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Development of supply chain risk management approaches for construction projects: A grounded theory approach

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ABSTRACT

Construction projects face numerous risks during their lifecycle due to their inherent complexities and intricate relationships between different parties involved in the construction process. Accordingly, an effective management of risks throughout the project's supply chain is critical to avoid time and cost overruns, that if not controlled properly, will ultimately result in project failure. Despite the great significance of this issue, there is a gap between the literature and practice of project risk management, where managers mostly prefer to rely on their own experiences rather than using available analytical tools. On the other hand, the application of the best practices (such as supply chain management and supply chain risk management) from the manufacturing industry in the service industry is highly neglected. To this end, these two gaps are bridged by proposing a comprehensive supply chain risk management approach for construction projects that uses, grounded theory, fuzzy cognitive mapping, and grey relational analysis. A real world case study is presented to show the applicability and effectiveness of the proposed approach. Various risk mitigation scenarios are developed and evaluated by the proposed approach. These scenarios are ranked and the best risk mitigation scenarios are identified. By comparing the proposed approach with similar researches in the literature, it is shown that the proposed approach is capable of capturing and representing expert's perceptions of risks in an effective and time efficient manner. Moreover, decision-makers are enabled to simulate the long term effects of different risk mitigation strategies on the risks and make more informed decisions. Along with the novel approach proposed, the major contribution of this study is setting the stage for a discussion between project management field's scholars and practitioners with those in the manufacturing industry to benefit from an opportunity for mutual growth.

1. Introduction and theoretical background

It is emphasized by both practitioners and scholars, that construction projects are exposed to more risks compared to other industries due to their complexities. These risks can cause performance reductions, increased costs, scheduling delays, and ultimately project failures (Nieto-Morote & Ruz-Vila, 2011; Taroun, 2014; Taylan, Bafail, Abdulaal, & Kabli, 2014; Zou, Kiviniemi, & Jones, 2017). Poor supply chain management (SCM) may be viewed as a potential source of some of the cost overruns and delays related to the construction industry. Although, the concept of SCM is rooted in the manufacturing industry, firms in the construction industry can also benefit from applying such best practices to some of their processes (Ellram, Tate, & Billington, 2004). Nevertheless, SCM is still not a mature subject within the construction industry (O'Brien & Formoso, 2008). Despite its great potentials, application of supply chain risk management (SCRM) concepts (as a sub-field of SCM) to the construction industry is not yet explored.

Over previous decades, there have been numerous natural and man-made disasters (e.g. earthquakes, economic crises, war, terrorist attacks and sanctions), disrupting supply chain operations. Coleman (2006) found out extensive evidences representing that the frequency of man-made disasters creating disruptions, is growing exponentially since the 20th century. These disruptions have been observed increasing, both in potential of occurrence and their magnitude (Blackhurst, Craighead, Elkins, & Handfield, 2005). Supply chain disruptions are inevitable, that makes all supply chains inherently risky (Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007). Therefore, effective management of risks in construction supply chains plays a pivotal role in the successful delivery of construction projects.

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During the past decades, a vast body of knowledge formed around the subject of SCRM. These studies cover three general tasks of SCRM including, risk identification (Gaudenzi & Borghesi, 2006; Kayis & Dana Karningsih, 2012; Trkman & McCormack, 2009; Tsai, Liao, & Han, 2008), risk assessment (Bogataj & Bogataj, 2007; Harland, Brenchley, & Walker, 2003; Hendricks and Singhal, 2003, 2005; Treleven & Schweikhart, 1988), and risk mitigation (Blackhurst et al., 2005; Chopra & Sodhi, 2004; Christopher & Lee, 2004; Johnson, 2001; Zsidisin, Ellram, Carter, & Cavinato, 2004). These tasks have been investigated with both quantitative and qualitative methods, however, in order to mitigate supply chain risks effectively, it is crucial to understand how risks are generated, how they propagate through their interdependencies, and how they influence firms' operations. It is argued that the majority of SCRM studies are only focused on certain tasks of SCRM and there is still a lack of comprehensive SCRM approach in the present literature that integrates these three tasks (Ghadge, Dani, & Kalawsky, 2012; Juttner, Peck, & Christopher, 2003; Qazi, Quigley, & Dickson, 2015).

In the process of SCRM, risk identification task plays a pivotal role for the success of risk management efforts (Neiger, Rotaru, & Churilov, 2009; Wu, Blackhurst, & Chidambaram, 2006). Puljić (2010) contend that there are myriad of factors (e.g. cognitive biases) affecting managers' perception of supply chain risks that in turn might lead to suboptimal decisions. Therefore, in order to develop a more realistic and effective risk management model, it is crucial to capture managers' perception of risks, and incorporate them in the decision process (Wood, Bostrom, Bridges, & Linkov, 2012).

The focus of this study is on projects that are defined by the Project Management Institute (2013, p. 5) as, "A temporary endeavor undertaken to create a unique product, service, or result. The temporary nature of projects indicates a definite beginning and end. The end is reached when the project's objectives have been achieved or when the project is terminated because its objectives will not or cannot be met, or when the need for the project no longer exists". Accordingly, uniqueness is a significant characteristic of each project. This attribute is one of the key differences between the manufacturing industry and construction industry, where established methods used to address the manufacturing firms' supply chain issues might not work efficaciously to solve problems in the construction industry. Therefore, finding effective solutions for project problems requires methods that are capable of capturing this uniqueness and provide customized solutions.

In the present research, a comprehensive supply chain risk management approach for construction projects is proposed that combines both qualitative and quantitative approaches. To this end, a theoretical explanation of a real world construction project (i.e. gas transfer pipeline project) risks is provided using grounded theory (GT) and mapped using fuzzy cognitive maps (FCMs). Risk mitigation scenarios are developed by the experts and simulated using FCMs inference process. Based on grey relational analysis (GRA) method, each risk mitigation scenario is ranked and the best scenario is identified. The contribution of this paper is threefold. First, the grounded theory is used to identify all elements that are directly or indirectly contributing to the supply chain risks in a construction project. Invaluable insights about the causal relationship among the components of a risk management system are provided. Second, given the extremely uncertain environment in which firms operate, the proposed approach enables decision-makers to simulate different scenarios and observe how the system responds to their decisions and optimize their long-term strategies proportionately. Third, by using FCMs the project managers' perceptions of risks are represented along with their possible cognitive biases in order to be evaluated and improved. Furthermore, this study promotes the application of manufacturing industry best practices (i.e. SCRM), to the construction industry and project management. Consequently, project managers will be able to expand their decision-making toolbox, and supply chain managers will be able to develop a deeper understanding of less investigated types of supply chains such as make-to-order supply chains.

As in this paper supply chain risk management for construction projects is investigated, in the following sub-sections, a brief review of the SCRM and construction project risk management literature is presented.

1.1. Supply chain risk management

As a result of increasing attraction of SCRM in the previous decades, many researchers focused on developing a robust foundation of knowledge for this topic by contributing to the areas of defining, operationalizing and mitigating risks (Ho, Zheng, Yildiz, & Talluri, 2015). Despite all these efforts, a gap of definition still exists in the literature (Diehl & Spinler, 2013; Ho et al., 2015; Sodhi, Son, & Tang, 2012; Tang & Musa, 2011). Academics defined supply chain risk management from numerous perspectives. Juttner et al. (2003, p. 211) defined it as "The identification and management of risks for the supply chain, through a coordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole". This definition emphasized the risk identification and management process. However, Tang (2006, p. 453) defined it by focusing on its generic process as, "The management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity". The latter definition is used in the present study.

Innumerable approaches (both quantitative and qualitative) had been proposed to undertake SCRM tasks (for more comprehensive overview of the literature see: Fahimnia, Tang, Davarzani, & Sarkis, 2015; Qazi et al., 2015; Colicchia & Strozzi, 2012; Prakash, Soni, & Rathore, 2017). Quantitative approaches incorporated different methods including, fuzzy set theory, analytical hierarchy process (AHP), goal programming (GP), genetic algorithms (GA), bayesian networks and etc. (Gaudenzi & Borghesi, 2006; Kull & Talluri, 2008; Kumar, Tiwari, & Babiceanu, 2010; Lockamy & McCormack, 2010; Wang, Chan, Yee, & Diaz-Rainey, 2012). Another quantitative approach is the GRA method that is a part of the grey systems theory (GST), and proved to be an effective method for solving problems with intricate dependencies between multiple factors and variables (Kuo, Yang, & Huang, 2008a). However, GST has only been used in a few studies to address SCRM problems (e.g. Rajesh, Ravi, & Venkata Rao, 2015; Rajesh & Ravi, 2015), and there exists a great potential to use this approach in the context of SCRM as it has been acknowledged to be superior to comparable methods in the mathematical analysis of systems with uncertain information (Li, Yamaguchi, & Nagai, 2007). Meanwhile, researchers also created a foundation for this area by using qualitative methods (Chopra & Sodhi, 2004; Christopher & Lee, 2004; Harland et al., 2003; Ritchie & Brindley, 2007; Wagner & Bode, 2008).

