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A Weighted Fuzzy Social Network Analysis-Based Approach for Modeling and Analyzing Relationships Among Risk Factors Affecting Project Delays

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Abstract: In the last decade, it has been increasingly recognized that efforts to address project delays without understanding the relationships among risk factors (*RFs*) could be futile. In light of the limitations of previous research that has addressed this issue, this study seeks to contribute to the literature by developing a novel weighted fuzzy social network analysis (SNA)-based approach, which accounts for the likelihood of occurrence and the impact of *RFs* on one another. To validate its practicality, the approach is applied to a demonstrative study in which the causes of delays in real-world electrical installation projects were modeled and analyzed. In addition to providing a holistic view of relationships among *RFs*, the proposed approach enables engineering managers to identify the root causes of delays and their corresponding critical propagation paths. Compared to other approaches in the literature, the value of the approach lies in its simplicity and utility for supporting engineering managers in developing effective risk-mitigation plans to minimize the severity of project delays.

Keywords: modeling, network, project delays, risk factors

EMJ Focus Areas: Decision making & risk management, program & project management

Introduction

Over the past several decades, organizations have increased their use of projects to deliver and structure operational objectives (Chipulu et al., 2019). However, despite the mature use and advances made in project management, a delay is still considered typical for all types of projects, regardless of their context (Sekar et al., 2018; Senesi et al., 2015). For instance, Kumar and Thakkar (2017) reported that a public R&D project in India, which was initially planned for seven years, took 12 years to complete. Calvo et al. (2019) indicated that between 2011 and 2016, 42% of public projects in the United States were behind schedule. In Tanzania, 82% of power construction projects that a major electric supply company carried out had an average delay of six months (Kikwasi, 2012). According to Pall et al. (2020), approximately 80% of foreign-aided development projects related to power transmission were delayed in Bangladesh.

Apart from its negative impact on project delivery, a delay can cause several significant consequences (Pehlivan & Öztemir, 2018; Sambasivan & Soon, 2007). For instance, Haseeb et al. (2011) pointed out that a delay means a loss of income and the unavailability of facilities for an owner. For a contractor, a delay means a financial loss due to extra expenses for materials and equipment, labor costs, and loss of time. Kikwasi (2012) identified that project delays cause disputes, waste of resources, overruns in cost and time, and negative social impacts. Owolabi James et al. (2014) studied the causes and effects of delays on project delivery time. They found that delays may result in increases in expenditure, which could lead to an increase in the final costs of a project and the wastage and underutilization of manpower and resources.

Understanding the causes of delay can assist in the development of proactive risk management strategies to minimize negative consequences. A considerable amount of research has therefore been conducted to investigate the causes of delays in different types of projects, including electrical installation projects (e.g., Hamdan et al., 2019), research and development projects (e.g., Alnemer et al., 2020; Grant et al., 2006; Tohumcu & Karasakal, 2010), and software development projects (e.g., Akrofi, 2017; Ma et al., 2000). However, greater emphasis has been placed on construction projects, as the literature reviews of Sanni-Anibire et al. (2020) and Zidane and Andersen (2018) demonstrate.

Until the early 2000s, the common objective of most studies investigating the causes of project delays was to identify the major general risk factors (*RFs*) causing delays in a particular country through opinion surveys of contractors, clients, and/or consultants. Statistical tools were then used to rank the contributing factors and identify the most important ones. The underlying assumption of most previous studies on ranking *RFs* is that each *RF* is directly related to project delays, and the *RFs* are independent. In other words, the relationships between project delays and *RFs* can be modeled by a "hub-and-spoke" model, ignoring the fact that relationships exist among the various *RFs*. However, in reality, project delays are not the result of independent events. They often occur as a result of a domino effect, where events are triggered as result of one or more other events (Bashir et al., 2020).

However, in the late 2000s, several studies recognized that an understanding of the relationships among *RFs* was crucial for the development of effective mitigation plans (Fang & Marle, 2012). Considering the limitations of these studies (see the following section), this article presents a novel weighted fuzzy network theory–based analysis approach for modeling and analyzing the vagueness and uncertainty of relationships among *RFs*. In addition to assessing the strengths of the

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relationships among *RFs* in terms of both likelihood of occurrence and impact, the approach enables engineering managers to identify the root causes of project delays and their corresponding critical propagation paths, which would enable them to develop and evaluate mitigation plans.

Review of Literature

As mentioned above, until the late 2000s, the focus of almost all studies was on identifying and ranking the primary *RFs* causing project delays without considering the relationships among *RFs*. Since the late 2000s, increasing recognition has been given to the importance of modeling and analyzing the relationships among *RFs* causing delays or other *RFs* affecting a project's performance, as a prerequisite step in the development of effective mitigation plans. Accordingly, several studies have been proposed in the literature. These studies modeled the relationships using structural equation modeling (SEM), design structure matrix (DSM), interpretive structural modeling (ISM) with cross-impact matrix multiplication applied to classification (MICMAC) analysis, or network-based approaches.

