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An advanced DYNAMIC RISK MODELING AND ANALYSIS in projects management

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• ABSTRACT •

Risk is inherently present in all projects. Quite often, many projects fail to achieve their time, quality, and budget goals. Despite its high relevance to the success of projects, risk management remains one of the least developed research issues. Therefore, advanced risk assessment is essential in minimizing losses and enhancing profitability. This paper proposes an advanced decision support tool using Fuzzy Cognitive Maps (FCMs) for dynamic risk assessment in project management. The proposed tool is able to predict the impact of each risk on the other risks or the outcomes of projects by considering uncertainties and complex interdependencies among risk factors. This tool could help project managers to manage the risks in a more effective and precise way and offer better risk mitigation solutions. The proposed tool could be undertaken by all organizations with the highest level of risk management maturity in the largest and most complex projects. In addition, it can be applied as an advanced decision support tool in variety of problems such as prioritization, failure analysis, etc. An academic numerical example related to outsourcing illustrates the applicability and simplicity of the proposed method.

1. INTRODUCTION

A well-structured and cost-effective risk management program is a necessary ingredient of a successful project. Risk management is a systematic process of identifying, assessing and responding to project risks. It consists of six steps: planning, risk identification, qualitative risk analysis, quantitative risk analysis, risk response planning, risk monitoring and control (Dey, 2012). In addition, it can be used not only for control against loss, but also as a way to attain greater rewards (Wu, 2008). Risk management is beneficial if implemented in a systematic manner from the planning stage through project completion in order to make better and more informed decisions. The unsystematic and arbitrary management of risks can endanger the success of the project since most risks are very dynamic throughout the project lifetime. Indeed, risks may vary from appraisal, design, tendering, construction and commissioning. To meet these demands, human and organisational dimensions play a key role in the whole process of risk management. Each project includes many risk factors that can cause delays or failures during the project life cycle. Thus, it is important to establish a method and system to manage these risk factors effectively in advance. Moreover, it is necessary to reduce the probability of such risk factors causing failures in the project by implementing models or mitigation measures.

The aim of this paper is to present an advanced decision support tool using Fuzzy Cognitive Maps (FCMs) for dynamic risk assessment in project management. FCM represents a system in a form that corresponds closely to the way humans perceive it. Therefore, it is easily understandable, even by a non-professional audience and each parameter has a perceivable meaning. The model can be easily altered to incorporate new phenomena, and if its behaviour is different than expected, it is usually easy to find which factor should be modified and how. The resulting fuzzy model can be used to analyse, simulate, test the influence of parameters and predict the behaviour of the system (Jamshidi, Abbasgholizadeh Rahimi, Ruiz, Ait-Kadi, & Rebaiaia, 2016).

FCM is a useful artificial intelligence technique which represents and analyzes the dynamic behavior of complex systems composed of interrelated variables (Kosko, Fuzzy cognitive maps, 1986; Jamshidi, Abbasgholizadeh Rahimi, Ait-Kadi, & Ruiz, 2015). This tool recently has been applied successfully in evaluating risks in complex and critical environments such as Enterprise Resource Planning (ERP) maintenance (Lopez & Salmeron, Dynamic risks modelling in ERP maintenance projects with FCM, 2014) (Ahmad & Kumar, 2012) and IT projects (Salmeron J. , 2010), and therefore we think it has a good potential to be applied in evaluating the risks of complex projects by forecasting the impact of risks on the project outcomes.

The remainder of this paper is organised as follows. Section 2 describes the FCM theoretical background. Section 3 explains the proposed methodology. Section 4 illustrates the applicability of the proposed method through a numerical example related to outsourcing. Finally, conclusions and future research are presented in section 5.

