map's metrics are shown.

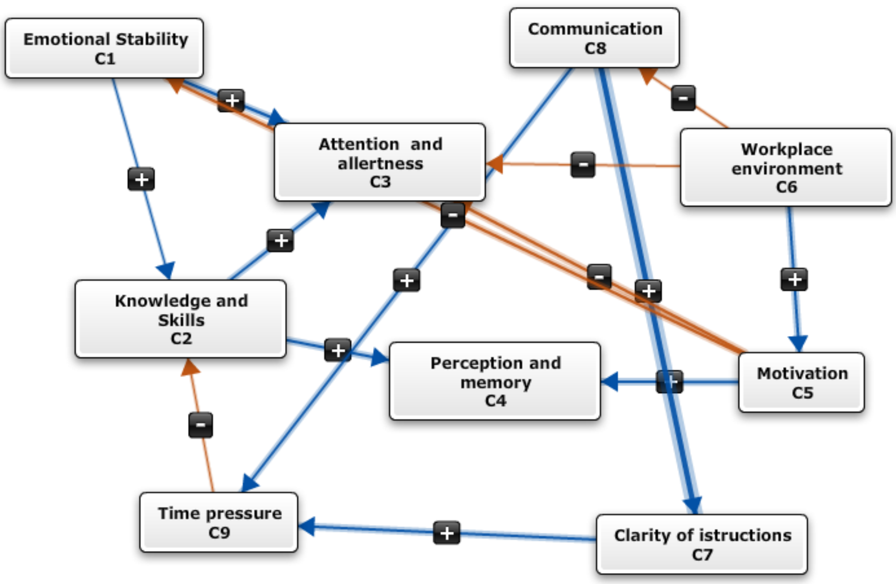
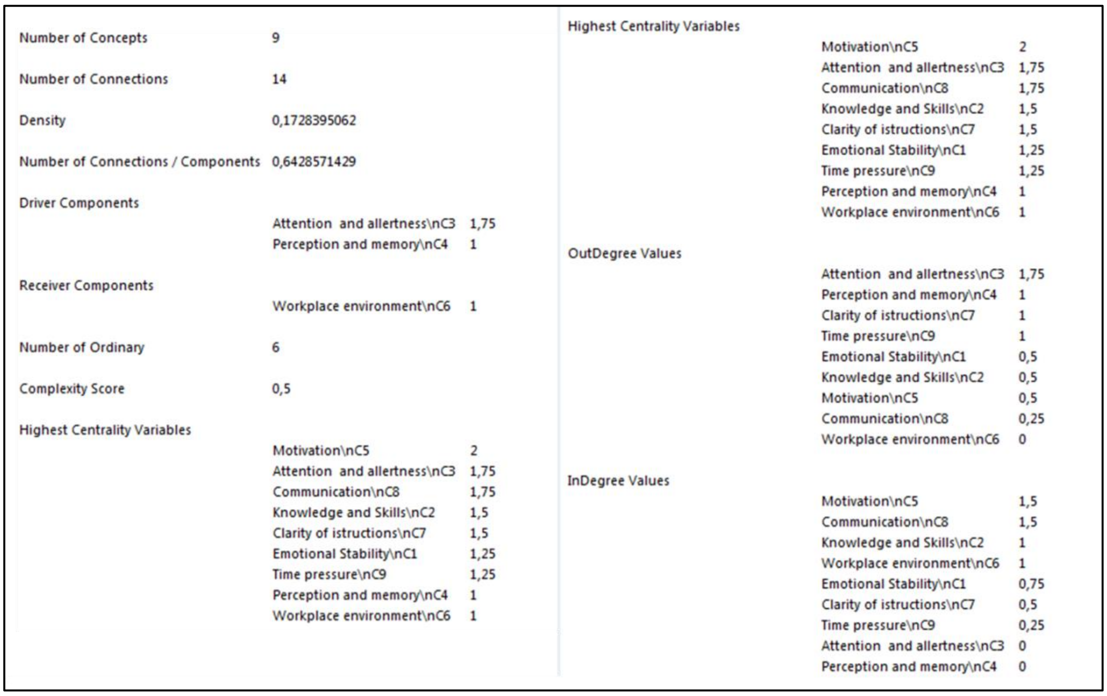