1.2. Construction project risk management

In the literature of project management, risk management is increasingly seen as an aid to improve the possibility of success in complicated engineering projects (Olechowski, Oehmen, Seering, & Ben-Daya, 2016). Although, studies show that risk management practices are insufficiently employed by project managers (Kutsch & Hall, 2009; Papke-Shields, Beise, & Quan, 2010; Raz, Shenhar, & Dvir, 2002). More specifically, compared to other industries, construction industry has been facing a great deal of risks due to factors such as, strategic nature of their products, the complexities of construction techniques, changing building environment, involvement of various stakeholders, and long production time (Taroun, 2014; Zeng, An, & Smith, 2007). Therefore, the necessity of having an effective risk management system to avoid project performance reductions, time delays, and unwanted costs, compelled project management scholars to propose a variety of risk management approaches (for comprehensive overview of available approaches see, Taroun, 2014; Xia, Zou, Griffin, Wang, & Zhong, 2018; Cagliano, Grimaldi, & Rafele, 2015).

By reviewing 5 decades of construction projects risk modelling and assessment, Taroun (2014) concludes that, there exists a gap between practice and theory where managers mostly rely on their experiences, and the application of analytical tools proposed in the literature is very limited. In this study this gap is bridged by eliciting and aggregating the managers' perception of what create risks and how different strategies mitigate these risks using grounded theory and fuzzy cognitive maps. Further, simulations and a ranking technique are used to enable managers to use analytical tools along with their valuable experiences to select the best risk mitigation strategy. On the other hand, analytical hierarchy process (AHP) is the analytical method used predominantly in the literature (Abdelgawad & Fayek, 2010; Mustafa & Al-Bahar, 1991; Taroun, 2014). However, AHP method is not able to address the interdependencies amongst various risk elements, which creates the possibility of producing unrealistic results. Conversely, by using FCMs these interdependencies are captured and presented in the form of causal relationships, and then integrated into the decision process.

The rest of the paper is structured as follows. Section 2 introduces the techniques included in our proposed approach (i.e. GT, FCMs, and GRA method), along with our proposed methodology. In Section 3, a real world case study is presented that illustrates the applicability and effectiveness of the proposed approach. The results are discussed in Section 4. Conclusion and future research opportunities are finally given in Section 5.

2. Methodology

This paper aims to propose a comprehensive SCRM model for construction projects. To this end, three methods including GT, FCM and GRA are used as demonstrated in Fig. 1. First, experts with appropriate work experience are selected and interviewed. Afterwards, by using GT, essential abstract concepts of the SCRM system are extracted from the data gathered by interviews, and grouped under six main categories (i.e. causal conditions, intervening conditions, contextual conditions, strategies, consequences and main phenomenon). Each of these concepts are assigned specific codes which will be used to represent each concept in the FCMs. Next, six risk mitigation scenarios developed by the experts are simulated using the inference process of FCMs. In the last step of the proposed approach, results of the inference process are used to rank risk mitigation scenarios by applying GRA method. For this purpose, relative importance of each risks (weights) are calculated using Shannon's entropy. In the following sub-sections each of the methods used in this paper will be elaborated in details individually.

2.1. Grounded theory

Grounded Theory (GT) is a systematic qualitative research method introduced by Glaser and Strauss in 1967 (Charmaz, 2000). As they meticulously defined, “It is a way of arriving at theory suited to its supposed uses” (Glaser & Strauss, 2009). GT is generated through the abstraction of concepts and their interdependencies that are obtained from analyzing qualitative data (e.g. interview transcripts). There are three approaches in adopting GT, which are listed as follows:

- Straussian approach (Strauss & Corbin, 1990)
- Glaserian approach (Glaser, 1992)
- Constructive approach (Charmaz, 2000)

Heath and Cowley (2004) contend that researchers should choose their methodology of GT, congruent to their cognitive style. Also it has been emphasized, not to mix different approaches of GT together (Van Niekerk & Roode, 2009). Therefore, in this research Straussian approach is adopted since its more prescriptive and provides more guidelines compared to others (Heath & Cowley, 2004; Van Niekerk & Roode, 2009). Strauss and Corbin (1990) maintain that systematic research design of GT highlights the use of data analyzing stages through open coding, axial coding, and selective coding.

Open Coding is an analytic process that by means of line-by-line analysis of the data, concepts are identified and their properties and dimensions are discovered (Strauss & Corbin, 1990). Also categories are emerged, which will encompass all objects, events or action/interactions related to research phenomenon (i.e. supply chain risks) that they will be coded. When categories emerged, by comparing its members to each other, it will be clear that all of the classified elements (objects events or action/interaction) vary in terms of properties and dimensions. Therefore, they will be classified as subcategories which is the final output of this stage.

Axial coding is the act of relating categories to their sub-categories along the lines of their properties and dimensions, in order to form a more precise and complete explanation of the phenomenon. Since this process occurs around the axis of a category it is called axial coding (Strauss & Corbin, 1990). At this stage researcher tries to understand the answers to the questions like “How?” and “Why?” by locating the phenomenon in its conditional context (structure) and by denoting response action/interaction over time to certain problems and issues (process). By studying both structure and process the followings will be elicited (Strauss & Corbin, 1990):

1. Causal conditions (C)
2. Intervening conditions (I)
3. Contextual conditions (G)
4. Actions/Interactions (Strategies) (S)
5. Consequences (O)

Concepts will be classified under above five labels. All these groups of concepts are organized around a sixth group of concepts which is the main phenomenon (i.e. supply chain risks). That said, these groups names are quite self-explanatory.

Selective coding is the last stage of the GT in which the theory will be refined and integrated. As Strauss and Corbin (1990) precisely remarked, at this point the researcher reaches a level that no new properties, dimensions or relationships emerge during the analysis. In this stage the researcher decides on the central category that will represent the main theme of the research and then integrate all categories using different methods such as diagrams or storytelling memos (Strauss & Corbin, 1990). In this research the goal of this stage achieved through reviewing the researchers' technical memos that been gathered during the analysis and interviews.

2.2. Fuzzy cognitive maps

The concept of cognitive maps (CMs) first proposed and applied in political science by Axelrod (1976). A CM is a graphical representation of experts' documents and their perception of a phenomenon's causality. Fuzzy cognitive maps (FCMs) introduced by Kosko (1992) to develop the idea of cognitive maps by enabling the use of fuzzy causal relationships rather than precise ones. FCM is a signed fuzzy weighted digraph. Nodes represent concepts, and edges indicate strength, sign, and direction of causal relationships (Papageorgiou, 2012; Salmeron, 2009). By synthesizing ideas from artificial neural networks and fuzzy sets, FCM is a well-established artificial intelligence technique (Feyzioglu, Buyukozkan, & Ersoy, 2007). FCMs are utilized to analyze the effects of different strategies with respect to achieving certain goals (Kosko, 1986; Rodriguez-Repiso, Setchi, & Salmeron, 2007). FCMs have been applied in various disciplines including, business, control, medicine, robotics, environment and information technology (for a detailed review see: Papageorgiou & Salmeron, 2013). In the field of business, FCMs have been used with different purposes namely, planning, management, decision making, modeling, prediction, and decision support systems (DSSs) (Papageorgiou & Salmeron, 2013; Papageorgiou, 2012; Salmeron, 2009). In this paper, the FCM development is based on the concepts extracted from grounded theory. Each of those concepts will act as a single node of the FCM graph.

