# Modeling and Analyzing Factors Affecting Project Delays Using an Integrated Social Network-Fuzzy MICMAC Approach

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**Abstract:** Factors that cause project delays are directly and indirectly interrelated and asymmetrical in nature. Despite this, the majority of prior studies that have been conducted to identify and rank project delay factors have failed to account for interrelationships between factors. Arguably, without taking these interrelationships and their cumulative effect into account, it is unlikely that the challenges associated with construction project delays will be fully addressed. With this in mind, this article presents an integrated Social Network-Fuzzy *Integrated Network-fuzzy Cross-impact matrix multiplication analysis* (MICMAC) approach that considers the largely imprecise interrelationships between multiple project delay factors. The effectiveness

This is a peer-reviewed, accepted author manuscript of the following article: Bashir, H., Ojiako, U., & Mota, C. (2020). Modeling and analyzing factors affecting project delays using an integrated social network-fuzzy MICMAC approach. *Engineering Management Journal*, *32*(1), 26-36. https://doi.org/10.1080/10429247.2019.1656595

of the developed approach is shown through an illustrative demonstration that indicates the approach is effective in determining and analyzing the direct and indirect relational structures between the individual project delay factors. The value of the approach lies in its use for developing an effective risk-mitigation plan for minimizing the severity of project delays.

**Keywords:** Project Delays, Social Network, Fuzzy, *Integrated Network-fuzzy Cross-impact matrix multiplication analysis* (MICMAC)

## Introduction

The literature alludes to the critical role of projects in the delivery and structuring of operational objectives (Chipulu et al., 2019). In particular, organizations employ projects as platforms to plan, implement, and control value-driven initiatives (Parvan, Rahmandad, & Haghani, 2015). The construction industry is one of the most mature users of project management (Ibbs & Kwak, 2000; Cooke-Davies & Arzymanow, 2003); however, despite such mature use, numerous studies have reported that construction projects are particularly susceptible to delays (Senesi, Javernick, & Molenaar, 2015; Sekar, Viswanathan & Sambasivan, 2018). In fact, the literature notes that project delays in construction are "endemic" (Aibinu & Jagboro, 2002, p. 593; Padroth et al., 2017, p.1). Drawing upon Assaf and Al-Hejji (2006), project delays are construed as occurring when the completion of a construction project involves "…time overrun[s] either beyond completion date specified in a contract or beyond the date that the parties agreed upon for delivery of a project" (p. 349). There is substantial literature available on the causes of project delays in construction. Most recently, Zidane and Andersen (2018) undertook a comprehensive review of the literature on the causes of construction project delay in 45 countries extending from Afghanistan (Gidado & Niazai, 2012) to Zimbabwe (Nyoni & Bonga, 2017).

**Study rationale**

As perhaps expected, project delays generate negative consequences not only for project stakeholders but also for the wider construction industry (Senesi et al., 2015). For example, in addition to the cost of overruns (Kikwasi, 2012; Pehlivan & Öztemir, 2018), some studies have identified the prevalence of disputes (and associated litigation) as a consequence of construction project delay (Kikwasi, 2012; Gibbs et al., 2016; Padroth, Davis, & Morrissey, 2017). Other scholars have identified project failure in the form of project abandonment as a potential (and perhaps unintended) consequence of construction project delays (Aibinu & Jagboro, 2002; Sambasivan & Soon, 2007; Ojiako et al., 2018).

As mentioned above, construction project delay studies have been undertaken on a global scale as succinctly summarized by Zidane and Andersen (2018). That being the case, however, we advance arguments based on recent work by Chipulu et al. (2019) that there are limitations within the wider project success and project failure literature which apply to project delays. Among these arguments is that the extant literature appears to suggest that project success and project failure factors are directly related to project delays and are symmetrical. We contend that the limitations discussed by Chipulu et al. (2019) are evident in various project delay studies. In effect, our contention is that existing project delay literature has not fully acknowledged that individual project delay factors are not independent events; rather, they are directly and indirectly interrelated. Accordingly, it is of particular scholarly and practical importance that studies are undertaken not only to identify and rank the major causes of project delays as reported in the literature, but also to determine (by analysis) the nature of the relational structures of these individual delay factors. Our main contention is that addressing these two objectives will facilitate the mitigation of delay risk and minimize the severe impact of unintended consequences of project delays.