Figure 2: Fuzzy cognitive map



Number of Concepts	9	
Number of Connections	14	
Density	0,1728395062	
Number of Connections / Components	0,6428571429	
Driver Components		
	Attention and allertness\nC3	1,75
	Perception and memory\nC4	1
Receiver Components		
	Workplace environment\nC6	1
Number of Ordinary	6	
Complexity Score	0,5	
Highest Centrality Variables		
	Motivation\nC5	2
	Attention and allertness\nC3	1,75
	Communication\nC8	1,75
	Knowledge and Skills\nC2	1,5
	Clarity of istructions\nC7	1,5
	Emotional Stability\nC1	1,25
	Time pressure\nC9	1,25
	Perception and memory\nC4	1
	Workplace environment\nC6	1

Highest Centrality Variables		
	Motivation\nC5	2
	Attention and allertness\nC3	1,75
	Communication\nC8	1,75
	Knowledge and Skills\nC2	1,5
	Clarity of istructions\nC7	1,5
	Emotional Stability\nC1	1,25
	Time pressure\nC9	1,25
	Perception and memory\nC4	1
	Workplace environment\nC6	1
OutDegree Values		
	Attention and allertness\nC3	1,75
	Perception and memory\nC4	1
	Clarity of istructions\nC7	1
	Time pressure\nC9	1
	Emotional Stability\nC1	0,5
	Knowledge and Skills\nC2	0,5
	Motivation\nC5	0,5
	Communication\nC8	0,25
	Workplace environment\nC6	0
InDegree Values		
	Motivation\nC5	1,5
	Communication\nC8	1,5
	Knowledge and Skills\nC2	1
	Workplace environment\nC6	1
	Emotional Stability\nC1	0,75
	Clarity of istructions\nC7	0,5
	Time pressure\nC9	0,25
	Attention and allertness\nC3	0
	Perception and memory\nC4	0

Figure 3: Fuzzy cognitive map's metrics

The degree of relationships among the considered factors is established following consensus group method. Here, each member contributes to the discussion, and the group as a whole then arrives at an estimate upon which all members of the group agree. After concepts in the model have been determined, relationships between concepts can be added by using directional arrows which indicate the amount of influence one component can have on another, called edge relationships. Concepts included in the model can have positive (high, medium, or low), negative (high, medium, or low) or no (no relationship defined) edge relationships.

The qualitative weights of edge relationships (i.e. “fuzzy” approximation of influence) between components are then translated into the quantitative values between -1 (high negative) to 1 (high positive) used in the matrix interface (Table 1).

Table 1: The qualitative weights of edge relationships

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0	0,5	0,25	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0
C3	0	0,5	0	0	0,5	0	0	0	0
C4	-0,5	-0,5	0	0	0,5	0	0	0	0
C5	0	0	0	0	0	0	0	0	0
C6	0	-0,25	0	0,5	0	0	-0,25	0	0
C7	0	0	0	0	0	0	0	1	0,5
C8	0	0	0	0	0	0	0	0	0,5
C9	0	0	-0,25	0	0	0	0	0	0

Mental Modeler also includes a Matrix interface that converts the concept map built in the Concept Mapping interface into a structural matrix. The Matrix interface can easily be revised based on the original concept map once the users familiarize themselves with the structure of the tool (Figure 4).