2. FUZZY COGNITIVE MAPS

FCM was originally introduced by Kosko (1986) as a soft computing technique which is able to take into account the dependencies among the main concepts/nodes and analyse inference patterns (E.I. Papageorgiou, 2004). FCMs constitute a modeling methodology that combines fuzzy logic and neural networks and are used to represent both qualitative and quantitative data (Elpiniki I. Papageorgiou, Fuzzy Cognitive Maps Learning Using Particle Swarm Optimization , 2005).

FCMs are developed based on the experience and knowledges of experts through an interactive procedure of knowledge acquisition. Various methodologies such as Delphi could be used in order to reach a consensus among the experts in FCM (Glykas, 2010).

Requirements	Modelling techniques			
	Systems dynamics	Bayesian networks	Neural networks	FCM
Capable of representing all possible connections	*	*	*	*
Does not ignore the uncertainty		*	*	*
Directed graph with cycles	*			*
The propagation does not follow an established pattern	*			*
Assumes information is scarce			*	*

TABLE 01. Comparing the modeling techniques in terms of the requirements demanded (Salmeron J. , 2010).

Table 1 shows the requirements demanded in the modelling tool selection. As shown in this table, FCM is the only modelling tool that meets all the requirements demanded in risk analysis of complex and dynamic systems. Considering these benefits of FCM in comparison with other existing tools, it is evident that why FCM is evolving and gaining importance each day.

Fuzzy Cognitive Maps (FCMs) are graphs which consist of nodes and weighted arcs between nodes. The following figure illustrates a FCM graph with 5 nodes and 9 arcs. The value of each concept C_i stands in the interval [0, 1], and the weighted arcs among nodes C_i and C_j (W_{ij}) can range in the interval [-1, 1] which represent the influence of each node on the others.

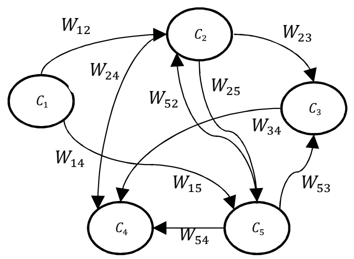

FIGURE 01. A simple Fuzzy Cognitive Map

The values of initial weight matrix (W_{ij}) are suggested by different experts using fuzzy linguistic terms such as Very High (VH), Low (L), etc. in order to determines the dependencies among nodes. Then, the linguistic variables are aggregated and defuzzified to numerical values (Papageorgiou E. I., 2014). When the FCM is initialized, it converges to a steady state through the interaction of equation (1). At each simulation step, the value A_i of the concept C_i is influenced by the values of concepts connected to it and it is updated through the following reasoning process (Papageorgiou E. I., 2014):

(1) $A_i^{k+1}=f\,(A_i^{(k)}+\sum_{\substack{j=1\\ j\neq i}}^{n} W_{ji}A_j^{(k)})$

where, W_{ji} shows the initial dependencies weight between concepts C_j and C_i;

$A_i^{(k+1)}$ is the value of concept C_i at simulation step k+1;

$A_j^{(k)}$ is the value of concept C_j at simulation step k;

The initial values of concepts are shown by initial concept vector c as c= [A_1,…,A_j,..., A_n];

k shows the simulation step;

f is a threshold function, which is used to restrict the concept value into [0,1] range. The most common types of f are: bivalent function (f (x) = 0 or 1), tangent hyperbolic (f (x)=tanh(x)), trivalent function (f (x) = -1, 0 or 1), and sigmoid function (f (x) = $1/(1+e^{-\lambda x})$) (Glykas, 2010). In this study, sigmoid function is adopted.

At each iteration, values of all concepts are recalculated and this process continues until FCM reaches one of the following states (Papageorgiou E. I., 2014):

1) The value of concepts has stabilized at a fixed equilibrium point,

2) A limited state cycle is exhibited, and

3) Chaotic behavior has appeared.

