Fuzzy Weighted Interpretive Structural Modeling: Improved Method for Identification of Risk Interactions in Construction Projects

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Abstract: The construction industry has a major role in the economic development of any country. Because of the nature of the construction industry and its unique characteristics, and the overtime work and overbudget funds spent on these projects, there are many risks which may occur during a project's lifecycle. Should a specific risk happen, the probability and impact of the other risks will be affected, which often affects the project's objectives. Therefore it is necessary to consider risk interaction in order to improve the management of project risks. This paper proposes the fuzzy weighted interpretive structural modeling (FWISM). A two-round Delphi method is applied by asking 10 experts to specify the importance of each risk interaction with a fuzzy number due to the uncertain nature of the risks. This paper presents a network of risk interactions in construction projects which then provide the necessary means for exploring the influence of and dependence among the risk factors. In order to identify the key factors that drive the system, MICMAC analysis is applied. The results show that contractual anomalies most influence the other risks of a given project, whereas certain risks such as construction delay or interruptions are more susceptible to these influences than are other risks. **DOI: 10.1061/(ASCE)CO.1943-7862.0001395.** *© 2017 American Society of Civil Engineers.*

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Introduction

Construction projects involve risks in all phases of the project's development up to its final fruition, that is, starting from the feasibility phase to the operational phase. Risks involved in heavy construction have a direct impact on the project's schedule, cost, and overall performance (Salah and Moselhi 2016; Wang and Yuan 2016; Choudhry et al. 2014). An appropriate strategy such as a risk-management system is thus essential for reducing and controlling the risks. The general principle of risk management is that risks should be assigned as the responsibility of those who are the most highly capable of controlling and managing them (Tam and Shen 2012). It has become increasingly important in this very regard to effectively and efficiently manage project risks in order to give a higher guarantee of success and comfort to a project's stakeholders, or at least to warn them against potential problems or disasters (Fang and Marle 2012). A risk-management process, however, is generally defined as an integrative process that starts with the identification of risk factors, followed by qualitative and/or quantitative assessment of the possible risk effects on the project, and, finally, ends with the development of risk-mitigation strategies to maintain an optimum risk–return structure among the project participants (Zhi 1995; Wang et al. 2004; Han et al. 2008). In many studies, the focus is mainly placed on the analysis of individual risks, and, because of this, the characteristics of risks are evaluated independently. But this technique deals with one risk at a time, and therefore fails to notice the interactions or interdependencies among different risks (Han et al. 2008). Because many risks are interdependent and have multiple effects, it becomes cumbersome for the project decision makers to trace the actual source of these risks. Rather than focusing on the root cause, they often merely tend to focus on the immediate preceding activity (Iyer and Sagheer 2010). Considering the interaction of a risk factor with other risks will change the probability and impact of that risk, which results in reconsideration of the approach for a more complete analysis of the assessment, response, control, and monitoring of that particular risk.

In addition, in order to find the appropriate method for risk management, project risks should be analyzed in order to determine and trace the interactions among them. This paper proposes the fuzzy weighted interpretive structural modeling (FWISM). The researchers developed a network illustrating the project risk interactions and identified to what extent a given risk can influence the other risks or may, in turn, be influenced by them. In addition, the obtained risk interaction network illustrates how much a risk influences the project objectives. In this paper, project cost is considered as the only objective of the project, whereas the other objectives such as time and quality are considered as individual risk factors influencing the project cost.

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Literature Review

Project risk management is an integral part of every project-driven organization (Govan and Damnjanovuc 2016). Therefore, because risk management is an important part of many construction projects, it has been investigated by many studies around the world. For example, Wang et al. (2004) identified critical risk factors affecting construction projects in developing countries and classified

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them under three primary levels, ranked them, and finally proposed certain response strategies to enable project managers and other related decision makers to cope with these identified risks. Tah and Carr (2000), with the same focus and on the basis of similar risk-related concerns, proposed a hierarchical risk-breakdown structure to classify diverse risks that may affect construction projects. This led to the claim that three attributes of each risk, called risk factors, risks, and consequences, are assumed to be causally interdependent and are thus assessed by the use of a structured fuzzy risk-rating approach. Dikmen et al. (2007), on the other hand, utilized a fuzzy risk-rating approach to qualitatively assess the risk of cost overrun in the bidding stage of international projects by taking into account the interrelations among various risk factors and the effects of project-related factors along with the contract conditions on the determination and formation of the risk level of projects. Han et al. (2008) developed an integrated risk-management system for international construction projects. They proposed the identification of the risk paths by means of showing the cause–effect relations involved among risk factors.

However, in such research there is still a lack of a systematic approach to describing the interactions among project risks with regard to all complex and dynamic conditions of construction projects with the aim of arriving at a better understanding and setting forth an effective management (Boateng et al. 2012).

In addition, in order to recognize the risk interactions in question, structural equation modeling (SEM) has been used. Structural equation modeling is a causal modeling technique that is capable of analyzing complex interrelations among observed or latent variables (Hair et al. 2006; Byrne 2006; Ullman 2006). Additionally, it has been considered as one of the most suitable techniques for analyzing the relationships among variables (Liu et al. 2016; Le et al. 2014; Xiong et al. 2014; Zhao et al. 2013). Bentler (2006), for instance, considered SEM as an important methodology that can be utilized for describing the possible interrelationships among variables, for testing a hypothesis, and for estimation purposes. One of the noteworthy efforts in this regard is the risk-based model developed by Kim et al. (2009). Their research compared the accuracy of SEM in the prediction of cost performance of construction projects with certain other related techniques such as regression analysis and neural networks. They came to the conclusion that SEM shows a better and more viable prediction performance, primarily because it takes into account the complexities of real cases, which is its distinctive feature in comparison with other similar models.

In a similar study using the SEM method, Eybpoosh et al. (2011) considered the causal relationships existing among various risk factors of 166 international construction projects. They identified the risk paths and the total effect of each risk factor and risk path on the project cost overrun.

There are two types of SEM: covariance-based SEM (CB-SEM) and partial least-squares SEM (PLS-SEM). The covariance-based method requires a very large data set and accuracy of parameter estimation, whereas the PLS method is based on soft assumptions of distributions and predictive needs (Thirupathi and Vinodh 2016; Zhao et al. 2013; Sarstedt et al. 2014; Hair et al. 2012). Both types have been used in different related research. For instance, Kim et al. (2009) and Eybpoosh et al. (2011) adopted CB-SEM, whereas Liu et al. (2016) used PLS-SEM. However, in both types of SEM method a certain deficiency results from the fact that the dynamic behavior of the risk factors and risk paths during the design and development of the project schedule was not taken into account. In addition, assigning a crisp number as the total effect of risk paths is not realistically and reliably compatible with the uncertain nature of the risks (Thirupathi and Vinodh 2016; Liu et al. 2016).