Utilizing Structural Equation Modeling

The work by Yang and Ou (2008) was perhaps one of the earliest studies considering the relationships among *RFs* affecting project delays by utilizing SEM. Yang and Ou (2008), developed a model consisting of 37 *RFs* causing project delays grouped under six categories; the authors used data collected via a questionnaire from 253 clients and practitioners in the Taiwanese construction industry. Eybpoosh et al. (2011) and Liu et al. (2016) also used the SEM technique. In the former study, the technique was used to model the relationships among *RFs* based on data collected from 104 professionals from Chinese international contractors. In the latter study, the SEM technique was used to model the relationships among *RFs* affecting schedule, quality, and cost based on data collected from 104 professionals from Chinese international contracting firms.

Modeling with DSM

Fang and Marle (2012) developed a framework for modeling and analyzing project *RFs*. This framework includes assessing the strengths of *RF* relationships using an AHP-based method, using a DSM (referred to as a risk structure matrix) to create a network, and analyzing the propagation behavior in the network using simulation to prioritize the *RFs*. The proposed framework was applied to staging a musical show in France. Fang et al. (2012) proposed an approach to addressing *RF* relationships, which (like the study by Fang and Marle (2012) involved using a *RF* structure matrix to represent the relationships among the *RFs*. However, the approach used a scale (from 0 to 10) instead of AHP for assessing both the impact and likelihood occurrence for each *RF*. Then based on their consequences values, the *RFs* are ranked in terms of their criticalities. The same scale was used to conduct a topological analysis of the project *RF* network to assess the strengths of the *RF* relationships, which were then used as inputs for a number of selected metrics.

Modeling with an ISM-MICMAC Analysis

Alzebdeh et al. (2015) and Arantes and Ferreira (2021) used ISM with the classical version of MICMAC analysis for modeling and analyzing *RFs*. Alzebdeh et al. (2015) applied this combination to *RFs* that caused cost overruns in construction projects in Oman, whereas Arantes and Ferreira (2021) applied it to *RFs* that caused delays in construction projects in Portugal. Alnemer et al. (2020) and Tavakolan and Etemadinia (2017) used ISM with a fuzzy version of a MICMAC analysis to account for the strengths of the relationships among *RFs*. Alnemer et al. (2020) focused on modeling and analyzing *RFs* that caused delays in public R&D projects in the United Arab Emirates, whereas Tavakolan and Etemadinia (2017) used a similar approach for modeling and analyzing *RFs* that caused cost overruns in construction projects in Iran.

Modeling with Network-Based Approaches

Kumar and Thakkar (2017) used an analytic network process based on a quantitative approach for measuring *RF* interdependence, to prioritize *RFs* that affected schedule and cost overruns for a public R&D project in India. A systems dynamics approach was subsequently implemented to build two models (technological and economic) representing the dependencies among the *RFs*. Zarei et al. (2018) adopted a semantic network analysis approach to visualize and thus understand the relationships among the causes of delays. This approach was demonstrated using a case study that involved analyzing the causes of delay for three Iranian petrochemical construction projects. Chen et al. (2020) developed an approach in which construction schedule *RFs* were first identified from the perspective of dialectical systems at the industry level. Global experts further verified these *RFs*, and a questionnaire survey was conducted based on the Chinese infrastructure industry. The key challenges and solutions were then identified using a network theory-based analysis at the project level for a real infrastructure case. Bashir et al. (2020) proposed the use of social network analysis (SNA) with a fuzzy MICMAC analysis for modeling *RFs* that caused project delays. This approach was illustrated via a demonstrative study that involved modeling and analyzing *RFs* that caused delays in construction projects carried out by an organization in the United Arab Emirates. Ganbat et al. (2020) aimed to identify critical *RFs* in international engineering procurement construction projects of Chinese contractors using SNA metrics.

Other studies considered uncertainty using a Bayesian belief network (BBN) to model the relationships among *RFs*, such as Qazi and Dikmen (2019) and Qazi et al. (2020). For instance, Qazi et al. (2020) modeled the relationships among *RFs* with a BBN to develop a prioritization scheme to support a decision maker. Their tool ranked *RFs* and opportunities in accordance with their loss-averse/gain-seeking behaviors.