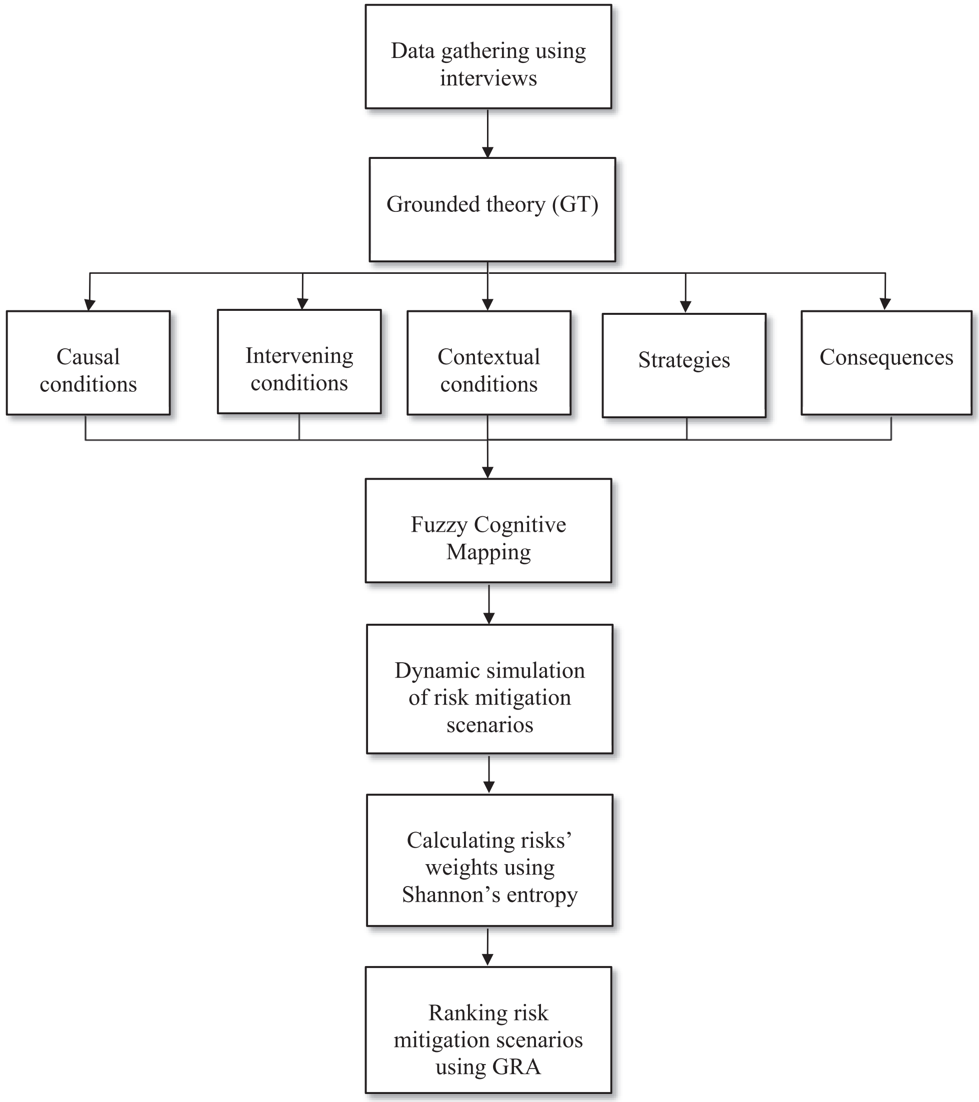

Fig 1. Flowchart of the proposed method.

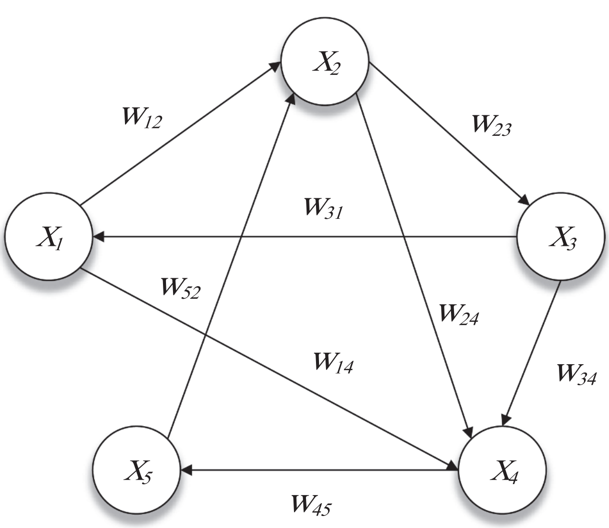

Fig. 2. An example of fuzzy cognitive maps.

Table 1
Linguistic variables to measure causal relationships' intensities.

Linguistic variable	Fuzzy number
Negatively very strong	(−1, −1, −0.75)
Negatively strong	(−1, −0.75, −0.5)
Negatively medium	(−0.75, −0.5, −0.25)
Negatively weak	(−0.5, −0.25, 0)
Zero	(−0.25, 0, 0.25)
Positively weak	(0, 0.25, 0.5)
Positively medium	(0.25, 0.5, 0.75)
Positively strong	(0.5, 0.75, 1)
Positively very strong	(0.75, 1, 1)

2.2.1. FCM fundamentals

FCMs, represent human tacit knowledge through a network of interconnected nodes in which each node is a variable that indicates a concept (Salmeron & Papageorgiou, 2012). FCMs are dynamic systems involving feedbacks that allow an effect of change in one node, propagate through the whole system and affect the initiating node. In FCMs, directed edges linking nodes model the influence of cause concept on the effect concept, and the intensity of each edge is represented

Table 2
List of concepts, final codes, and code labels extracted from grounded theory.

Concepts	Final codes	Code labels	Concepts	Final codes	Code labels
Uncertainty	Gas industry growth	C1	Intra-organizational risk	Different contract types risk	M8
	Sanctions impact	C2		Project pre-commission risk	M9
	Gas demand pressure	C3		Loss of workforce risk	M10
Outsourcing policy	Government downsizing policy	C4		Contract termination risk	M11
Project orientation	Project structure	C5	Network factors	Suppliers' lead-time risk	M12
	Project type	C6		Suppliers' products quality risk	M13
Governmental structure	Budget	G1		Project commissioning risk	M14
	Non-profit goal	G2	Preventive strategies	Using guarantee as a control tool	S1
	Governmental bureaucracy	G3		Using suppliers blacklist as a control tool	S2
Regulations	Regulation-based supplier/contractor selection	G4		Suppliers filtering using previously approved lists	S3
	Strict contracts	G5		Pre-project planning	S4
	Technical committee role in supplier selection	G6		Using standards as a control tool	S5
Economic conditions	Inflation and currency exchange rate fluctuation	G7		Outsourcing	S6
	Equipment kind effect on supply	G8	Flexibility strategies	Using multiple suppliers	S7
	Current supply chain failure	G9		Using hybrid contracts	S8
	Contractor as supplier	G10		Using local suppliers	S9
Industry organization	Political decision-making	I1	Adaptive strategies	Supply by the company	S10
	Multiple supervisory institution	I2		Client intervention	S11
Supply issues	Relative national self-sufficiency in supply	I3		Using different kinds of tenders	S12
	Numerous suppliers	I4		Withdraw the tender	S13
Management considerations	Reasonable price than lower price	I5	Institutionalizing selection criteria	Performance equality of major gas companies	O1
	Staff training level	I6		Supplier selection criteria	O2
	Coordination between the units	I7		Contractor selection criteria	O3
	Weak management	I8	Credibility improvement	Company's reputation	O4
Inter-organizational factors	Risk of getting different licenses	M1		Macro-level involvement in solving problems	O5
	Risk of competing with other organizations	M2	Institutionalizing communication	Systematic association with other organizations	O6
	Risk of land taking and ownership	M3	The necessity of planning	Time consuming nature of tenders	O7
	Risk of macro-economic changes	M4		Planning based on forecasts	O8
	Risk of government's policies changes	M5	Achieving the project goals	Costs control	O9
Intra-organizational factors	Project design risk	M6		Reducing delivery delays	O10
	Incorrect supplier selection risk	M7		The quality of the project	O11

as w_{ij}, where i is the cause (pre-synaptic) node and j is the effect (post-synaptic) one. Fig. 2 illustrates an example of FCMs and A is its adjacency matrix (Eq. (1)).

$$A = \begin{pmatrix} 0 & w_{12} & 0 & w_{14} & 0 \\ 0 & 0 & w_{23} & w_{24} & 0 \\ w_{31} & 0 & 0 & w_{34} & 0 \\ 0 & 0 & 0 & 0 & w_{45} \\ 0 & w_{52} & 0 & 0 & 0 \end{pmatrix} \tag{1}$$