In order to analyze the dynamic and time-related behavior of risks, researchers have used system dynamics (SD) modeling. System dynamics is a tool to investigate, formulate, and model complex dynamic problems in terms of stocks (the accumulation of things), flows (the motion of things), and feedback loops at any level of aggregation (Marco et al. 2016; Wan and Liu 2014; Richardson 2011). Some researchers, however, have used a system dynamics approach to find the network of interactions between and among interdependent factors. For example, Boateng et al. (2012) used SD modelling for social and environmental (SE) risk management during megaproject development. Wan and Liu (2014) presented an approach to develop a system dynamics model for risk analysis during the project construction process.

Although system dynamics can easily provide a sustainable model for estimating and determining the quantifiable risks such as inflation, escalation, and so on, as well as the more intangible and qualitative risks such as subcontractor incompetency (Toole 2005), it has a fundamental limitation with regards to the structure of the overall system. Different experts with different technical or managerial points of view might bring into being different assumptions and thus see and shape a quite different perspective to project management. In that case, it can be hard enough to confirm the dynamic hypothesis used to construct the final feedback model because it may vary from one expert to another one (Boateng et al. 2016).

This paper uses interpretive structural modeling (ISM) to construct an aggregated network of the interrelated risk factors. Interpretive structural modeling is an interactive learning process in which a set of different directly and indirectly related elements are structured into a comprehensive systematic model (Attri et al. 2013a; Sage 1977; Warfield 1974).

Attri et al. (2013a) enumerated ISM advantages for level partitioning. They presented this process as a systematic and efficient method. The process is systematic because the computer is programmed to consider all possible pairwise relations of system elements, either directly extracted from the responses of the participants or by the application of transitive inference. The process is efficient because the use of transitive inference may reduce the number of the required relational queries by 50–80%. The other advantage of ISM is that it guides and records the results of group deliberations on complex issues in an efficient and systematic manner. In spite of the many advantages of the ISM method, its main limitation is that it cannot be statistically validated.

As far as its application is concerned, ISM has been used in many studies to categorize the level partitions. Attri et al. (2013b) applied this approach for identifying and analyzing their mutual interaction of the enablers in the implementation of total productive maintenance (TPM). Raj et al. (2012) utilized an ISM approach for analyzing the mutual relationships among the factors affecting the flexibility in any given flexible manufacturing system (FMS). Singh et al. (2003) utilized this technique for the implementation of knowledge management in engineering industries. Thakkar et al. (2007), in a quite different fashion, used an ISM approach for evaluating and comparing supply chain relationships, specifically, when a small and medium scale enterprise (SME) is considered as a focal company. Raj and Attri (2011) applied an ISM approach for identifying and analyzing the barriers in the implementation of total quality management (TQM). Singh et al. (2007) utilized this technique to identify and develop the structural relationship needed among different factors for the successful implementation of advanced manufacturing technologies (AMTs). Bolanos et al. (2005) utilized this approach to improve decision-making processes among executives working in different functional areas. Iyer and Sagheer (2010) suggested the use of ISM for the purpose of preparing a hierarchical structure as well as the interrelationships of these risks that would enable decision makers to take appropriate steps forward in the course of the development of the project.

In those studies, the ISM method used a certain binary matrix for comparing each factor with the others (Attri et al. 2013a). By using a binary matrix, all related factors are compared with the same weight. Therefore this method ignores the weight of the relationship between factors. In this paper, ISM is used by considering the weighted factors in a comparison-oriented matrix, and therefore the weight of each risk path affecting the project cost can be specified.

Furthermore, almost all of the previously mentioned works employed ISM along with crisp inputs. Construction project risks, however, have an uncertain nature and cannot be assigned precise crisp numerical values as their interaction magnitude, which in this paper refers to the extent to which the occurrence of one risk factor during the project renders the probability of the other risk factor susceptible to change. Therefore it is necessary to extend the ISM method to treat the uncertain variables and/or parameters (Shaheen et al. 2007). In many studies, fuzzy logic has been used in construction projects because it is a practical risk-management tool when the translation of the condition ratings of asset infrastructures to a criticality index is imprecise and involves subjective judgment (Elsawah et al. 2016; Fares and Zayed 2010). Abdelgawad and Fayek (2010), by means of illustration, used fuzzy logic and a fuzzy analytical hierarchy process (AHP) to address the limitations of traditional failure mode and effect analysis (FMEA). Karakas et al. (2013) used fuzzy logic to develop a multiagent system (MAS) that simulates the negotiation process between and among parties (mainly, contractor and client) about risk allocation and sharing of cost overruns in construction projects. Interpretive structural modeling helps notably with the task of converting fuzzy thoughts into intuitive models based on team discussion and qualitative analysis (Khan et al. 2015). The various steps needed to be taken in the application of this model include factor identification, idea generation, logical mapping, and insight. Interpretive structural modeling thus provides an opportunity for the further identification of structure within a system (Thirupathi and Vinodh 2016). This study integrates fuzzy logic into the proposed ISM method in order to consider uncertainties.

This paper proposes the fuzzy weighted interpretive structural modeling in order to identify the risk interaction network. By referring to and grounding the work in experts' opinions, the importance factor for each risk factor and the risk interactions are determined together by a fuzzy number.

Methodology

Interpretive structural modeling methodology explicitly suggests the use of expert opinions based on various management techniques such as brainstorming, surveying, and so on, in the course of developing the contextual relationship among the variables. In this methodology, no knowledge of the underlying process is required from the participants; they simply must possess enough understanding of the object system in order to be able to respond to the series of relational queries generated by the computer (Attri et al. 2013a).

This method encourages issue analysis by allowing participants to explore the adequacy of a proposed list of system elements or issue statements for illuminating and justifying a specified situation, and it permits action or policy analysis by assisting participants in identifying particular areas for policy action which offers advantages or leverage, depending on the situation, in the course of pursuing specified objectives (Attri et al. 2013a).

Because the ISM method can be used only for identifying relationships among specific items, an important limitation is that it cannot consider how much they may influence or be influenced by each other. In this paper, considering the importance of the amount of risk factors' influence on each other, a new method is proposed called weighted ISM, in which the amount (weight) of the mutual relationship between each pair of factors is specified.

In addition, as was previously stated, project risks have an uncertain nature and it is impossible to assign precise crisp numerical values to them as their interaction magnitude. Therefore the standard reasoning methods are not appropriate for measurement of risk interaction. Fuzzy logic is, on the contrary, quite appropriate for the task of considering the uncertain nature of risks based on experience and managerial subjective judgment (Nasirzadeh et al. 2008b).

In this paper, by using the fuzzy logic for the assessment of the risk interaction amounts, uncertain nature of the risk interaction has been considered in order to make the final results much closer and applicable to the project's actual conditions.

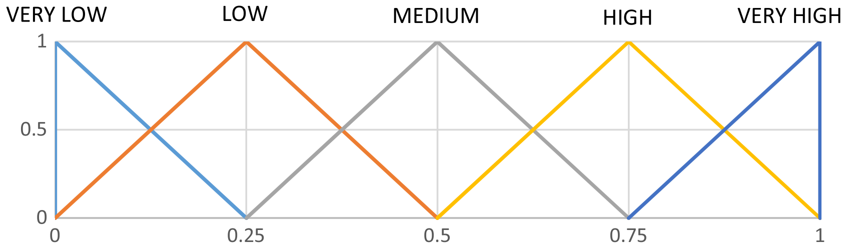
The various steps involved in FWISM are as follows:

1. Identify the elements which are relevant to the problem. This could be done by a survey or group problem-solving technique.
2. Develop a structural self-interaction matrix (SSIM) of elements. This matrix indicates the pair-wise relationship among elements of the system. For analyzing the factors, a contextual relationship of a *leads to* or *influences* type must be chosen and measured. This, consequently, means that one factor influences another factor.