A major deficiency of FCM is its potential convergence to undesired steady states. In order to overcome this shortcoming, some learning algorithms have been developed such as particle swarm optimization (PSO) (Elpiniki I. Papageorgiou, Fuzzy Cognitive Maps Learning Using Particle Swarm Optimization , 2005), Differential Hebbian Learning [11,14], Simulated Annealing (SA) (Somayeh Alizadeh, 2009), and etc.

3. METHODOLOGY

In this paper, we propose an advanced approach for dynamic risk analysis of complex projects using FCM tool. This tool is able to prioritize the complex risks by considering interdependencies among risk factors and predict the impact of each risk on the rest of the risks and also project outcomes by developing several what-if analyses and eventually to avoid undesired outcomes. The steps of our proposed model are as follows:

Step 1: Form a group of experts in order to identify potential risks.

Step 2: Depict the FCM for the identified risk factors and obtain the initial weight matrix ($W^{Initial}$). Experts should first reach consensus on the sign and direction of arcs between risks. In order to determine the level of influence of each risk on the other risk and vice versa, each expert individually assigns a linguistic term for each arc (W_{ij}) using **Table 2**. In this study, fuzzy triangular numbers parametrized by a triplet (l, m, u) are used in order to consider the uncertainties in experts' opinions. Then, for each arc, the opinions of all expert are aggregated using the average value of assigned linguistic terms in order to obtain the overall linguistic weight. Finally, the overall linguistic weight should be defuzzified in order to find the initial influence weight ($W^{Initial}$). There are different defuzzification methods available in literature (Talon & Curt, 2017). In this paper, we apply the defuzzification method proposed by Çelik & Yamak (2013). According to this method, the defuzzification value t of a triangular fuzzy number (l, m, u) is equal to:

(2) $$t = \frac{l+m+m+u}{4}$$

(3) $$W^{Initial} = \begin{matrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{matrix}$$

Dependencies	Fuzzy rating
Very Low (VL)	(0, 0, 1.5)
Low (L)	(1, 2.5, 4)
Moderate (M)	(3.5, 5, 6.5)
High (H)	(6, 7.5, 9)
Very high (VH)	(8.5, 10, 10)

TABLE 02. Fuzzy ratings for dependencies among risk factors.

Step 3: Dynamic analysis of FCM requires the definition of an initial scenario, which represents a proposed initial situation to assess (Lopez & Salmeron, 2012). In this step, several "what-if" scenarios should be defined. In each scenario, a risk or a set of risks are activated. The value of activated risk/s in the initial concept vector (c) is considered as 1 and this number is 0 for the rest of risks. In order to achieve precise results, all of the risks should be taken into account and the total effects for each risk should be evaluated to determine their influences on the other risks or consequences.

Step 4: Calculate the impact of activated risks by updating the initial concept vector (c). To do so, each initial concept vector is trained through Eq. 1 and using a learning algorithm in order to obtain the steady state vector C*. The aim of this step is to identify the impact of each risk on the other risks and also project outcomes. This process is illustrated through a numerical example in the following section.

4. NUMERICAL EXAMPLE

In order to illustrate the proposed tool, we adopted the risks related to outsourcing projects identified by Jimmy et al. (2012). Outsourcing is comprehensively used by many companies. However, it does not guarantee business success. While outsourcing is a powerful tool to cut costs, improve performance, and refocus on the core business, it is associated with some major risks. Outsourcing failures are rarely reported because firms are reluctant to publicize them (Baitheiemy, 2003). Outsourcing is one of the best solutions or strategies available for each company that can lead to greater competitiveness and it has a major part to play in the design, installation and commissioning of an asset, and is instrumental in driving post commissioning improvements. However, outsourcing is a complex arrangement associated with uncertainties in dynamic business environments. This uncertainty and complexity could lead to critical risks that can impact on the enterprises' performance. Effective risk evaluation of outsourcing projects is a complex task since several risk factors should be taken into account.

In addition, there are always some dependencies among risks that can influence each other mutually and these dependencies make the evaluation process more complex and challenging.