According to Salmeron (2010), dynamics of FCMs begin with the determination of the initial vector state $\vec{C}^0$, that denotes a proposed initial stimuli. The initial vector state with n nodes is defined as:

$$\vec{C}^0 = (C_1^0 C_2^0 \cdots C_n^0) \tag{2}$$

The updated value of each node is computed by an iterative inference process using an activation function (Salmeron, 2010), that monotonically maps nodes' values into a normalized range [0, +1] or [−1, +1]. Moreover, Eq. (3) is used to calculate the updated value of each node.

$$C_j^{t+1} = f\left(C_j^t + \sum_{\substack{i=1 \\ j \neq i}}^{N} w_{ij} \cdot C_i^t\right) \tag{3}$$

Numerous activation functions have been proposed in the literature including, bivalent function, trivalent function, unipolar sigmoid (logistic) function and hyperbolic tangent function (Yesil, Urbas, & Demirsoy, 2014). The most frequently used activation function when concepts values map in the range [0, +1], is the unipolar sigmoid activation function (Bueno & Salmeron, 2009). On the other hand if the concepts' values map in the range [−1, +1], then the hyperbolic tangent activation function is used. In this paper since nodes' values are in the range of [−1, +1], the hyperbolic tangent activation function is used as follows:

$$f(x) = \tanh(x) \tag{4}$$

As the system evolves through the inference process, there will be three possible final conditions for the steady vector state, that demonstrates the impact of the initial vector state on the state of each FCM node (Salmeron & Papageorgiou, 2012). These conditions are as follows:

- Fixed-point attractor or hidden pattern: Values of the vector state could settle down to a fixed pattern of nodes' states.
- Limit cycle: The vector state's values could enter a cycle in which they keep cycling between several fixed states.
- Chaotic attractor: The FCM continues to produce different vector state for each iteration.

2.2.2. FCM construction

Generally, there are two main approaches to develop and construct FCMs including, expert-based approaches (deductive modeling) and the computational methods (inductive modeling) (Stach, Kurgan, & Pedrycz, 2010). The expert-based approach relies solely on human expertise and domain knowledge. However, the computational method

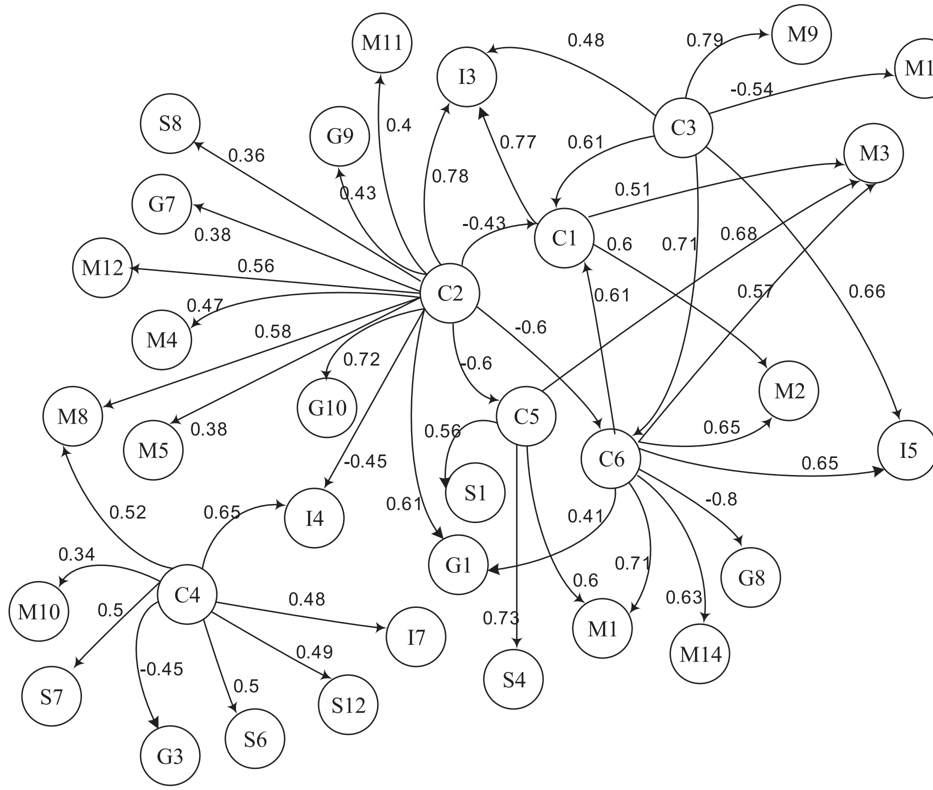

Fig. 3. FCM of the causal conditions (C).

employs available data and a learning algorithm to construct or support development of a FCM model for a given system. The approach used in this research is the expert-based one.

The expert-based approach uses the following three steps to construct FCMs (Khan & Quaddus, 2004):

- Identification of important concepts (nodes)
- Identification of causal relationship between these concepts
- Estimation of the strength of the causal relationship.

A panel of experts is used to accomplish the abovementioned three steps. Each expert determines the degree of influence (causal relationship) between nodes using linguistic variables, such as strong influence, medium influence, weak influence, etc. (Papageorgiou, Stylios, & Groumpos, 2006). In this study, experts are asked to express their perception of the degree of intensities between concepts using linguistic variables as presented in Table 1. These values are then defuzzified using center of gravity (COG) method.

Note that in the process of constructing expert-based FCMs, each expert will possibly develop a distinct FCM, therefore, it is crucial to integrate various maps into a single one. Multiple approaches have been proposed to address this issue such as, Delphi method (Dickerson & Kosko, 1994) which strives to reach a consensus among experts by constantly returning to experts so they can modify their judgments. Nonetheless, the augmented approach (Salmeron, 2009) does not require that experts change their judgments. The augmented adjacency matrix is built by adding the adjacency matrix of each expert.

Consider two distinct FCMs as, FCM_x and FCM_y with no common nodes and, $C^{[xi]}$ and $C^{[y_i]}$ as their nodes respectively. The adjacency matrix of FCM_x is denoted as $(w^x_{i\to j})$, and the adjacency matrix of FCM_y is considered as $(w^y_{i\to j})$. The augmented adjacency matrix is:

$$Adj_{Aug} = \begin{pmatrix} w^x_{i\to j} & 0 \\ 0 & w^y_{i\to j} \end{pmatrix} \tag{5}$$

If there are common nodes, then the element $w^{Aug}_{i\to j}$ in the augmented matrix is calculated as:

$$w^{Aug}_{i\to j} = \frac{\sum_{i=1}^{n} w^k_{i\to j}}{n} \tag{6}$$

where n is the number of FCMs added, k is the identifier of each FCM, and i and j are the identifier of the relationships.

2.3. Grey relational analysis (GRA)

GRA introduced by Deng (1989) as a part of the GST, which is capable of solving problems with intricate interrelationship between various factors and variables. GRA method has been extensively used for solving problems associated with ambiguity under the discrete data and incomplete information (Wei, 2011a, 2011b; Wu, 2009). This method firstly translates the performances of each alternative into comparability sequences through a process analogous to normalization (Kuo et al., 2008a). Afterwards, an ideal or a reference sequence is defined which will be then used to calculate the grey relational coefficient between all comparability sequences and the reference sequence. At last, based on the computed grey relational coefficients, the grey relational degree between every comparability sequence and the reference sequence is calculated and alternatives are ranked accordingly. This procedure is done through the following steps:

1. Step one: A decision-making matrix is determined based on the experts' opinions, that is assumed to have m alternatives characterized with n criteria as follows:

$$G = \begin{bmatrix} G_{11} & G_{12} & \cdots & G_{1n} \\ G_{21} & G_{22} & \cdots & G_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ G_{m1} & G_{m2} & \cdots & G_{mn} \end{bmatrix} \tag{7}$$

where G_{ij} represents the performance of alternative i with regard to

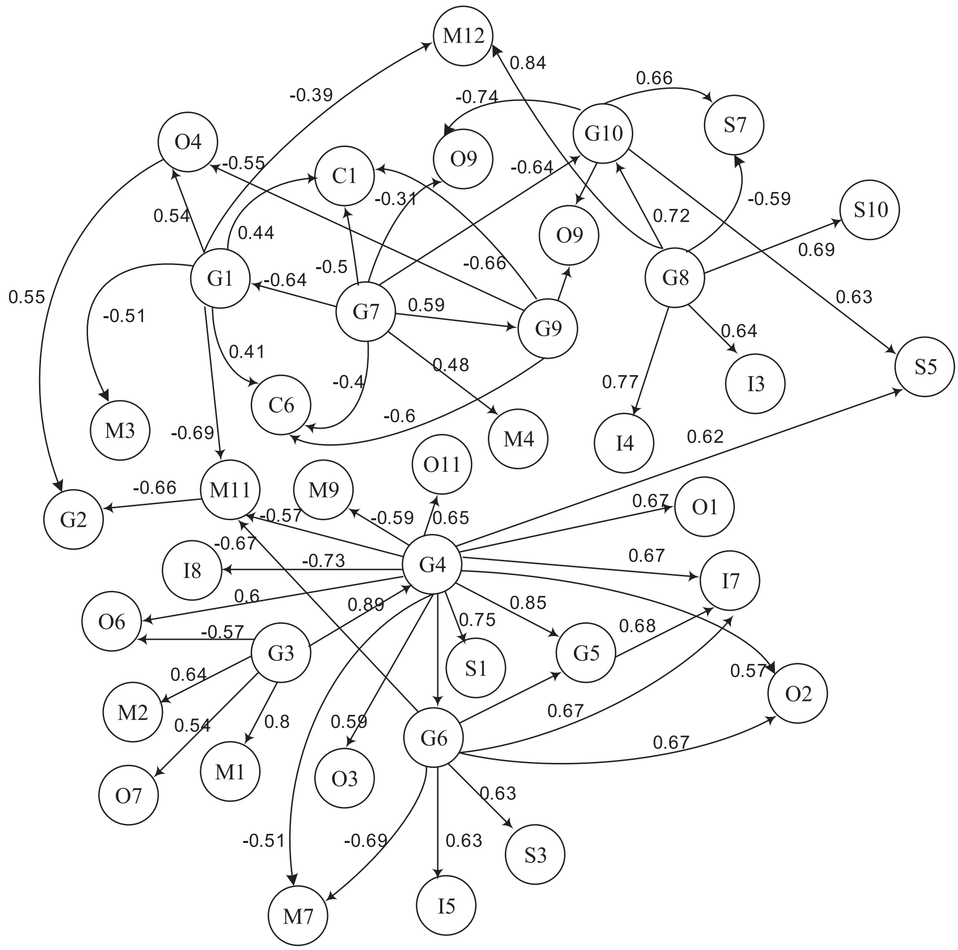

Fig. 4. FCM of the contextual conditions (G).

criterion j.

2. Step two: All performance values for each alternative are normalized and processed into a comparability sequence $Y_i = (y_{i1}, y_{i2}, y_{i3}, \cdots, y_{in})$ using Eqs. (8) and (9) for the larger-the-better criteria and the smaller-the-better criteria respectively:

$$y_{ij} = \frac{G_{ij} - \text{Min}\{G_{ij},\ i = 1,\ 2,\ \cdots m\}}{\text{Max}\{G_{ij},\ i = 1,\ 2,\ \cdots m\} - \text{Min}\{G_{ij},\ i = 1,\ 2,\ \cdots m\}},\quad i = 1,\ 2,\ \cdots, m;\quad j = 1,\ 2,\ \cdots, n \tag{8}$$

$$y_{ij} = \frac{Max\{G_{ij},\ i = 1,\ 2,\ \cdots m\} - G_{ij}}{\text{Max}\{G_{ij},\ i = 1,\ 2,\ \cdots m\} - \text{Min}\{G_{ij},\ i = 1,\ 2,\ \cdots m\}},\quad i = 1,\ 2,\ \cdots, m;\quad j = 1,\ 2,\ \cdots, n \tag{9}$$

It is important to note that in this paper, since different risk mitigation scenarios are being ranked all of our criteria are supply chain risks, therefore, all criteria are considered as the smaller-the-better criteria.

3. Step three: In this step, a reference sequence must be defined, by which each comparability sequence (from Step two) will be compared with. The reference sequence is calculated as follows:

$$y^0 = (y_1^0, y_2^0, \cdots, y_n^0) = (\max_{i=1}^m y_{i1},\ \max_{i=1}^m y_{i2},\ \max_{i=1}^m y_{i3}, \cdots, \max_{i=1}^m y_{in}) \tag{10}$$

where y^0 is the reference value related to the criterion j, and y_{ij} are the values obtained from the normalized matrix calculated in Step two.

4. Step four: The values of grey relational coefficients are calculated using Eq. (11) that indicates how close are the values of y_{ij} to the reference sequence y^0.

$$\varphi(y^0, y_{ij}) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{ij} + \zeta\Delta_{max}}\ \text{ for }\ i = 1,\ 2,\ \cdots, m;\quad j = 1,\ 2,\ \cdots, n \tag{11}$$

where $\varphi(y^0, y_{ij})$ is the grey relational coefficient between y^0 and y_{ij}, and

$\Delta_{ij} = |y^0 - y_{ij}|$,

$\Delta_{min} = \text{Min}\{\Delta_{ij},\ i = 1,\ 2, \cdots, m;\ j = 1,\ 2, \cdots, n\}$,

$\Delta_{max} = \text{Max}\{\Delta_{ij},\ i = 1,\ 2, \cdots, m;\ j = 1,\ 2, \cdots, n\}$,

ζ is the distinguishing coefficient and $\zeta \in [0, 1]$.

The value of ζ reflects the degree to which the minimum scores are emphasized relative to the maximum scores (Zhang, Wu, & Olson, 2005). The distinguishing coefficient is determined by decision-makers (Kuo, Yang, & Huang, 2008b), which in this study decision-makers set it as 0.5.

5. Step five: After all grey relational coefficients $\varphi(y^0, y_{ij})$ are calculated, the grey relational degree is calculated as follows:

$$\Phi(y^0, y_i) = \sum_{j=1}^{n} w_j \varphi(y_j^0, y_{ij})\ \text{ for }\ i = 1,\ 2,\ \cdots, m \tag{12}$$

In Eq. (12), $\Phi(y^0, y_i)$ is the grey relational degree between y^0 and y_i that demonstrates the degree of correlation between the reference sequence and the comparability sequence. w_j is the weight of criterion j, and $\sum_{j=1}^{n} w_j = 1$. Accordingly, higher values of grey relational degrees represent that a specific alternative is closer to the reference sequence. Therefore, the alternative with the highest grey relational degree value represents the best choice.

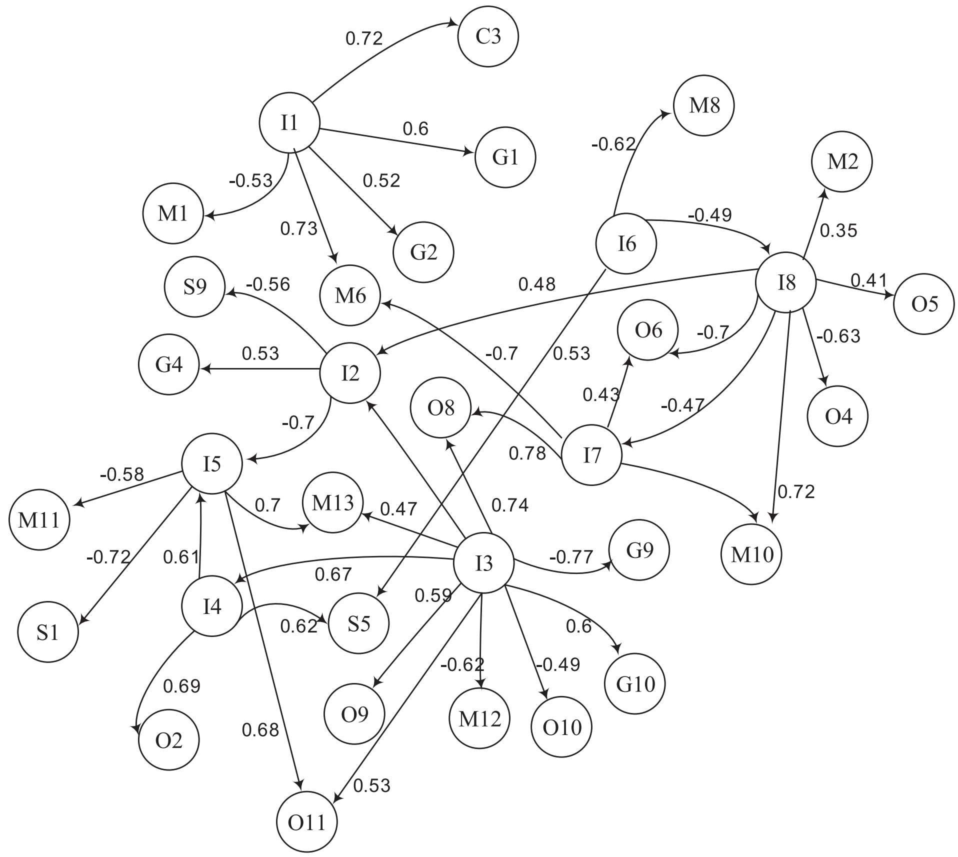

Fig. 5. FCM of the intervening conditions (I).