## Review of literature

### *Relevant studies*

While there is arguably a recognition of the need for studies that not only identify and rank the major causes of project delays but also determine the nature of relational structures between individual delay factors, the authors are only aware of two studies that have accomplished this. Yang and Ou (2008) employed Structural Equation Modeling (SEM) to analyze the relationships between the key causes of construction project delays. Based on data collected from 253 construction clients and contractors (via a questionnaire survey) as well as feedback from scheduling experts and senior engineers, they developed a model consisting of 37 interrelated key causes of project delays in the Taiwanese construction industry, which were grouped into six categories. Meanwhile, Zarei, Sharifi, and Chaghouee (2018) adopted a semantic network analysis approach to facilitate the generation of more accurate identification of the main factors causing delays in Iranian petrochemical construction projects. Using a focus group, they identified and ranked the major causes of project delays as reported in the literature. Accordingly, a semantic network was developed to serve as a visual tool for understanding the interactions between individual project delay factors.

The challenge with Yang and Ou's (2008) study is that applying SEM requires two main conditions to be satisfied. The first condition is that the sample size must be sufficiently large.

According to heuristics proposed by Jackson (2003), it is recommended that the number of cases to the number of parameters (factors) is at least 20:1. The second condition is that the maximum likelihood method, which is commonly used for estimating parameters and computing model fit, requires the availability of multivariate normally distributed continuous variables. Alternatively, a distribution-free method known as weighted least squares can be used, but the sample size must be exceptionally large (Kline, 2016). However, neither the study by Yang and Ou (2008) nor the study by Zarei et al. (2018) proposed the use of measures that numerically characterized the attributes of each cause compared with the other causes. Without such measures, comparisons that highlight the differences between important and unimportant causes are rather difficult to achieve; neither can sensitivity analyses be readily performed. It is important to note that the common objective of the above mentioned studies is to determine the major factors causing project delays at country level. Therefore, the reported results of such studies need to be supported with further work which organizations can carry out to identify the relevance and importance of any identified factors that are applicable to their own context. Taking the limitations of previous studies into account, we model and analyze factors causing project delays using a new approach that integrates social network analysis with fuzzy MICMAC analysis. In the next two sections of this article, we present an overview of *Social Network Analysis* (*SNA*) and *Cross-impact matrix multiplication analysis* (*MICMAC*), which both represent the key elements of the proposed approach.

### *Social Network Analysis* (*SNA*)

Social network analysis emerged from movements in the field of sociology, which in the 1930s began to employ statistical and computational methods, including some aspects of graph theory, to study the relationships between social entities referred to as *actors* (Moreno, 1960). Early SNA applications can be found in anthropology and psychology, particularly *sociometry* (Tichy, Tushman, & Fombrun, 1979).

There have been several applications of SNA in project and engineering management research; examples of recent studies being those of Parraguez, Eppinger and Maier (2015), Pryke et al. (2018) and Zarei et al. (2018). While it appears that early SNA applications considered either binary or weighted relationships among actors, the use of fuzzy SNA approaches to cater for imprecise and vague relationships between actors in some applications is growing. Recent examples of studies which have adopted this fuzzy approach are Brunelli, Fedrizzi and Fedrizzi (2014) and Chu, Liu and Wang (2016). However, there is still very limited application of fuzzy social relational networks to project delay studies.

A major step in the use of SNA is to visualize the relationships among the actors (the objects being investigated, such as people, organizations, and factors) by constructing a network consisting of *nodes* and *arcs* (Wasserman & Faust, 1994, p. 7). The nodes represent the actors, and the arcs represent the relationships (either binary or weighted) among them. The arcs can also be undirected or directed. In addition to visualizing the problem, SNA involves analyzing the structure of the network using a set of network-level measures and node-level measures.

*Network density* measures the relative number of ties between nodes in the network and is calculated as a ratio of the number of relationships that exist among nodes compared with the total number of possible ties if each node was tied to every other node (Wasserman & Faust, 1994). In an un-dichotomized network, the number of relationships is replaced with the sum of the weights assigned to the relationships. In the context of this article, this measure can be used as an indication of the complexity of the interrelationships among factors affecting project delays: as complexity increases, the risk of project delays increases. The implication is that, if the computed *network density* is found to be high, an action plan will need to be implemented in order to reduce the density of the network, thus minimizing the complexity of managing the risks of project delays. However, *network* density does not indicate which factors are highly dependent on others and which factors are more highly depended upon by others. To determine this, we propose the use of *degree-centrality* measures.