   In the standard ISM method, the following four symbols are used to denote the direction of relationship between two factors (i and j): (1) V is the relation from factor i to factor j (i.e., factor i will influence factor j); (2) A is the relation from factor j to factor i (i.e., factor i will be influenced by factor j); (3) X is the bidirectional relationship (i.e., factors i and j will influence each other concurrently or alternately); and (4) O denotes no relation between and among the factors (i.e., barriers i and j are unrelated). Based on the contextual relationships, the SSIM is then developed. To obtain a firm consensus, the SSIM should be further discussed and put to peer analysis by a group of experts. On the basis of their responses, the SSIM is then finalized.

   In contrast to standard ISM, in which the relationships are specified by O, V, X, and A in order to show whether factors are related or not, the fuzzy weighted ISM method uses the linguistic terms *very low*, *low*, *medium*, *high*, and *very high* to show the weighted relationship between two factors.
3. Develop a reachability matrix from and on the basis of the SSIM. The next step in the FWISM approach, in the context of its procedural standards, is to develop an initial reachability matrix from SSIM. To this end, SSIM is converted into the initial reachability matrix by transforming the experts' opinions in linguistic terms of a Likert scale to triangular fuzzy numbers (TFNs) (Fig. 1). Triangular numbers are very often used in applications (e.g., fuzzy controllers, managerial decision making, business and finance, social sciences). They have a membership function consisting of two linear segments (left and right) joined at the peak, which makes graphical representations and operations with triangular numbers very simple. Furthermore, it is important that they can be constructed easily on the basis of little information (Ngai and Wat 2005).

   Therefore the initial reachability matrix will be constructed in the form of fuzzy numbers by calculating and assessing the average of the experts' opinions.



Linguistic Term	Triangular Fuzzy Number
Very Low	[0.0 0.0 0.25]
Low	[0.0 0.25 0.5]
Medium	[0.25 0.5 0.75]
High	[0.5 0.75 1.0]
Very High	[0.75 1.0 1.0]

Fig. 1. Equivalent TFN for Likert scale

4. Develop the final reachability matrix by considering the direct or indirect (through the intermediate factors) relationships and also finding the maximum weight of relationships between and among the aforesaid factors. To do this, the intermediate reachability matrix should be constructed as

$$\mathbf{F}^{n+1} = [f_{ij}^{n+1}]_{M\times M} \cdot f_{ij}^{n+1} = \mathrm{MAX}\{(f_{i1}^{n} \times f_{1j}^{n}) \cdot (f_{i2}^{n} \times f_{2j}^{n}) \cdot \cdots \cdot (f_{iM}^{n} \times f_{Mj}^{n})\} \quad (1)$$

where $\mathbf{F}^0 = [f_{ij}^0]_{M\times M}$ = initial reachability matrix; and $\mathbf{F}^n = [f_{ij}^n]_{M\times M}$ = intermediate reachability matrix representing the weight of relationship with n intermediates.

This matrix should be developed further until $\mathbf{F}^{k+1}$ equals $\mathbf{F}^k$. At this point, $\mathbf{F}^{k+1}$ is the final reachability matrix with the maximum weight of relationships.

Considering the fact that the initial reachability matrix is constructed in the form of fuzzy numbers, in order to use Eq. (1) the maximum value of the fuzzy numbers must be found first. To do this, the centroid point $(\bar{X}_A \cdot \bar{Y}_A)$ and distance index (R_A) of each fuzzy number should be calculated (Li and Zou 2012; Kaufmann and Gupta 1985; Cheng 1998)

$$\bar{X}_A = \frac{\int_a^b x f_A^L dx + \int_b^c x dx + \int_c^d x f_A^R dx}{\int_a^b f_A^L dx + \int_b^c dx + \int_c^d f_A^R dx} \quad (2)$$

$$\bar{Y}_A = \frac{\int_0^1 y g_A^L dy + \int_0^1 y g_A^R dy}{\int_0^1 g_A^L dy + \int_0^1 g_A^R dy} \quad (3)$$

$$R_A = \sqrt{\bar{X}_A^2 + \bar{Y}_A^2} \quad (4)$$

where

$$A\text{:a fuzzy number} = \begin{cases} f_A^L(x) & \text{if } a \le x \le b \\ 1 & \text{if } b \le x \le c \\ f_A^R(x) & \text{if } c \le x \le d \\ 0 & \text{otherwise} \end{cases}$$

where $g_A^L(x)$ and $g_A^R(x)$ = inverse function of $f_A^L(x)$ and $f_A^R(x)$, respectively.

For a triangular fuzzy number $A = (a, b, c)$, Eqs. (2) and (3) are simplified as Eqs. (5) and (6), respectively

$$\bar{X}_A = \frac{a+b+c}{3} \quad (5)$$

$$\bar{Y}_A = \frac{a+4b+c}{3a+6b+3c} \quad (6)$$

Triangular fuzzy numbers are compared according to Eqs. (7)–(9)

$$A > B \quad \text{if } R_A > R_B \quad (7)$$

$$A < B \quad \text{if } R_A < R_B \quad (8)$$

$$A_i = \mathrm{MAX}\{A_1, A_2, \ldots, A_n\} \quad \text{if } R_{A_i} = \mathrm{MAX}\{R_{A_1}, R_{A_2}, \ldots, R_{A_n}\} \quad (9)$$

5. Transform the final reachability matrix to the binary reachability matrix. All the elements of the final reachability matrix which are less than the fuzzy number of the Medium term of the Likert scale, i.e., (0.3, 0.5, 0.7), will be transformed to 0, and the elements greater than or equal to the Medium term will be transformed to 1. This comparison is done according to Eqs. (7) and (8).
6. Partition the reachability matrix into different levels. From the binary reachability matrix, for each and every factor involved, the reachability set and antecedent sets are then derived. The reachability set consists of the factor itself and the other factor that it may affect, whereas the antecedent set consists of the factor itself and the other factor that may affect it. Thereafter, the intersection of these sets is derived for all the factors, and levels of different factors are determined. The factors for which the reachability and the intersection sets are the same occupy the top level in the FWISM hierarchy. The top-level factors are those factors that will not lead to the other factors in the hierarchy. Once the top-level factor is identified, it is removed from consideration. This process is repeated in order to determine the factors at the next level.
7. Draw the digraph. The preliminary digraph including transitive links is obtained from the conical form of the reachability matrix. It is generated by nodes and lines of the edges. After

removing the indirect links, a final digraph is developed. A digraph is then used to represent the elements and their interdependencies in terms of nodes and edges; in other words, the digraph is the visual representation of the elements and their interdependencies. In this course of development, the top-level factor is positioned at the top of the digraph, the second-level factor is placed at the second position, and so on until the bottom level is placed at the lowest position in the digraph.