2.4. Shannon's entropy

As it is said above, the weights of each criterion is required to evaluate and rank each alternative. To this end, the well-established concept of Shannon's entropy is used to calculate each criterion's weight as proposed by Wang and Lee (2009). In order to compute the criteria weights based on the entropy concept, first the decision matrix (see Eq. (7)) must be normalized using Eq. (13):

$$p_{ij} = \frac{G_{ij}}{\sum_{i=1}^{m} G_{ij}} \tag{13}$$

Subsequently, the entropy values e_j are calculated as follows:

$$e_j = -k \sum_{j=1}^{n} p_{ij} \ln p_{ij}, \tag{14}$$

where k is a constant and is $k = \frac{1}{\ln m}$. Using the value of entropy, the degree of divergence d_j is calculated using Eq. (15) that represents the inherent contrast intensity of each criterion.

$$d_j = 1 - e_j \tag{15}$$

The greater the value of d_j, the higher the importance of its respective criterion. Therefore, the weight of each criterion is computed using the following equation:

$$w_j = \frac{d_j}{\sum_{k=1}^{n} d_k} \tag{16}$$

3. A real world case study

The significance of construction industry is well emphasized by both scholars and practitioners. Among these projects, those in the oil, gas, and petroleum industry are critically important due to various reasons such as, the complexity of construction process, strict time schedules, extreme penalties for delivery delays, highly interdependent supply chains, and etc. In this study, the proposed supply chain risk management model is implemented in a private company responsible for the construction of a few gas transfer pipeline projects in the south region of Iran. Accordingly, 5 senior managers with more than 15 years of experience in the construction industry are selected as the panel of experts to develop FCMs based on the results of the GT, and define risk mitigation scenarios. For the purpose of selecting experts, we used theoretical sampling to find the best individuals that are most likely helpful in the process of theory development (for more details on the theoretical sampling please see, Charmaz and Belgrave (2007)). In the followings, the results of each phase of the proposed methodology is presented.

After two rounds of deep interviews with the experts, grounded theory is applied to the gathered data, and concepts along with their final codes are extracted and categorized into six groups as elaborated in Section 2.1. These concepts are presented in Table 2. Final codes that are used as FCM nodes in the subsequent step (62 nodes), are grouped under certain concepts in each category. Please note that the main phenomenon category is labeled as M, and the labels for other categories are stated in Section 2.1.

In order to better understand these codes, it must be noticed that they are elicited from the experts of specific types of projects (i.e. gas transfer pipeline project), and are representing the current status of these projects along with their uniqueness, and the complexities associated with them might not be the same as other projects around the world. For example, one key aspect that is heavily affecting the performance of these projects, is the international economic sanctions against Iran. In this study with regard to the Iran's nuclear agreement with the European Union in 2015, it is expected that some of these sanctions are going to be lifted, enabling Iranian companies to

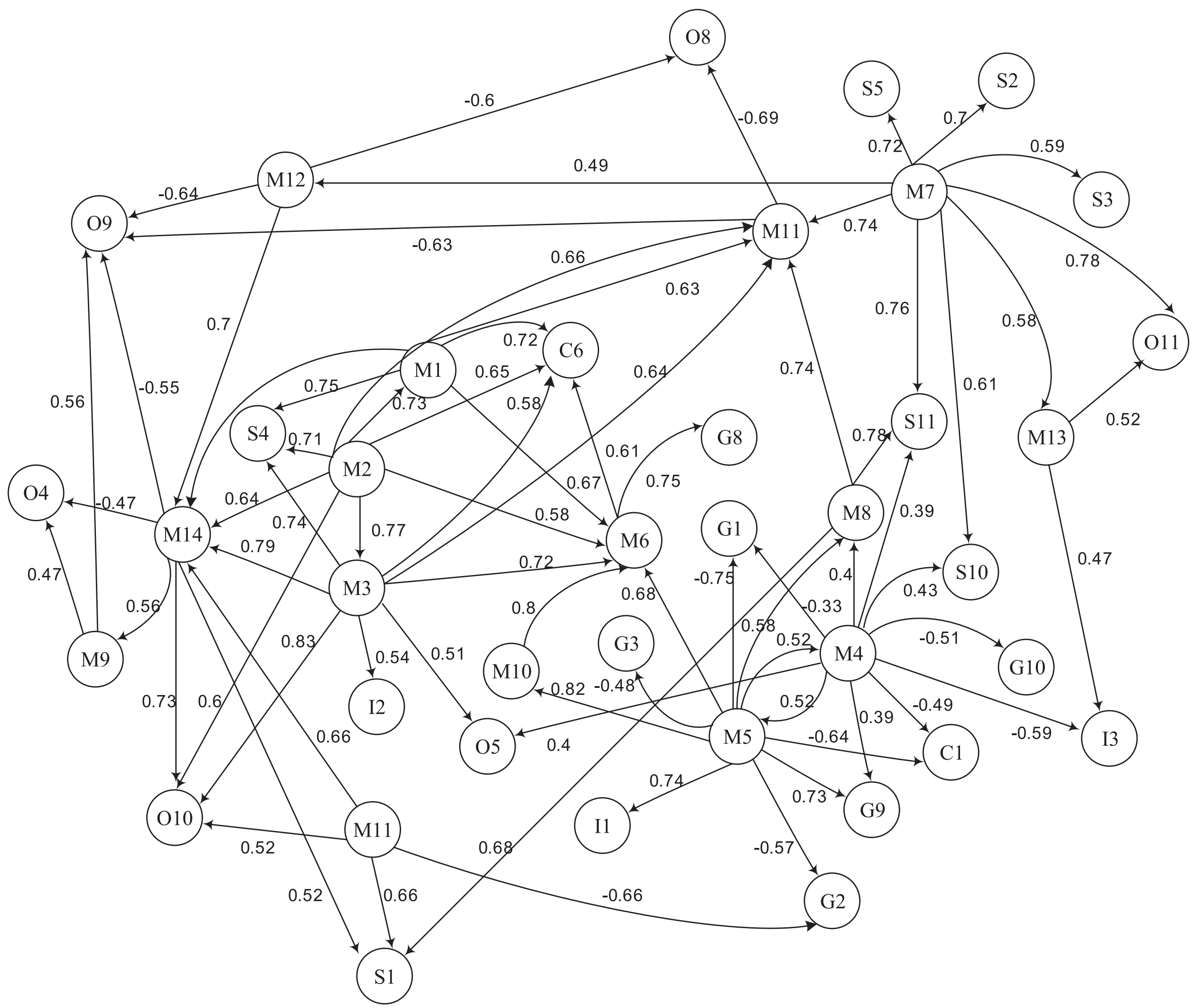

Fig. 6. FCM of the main phenomenon (M).

collaborate with international corporations, which improves their supply chain performance significantly. Considering sanctions as events disrupting supply chains, in this paper risk mitigation scenarios in the post-sanction conditions are investigated by considering the initial value of the “sanctions impact” node (C2) zero within each scenario inference process.

In the next phase, the concepts presented in Table 2 are used to form FCMs using the steps illustrated in Section 2.2. Given the great number of nodes in these FCMs and space limitation, graphical representation of them are provided in Figs. 3–8, for each of the following six categories respectively, causal conditions, contextual conditions, intervening conditions, main phenomenon, strategies, and consequences.

Subsequently, the panel of experts defined six different risk mitigation scenarios using different combination of strategies. In each scenario, strategy nodes were assigned different initial values and the rest of the nodes' values were held constant, where the initial values of the causal conditions, contextual conditions, and intervening conditions were set to be 1. The initial values of the main phenomenon and the consequences were set to be 0. In order to determine the initial values of each strategy node, experts are asked to answer the question of, “To what extent do you suggest each strategy to be implemented?”. They were able to choose a linguistic variable (see Table 3) to express their answer. These answers are aggregated using SUM method and the results are then defuzzified using COG method (for more details on COG and SUM method please see, Stylios and Groumpos (2004)).