*Degree-centrality* measures are commonly used to determine the importance and/or classification of actors based on their direct relationships with others in the network (Freeman, 1979; Borgatti, 2005). Drawing from this literature, *degree centrality* is defined as the number of direct relationships that a node has. For a directed network, degree centrality is measured in terms of two separate measures (namely *in-degree* and *out-degree)*. Herein, *in-degree centrality* is construed as the number of direct incoming ties *to* a specific node, whereas *out-degree centrality* refers to the number of direct outgoing ties *from* a particular node. Again, in an un-dichotomized network, the number of relationships in both measures is replaced with the sum of the weights assigned to the relationships.

Based on these two measures, a node can be classified as one of five types: *isolate*, *transmitter*, *receiver*, *carrier*, or *ordinary*. An isolate node has a zero value in both *in-degree* and *out-degree* measures. If a node only has arcs originating outwards from it, then it is called a transmitter. If a node only has incoming arcs, then it is called a receiver. Both carrier nodes and ordinary nodes have positive *in-degree* and *out-degree*. However, if both *in-degree* and *out-degree* values are equal to one, then a node is called a carrier (Wasserman & Faust, 1994). In the context of project delays, it may be useful to analyze the factors in terms of their direct impacts on each other using *in-degree* and *out-degree* centrality measures. For instance, a factor with a high *out-degree* centrality can be considered critical because, if it occurs, it will directly trigger a large number of factors simultaneously. However, one of the limitations of the *out-degree* and *in-degree* centrality measures is that they do not consider accumulated or multilevel impacts. In other words, they only consider first-order interdependencies. For instance, if Factor *A* has an impact on Factor *B* and Factor *B* has an impact on Factor *C*, then both Factor *A* and Factor B are considered equally important since each has an *out-degree* centrality value of one. This means that the indirect relationship between Factor *A* and Factor *C* is ignored. However, if all relationships (direct and indirect) are considered, then it becomes reasonable to presume that Factor *A* is the most important factor due to its cumulative effects on two factors. Therefore, to analyze the interrelationships among factors, it is not enough to use *out-degree* centrality and *in-degree* centrality measures; they need to be complemented by measures that consider both direct and indirect relationships (higher-order interdependencies). For this purpose, we recommend supplementing the use of selected SNA measures with a Cross-impact matrix multiplication analysis (MICMAC).

*MICMAC Analysis*

The classic version of MICMAC analysis was developed by Duperrin and Godet (1973) in order to analyze the *driving power* and *dependence power* of variables. This is undertaken by considering not only their direct but also their indirect impacts. Accordingly, the variables are classified into four categories. The first category contains *autonomous* variables, which have a weak *driving power* and weak *dependence power*. The second category contains *dependent* variables, which have a weak *driving power* but a strong *dependence power*. The third category contains *linkage* variables, which have a strong *driving power* as well as a strong *dependence* *power*. Finally, the fourth category consists of *independent* variables, which have a strong *driving power* but a weak *dependence power*. One of the limitations of the classic version of MICMAC analysis is the use of only binary-type relationships (Dubey & Ali, 2014). To overcome this limitation, a *fuzzy* version of the classic MICMAC analysis has been integrated with interpretive structural modeling (ISM) and used in a number of applications such as logistics and supply chain management (Bhosale & Kant, 2016; Mishra, Singh, Rana, & Dwivedi, 2017). The use of MICMAC analysis has also extended to project and engineering management research. For example, Bredillet, Tywoniak and Tootoonchy (2018) utilized MICMAC analysis to explore the interrelationships that were prevalent in project management office changes.

## Methodological Approach

### *Overview*

The integration of social network analysis with a fuzzy MICMAC approach involves the following major steps: (i) identify factors causing project delays, (ii) identify interrelationships among factors, (iii) develop Fuzzy Adjacency Matrix, (iv) obtain MICMAC-stabilized matrix, (v) visualize the network, and (vi) conduct a quantitative analysis of interrelationships to identify the most critical factors.