Research Gap and Study Justification

One limitation of applying SEM (Eybpoosh et al., 2011; Liu et al., 2016; Yang & Ou, 2008) is that two main conditions must be met: sample size and distributional assumptions. The sample size must be sufficiently large. According to the heuristics proposed by Jackson (2003), the ratio of the number of cases to the number of parameters should be 20:1. The other condition is that the maximum likelihood method, typically utilized for estimating parameters and computing model fit, requires normally distributed continuous variables. Alternatively, a distribution-free method known as weighted least squares can be utilized, but the sample size must be exceptionally large (Kline, 2016). Unfortunately, neither of these two conditions can be easily met in the context of the problem described in this article. Moreover, none of the studies by Fang and Marle

(2012), Fang et al. (2012), Kumar and Thakkar (2017), Yang and Ou (2008), and Zarei et al. (2018) utilized metrics that numerically characterized the attributes of each *RF* compared with the others. In contrast, Alzebdeh et al. (2015), Bashir et al. (2020), and Fang et al. (2012) and utilized a number of metrics. Finally, all the previously mentioned studies excluding Alnemer et al. (2020), Bashir et al. (2020), and Tavakolan and Etemadinia (2017), used binary relations (0 or 1) or weightings to measure the strengths of the relationships among the *RFs*. However, such relationships are often vague and cannot be precisely assessed. Alnemer et al. (2020), Bashir et al. (2020), and Tavakolan and Etemadinia (2017) overcame this limitation by utilizing fuzzy set theory. However, none of these studies accounts for both the likelihood of occurrence and the impact of *RFs* on one another. In Alnemer et al. (2020) and Bashir, the relationships among the *RFs w*ere measured in terms of their level on impact on one another, whereas Tavakolan and Etemadinia (2017) measured the relationships among the *RFs* in terms of likelihood of occurrence. Moreover, a common limitation of these studies is that the use of ISM requires removing transitivity, which means that not all the *RF* propagation paths can be shown in the graphical models produced to visualize the relationships among the *RFs*.

Finally, in addition to the complexity that might limit their practicality, the use of the BBN-based methods presented in Qazi and Dikmen (2019) and Qazi et al. (2020) might be more meaningful and valuable if experts identify prior probabilities and then use empirical data to update the models. However, such requirements might not be attainable in practice (Chen & Pollino, 2012).

Noting the limitations mentioned above, this study contributes to the literature by proposing a weighted fuzzy SNA approach for modeling and analyzing the vagueness and uncertainty of relationships among *RFs*, assessing both the likelihood and impact of occurrence. In addition to providing a holistic view of the nature of relationships among *RFs*, the proposed approach enables engineering managers to identify the root causes of delays and their corresponding critical propagation paths. The practicality of the approach is shown through an illustrative study involving modeling and analyzing *RFs* that cause delays in real-world electrical installation projects.

Social Network Analysis

Social network analysis (SNA) grew from movements in sociology in the 1930s, which employed statistical and computational methods, including some aspects of graph theory, to study the relationships between social entities, referred to as actors (Moreno, 1960). However, in the past three decades, SNA has been increasingly applied to various other fields, where its applications have been extended to modeling relationships among non-human objects. In addition to its application to project risk management as indicated earlier, there have been several applications of SNA in engineering management research. Examples of recent studies include those of Al Zaabi and Bashir (2018), Mok et al. (2017), and Pryke et al. (2018), and while early SNA applications considered either binary or weighted associations among actors, the use of fuzzy SNA approaches to cater to imprecise and vague relationships between actors in some applications is growing in popularity. Recent examples of studies that have adopted this fuzzy approach are Al Zaabi and Bashir et al. (2020), Bashir et al. (2022), and Chu et al. (2016).

A major advantage of using SNA is that it enables users to visualize the relationships among the actors (the objects being investigated, such as people, organizations, factors, etc.) by constructing a network comprised of *nodes* connected by either directed or undirected *links*. In addition to visualizing the problem, SNA involves analyzing the network's structure utilizing a set of network-level metrics and node-level metrics.

Methodological Approach

The proposed approach involves the following major four steps: (1) identification of *RFs* causing project delays and the binary relationships among them, (2) the development of a fuzzy weighted impact matrix, (3) the construction of the network of *RFs*, and (4) conducting a quantitative analysis. These steps are illustrated via a real-world study that involves modeling and analyzing the *RFs* that caused delays in electrical installation projects conducted by a major utility company. The projects carried out by this company have an average delay of 40%. Notably, a typical electrical installation project can take between six and eight months and involves the following major activities:

- Designing the internal electrical system.
- Fixing all of pipes, conduits, and ducts either vertically on the walls or horizontally on the ground.
- Pulling all of wires and cables.
- Installing, connecting, and tightening all distribution boards (DBs) in readiness for the final power supply connection.
- Approving drawings of the electrical system design completed by the service providers for the project.
- Performing inspections.
- Fixing the transformers and switchgears in the electrical room of the building and laying the external main cables.