Table 4 illustrates different scenarios that are determined by the panel of experts in the form of different initial values for each strategy node. These values are used in the inference process of the FCMs as previously stated in Section 2.2.2, so the best risk mitigation scenario is identified. It is important to notice that the panel of experts first decided to see the effect of employing all available strategies to mitigate risk. Therefore, in the first scenario they activated all strategy nodes by giving the initial value of 1 to all of them. On the other hand, in order to prove that the developed strategies are effective, in the second scenario they deactivated all strategy nodes by setting their values as 0.

In the inference process of the FCMs, the effect of one node propagates through the network and affect other nodes. Therefore, after the inference process, the effects of different risk mitigation scenarios on the project's supply chain risks (the main phenomenon nodes) are examinable. In order to compare different scenarios to identify the best one, after the system reached a steady state, the final values of the main phenomenon nodes are used to evaluate and rank risk mitigation scenarios. These final values are given in Table 5 in the form of a decision-making matrix in which scenarios are assumed to be the alternatives, and project's supply chain risks are the evaluation criteria. Each component of this matrix is the final value of the project's supply chain risks

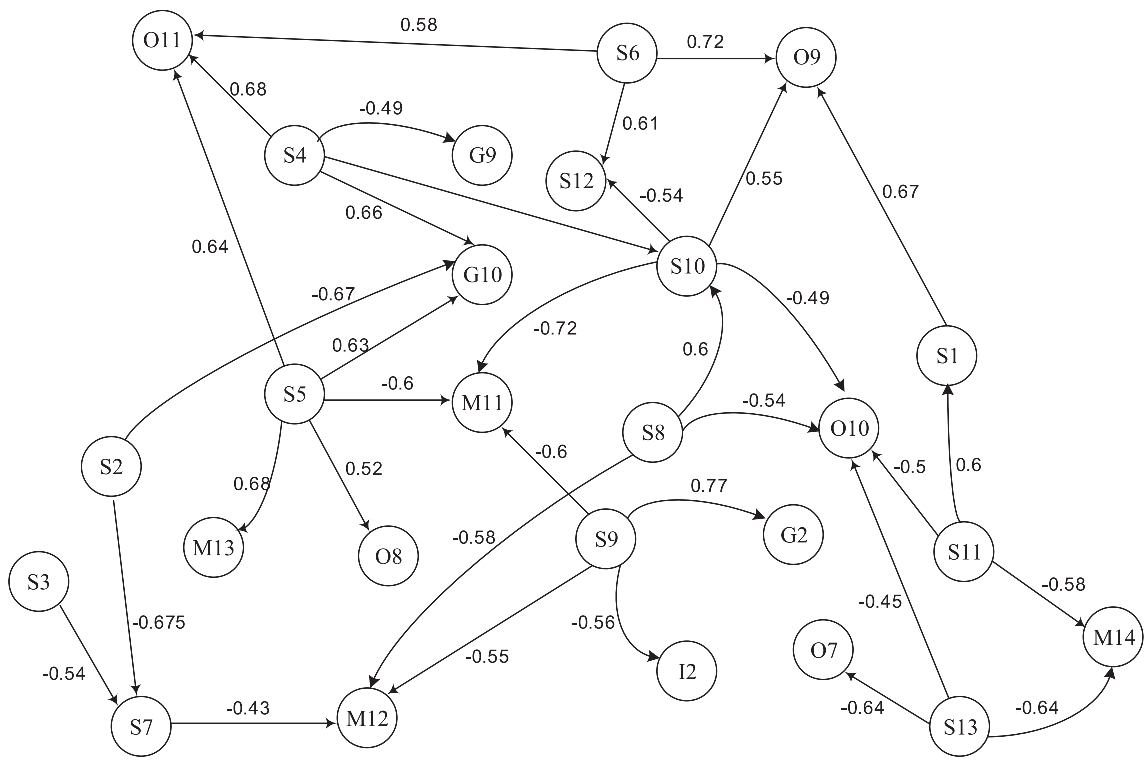

Fig. 7. FCM of the strategies (S).

with regard to each scenario after the inference process.

In order to identify the best risk mitigation scenario, GRA method is employed that requires a relative weight for each criterion (M1-M14). To this end Shannon's entropy concept is used as detailed in Section 2.3, and the results are shown in Table 6.

Using the values from Tables 5 and 6, the grey relational degree of each scenario is computed, and risk mitigation scenarios are ranked accordingly (see Table 7).

Considering the grey relational degree of each scenario, the one with the highest value (S3) is the best risk mitigation scenario, and we have the following ranking:

S3≻S5≻S4≻S1≻S2≻S6

4. Discussion

The main objective of the present study is to develop a comprehensive supply chain risk management approach that captures the perception of major decision-makers about how supply chain risks in construction projects are generated, how they interact with each other, and what are the best strategies to mitigate these risks. To attain this objective, grounded theory is first used to elicit the significant contributing factors to the supply chain risks in a construction project. Secondly, fuzzy cognitive maps are used to represent how these factors are affecting each other. Subsequently, decision-makers developed different feasible scenarios that comprised of a combination of risk mitigation strategies. The long term effects of these scenarios on the supply chain risks are simulated using the inference process of the FCMs, and these effects are reflected in the final values of risk nodes. These final values are then used to identify the best risk mitigation scenario by GRA. Given that the relative importance of the risks are required by GRA to rank risk mitigation scenarios, Shannon's entropy is employed to find the weights of each supply chain risk node. Accordingly, the ranking results as represented in Section 3 indicate that scenario 3 is the best combination of strategies to mitigate supply chain risks in a construction project. On the other hand, the first scenario in which all strategies are adopted simultaneously, the result is on the contrary, and this scenario is ranked 4th amongst six scenarios. In other words, it is possible that using different risk mitigation strategies at the same time, nullify the positive effects of each of them.

There are other similar methodologies available in the literature, that try to address the issue of interdependencies between projects' risks. However, the proposed method in this paper overcomes the limitations of the previous studies. Ackermann, Howick, Quigley, Walls, and Houghton (2014) proposed a qualitative modeling process by using a group support system and causal mapping process to elicit project risks, and gain an understanding of their interactions. The limitation of this study is mainly its time consuming nature due to having several 4–5 h workshops. Moreover, the final map of the project risks fails to provide any information about the intensity of the relationships amongst risk factors. Nevertheless, the proposed approach in this paper is capable of mapping stakeholders' perception of project risks interconnectedness in a more time efficient manner along with their intensities. Fang, Marle, Zio, and Bocquet (2012) used network theory to analyze risk interactions in large engineering projects. The major shortcoming of this study is that it does not provide any insight about how project risks are generated, therefore, decision makers will not be able to identify high leverage points to develop effective risk mitigation strategies. However, the proposed method in this study uses grounded theory that gives valuable insights about what factors are contributing to risk generation in terms of causal, intervening and contextual conditions. Qazi, Quigley, Dickson, and Kirytopoulos (2016) proposed a modeling approach that addresses the interdependencies between project risks using the theoretical framework of expected utility theory and Bayesian belief network. Despite their great effort, their modeling approach suffers from a major shortcoming. They identified 14 risks along with 8 complexity elements that drive project risks. However, as the scale of construction projects increases, their complexity level will increase significantly. Therefore, the number of factors that must be considered for a more realistic decision-making will increase inevitably. However, their model imposes computational challenges as the number of nodes increases, that limits its real world applicability. In contrast, by