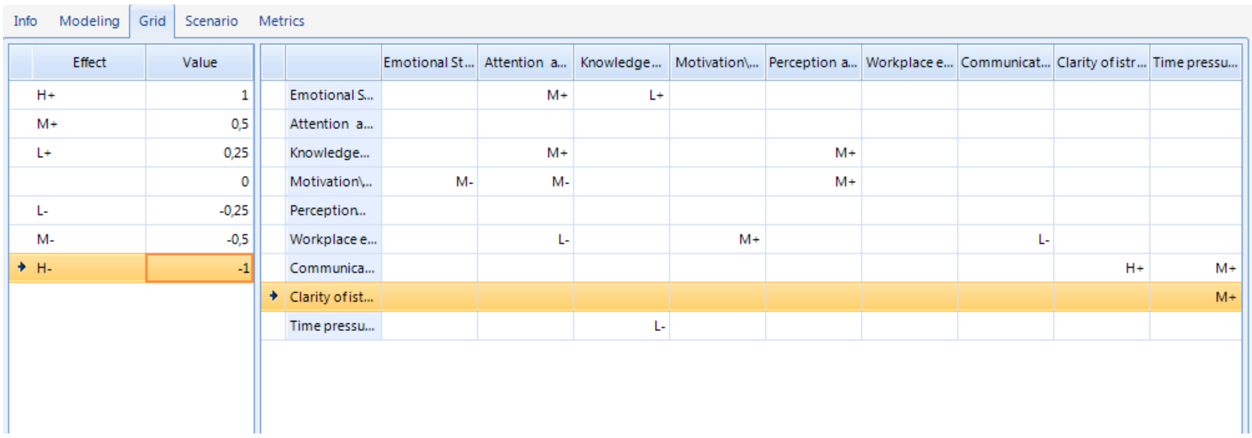


Figure 4: Matrix

Step#4: Scenario analysis

Changing the weight of the components selected from each of the scenarios, it is possible to estimate how the system reacts to changes induced described. In other words, the scenario interface indicates the amount of relative change in the components included in the model based on the edge relationships defined in the Concept Mapping interface for the chosen scenario. It is possible to decide what scenario to run based on probable, improbable, gradual and extreme changes to the system.

It is important to note, that the results presented here must be read in a comparative way, not absolute, that is used to check which components, given the structure of the map, are affected more than the other simulated change and with what results. This type of analysis is useful to deepen the knowledge of the system and to develop strategies and assumptions useful to react to the occurrence of events simulated. Scenario analysis was discretized into three modes in ascending order of control and performance reliability, and thus in descending order of human failure probability: scrambled, tactical and strategic, as defined below:

- *Scrambled scenario*: choice of forthcoming action is unpredictable or haphazard;
- *Tactical scenario*: performance typically follows planned procedures while some ad-hoc deviations are still possible;

- *Strategic scenario*: plentiful time is available to consider actions to be taken in light of wider objectives to be fulfilled and within the given context.
  Figures 5, 6 and 7 show the three different scenario.

  In the **first scenario**, suppose the C1, C2, C3 and C6 "high", according to the adopted linguistic scale. The output indicates that a positive change influences positively the factors C5 and C4. In the **second scenario** suppose the C6, C7 and C8 "high", according to the adopted linguistic scale. he output indicates that a positive change influences positively the factors C5, C4 and C9. In the **third scenario** suppose the C1, C6 and C9 "high", according to the adopted linguistic scale. he output indicates that a positive change influences positively the factors C2, C3, C4 and C5.