8. Review the model to check for conceptual inconsistency and make necessary modifications to it.
9. Conduct a MICMAC analysis. Cross-impact matrix multiplication applied to classification (MICMAC) analysis is used to understand the appropriate approach to properly respond to each individual factor by and through the identification of the key factors that drive the system in various categories. In FWISM, MICMAC analysis is done with the use of the drive/dependence power of the factors, which are then calculated by the weighted relationships in the final reachability matrices. The drive power and dependence power of a factor are derived by summing the TFNs in the factor's own row and own column, respectively, of the final reachability matrix. In order to use fuzzy number in MICMAC analysis, they should be transformed into crisp numbers by

$$\text{Defuzzy}\, A(a,b,c) = \frac{a+2b+c}{4} \tag{10}$$

Based on their drive power and dependence power, the factors have at this point been classified into four categories, i.e., autonomous factors, linkage factors, dependent factors, and independent factors.

- Autonomous factors: These factors have a weak drive power and a weak dependence power. They are relatively disconnected from the system, with which they have few links; however, the links may be very strong.
- Linkage factors: These factors have a strong drive power as well as a strong dependence power. These factors are unstable because any action directed toward or exerted on these factors will have a subsequent effect on the others and also a feedback effect reflected on themselves.
- Dependent factors: These factors have a weak drive power but a strong dependence power.
- Independent factors: These factors have a strong drive power but a weak dependence power.

A factor with a very strong drive power, called the key factor, falls into the category of independent or linkage factors.

Categorized Fuzzy Weighted Interpretive Structural Modeling

One of the main limitations of the ISM approach is that there may indeed be many variables to a problem or issue. Any increase in the number of variables to a problem or issue increases the complexity of the ISM methodology. Therefore it is expected that only a limited number of variables will be considered in the course of the development of ISM model. Other variables which affect a problem or issue to a lesser degree thus may not be addressed in the development of the ISM model (Attri et al. 2013a).

This paper solves this limitation by proposing the categorized FWISM method in which the identified factors are classified into different categories. Assuming N as the number of the categories, $N+1$ SSIMs are developed (one matrix for each category and one matrix shared among the categories themselves). In this way, the number of pairwise relationships is reduced to a much smaller number. For example, this research identified 63 factors, for which the expert should specify $63 \times 62 = 3{,}906$ pairwise relationships; by classifying them into nine categories, this number was reduced to 506 (87% reduction).

The FWISM method should be executed for each SSIM, which provides a digraph for each SSIM. To conduct the MICMAC analysis for the proposed method, the drive powers and dependence powers for the factors of each category are calculated, which are then divided by the number of the factors in that specific category. In this way, all the drive or dependence powers are normalized in the interval [0 1]. Next, the same procedure is used to calculate the normalized drive/dependence power of the categories themselves. The final drive/dependence power of each factor is calculated by multiplying its normalized drive/dependence power the by normalized drive/dependence of its category

$$\text{Final drive power of factor } y = \frac{\sum_{j=1}^{M} d_{yj}}{M} \times \frac{\sum_{j=1}^{N} c_{xj}}{N} \tag{11}$$

$$\text{Final dependence power of factor } y = \frac{\sum_{i=1}^{M} d_{iy}}{M} \times \frac{\sum_{i=1}^{N} c_{ix}}{N} \tag{12}$$

where $\mathbf{C} = [c_{ij}]i, j{:}1, 2, \ldots, N$ is the reachability matrix for main categories; and $\mathbf{D}_x = [d_{ij}]i, j{:}1, 2, \ldots, M$ is the reachability matrix for factors of the xth category.

Application of Proposed Framework

Step 1. Identification of Risk Factors

Risk identification determines which risks might affect a project, including both threats to the project's objectives and opportunities to improve on those objectives (PMI 2008).

In this paper, consequently, risk identification was done by reviewing the literature in the field of risk management of construction projects. The most related studies from the design phase up to the construction phase of the projects covered are

- "Risk Management in ERP Project Introduction: Review of the Literature" by Aloini et al. (2007);
- "The Allocation of Risk in PPP/PFI Construction Projects in the UK" by Bing et al. (2005);
- "Cost and Schedule Risk Analysis of Bridge Construction in Pakistan: Establishing Risk Guidelines" by Choudhry et al. (2014);
- "Identification of Risk Paths in International Construction Projects Using Structural Equation Modeling" by Eybpoosh et al. (2011);
- "Managing Risk in Procurement Guideline" by Treadwell (2015);
- "System Dynamics Approach for Construction Risk Analysis" by Nasirzadeh et al. (2008a);
- "Fuzzy AHP-Based Risk Assessment Methodology for PPP Projects" by Li and Zou (2012);
- "The Design of a DSS for Supply Chain Risk Management" by Deshmukh (2007);
- "Risk Management in Procurement Phase of Power Plant Projects, Case Study: Jahrom Combined Power Plant" by Etemadinia (2011); and
- "The Relationship Between Success Level of Projects and Risk Management Implementation in the Repetitive Power Plant Projects" by Gholami (2014).

Table 1. List of Risk Factors and Categories

Number	Risk category	Risk factor	Explanation/cause/examples
1	Financial	Unavailability of funds	—
2		Low financial attraction	Low foreign financial attraction Low private financial attraction inflation
3		High financial cost	Interest rate volatility
4		Financial delay	
5		Bankruptcy	Bankruptcy of contractors Bankruptcy of the owner
6	Contractual	Change in scope	Change in scope of work Change in scope of supply
7		Contractual anomalies	—
8		Claims and disputes	—
9		Unrealistic estimation	Unrealistic estimation of time Unrealistic estimation of cost
10		Vagueness of contract clauses	—
11		Low quality of the contract	Technical inconsistency
12	Design	Change in design	—
13		Design complexity	—
14		Design deficiency	Design errors
15		Inadequate site investigation	Lack of feasibility study
16		Conflict with consultant	—
17		Delay in design	—
18		Design cost escalation	—
19	HSE	Damages	Equipment damage Property damages
20		Fatalities	—
21		High HSE cost	—
22		Low quality of HSE	Inadequate personnel training
23		Strict regulations	—
24	Management	Inadequate planning	Poor management of resources Poor risk management
25		Poor project team skills	Lack of motivation Inadequate experience in similar projects
26		Poor coordination	Poor coordination with the owner Poor coordination with consultants Poor coordination between site and office Poor coordination between design and commercial teams Poor coordination with the end-user
27		Poor site management and supervision	Poor management from the main office Poor supervision at site
28		Incompetent contractors	Inadequate experience in similar projects Inadequate experience with the owner Unfamiliarity with the country's condition (for foreign contractors) Unavailability of the labor
29		Instability of project team	Change in owner/consultant personnel Change in contractors' personnel Change in design/commercial team's personnel
30		High project traffic	Conflict with other projects Conflict with suppliers
31		High management costs	Too much overhead
32	Construction	Construction delay	—
33		Increase in construction costs	Rework Escalation of material prices Escalation of salary
34		Construction deficiency	Insufficient technology Inconsistency with design Inconsistency of site conditions with supplied equipment
35		Low labor productivity	Too few laborers Untrained labors
36		Material shortage	Unavailability of material Low quality of material
37		Excessive audits	Too much inspections and testing
38		Unexpected site condition	Bad weather
39		Interruption	Lack of space Conflict of work groups
40		Rework	Failure in tests
41		Construction complexity	Low constructability Complex construction methods

Table 1. (*Continued*.)