Step 1: Identification of Risk Factors and Their Binary Relationships

The key *RFs* that cause project delays can be identified from the collective experience of project teams using different techniques, such as Delphi, brainstorming, or others. In this illustrative study, we formed an expert panel comprising five project managers (who were involved in past projects undertaken by the company). In a brainstorming session, the panel of experts identified the following 13 *RFs*:

1. Poor management of schedules by the contractor
2. Failure to fulfill building requirements
3. Changing orders by owners
4. Delays in material delivery/out-of-stock material
5. Miscommunication or lack of communication between project stakeholders
6. Conflict between owners and contactors
7. Lack of owner experience
8. Poor qualifications among the contractor's technical staff
9. Delays in performing inspections
10. Delays in performing rectifications
11. Delays in getting permits/approvals from the municipality/various government authorities
12. Regulatory changes based on building type, safety, and quality requirements
13. Delays in submitting as-built drawings

Exhibit 1. Binary adjacency matrix

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14
RF1	0	0	0	1	0	1	0	0	1	1	0	0	1	0
RF2	0	0	0	0	0	1	0	0	0	0	0	0	0	0
RF3	0	0	0	0	0	0	0	0	0	0	0	0	1	0
RF4	0	0	0	0	0	0	0	0	1	0	0	0	0	0
RF5	0	0	1	0	0	1	0	0	0	0	0	0	0	0
RF6	0	0	0	1	0	0	0	0	0	0	0	0	1	0
RF7	0	0	1	0	0	1	0	0	0	0	0	0	0	0
RF8	0	1	0	0	1	0	0	0	1	1	0	0	0	0
RF9	0	0	0	0	0	0	0	0	0	1	1	0	0	0
RF10	0	0	0	0	0	0	0	0	0	0	1	0	0	0
RF11	0	0	0	0	0	0	0	0	0	0	0	0	0	1
RF12	0	0	0	0	0	0	0	0	0	1	0	0	0	0
RF13	0	0	0	1	0	0	0	0	0	0	0	1	0	0
RF14	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Following this, the expert panel identifies the relationships between the *RFs* using an n x n matrix, termed a binary adjacency matrix (where n is the number of *RFs*). In this matrix, if the occurrence of RF_i would trigger the occurrence of RF_j, then the value of element e_{ij} (the element in row i and column j) is one; otherwise, the value is zero. For this illustrative study, the produced binary adjacency matrix produced is shown in Exhibit 1. This matrix represents the binary relationships among the identified 13 *RF*s and the project delays (*RF* 14).

Step 2: Development of a Fuzzy Weighted Impact Matrix

In this step, the off-diagonal elements with a value of one in the binary adjacency matrix are replaced with weights representing direct relationships between *RFs* in terms of both likelihood-of-occurrence and the impacts of the *RFs* on one another based on the fuzzy set theory by Zadeh (1976) in order to account for uncertainty and vagueness. A fuzzy set is commonly used to permit a gradual assessment of the membership of elements in a set. Membership functions can have different shapes, but triangular membership functions are utilized most often (Pedrycz, 1994). A triangular function is defined by a lower limit k, an upper limit m, and a value l, where $k < l < m$. Points k, l, and m represent the x coordinates of the three vertices of a membership function "$\mu_{\tilde{A}}(x)$" in a fuzzy set A, as defined by Equation (1).

$$\mu_{\tilde{A}}(x) = \begin{bmatrix} 0 & x < k \\ \frac{x-k}{l-k} & k \le x \le l \\ \frac{m-x}{m-l} & l \le x \le m \\ 0 & x > m \end{bmatrix} \tag{1}$$

As shown in Exhibit 2, the first task in this step is to develop linguistic likelihood and impact matrices. The linguistic likelihood matrices were constructed as follows: Each member of the panel of experts is asked to develop a linguistic likelihood matrix by replacing each element (e_{ij}) of one in the binary adjacency matrix by his/her subjective opinion of the likelihood that the occurrence of RF_i would trigger the occurrence of RF_j using linguistic variables described in Exhibit 3. The produced "N" linguistic likelihood matrices (where N is the number of experts involved) are then transformed into a single matrix, known as a fuzzy direct likelihood matrix. Similarly, the linguistic impact matrices are constructed as follows: Each member of the experts is asked to develop a matrix by replacing each entry e_{ij} of one in the binary adjacency matrix by his/her subjective opinion of the impact level of RF_i on the occurrence of RF_j (should RF_i materialize) using the linguistic variables given in Exhibit 4. The produced N linguistic impact matrices are then transformed into a single matrix known as a fuzzy direct impact

Exhibit 2. Development of a Fuzzy Weighted Impact Matrix

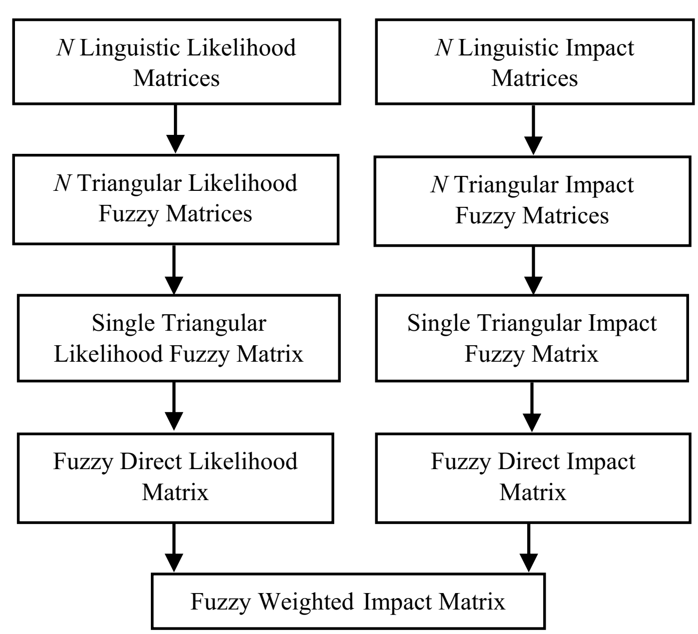


Exhibit 3. Linguistic Variables and their Triangular Fuzzy Transformation for the Likelihood