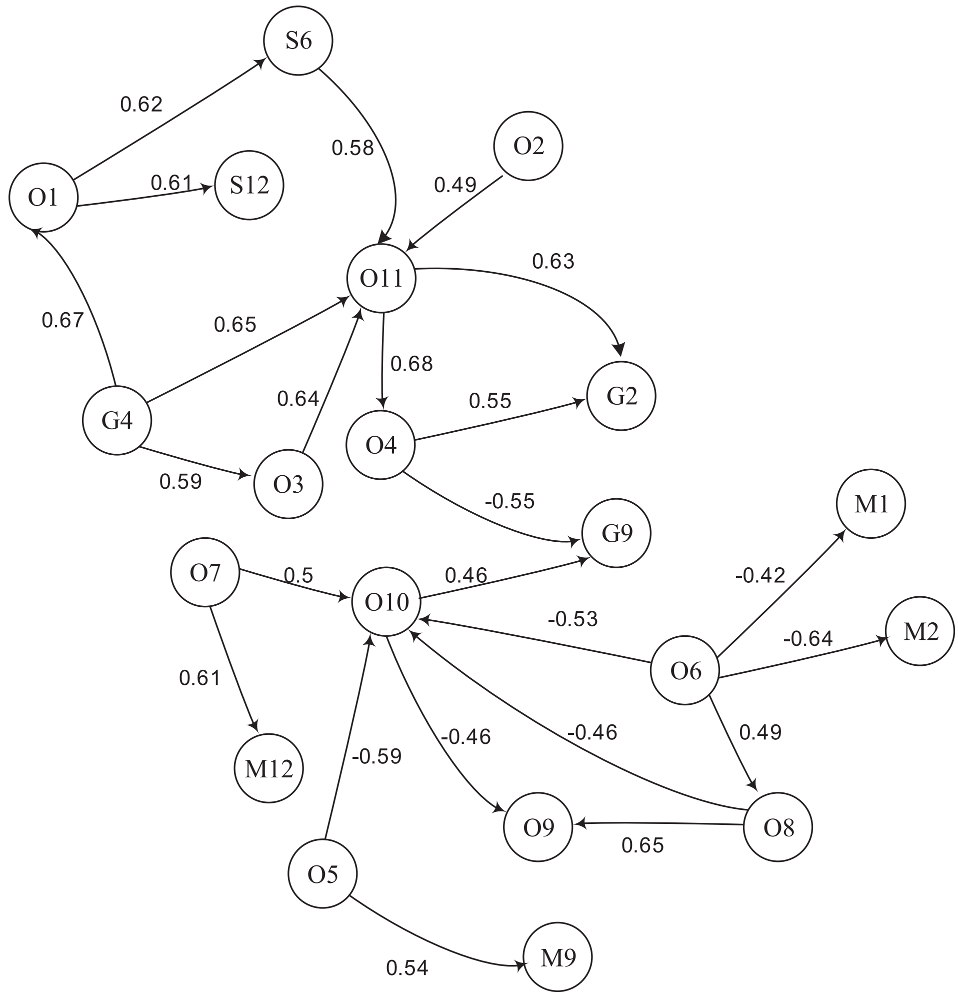

Fig. 8. FCM of the consequences (O).

Table 3
Linguistic variables to determine the initial values of strategy nodes.

Linguistic variable	Fuzzy number
Very high	(0.75, 1, 1)
High	(0.5, 0.75, 1)
Medium	(0.25, 0.5, 0.75)
Low	(0, 0.25, 0.5)
Very low	(0, 0, 0.25)

using FCMs decision-makers are enabled to consider great number of nodes (62 nodes in this study), and are able to simulate various scenarios without any computational challenges. Another similar research is done by Nepal and Yadav (2015) that also used Bayesian belief networks. This paper in the same manner suffers from imposing computational burdens.

5. Conclusion and future research

Compared to other industries, construction industry has been facing numerous risks that if they are not managed properly, project failure is an inevitable result. Despite the great importance of this issue, project managers mostly prefer to rely on their own experience to manage projects' risks rather than using the analytical tools available in the literature. On the other hand, in the manufacturing sector, an immense body of knowledge and experience has been formed around the best practices such as supply chain management and supply chain risk management. Given this situation, there exist a unique opportunity for both the scholars and practitioners in the field of project management to begin exploiting this rich source of knowledge to address their own problems. Given many differences between industries in the construction sector and those in the manufacturing sector, this task requires major modifications and customizations, so the tools that work well in the manufacturing companies also work well in construction companies. Therefore, in this study a novel supply chain risk management model is proposed for construction projects using GT, FCMs and GRA method.

Since each construction project has specific complexities and uniqueness, it is necessary to take these factors into account while proposing a new decision-making tool for project managers. Further, as there is a gap between the literature and practice in the field of project risk management, considering the managers experience along with using analytical tools in decision-making activities, plays a pivotal role in the success of bridging this gap. Therefore, both GT and FCMs are used to reserve and exploit valuable experience of project managers, while capturing a clear image of their perception of this system (projects' supply chain risk management) and its dynamics. Moreover, GRA method is also used to identify the best risk mitigation scenario.

The major goal in this study is to set the stage for linking two well-developed literatures (i.e. project risk management and supply chain risk management), that will possibly result in the proliferation of each of them individually. The present study puts forward a possibility of discussion between project management scholars and practitioners with

Table 4
The initial values of risk mitigation scenarios.

Strategies	Risk mitigation scenarios					
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
S1	1.0	0.0	0.7	0.1	0.1	0.0
S2	1.0	0.0	0.0	0.0	0.0	0.0
S3	1.0	0.0	0.5	0.0	0.0	0.0
S4	1.0	0.0	0.6	1.0	0.0	0.0
S5	1.0	0.0	0.8	1.0	0.0	0.8
S6	1.0	0.0	0.0	0.0	0.0	0.0
S7	1.0	0.0	0.0	0.0	0.0	0.0
S8	1.0	0.0	0.0	0.4	0.1	0.0
S9	1.0	0.0	0.0	0.9	0.8	0.0
S10	1.0	0.0	0.7	0.0	0.0	0.0
S11	1.0	0.0	0.0	0.0	0.0	1.0
S12	1.0	0.0	0.0	0.3	0.2	0.0
S13	1.0	0.0	0.0	0.0	0.0	1.0

Table 5
The main phenomenon's final values after the inference process.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
S1	0.930916	0.98773	0.996451	0.886271	0.869224	0.999977	0.802317	0.947516	0.999042	0.982961	0.999429	−0.76693	0.997035	0.978565
S2	0.915328	0.867748	0.971603	0.886271	0.869224	0.999972	0.802358	0.947516	0.999156	0.982961	0.999959	0.975469	−0.7799	0.997766
S3	0.930858	0.987244	0.99631	0.885791	0.869142	0.999977	0.802315	0.947487	0.999067	0.982958	0.99944	−0.69813	0.997025	0.980595
S4	0.930916	0.987729	0.996451	0.886271	0.869224	0.999977	0.802317	0.947516	0.999042	0.982961	0.99943	−0.7644	0.997035	0.978645
S5	0.930914	0.987711	0.996446	0.886271	0.869224	0.999977	0.802317	0.947516	0.999044	0.982961	0.999435	−0.74208	0.997035	0.979334
S6	0.919065	0.871756	0.971788	0.886271	0.869224	0.999972	0.798559	0.938726	0.999142	0.981173	0.999959	0.975489	−0.78597	0.997794

Table 6
The weights of project’s supply chain risks based on Shannon’s entropy.

Project's supply chain risks	Weight
M1	0.000275
M2	0.001518
M3	0.000308
M4	0.000257
M5	0.000257
M6	0.000257
M7	0.000258
M8	0.000261
M9	0.000257
M10	0.000257
M11	0.000257
M12	0.705978
M13	0.289574
M14	0.000286

Table 7
The grey relational degrees of each scenario.

Scenarios	$\Phi(y^0, y_i)$	Rank
S3	0.546264	1
S5	0.546249	2
S4	0.546243	3
S1	0.546242	4
S2	0.333344	5
S6	0.33333	6

those active in the field of supply chain management, by proposing a novel supply chain risk management approach for construction projects. This discussion has a great potential to bring upon a wide horizon of possibilities to expand project managers' problem-solving toolbox, while developing more neglected concepts such as make-to-order and construction supply chains. Having this goal in mind, our proposed approach contributes to the literature and practice of both SCM and project management in three major ways. First, employing GT along with FCMs shed light on the building blocks of a complicated system in which project's supply chain risks are generated, propagated, and mitigated through time. Additionally, intricate causal relationships between these blocks are identified and presented. Second, construction industry has been dealing with a great deal of uncertainties during each project's lifecycle. On the other hand, extreme penalties for projects' delivery delay limits the ability of project managers to use the trial and error approach to manage risks. The proposed approach enables managers to simulate and examine their risk mitigation scenarios with the minimum cost, and be prepared for any unintended consequence of their scenarios. Finally, as it is stated above, the proposed approach captures a clear image of the experts' perception of the risk management system. This characteristic, enables managers to see how might their cognition of the system be flawed and requires major modification, or even how they can improve it.

As it is argued before, great potentials lie in the application of manufacturing industry's best practices in the construction industry. To this end, various quantitative approaches and techniques previously used in the context of SCM (or SCRM as a sub-field) can be used to address managerial issues in the construction industry. Nevertheless, qualitative researches are also required to exactly elaborate on how the concepts related to the SCM (including SCRM) are applicable in the context of construction industry and project management. The differences between these two fields can be identified and addressed thoroughly in the future researches.

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