Number	Risk category	Risk factor	Explanation/cause/examples
42	Social/political	Unstable government	Conflict with government
43		Immaturity of legal system	Change in laws and regulations
44		High level of bureaucracy	—
45		Social unrest	Revolution Rebellion Strike
46		Instability of international relations	Sanction War
47		Unavailability of resources	Labor Equipment Material
48		Restrictions for foreign companies	—
49		Insufficient infrastructure	—
50	External	Delay in approval from regulatory bodies	Change in priority on projects
51		Third-party delays	
52		Unstable government policies	
53		Restriction of the access to the site	
54	Procurement/supply	Incompetent commercial team	Incompetent supply manager at site Unfamiliarity with the market
55		Incompetent suppliers	Lack of professional ethics Lack of flexibility Purchase from intermediaries
56		Incompetent manufacturers	Lack of professional ethics Lack of flexibility Low capacity Insufficient quality control Material shortage
57		Change in technical specifications	Errors in estimation Change in basic design
58		Delay in procurement	Delay in cash flow Delay in custom work Delay in proposals Delay in manufacturing
59		Escalation	Exchange rate volatility Custom/tax changes Escalation due to better technology
60		Limited number of approved vendors	Sanction Monopolism Too much insistdence on local vendors
61		Unavailability of suitable guarantees	Bank guarantees
62		Inadequate transportation	Foreign transportation delays Insufficient road and railway infrastructure Lack of access to the airports Difficulty in insurance of transportation Equipment damages during transportation
63		Low quality of the products	—

After studying these papers, more than 200 factors were identified as the risk factors of the construction projects. Table 1 summarizes these factors as 63 unique risk factors and classifies them in nine different risk categories.

Step 2. Development of Structural Self-Interaction Matrices

After the identification of the risk factors and their classification into certain risk categories, the pairwise relationship must be indicated among the risk factors and among the risk categories. A questionnaire with nine tables was prepared in which an individual table is specified for the risk factors of each category. In addition, a tenth table was prepared for the relationships among the risk categories. After taking preparatory steps, the questionnaire was sent to 10 experts with more than 10 years of experienced in the area of the management of construction projects. Two of the experts were project executive managers at National Iranian Oil Design and Construction Company (NIOEC), a client of refinery projects. Five were project managers at Moham Shargh Group (MSG), a general contractor of electrical substations, transmission lines, and power plants. The other three were project managers at Ghods Niroo Engineering Consultant (GNEC), the main consultant of power plant projects in Iran. The experts were clearly asked to specify the contextual relationship of the type of influence between two risk factors, meaning if one factor occurs during the project, to what extent is the probability of the other risk rendered susceptible to change. This relationship was denoted in the qualitative form of a five-point Likert scale (i.e., very low, low, medium, high, and very high). After obtaining the individual responses, a Delphi technique was used to generate consensus among the experts (Step 3).

On the basis of the experts' responses, the SSIMs then were developed for each individual expert.

Step 3. Development of Initial Reachability Matrices

The next step in the proposed method is to develop an initial reachability matrix from each SSIM. To this end, each SSIM is quantified by certain TFNs (Fig. 1). By using the fuzzy numbers, the uncertain natures of both risk interaction and human judgment are taken into consideration.

For each SSIM, a reachability matrix was developed. The results were returned to the experts, indicating the level of difference in opinion. The experts were asked to revise their responses in light of the replies from other members of the group. This Delphi process could have been continued, but after the second round the average of the TFNs was calculated, transformed from the latest experts' responses, and an initial reachability matrix was developed for each SSIM. The average of the TFNs was calculated as follows (Nasirzadeh et al. 2014):

$$F_{\mathrm{avg}}(a_{\mathrm{avg}}, b_{\mathrm{avg}}, c_{\mathrm{avg}}) = \frac{1}{n}\sum A_i = \frac{1}{n}\left(\sum a_i, \sum b_i, \sum c_i\right) \quad (i = 1 \text{ to } n) \tag{13}$$

where $A_i = (a_i, b_i, c_i)$, are the TFNs from the experts' responses.

This matrix shows the fuzzy weighted relationships among the risk factors. Table 2 shows the initial reachability matrix for designing the risk factors as an exemplary case.

At the final stage of this step, there were 10 initial reachability matrices, nine of which denoted the risk factors of the nine risk categories, and one which denoted the risk categories themselves.

Step 4. Development of Final Reachability Matrices

In this step, considering the indirect interactions involved, the maximum possible relationships among the risk factors and risk categories are found. To do this, a final reachability matrix was developed for each initial reachability matrix using Eqs. (1)–(9). As in the previous step, 10 fuzzy matrices were developed in this step.

Step 5. Development of Binary Reachability Matrices

Using Eqs. (7) and (8), fuzzy numbers of the final reachability matrices are compared with the equivalent fuzzy number of the medium term of the Likert scale, i.e., (0.25, 0.5, 0.75). For the purpose of developing 10 binary reachability matrices at this step, any fuzzy number greater than the medium term was transformed to the binary 1, and low-weighted relationships were neglected by transforming the fuzzy numbers less than the medium term to the binary 0.

Table 3 shows the transformed binary matrix for the design risk category.

Table 2. Initial Reachability Matrix for Design Risk Factor

Parameter	Change in design	Design complexity	Design deficiency	Inadequate site investigation	Conflict with consultant	Delay in design	Design cost escalation
Change in design	1.00	0.01	0.05	0.07	0.05	0.74	0.76
	1.00	0.11	0.21	0.19	0.17	0.87	0.89
	1.00	0.23	0.37	0.31	0.29	1.00	1.00
Design complexity	0.71	1.00	0.75	0.01	0.10	0.56	0.75
	0.84	1.00	0.88	0.11	0.26	0.71	0.88
	0.97	1.00	1.00	0.23	0.42	0.86	1.00
Design deficiency	0.75	0.08	1.00	0.03	0.05	0.36	0.70
	0.88	0.24	1.00	0.15	0.21	0.50	0.83
	1.00	0.40	1.00	0.27	0.37	0.64	0.96
Inadequate site investigation	0.70	0.06	0.76	1.00	0.08	0.68	0.71
	0.83	0.18	0.89	1.00	0.20	0.81	0.84
	0.96	0.30	1.00	1.00	0.32	0.94	0.97
Conflict with consultant	0.68	0.09	0.11	0.02	1.00	0.73	0.57
	0.81	0.25	0.27	0.14	1.00	0.86	0.72
	0.94	0.41	0.43	0.26	1.00	0.99	0.87
Delay in design	0.11	0.07	0.13	0.04	0.03	1.00	0.76
	0.27	0.19	0.29	0.16	0.15	1.00	0.89
	0.43	0.31	0.45	0.28	0.27	1.00	1.00
Design cost escalation	0.09	0.07	0.11	0.01	0.05	0.06	1.00
	0.25	0.19	0.27	0.13	0.17	0.22	1.00
	0.41	0.31	0.43	0.25	0.29	0.38	1.00