Linguistic variables	Triangular fuzzy number(*k, l, m*)
Very Unlikely (VU)	(0.0, 0.1, 0.3)
Unlikely (U)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Likely (L)	(0.5, 0.7, 0.9)
Very Likely (VL)	(0.7, 0.9, 1.0)

Exhibit 4. Linguistic Variables and their Triangular Fuzzy Transformation for the Impact

Linguistic variables	Triangular fuzzy number(*k, l, m*)
Very Low (VL)	(0.0, 0.1, 0.3)
Low (L)	(0.1, 0.3, 0.5)
Moderate (M)	(0.3, 0.5, 0.7)
High (H)	(0.5, 0.7, 0.9)
Very High (VH)	(0.7, 0.9, 1.0)

matrix. Multiplying the corresponding elements of the single fuzzy direct likelihood and fuzzy direct impact matrices produces a matrix known as a fuzzy weighted impact matrix.

The procedure of converting linguistic (likelihood or impact matrices) into the corresponding single fuzzy direct (likelihood or impact) matrix is undertaken as follows:

a. The elements of each of the N linguistic matrices are replaced with the corresponding triangular fuzzy number to obtain N triangular fuzzy matrices. It should be noted that the linguistic variables and their respective triangular fuzzy numbers can be defined in different ways (Hamdan & Cheaitou, 2017). However, those presented in Exhibit 3 and 4 are commonly used in relevant applications (e.g., Albastaki et al., 2021; Alnemer et al., 2020; Bashir et al., 2022; Bashir et al., 2020; Chen, 2000; Deng & Chan, 2011). In addition, those triangular numbers correspond to equally spaced crisp values (non-fuzzy values).
b. The N triangular fuzzy matrices are aggregated into a single matrix utilizing the average score method. No other statistics such as standard deviation or mode are required since the procedure does not require a comparison between different data sets. Moreover, the judgments on the relationships among the *RFs* are not expected to be widely scattered since they need to be provided by a small number of experts with comparable experience.
c. Each of the aggregated triangular fuzzy numbers in the single matrix is defuzzified to obtain the best non-fuzzy performance (BNP) values, as defined by Equation (2) —

$$BNP_{ij} = \frac{[(m-k)+(l-k)]}{3} + k \qquad (2)$$

—where ij indicates the crisp possible rating of the strength of relationship between RF_i and RF_j

Based on the inputs provided by the five experts, Exhibit 5 shows the produced fuzzy weighted impact matrix for the demonstrative study.