These steps will be explained via a demonstrative study that involves modeling and analyzing the causes of delays in construction projects carried out by an organization in the United Arab Emirates (*henceforth*, UAE). The projects carried out by this organization have an average delay of 50%. It is, however, noted that the developed approach can be utilized by any project-based organization in any industry. The choice of a construction organization situated in the UAE was driven by the importance of the construction industry to the country's national economy. Construction and building services for example contribute about 8.73% of the country's Gross Domestic Product (Ministry of Economy, 2018). However, despite the importance of construction to the UAE economy, about 50% of all construction projects in the country do experience project delays (particularly in the form of time overruns) (Faridi & El Sayegh, 2006; Johnson & Babu, 2018). Findings on construction project delays in the UAE appear to be corroborated by similar studies conducted in the wider Gulf co-operation region, including, for example, the Sultanate of Oman (Ruqaishi & Bashir, 2015).

*Step1: Identify Factors Causing Project Delays*

The first step of the proposed approach involves the identification of factors causing project delays. These factors are identified from the literature based on expert opinion. In the demonstrative study, we formed an expert panel consisting of three practicing/practitioner project managers (who were involved with the projects under exploration) and two academics for this purpose. Most notably, a key selection criterion for the practitioner members of the expert panel was their demonstrated level of professional construction management experience which was considered approximate to the status of a Professional Engineer (PE). The two academic members of the panel both had substantial research experience in the areas of project success and project failure criteria. Identification of the factors causing project delays commenced with the collation of a comprehensive list of delay factors from UAE construction project delay literature wherein a total of nineteen delay factors were identified (Faridi & El-Sayegh, 2006; Motaleb & Kishk, 2010; Zaneldin, 2006; Ren, Atout, & Jones, 2008; Salama, Abd El hamid, & Keogh, 2008; Mpofu et al., 2017; Abdelhadi, Dulaimi, & Bajracharya, 2018). Following this, the expert panel then commenced with the examination of face validity of the identified delay factors. Accordingly, the total number of delay factors was reduced from nineteen to sixteen as follows:

1. Proposal drawing changes during construction
2. Poor and /or lack of monitoring and control
3. Work overload (of contractors)
4. Redoing work due to errors during construction
5. Poor and/or improper site inspection and testing
6. Unrealistic estimates of project duration
7. Poor management of schedules
8. Poor site management and supervision
9. Inadequate planning and scheduling
10. Poor coordination with subcontractors
11. Late delivery of materials
12. Manpower shortage
13. Low efficiency of equipment
14. Shortage of qualified and experienced manpower
15. Low manpower productivity
16. Poor interaction with vendors in engineering and procurement stages.

*Step 2: Identify Interrelationships among Factors*

This step focuses on the expert panel's identification of the interrelationships between the factors causing project delays. These interrelationships are represented in a $n$ x $n$ binary matrix, termed as an *adjacency matrix*, where $n$ is the number of factors. In this matrix, the factors are listed at the top and along the left-hand side. If factor $i$ influences factor $j$, then element $e_{ij}$ (the element in row $i$ and column $j$) is expressed as one (1); otherwise, it takes a zero value. In the demonstrative study, a *17* x *17* binary adjacency matrix was developed based on the literature review and in consultation with the expert panel. For simplicity, in the remaining sections of this article, the word *factors* refers to the sixteen identified influencing factors as well as to project delays (Factor 17), unless indicated otherwise.

*Step 3: Develop Fuzzy Adjacency Matrix*

The third step of the proposed approach is focused on development of a Fuzzy Adjacency Matrix. The adjacency matrix considers only binary relationships (0 or 1). In other words, the relationship that exists between any two factors is denoted by "1" if it exists or "0" if it does not exist. It is therefore assumed that all the existing relationships among factors are equally important. This limitation can be overcome by replacing the binary values in the initial adjacency matrix with weights representing the strength of the relationships among the factors. However, since they are imprecise and vague, it is generally not straightforward to identify the strengths among factors. The fuzzy set theory introduced by Zadeh (1965, 1976) is appropriate for dealing with this concern. Using a membership function valued in the real unit interval [0, 1], a fuzzy set is used to permit a gradual assessment of the membership of factors in a set. Membership functions can be of different shapes; however, triangular membership functions are used most frequently (Pedrycz, 1994). A triangular function is defined by a lower limit $l$, an upper limit $r$, and a value $m$, where $l < m < r$. The points $l$, $m$, and $r$ represent the $x$ coordinates of the three vertices of membership function"$\mu_{\tilde{A}}(x)$" in a fuzzy set $A$, defined by equation (1).