Table 3. Binary Reachability Matrix for Design Risk Category

Parameter	Change in design	Design complexity	Design deficiency	Inadequate site investigation	Conflict with consultant	Delay in design	Design cost escalation
Change in design	1	0	0	0	0	1	1
Design complexity	1	1	1	0	0	1	1
Design deficiency	1	0	1	0	0	1	1
Inadequate site investigation	1	0	1	1	0	1	1
Conflict with consultant	1	0	0	0	1	1	1
Delay in design	0	0	0	0	0	1	1
Design cost escalation	0	0	0	0	0	0	1

Table 4. Reachability, Antecedent, and Intersection Sets for Design Risk Factors

Number	Risk factors	Reachability	Antecedent	Intersection
1	Change in design	1,6,7	1,2,3,4,5	1
2	Design complexity	1,2,3,6,7	2	2
3	Design deficiency	1,3,6,7	2,3,4	3
4	Inadequate site investigation	1,3,4,6,7	4	4
5	Conflict with consultant	1,5,6,7	5	5
6	Delay in design	6,7	1,2,3,4,5,6	6
7	Design cost escalation	7	1,2,3,4,5,6,7	7

Table 5. Levels of Design Risk Factors

Risk factors	Level
Change in design	3
Design complexity	5
Design deficiency	4
Inadequate site investigation	5
Conflict with consultant	4
Delay in design	2
Design cost escalation	1

Step 6. Partitioning Binary Reachability Matrices

From the binary reachability matrices, for each risk factor or risk category, a reachability set, an antecedent set, and an intersection set are derived as described in detail earlier. The factors for which the reachability and the intersection sets are the same occupy the top level within their own category. Once the top-level factor is identified, it is removed from that category. This same process then is repeated to determine the factors at the next level.

Tables 4 and 5 show the result of this process for the Design risk factors as an exemplary case.

At the final stage of this step, a level for all 63 risk factors and all nine risk categories was specified.

Step 7. Drawing the Network

After partitioning the risk categories, and in order to represent the risk factors, risk categories, and their interactions in terms of nodes and edges, a network is developed. For each of these risk factors, this network explains how it may have an impact on the project's objectives, i.e., project cost in this particular study, through the other intermediate risk factors (Fig. 2).

Step 8. MICMAC Analysis

The network developed in previous step shows how the risk factors can interact with each other. To determine to what extent a given risk can influence the other risks or may be influenced by them, drive and dependence powers also must be calculated for each factor involved. Considering the final reachability matrices developed in Step 4, the related drive power and dependence power for each risk factor are calculated using Eqs. (10)–(12). For example, calculation details for the design (third) category are as follows:

$$\text{Fuzzy drive power} = \frac{\sum_{j=1}^{j=9} c_{3j}}{9} = (0.34, 0.47, 0.60)$$
$$\xrightarrow{\text{defuzzification}} \text{Final drive power} = \frac{0.34 + 2\times 0.47 + 0.60}{4} = 0.47 \tag{14}$$

$$\text{Fuzzy dependence power} = \frac{\sum_{i=1}^{i=9} c_{i3}}{9} = (0.43, 0.58, 0.75)$$
$$\xrightarrow{\text{defuzzification}} \text{Final dependence power} = \frac{0.43 + 2\times 0.58 + 0.75}{4} = 0.59 \tag{15}$$

where $\mathbf{C} = [c_{ij}]$, i, j:1, 2, ..., 9 is the reachability matrix for main categories.

In addition, drive/dependence power for change in design (Risk Factor 12) are calculated as follows:

$$\text{Fuzzy drive power} = \frac{\sum_{j=1}^{j=7} d_{12j}}{7} \times \frac{\sum_{j=1}^{j=9} c_{3j}}{9} = (0.4, 0.51, 0.63) \times (0.34, 0.47, 0.60) = (0.13, 0.24, 0.38)$$
$$\xrightarrow{\text{defuzzification}} \text{Final drive power} = \frac{0.13 + 2\times 0.24 + 0.38}{4} = 0.25 \tag{16}$$

$$\text{Fuzzy dependence power} = \frac{\sum_{i=1}^{i=7} d_{i12}}{7} \times \frac{\sum_{i=1}^{i=9} c_{i3}}{9} = (0.58, 0.70, 0.82) \times (0.43, 0.58, 0.75) = (0.25, 0.40, 0.61)$$
$$\xrightarrow{\text{defuzzification}} \text{Final dependence power} = \frac{0.25 + 2\times 0.40 + 0.61}{4} = 0.42 \tag{17}$$

where $\mathbf{C} = [c_{ij}]$, i, j:1, 2, ..., 9 is the reachability matrix for main categories; and $\mathbf{D}_3 = [d_{ij}]$, i, j:1, 2, ..., 7 is the reachability matrix for factors of the design (third) category.

Based on their final drive power and dependence power (Table 6), the risk factors were classified into four categories (Fig. 3). In addition, Fig. 4 illustrates the MICMAC analysis of the risk categories.

Results and Discussions

In this paper, a network of risks involved and expected in construction projects was obtained and outlined by the use of the FWISM method. In this method, the interactions among many risks can be specified by classifying the risks properly. In this way, the relations among the risks in each category and also the relationships among categories were determined.

After the thorough development of the network in question, it is necessary to ascertain the degree of relationship between the risks in each category; this was done via the application of MICMAC analysis, originally developed by Duperrin and Godet (1975). The objective of MICMAC analysis is to analyze the driver power and dependence power of each element involved (Mandal and Deshmukh 1994; Iyer and Sagheer 2010). This formal analysis complements and extends the impressions that experienced users draw from analysis of the influence structures. Specifically, MICMAC explores the influence of and dependence among issues and subsequently classifies them into the independent, linkage, dependent, and autonomous clusters.