Step 3: Construction of the Network of RFs

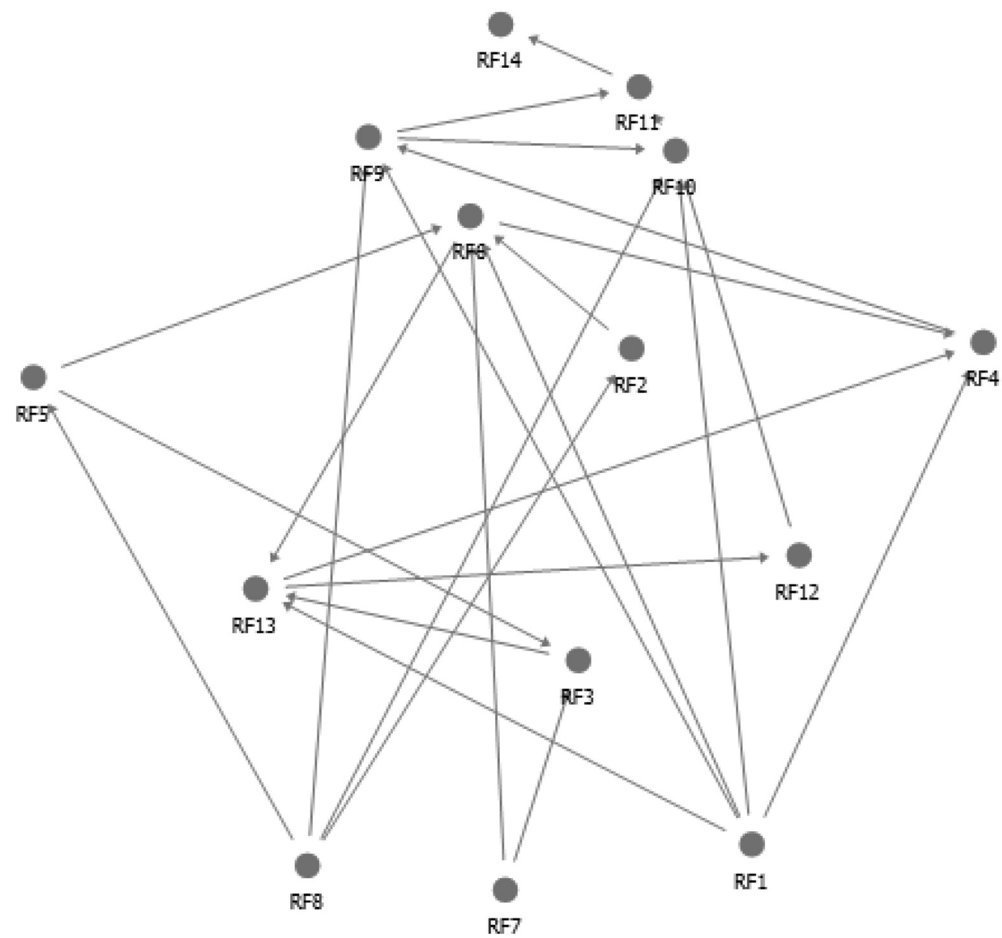
Visualizing the relationships among the *RFs* by constructing a simple graph consisting of nodes and links is an important step in the approach. This graph is useful because in multidimensional information-processing tasks, graphical feedback produces faster and more complete learning than numerical feedback (Hoffman et al., 1981). According to several studies (e.g., DeSanctis, 1984; Dickson et al., 1986), graphical displays improve the performance of decision makers in tasks such as identifying trends or detecting patterns of relationships among variables.

The network of *RFs* can be easily constructed utilizing any available SNA software package using the fuzzy weighted

Exhibit 5. Fuzzy Weighted Impact Matrix

	RF1	RF2	RF3	RF4	RF5	RF6	RF7	RF8	RF9	RF10	RF11	RF12	RF13	RF14
RF1	0	0	0	0.47	0	0.54	0	0	0.15	0.65	0	0	0.23	0
RF2	0	0	0	0	0	0.38	0	0	0	0	0	0	0	0
RF3	0	0	0	0	0	0	0	0	0	0	0	0	0.15	0
RF4	0	0	0	0	0	0	0	0	0.12	0	0	0	0	0
RF5	0	0	0.06	0	0	0.31	0	0	0	0	0	0	0	0
RF6	0	0	0	0.38	0	0	0	0	0	0	0	0	0.04	0
RF7	0	0	0.22	0	0	0.49	0	0	0	0	0	0	0	0
RF8	0	0.34	0	0	0.27	0	0	0	0.43	0.21	0	0	0	0
RF9	0	0	0	0	0	0	0	0	0	0.32	0.23	0	0	0
RF10	0	0	0	0	0	0	0	0	0	0	0.08	0	0	0
RF11	0	0	0	0	0	0	0	0	0	0	0	0	0	0.31
RF12	0	0	0	0	0	0	0	0	0	0.06	0	0	0	0
RF13	0	0	0	0	0	0	0	0	0	0	0	0.13	0	0
RF14	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Exhibit 6. Network of *RFs*



impact matrix as an input. The network shown in Exhibit 6 was constructed using the NetMiner Software Package for this illustrative study. This network consists of 14 nodes and 24 directed links, where the nodes represent the 13 *RFs* and the project delays (*RF 14*), and a link directed from RF_i to RF_j means that there is a likelihood that the occurrence of RF_i would trigger the occurrence of RF_j .

Step 4: Quantitative Analysis

Quantitative analysis involves using two SNA metrics, namely in-degree centrality and betweenness centrality (Wasserman & Faust, 1994), to identify the most critical *RFs*. It also involves identifying the critical propagation paths associated with the root causes of project delays.

During project execution, project delay is initiated by a combination of root causes that propagate through different paths in the *RF* network. Therefore, these paths should be considered during risk assessments (Yildiz et al., 2014). The knowledge of likely propagation paths and their impact on project delays, mitigation plan, can be directed toward avoiding the occurrence of *RFs* on critical paths, defined as those that have a high total weighted impact on project delays. Unlike previous studies that utilized SEM for identifying risk paths (Eybpoosh et al., 2011; Liu et al., 2016), this study defined a propagation path in a risk network as a sequence of linked *RFs* starting from a root cause node and ending with the project delays node. Root causes can be identified by determining the in-degree centrality value of each RF_i by computing the sum of all the values of column j of the fuzzy weighted impact matrix. *RF*s with zero in-degree centrality value are the root causes. If the network is simple, then the possible propagation paths can be easily identified on the risk network. Otherwise, any existing algorithm for finding all paths between specific nodes can be used, such as those developed by Migliore et al. (1990) and Tarjan (1972). The expected total effect of the *RFs* propagating along a path on project delay, referred to as the total weighted impact (TWP), can then be quantified using Equation (3). For each root cause, the path that has the maximum total weighted impact is considered critical.

$$TWP = \sum_{i}^{n} \sum_{j}^{n} WI_{ij} X_{ij} \tag{3}$$

Here WI_{ij} represents the impact of RF_i on RF_j, which can be obtained from a fuzzy weighted impact matrix; $X_{ij} = 1$ if RF_i and RF_j are directly linked, and 0 if not; and n is the number of *RFs*.