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

The expert panel assigns weight values to the relationships between factors using linguistic variables that are then converted into their corresponding triangular fuzzy numbers, as given in Exhibit 1. Assigning linguistic variables could be undertaken by consensus; alternately, each panel member could have been asked to use the linguistic variables to provide his or her subjective opinion on the strengths among the factors. The assigned linguistic variables are then converted into their corresponding triangular fuzzy numbers. It is noted that if the consensus approach is not adopted, then each relationship that exists between every two factors can be assigned different "*k*" triangular fuzzy numbers, where *k* is the number of people involved. These different triangular fuzzy numbers can then be combined into one triangular fuzzy number using the average score.

**[Insert Exhibit 1 here]**

Once a triangular fuzzy number is obtained for each relationship between every two factors, a fuzzy adjacency matrix is then obtained by *defuzzification* of the triangular fuzzy numbers into the best non-fuzzy performance (BNP) value, defined by equation (2) –

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

– where *ij* indicates the crisp possible rating of the strength between factors *i* and *j*.

The constructed fuzzy adjacency matrix for the demonstrative study is given in Exhibit 2.

**[Insert Exhibit 2 here]**

*Step 4: Obtaining a MICMAC-Stabilized Matrix*

To include the indirect relationships among the factors, the fuzzy adjacency matrix is multiplied by itself repeatedly until a stabilized matrix is obtained. The multiplication process is performed according to the principles of fuzzy matrix multiplication (Zadeh, 1965). For instance, the product of fuzzy matrix *A* and fuzzy matrix *B* is fuzzy matrix *C*, according to equation (3):

$$C = A, B = \max k \left[(\min \left(a_{ik}, b_{kj}\right)\right] \text{ where } A = [a_{ik}] \text{ and } B = \left[b_{kj}\right] \tag{3}$$

In the demonstrative study, the stabilized matrix shown in Exhibit 3 was obtained after two iterations.

**[Insert Exhibit 3 here]**

*Step 5: Visualize Network*

The fifth step of the proposed approach involves visualization. Visualization primarily involves representing data and information in the form of an image. One key advantage of visualization is that it facilitates the forming of greater and much more intricate understanding through its enabling mental images (Lengler & Eppler 2007). Of particular interest to this study is that the literature alludes to numerous advantages of visualization. For example, visualization enhances learning (Meyer, 1997) and information quality (Maltz, 2000). The advantages of visualization also extend to modeling (Crapo et al., 2000). In fact, the literature suggests that graphical displays improve decision-maker performances in tasks such as detecting and comparing trends or discovering patterns of relationships among variables (Liu et al., 2014).

The network could be easily plotted using any of the SNA software packages based on an adjacency matrix as an input. These packages have several features related to network plotting, including the ability to (i) display the weights on the arcs, (ii) to make an arc thickness that reflects weight, and (iii) to plot node size by *out-degree* or *in-degree* values. In the demonstrative study, the fuzzy adjacency matrix given in Exhibit 2 was used as an input to Social Network Visualizer (SocNetV) software, in order to construct a network consisting of 17 nodes and 26 arcs as shown in Exhibit 4. In this network, the nodes are sized to reflect their corresponding *out-degree* values. Accordingly, as reflected by their node sizes, it can be noted that Factors 3 and 9 have the maximum *out-degree* values. In contrast to extant literature, this network provided evidence that the relationships between project delays and the influencing factors cannot be represented by what can be colloquially described as a hub-and-spoke model.

**[Insert Exhibit 4 here]**

*Step 6: Quantitative Analysis and Discussion of Results*

The final step of the developed approach involves a quantitative analysis of interrelationships to identify the most critical factors. To analyze the interrelationships between the factors, the five measures mentioned earlier are used; namely, three SNA measures (*network density*, *in-degree* *centrality*, and *out-degree centrality*) and two MICMAC measures (*driving power* and *dependence power*).