There are four risk categories—social/political, external, contractual, and management—in the independent cluster (Figs. 2 and 4). The social/political risk category influences all the other risk categories but itself is influenced by none of them. Because

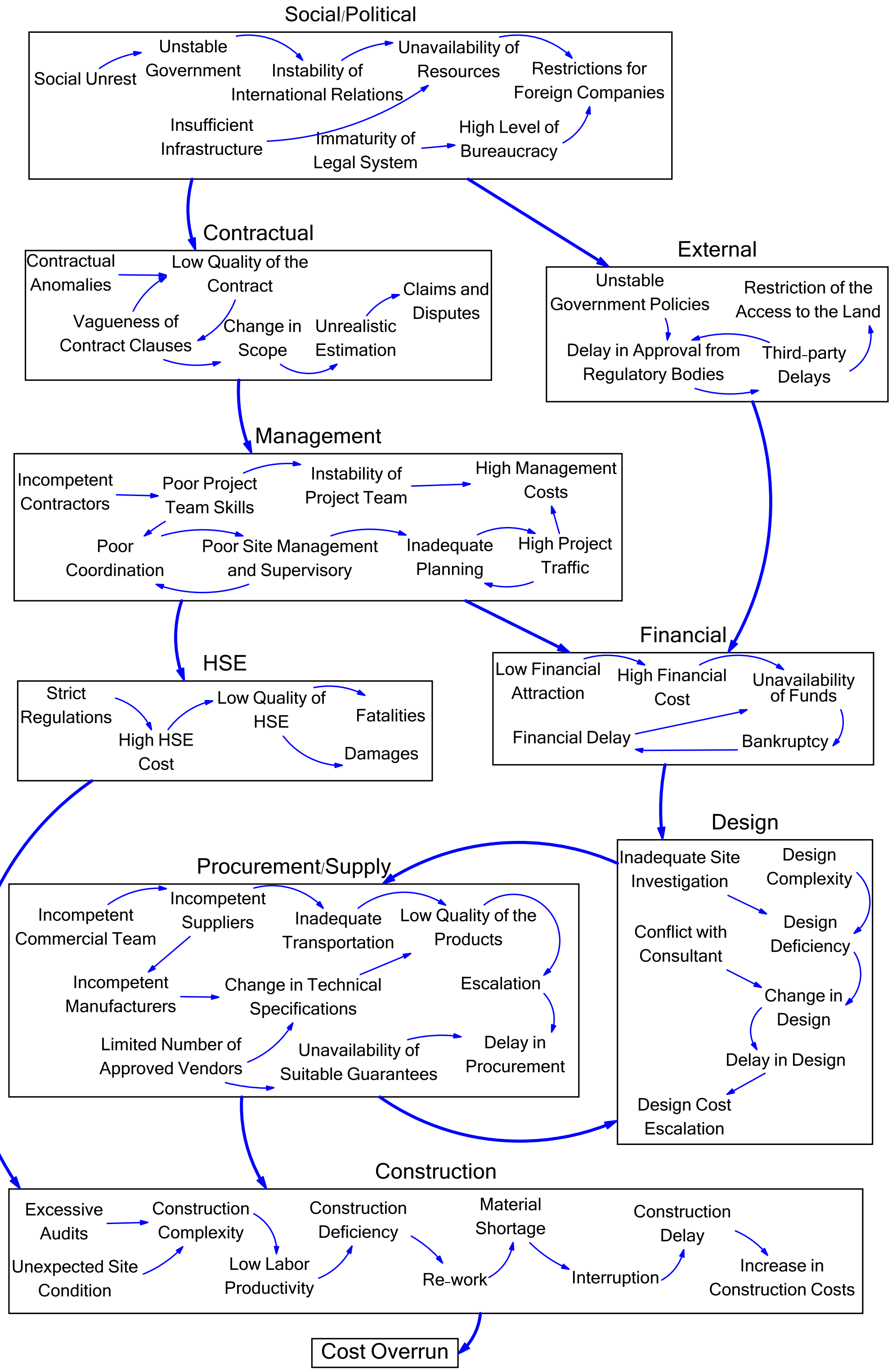


Fig. 2. Risk interaction network

the nature of political risks in actual projects is influenced only by the specific and idiosyncratic political and social conditions of any given country, the result is valid in the actual projects. As illustrated by the MICMAC analysis, the social/political category (with a dependence power of 0.24) is not completely independent from other categories. Therefore, as a basic purpose of the ISM method, Fig. 2 shows only the major risk interactions and ignores the minor interactions in order to illustrate the easier-to-comprehend network. The next level is the external and contractual risk categories, which are influenced only by the political and social conditions of any given country. In the linkage cluster there is only the financial risk category, which is considered to be the key factor of the network because it has both strong drive and strong dependence powers. In contrast there is the HSE (health, safety, and environment) risk category, which is the only autonomous factor and is somehow isolated from the other categories. The remaining three categories—construction, design, and supply/procurement—are located in the dependent cluster, having strong dependence power and weak drive

Table 6. Final Drive Power and Dependence Power

Risk factor	Drive power	Dependence power
Unavailability of funds	0.32	0.42
Low financial attraction	0.39	0.20
High financial cost	0.39	0.25
Financial delay	0.33	0.43
Bankruptcy	0.32	0.46
Change in scope	0.33	0.20
Contractual anomalies	0.51	0.12
Claims and disputes	0.18	0.30
Unrealistic estimation	0.26	0.25
Vagueness of contract clauses	0.46	0.20
Low quality of the contract	0.44	0.20
Change in design	0.24	0.41
Design complexity	0.32	0.19
Design deficiency	0.27	0.32
Inadequate site investigation	0.32	0.17
Conflict with consultant	0.27	0.18
Delay in design	0.20	0.44
Design cost escalation	0.15	0.51
Damages	0.15	0.25
Fatalities	0.14	0.25
High HSE cost	0.23	0.20
Low quality of HSE	0.27	0.21
Strict regulations	0.34	0.13
Inadequate planning	0.29	0.25
Poor project team skills	0.47	0.13
Poor coordination	0.35	0.21
Poor site management and supervisory	0.38	0.19
Incompetent contractors	0.45	0.11
Instability of project team	0.26	0.18
High project traffic	0.29	0.23
High management costs	0.15	0.33
Construction delay	0.12	0.61
Increase in construction costs	0.10	0.67
Construction deficiency	0.19	0.39
Low labor productivity	0.20	0.33
Material shortage	0.16	0.43
Excessive audits	0.22	0.19
Unexpected site condition	0.25	0.19
Interruption	0.14	0.56
Rework	0.18	0.46
Construction complexity	0.22	0.29
Unstable government	0.40	0.08
Immaturity of legal system	0.34	0.06
High level of bureaucracy	0.24	0.09
Social unrest	0.37	0.08
Instability of international relations	0.35	0.11
Unavailability of resources	0.26	0.15
Restrictions for foreign companies	0.23	0.19
Insufficient infrastructure	0.32	0.08
Delay in approval from regulatory bodies	0.37	0.16
Third-party delays	0.35	0.16
Unstable government policies	0.43	0.10
Restriction of the access to the site	0.22	0.20
Incompetent commercial team	0.34	0.16
Incompetent suppliers	0.30	0.20
Incompetent manufacturers	0.26	0.24
Change in technical specifications	0.21	0.31
Delay in procurement	0.12	0.51
Escalation	0.14	0.44
Limited number of approved vendors	0.24	0.16
Unavailability of suitable guarantees	0.15	0.18
Inadequate transportation	0.19	0.25
Low quality of the products	0.18	0.43

power. For example, the construction risk category has an influence only on the cost overrun category but is influenced by all the other risk categories involved.