The identified risks and their definitions are shown in **Table 3** and the related FCM graph is depicted in **Figure 2**. Besides, four consequences (Effects) are imagined as E1, E2, E3, and E4 to show how the proposed tool could consider all the interrelationships among risks and their effects on the project performance.

Risks	Definitions
Schedule (R1)	The inability to deliver the end product within the originally specified period of time
Technical (R2)	The inability of the technology to provide the expected performance
Financial (R3)	The inability to complete the project within a given budget
Vendor (R4)	The possibility of choosing an inappropriate vendor that could impact project performance
Culture (R5)	Occurrence of shared values and assumptions that govern acceptable behavior and thought patterns which could result in widely differing work ethics and quality standards
Reputation (R6)	Negative opinion of the stakeholders towards an organization
Intellectual property (R7)	The threat of the vendor using your ideas to produce a competing product or service
Flexibility (R8)	The inability of an organization to respond to potential internal or external changes in a timely and cost effective manner
Compliance (R9)	The inability of an organization to comply with appropriate regulations (local and global)
Quality (R10)	The inability of the end deliverable (product or service) to meet customer requirements

TABLE 03. Risk factors in outsourcing (Jimmy Gandhi, Gorod, & Sauser, 2012).

The FCM graph in **Figure 2** is depicted based on experts' opinions in order to show the dependencies and feedbacks among factors. In this numerical example, the interrelationships among ten risk factors are identified through Jimmy et al. (2012) study (black lines in **Figure 2**). In addition, som interrelationships are depicted among

W^{Aug}	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	C1	C2	C3	C4
R1	0	0	0.55	0	0	0	0	0.26	0	0.99	0.3	0	0	0.58
R2	0	0	1	0	0	0	0	0	0	0	0.1	0.7	0	0
R3	1	0	0	0	0	0.8	0	0.6	0.13	0	0.7	0.18	0	0
R4	0.78	0.45	0	0	0.2	0	0.01	0.5	0	0.8	0	-0.2	0	0.25
R5	0.71	0	0.59	0.4	0	0.6	0	0	0.23	0	0	0.47	0	0.17
R6	0.4	1	0	0	0.2	0	0	0.77	0	0	0	0.99	0.35	0.28
R7	0.29	0	0	0.3	0.6	1	0	0.5	0.81	0.5	0	0	0	0.29
R8	0	0.29	0	0.7	0	0	0.1	0	0.27	0	0	0	0.63	0
R9	0.94	0.35	0.47	0.7	0.5	0.11	0	0	0	0	0.1	0	0	0.66
R10	0.2	0.3	0.6	0.5	0.9	0.34	0.2	0	0	0	0	0.81	0.9	0
C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	0	0	1	0	0	0	0	0	1	0	0	0	0	0
C4	0	0	0	0	0	0	0	0	0	0	0	0	0	0