*Network density* can be used to assess the complexity of the interrelationships in a network. From the literature, it can be opined that as project complexity increases, the potential for project delays also increases (Mirza & Ehsan, 2017). *Network density* is computed by adding all the entries of the fuzzy adjacency matrix (the sum of the *out-degree* values or the sum of the *in-degree* values) and dividing this by the total number of possible ties on the basis that each node is tied to every other node. Mathematically, this measure can take any positive value in the range of 0–1. If the value is 0, then no interrelationships exist between the factors. If the value is 1, then each factor has a complete association with each of the others. In the demonstrative study, the computed *network density* is 0.06, which indicates that the interrelationships between the factors are of low complexity.

The *in-degree centrality* of factor $j$ is used to quantify its direct dependency on the rest by computing the sum of all the values of column $j$ of the fuzzy adjacency matrix. At the same time, the *out-degree centrality* of factor $i$ is used to quantify its direct influence over the rest by computing the sum of all the values of row $i$ of the fuzzy adjacency matrix. The *dependence power* of factor $j$ is also employed to quantify its total dependency on the rest by computing the sum of all the values of column $j$ of the MICMAC-stabilized matrix. Similarly, the *driving power* of factor $i$ is employed to quantify its total influence over the rest by computing the sum of all the values of row $i$ of the MICMAC-stabilized matrix. Based on the above, the *driving power* of factor $i$ simply represents the overall impact of that factor on project delays.

Our computed values of *in-degree centrality*, *out-degree centrality*, *driving power,* and *dependence power* are shown in Exhibit 5. Notably, Factors 2, 3, 8, 9, 10, 13, 14, and 16 are transmitters, since each has a zero *in-degree centrality* value. Also, it can be noted that each of these factors has a zero *dependence power*. In fact, based on the definitions of these two measures, if an actor has a zero *in-degree centrality* value, then its *dependence power* must also be zero, and vice versa. It is worth noting that if the network shown in Exhibit 4 is converted to a hierarchical graph, then the factors with zero *dependence power* and zero *in-degree centrality* values will be placed in the bottom level of that graph.

**[Insert Exhibit 5 here]**

Exhibit 5 also shows that Factor 3 (*work overload (of contractors*) obtained the maximum score in terms of *driving power*, which meant that this factor had the maximum impact on project delays resulting from cascading effects. These cascading effects can be identified from Exhibit 4, as follows:

- *Work overload (of contractors)* (Factor 3) leads to *poor schedule management by contractors* (Factor 7),
- *Poor schedule management by contractors* (Factor 7) leads to *late delivery of materials* (Factor 11),
- *Late delivery of materials* (Factor 11) leads to *low manpower productivity (Factor 15)*, and finally
- *Low manpower productivity* (Factor 15) leads to *project delays* (Factor 17).

The next step of the quantitative analysis involves classifying the factors in terms of their interrelationships. Classifying the factors in terms of their total influence (direct and indirect) on each other involves constructing a *driving-dependence power* diagram by plotting *driver power* values versus *dependence power* values, following which the diagram is divided into four quadrants. The first quadrant (I) contains autonomous factors, the second quadrant (II) contains dependent factors, the third quadrant (III) contains linkage factors, and the fourth quadrant (IV) contains independent factors. Since the *driving-dependence power* diagram classifies the factors in terms of their total influence (direct and indirect) on each other, a similar diagram is constructed by plotting *out-degree centrality* values versus *in-degree centrality* values in order to classify the factors (in terms of their direct influence on each other) into autonomous factors, dependent factors, linkage factors, and independent factors. In the demonstration study, the constructed *driving-dependence power* diagram and *out-in-degree centrality* diagram are shown in Exhibits 6 and 7, respectively.

**[Insert Exhibit 6 here]**

**[Insert Exhibit 7 here]**

The factors classified as either independent or linkage factors by either diagram (the *out-in-degree centrality* diagram or the *driving-dependence power* diagram) are the key factors impacting upon project delays. Therefore, they should be given priority during risk-mitigation and, arguably theorized as known-unknowns of the past that ideally should never be repeated. This is so because independent factors identified via an *out-in-degree centrality* diagram are those that have considerable direct influence on other factors, whereas independent factors identified via a *driving-dependence power* diagram are those that have considerable total influence on other factors. Linkage factors are similar to independent factors in terms of having great influence on others as identified by either diagram, but in addition to this property, they are greatly affected by other factors.