Since the in-degree centrality values are zeros for the three RFs, 1, 7, and 8 in this illustrative study, they were identified as the root causes of the project delays. As shown in Exhibit 7, 24 potential propagation paths could be triggered by these *RFs*. The paths were identified using the NetMiner software package,

Exhibit 7. Propagation Paths Associated with Root Causes

Root cause	Propagation Path	Total weighted impact
1	1 -> 4 -> 9 -> 10 -> 11 -> 14	1.30
	1 -> 4 -> 9 -> 11 -> 14	1.13
	1 -> 4 -> 9 -> 10 -> 11 -> 14	1.29
	1 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14	**1.75**
	1 -> 6 -> 4 -> 9 -> 11 -> 14	1.58
	1 -> 6 -> 13 -> 12 -> 10 -> 11 -> 14	1.16
	1 -> 9 -> 10 -> 11 -> 14	0.86
	1 -> 9 -> 11 -> 14	0.69
	1 -> 10 -> 11 -> 14	1.04
	1 -> 13 -> 12 -> 10 -> 11 -> 14	0.81
7	7 -> 3 -> 13 -> 12 -> 10 -> 11 -> 14	0.95
	7 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14	1.70
	7 -> 6 -> 4 -> 9 -> 11 -> 14	1.53
	7 -> 6 -> 13 -> 12 -> 10 -> 11 -> 14	1.11
8	**8 -> 2 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14**	**1.93**
	8 -> 2 -> 6 -> 4 -> 9 -> 11 -> 14	1.76
	8 -> 2 -> 6 -> 13 -> 12 -> 10 -> 11 -> 14	1.34
	8 -> 5 -> 3 -> 13 -> 12 -> 10 -> 11 -> 14	1.06
	8 -> 5 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14	1.79
	8 -> 5 -> 6 -> 4 -> 9 -> 11 -> 14	1.62
	8 -> 5 -> 6 -> 13 -> 12 -> 10 -> 11 -> 14	1.20
	8 -> 9 -> 10 -> 11 -> 14	1.14
	8 -> 9 -> 11 -> 14	0.97
	8 -> 10 -> 11 -> 14	0.60

Note: *Critical paths are in bold.

which implements a search method based on the algorithm by Migliore et al. (1990). The computed total weighted impact value for each potential propagation path is also given Exhibit 7. Accordingly, the paths 1 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14, 7 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14, and 8 -> 2 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14 are the most critical propagation paths that are initiated by *RFs* 1, 7, and 8.

Prioritizing the root node of each critical risk propagation path is one simple mitigation strategy. However, this may not always be an effective strategy because it ignores the fact that there might be some nodes that are of high importance because they are either part of multiple critical paths, such as *RFs* 4, 6, 9, 10, and 11, or they exist outside the most critical risk propagating paths but they have links with many *RFs* that belong to most critical propagation paths. We propose using betweenness centrality (BC_{i}) to identify such cases. This metric measures the number of paths in which a node participates (Wasserman & Faust, 1994). It is defined as follows:

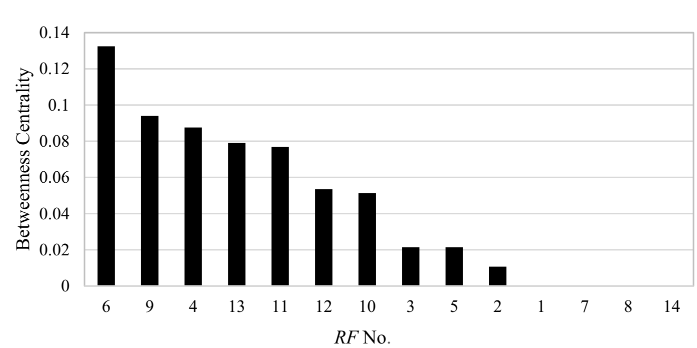
$$BC_i = \sum_{j<k} \frac{S_{jk}}{T_{jk}} \tag{4}$$

Where S_{jk} = the number of shortest paths connecting *RFs jk* passing through RF_i , and

T_{jk} = the total number of shortest paths connecting *RFs jk*.

Exhibit 8 shows the rank of the *RFs* in terms of their betweenness centrality values for the demonstrative study. Risk *RF 6* has the highest value; therefore, it should be considered one of the most critical *RFs* in addition to the root causes 1, 7, and 8.