TABLE 04. Initial weight matrix

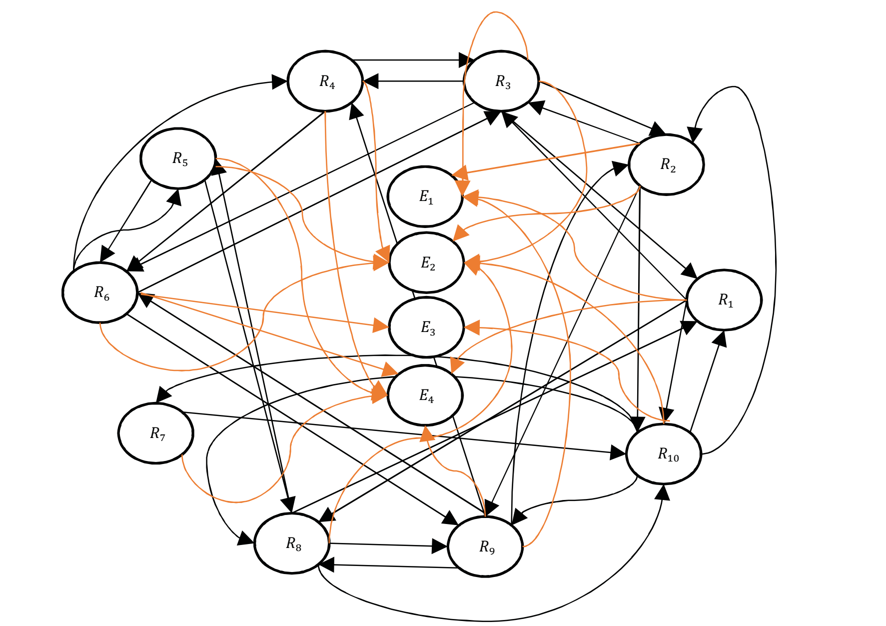

FIGURE 02. FCM for risk analysis on outsourcing risks.

risks & consequences (orange lines in **Figure 2**). To make the initial weight matrix (Wij), each expert individually determines the dependencies between concepts (risks), using fuzzy linguistic terms such as Very High (VH), Low (L), etc. Then, the linguistic variables are aggregated and defuzzified to numerical values (Elpiniki I. Papageorgiou, 2005). The defuzzified initial weight matrix is shown in **Table 4**.

To illustrate the risk evaluation process, in this paper we only assess the impact of "Schedule" risk on other risks and also four consequences. In this scenario, none of the risks and consequences in the initial vector are activated at the initial time, but schedule risk (R1) as following:

c = [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0];

Using Wij matrix, Initial concept vector c, Equation (1) and alearning algorithm, the training process starts. In this paper we applied NHL-DE algorithm for training FCM which is combined of differential evolution (DE) and nonlinear Hebbian learning (NHL) algorithms. The training process in NHL-DE has two steps. The first step starts with NHL algorithm and in the second step, the result of first step is used to seed the DE algorithm.

We imported the data into Matlab code to obtain the updated concept matrix (C*). The suggested values of learning rate parameter (η), mutation constant (μ), crossover constant (CR), and weight decay learning parameter (γ) have been selected 0.001, 0.5, 0.5, 0.98 respectively. The population size is equal to 30. For the algorithm, 100 independent experiments have been performed, to enforce the reliability of the results, and the algorithm was allowed to perform 5000 iterations (generations) per experiment.

C* = [0.66, 0.7, 0.95, 0.87, 0.99, 0.94, 0.8, 0.94, 0, 0.97, 0.2, 0.49, 0.98, 0.74];

The steady state vector C* shows that activating "Schedule" risk have a strong influence over the risks C5, C6, C10 and also it has a strong effect over the consequence E3. The same procedure should be done for all other risks by activating their risk each time. The results reveal that which risks are critical and which have a greater impact on the other risks. In addition, it reveals that each risk factor on which consequence(s) has strong effect. Therefore, decision makers will be able to manage the risks properly and accurately.

5. CONCLUSION

In this paper, we proposed an advanced decision support approach for dynamic risk analysis of projects management. Some features make our proposed tool distinguished form other risk assessment tools such as FMEA. First, all the interactions among variety of risk factors are considered by handling incomplete data and based on the opinions of several experts. To our best knowledge, this is the first time in the literature that the dependencies among risk factors are included in the risk assessment process. In addition, the proposed approach provides valuable information to practitioners for predicting impact of risks on the other risks or on the system performance by developing what-if analyses. In other words, practitioners are able to understand how any change in a risk factor could affect the other risks or outcomes of the project. Moreover, by transforming decision problems into causal graphs, decision makers with no technical background can easily understand all of the risk factors in a given problem and their relationships. The above features could lead to a more precise and accurate risk analysis of project management and practitioners will have a strong support for identifying critical risks/failures and mitigating them. Future research may include the performance of the proposed tool in a large-scale practical environment. ◆

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