Analyzing the risk factors, most of the risks are in the autonomous cluster (Fig. 3). This means they have a weak drive power and weak dependence power. Therefore, any changes in their probability do not have considerable effects on the overall cost overrun of projects. In the independent cluster there is only contractual anomalies. This means it has a strong drive power but weak dependence power. Because contractual anomalies can influence the other risks of a project, controlling this risk can decrease the probability of the occurrence of the other risks and of cost overruns in the entire project. The next group includes the dependent risks. Risk numbers 18, 32, 33, 39, and 58 are in this group, which means that design cost escalation, construction delay, increase in construction costs, interruption, and delay in procurement all have weak drive power but strong dependence. Therefore, these risks are acted upon and influenced more than the others, and by controlling them during the project's execution and development, the effect of the other risks on the cost overrun can be controlled.

Conclusions and Recommendations

In this paper, the risk interactions in construction projects were identified by proposing a new method, fuzzy weighted interpretive structural modeling. In this approach, the standard ISM method is improved by categorizing the risk factors and assigning a fuzzy weight for each interaction. To do this, 63 risks distributed in nine categories were identified in construction projects, and their interactions were carefully and clearly specified. The ISM is an effective method in modeling the relationships between and among the factors of a system because it produces a structured model or graphical representation of the original problem that can be communicated more effectively to others, and it also enhances the quality of the interdisciplinary and interpersonal communication in the context of the problem-related and problem-bearing situation by focusing the attention of the participants on one specific question at a time. One limitation of the ISM method is that it is not practical in systems with too many elements in operation. This paper, however, by categorizing the risks and modeling each category through the use of the ISM method, eliminated this limitation. Another limitation of the ISM method is its tendency to ignore the weight of the relationships among the factors involved. This paper solved this limitation by specifying and rating the amount of mutual relationship between each pair of risks as individually grouped fuzzy numbers. Fuzzy logic was thus used to consider the uncertain nature of the risk interaction and human judgement. In addition, ISM cannot be statistically validated. However, this paper applied the Delphi method so further construct validation could be employed by asking experts to validate the researcher's interpretation, categorization of the variables, and the results. The fact that Delphi is not anonymous (to the researcher) permits this validation step, unlike many surveys (Okoli and Pawlowski 2004). In this paper, the validation was carried out by presenting the results to experts. Finally, by considering the number of the relationships, a network of risks in construction projects was developed and designed. In addition, the MICMAC analysis performed on the risk network specified to what extent each risk influenced the other risks and was influenced by them. The result of the MICMAC analysis was that contractual anomalies influences the other risks of the project, so controlling this risk can subsequently decrease the probability of the occurrence of the other risks and project cost overrun. In addition, design cost escalation, construction delay, increase in construction costs,

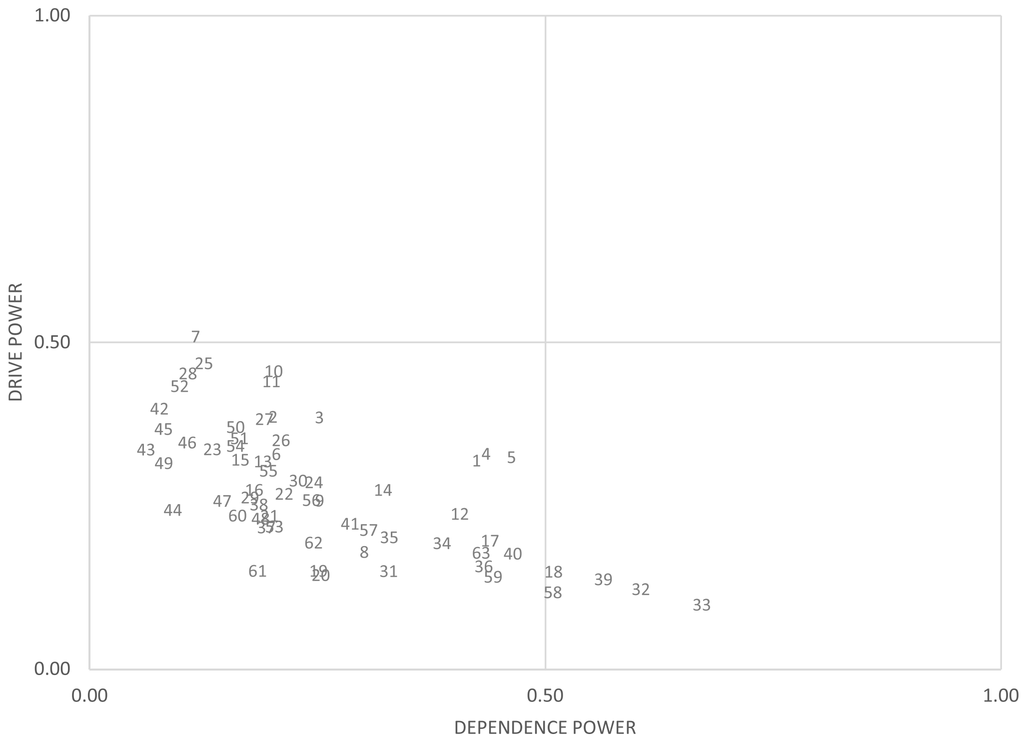


Fig. 3. MICMAC diagram for risk factors

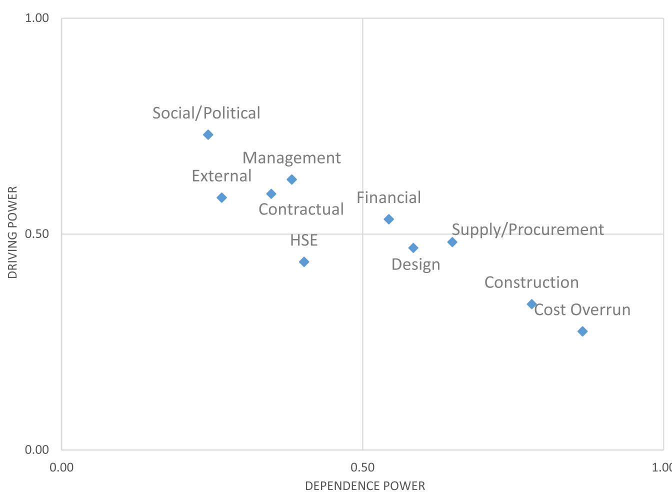


Fig. 4. MICMAC diagram for risk categories

interruption, and delay in procurement were influenced more than the others, and thus by controlling them during the project the effect of the other risks on the cost overrun in the project can be controlled properly.

Because this paper specified the interactions among the risk factors in each individual category and also among the risk categories themselves, one limitation is that it was assumed that the risk factors in separate risk categories are not directly related to each other. For instance, direct interaction of a design risk factor such as design complexity and a construction risk factor such as construction delay was not analyzed in this research. In practice, this limitation is inevitable when there are too many factors in a system.

Furthermore, the ISM method is unable to deal with the dynamic and time-related behavior of the risk factors. Therefore, it is recommended that the dynamic behavior of the resultant network of this paper should be analyzed using standard dynamic methods such as system dynamics.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal*'s data sharing policy can be found here: http://ascelibrary.org/doi/10.1061/%28ASCE%29CO.1943-7862.0001263.

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