Exhibit 8. Ranks of the *RFs*in Terms of Their Betweenness Centrality Values



Discussion and Implications for Engineering Managers

Decision-making in complex system environments necessitates identifying and understanding the relationships among the elements of the systems (Bendoly, 2014; Davies & Saunders, 1988; Größler et al., 2008; Saunders, 1992). This is also applicable to the development of an effective risk-mitigation plan for minimizing project delay severity. Therefore, engineering managers should consider that project delays are not a result of independent events; they occur as a result of a domino effect. As one or more events occur, they trigger other events. Accordingly, identifying and ranking the *RFs* causing project delays, analyzing their relational structures, and understanding their implications are vital to managing these *RFs* more effectively (Bashir et al., 2020). Failure to do so is perhaps one reason for the persistent problem of project delays in all types of industries–despite the emergence of advances in the practices, tools, and techniques of project management. Taking into account the limitations of previous research that has addressed this issue, this study equips engineering managers with a weighted fuzzy network theory-based analysis approach for modeling and analyzing relationships among *RFs* that affect project delays in terms of the two components of risks: likelihood and impact. By applying this approach, engineering managers are more likely to obtain an advantage in visualizing the relationships among the *RFs*, thus understanding how the occurrence of an *RF* will impact other directly and indirectly linked *RFs*. Moreover, the graphical modeling of the relationships among *RFs* is complemented by a quantitative analysis, which engineering managers can use to identify the root causes of delays and critical risk propagation paths.

Developing risk response strategies to cope with the identified critical *RFs* was beyond the scope of this study. However, the best mitigation strategy is to implement mitigation controls for the root causes that initiate critical risk propagation paths as well as those that have the highest betweenness centrality values. In the demonstrative study, three risks (1, 7, and 8) initiated 24 risk propagation paths for this demonstrative study.

Identifying risk propagation paths is very useful for predicting the sequence of *RFs* that will be triggered if an initiator *RF* occurs. For instance, as shown in Exhibit 7, if the owner of a project has a lack of experience (RF7), then four propagation paths could be triggered: 7 -> 3 -> 13 -> 12 -> 10 -> 11 -> 14, 7 -> 6 -> 4 -> 9 -> 10 -> 11 -> 14, 7 -> 6 -> 4 -> 9 -> 11 -> 14, and 7 -> 6 -> 13 -> 12 -> 10 -> 11 -> 14. One practical approach for developing a mitigation plan is to focus on *RFs* on the most critical path, which can be determined using the simple formula defined by Equation (3). Other *RFs* that should be prioritized are those with high values of betweenness centrality. Although these *RFs* may not initiate cascading risks or may not belong to a critical path, they contribute to multiple risk paths and therefore play an important role in the risk delay. For instance, in the demonstrative study, the conflict between owners and contractors (*RF6*) has the highest betweenness centrality when compared with the other *RF*s. This means that the occurrence of many *RFs* could lead to a conflict between the owners and contractors (*RF6)*, and the occurrence of *RF6* will lead to many other risks.

Conclusions

The major premise of this study is that, although several recent studies on facilitating the identification and ranking of *RFs* have taken into account the relationships among the *RFs*, very few studies have included the notions of imprecision and vagueness, and the modeling of the relationships among *RFs* in terms of both the likelihoods of concurrence and the impact. The novel weighted fuzzy SNA-based approach has been proposed in this article fills this knowledge gap, and its efficacy has been demonstrated through a real-world study. This approach uses subjective information about *RF* interrelationships gathered from a team of experts to enable the visualization of direct and higher-order dependencies among *RFs*. A quantitative analysis complemented this visualization, involving two SNA analysis metrics: measuring in-degree centrality and betweenness centrality. These metrics helped identify root causes and associated risk propagation paths that can lead to project delays. Accordingly, the outcome of this analysis helps engineering managers in developing effective mitigation strategies.

The proposed approach has several strengths, including the ability to use SNA to visualize all the relationships among the *RFs*, consideration of the uncertainty and fuzziness of measuring the relationships among the *RFs* in terms of the likelihood, occurrence and impact, and identification of the risk propagation paths. Furthermore, two of the main steps of this approach (network construction and quantitative analysis) can be easily performed using existing social network software packages, which makes the proposed approach easily transferable in practice. It is worth noting that one or more of these strengths can be found in existing approaches, but none of these approaches combines all of these characteristics.

Despite its strengths, the proposed approach has limitations that need to be addressed in future research. First, only two SNA analysis metrics were used to identify the most important nodes and thus prioritize the *RFs*. Second, experts are required to execute a large number of pair comparisons, and this may pose a challenge in implementation. Third, the approach does not model the dynamic and time-related behavior of the *RFs*. Finally, the efficacy of the approach was demonstrated using one real-world study to model *RFs* that cause delays in electrical installation projects carried out by a single company. Nonetheless, the results of this demonstration could encourage practitioners and researchers to further test the practicality of the approach in more real-world studies in different contexts.

Disclosure statement

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