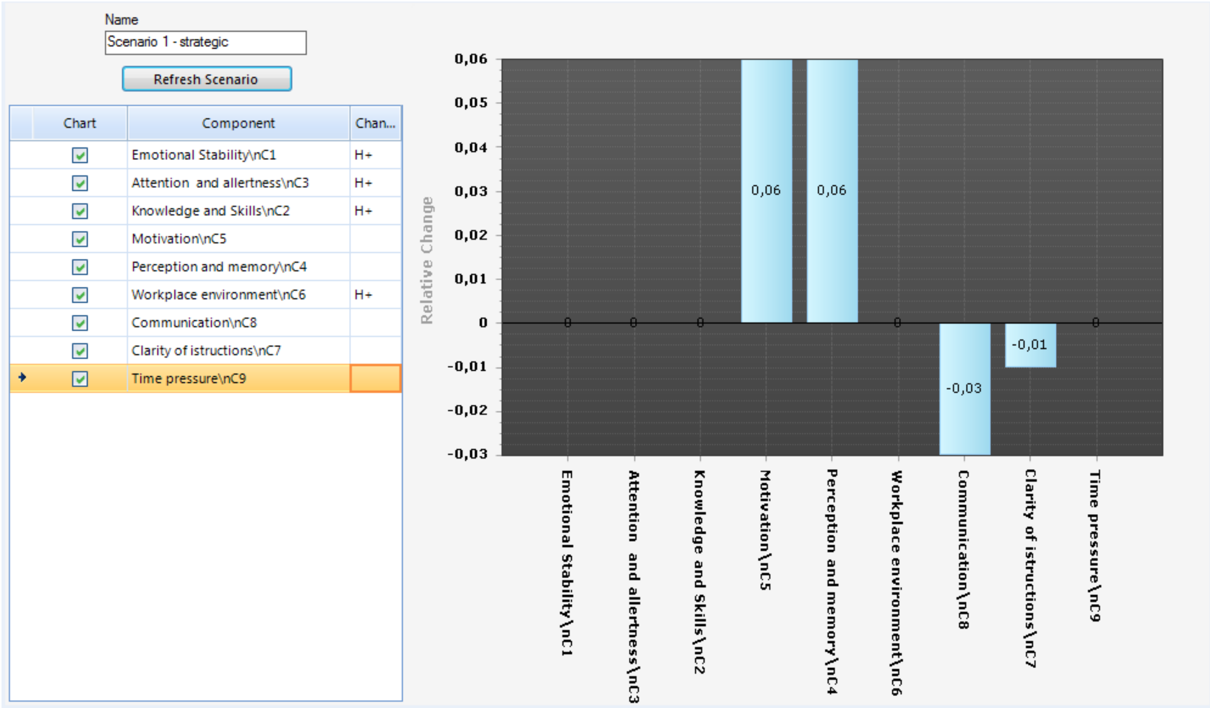


Figure 5: Strategic scenario

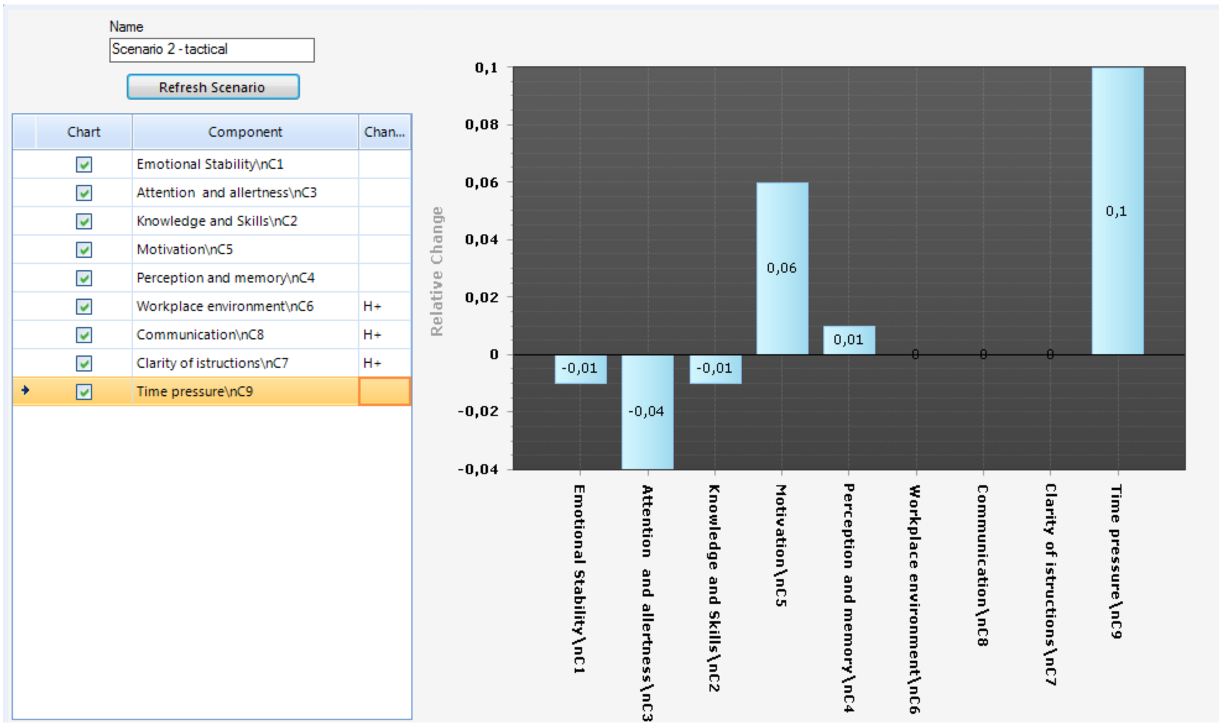


Figure 6: Tactical scenario

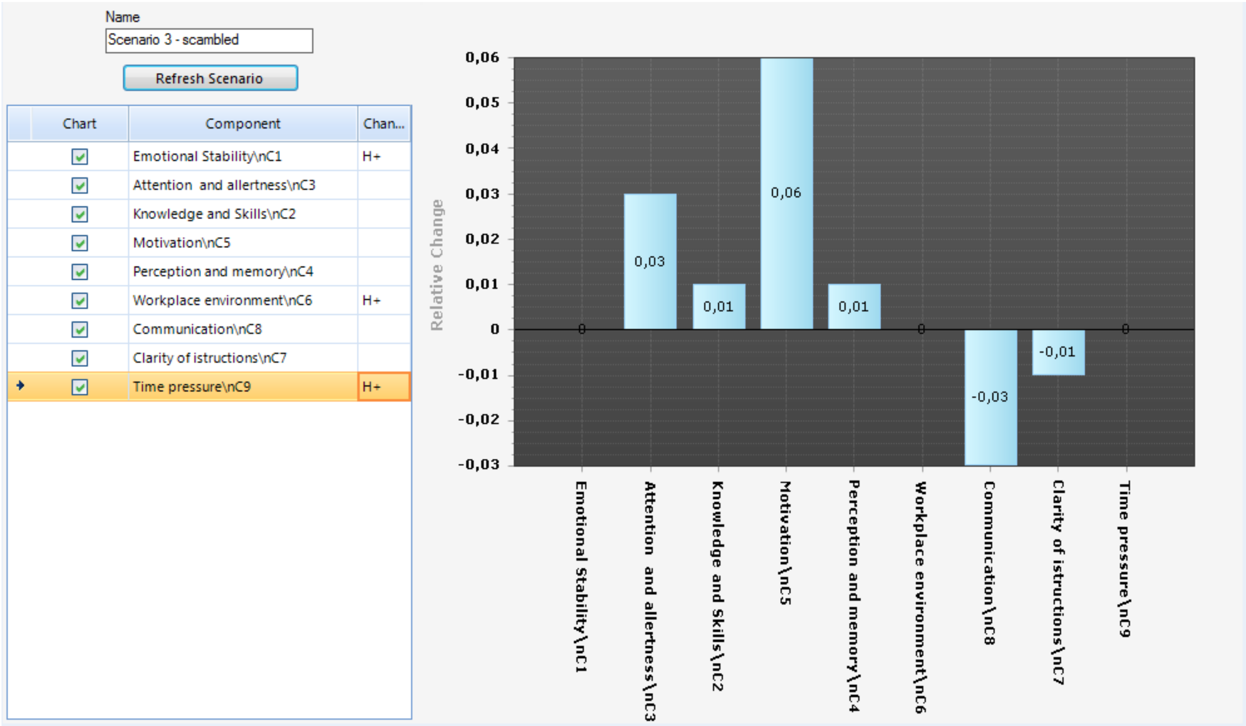


Figure 7: Scrambled scenario

6. CONCLUSION

The main question of risk evaluation is ‘‘how safe is safe enough?”

An fuzzy cognitive model was applied to manage the human factors in order to improve risk analysis.

Fuzzy systems in general have already proven themselves capable of dealing with the inherent imprecision encountered in real-world problem domains. Fuzzy cognitive maps combine this advantage with the well-established utility of cognitive maps as a decision support tool, and the dynamic and adaptive nature of artificial neural networks.

The proposed FCM methodology evaluates the influence of error inducing factors on human reliability and has potential to examine a scenario, where it is not easy to describe in terms of relations/mathematical formulas.

Future research will focus in the fuzzy quantification of the human error probability within the framework of the Cognitive Reliability and Error Analysis Method (CREAM) method and other methods within HRA approach in order to compare different results and approach.

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