No linkage factors were identified in the *driving-dependence power* diagram shown in Exhibit 6. Factors 1, 2, 3, 5, 9, and 14 are independent factors, Factors 11 and 15 are dependent factors, and the rest are autonomous factors. According to the *out-in-degree centrality* diagram shown in Exhibit 7, Factor 1 is a linkage factor, Factors 3, 7, 9, and 14 are independent factors, and the rest are autonomous factors. Thus, according to the classifications of factors obtained via the two diagrams, it can be concluded that *proposal drawing changes during construction* (Factor 1), *poor and/or lack of monitoring and control* (Factor 2), *work overload (of contractors)* (Factor 3), *poor and/or improper site inspection and testing* (Factor 5), *poor schedule management by contractors* (Factor 7), *poor and inadequate planning and scheduling* (Factor 9), and *shortages in qualified and experienced manpower* (Factor 14) are the key project delay factors. The ranking of these seven factors from highest to lowest in terms of their overall impact on project delays as measured by their *driving power* is Factor 3, 9, 5, 14, 2, 1, and then 7. Thus, *work overload (of contractors)* (Factor 3), has the most significant impact on project delays.

In addition to quantifying the interrelationships between the factors and then classifying them using the *out-in-degree* and *driving-dependence power* diagrams, it is deemed useful to conduct a what-if analysis that predicts specific decision outcomes. For instance, engineering managers and decision makers might be interested in quantifying the effect of eliminating a factor ($IF_i$) on project delays. This can be achieved by computing the overall *driving power* (*ODP*) obtained by adding the *driving power* values of all the factors affecting project delays and then applying equation (4) –

$$IE_i = \frac{DPF_i}{OPD} \times 100 \tag{4}$$

– where $DPF_i$ represents the *'driving power'* of Factor *i*.

For instance, if an action is taken that addresses concerns over *work overload (of contractors)*, then the impact of this action would be $(IE_3 = \frac{3.6}{25.10} \times 100 = 14.34\%)$. This means that, by addressing this issue, the overall risk of project delay would be reduced by 14.34%. However, if the decision is taken to address Factor 7, then the risk reduction would be 5.98%. These two examples demonstrate that decision makers can perform a form of sensitivity analysis to predict the outcomes of their decisions regarding the problem of project delays.

**Implications for Engineering Managers**

An important contribution of this article is developing a novel approach that integrates social network analysis with fuzzy MICMAC analysis for modeling and analyzing factors affecting project delays. This approach serves as a useful tool for engineering managers seeking ways to mitigate against project delays and their unintended consequences. The notion of project delay must be understood in the context of the nature of the complex interrelationship between the various individual delay factors. This requires that engineering managers not only focus on direct relationships but also on accumulative or multilevel impacts of the factors on each other. Drawing from Marshall et al. (2018), we contend that the developed approach is able to fulfill both risk mitigation and forecasting roles in that it is able to facilitate the transmission of *non-contextualized* risks (which are abstract and not project-specific) into *concrete* (in other words, project-specific) risk knowledge. By using the approach in this capacity for project risk management, engineering managers are more likely to gain an advantage from previous instances of project delays. One point that requires reiteration is that project delay may in fact be asymmetrically related to other project failure criteria (for example, cost overrun). For this reason, engineering managers must be fully aware that if a project is experiencing delay, this does not necessarily imply that the project should be construed as either a failed project or an unsuccessful project (both of which mean different things – see Baccarini (1999) Mahring and Keil (2008) and Bharadwaj et al. (2009)). In effect, being able to utilize this approach to identify, rank, and determine the nature of project delay factors is only one aspect of project delay mitigation. The second aspect involves engineering managers' ability to assess project outcomes or influence such assessment in a flexible manner.

## Conclusions

The major premise of this study is that, although the factors that cause construction project delays are directly and indirectly interrelated and also asymmetrical in nature, most prior studies that have sought to facilitate the identification, ranking, and determination of project delay factors have failed to take into account the nature of these interrelationships. To overcome this limitation, the authors encompassed notions of imprecision, indirectness, and vagueness to develop a novel integrated Social Network-Fuzzy MICMAC approach that was evinced for effective application through an illustrative demonstration. This approach employs subjective information about factor interrelationships obtained from a team of experts to enable the visualization and assessment of the influences on project delays induced by direct and higher-order dependencies among the factors. To quantify the interrelationships among factors causing project delays, the proposed approach involves the use of three SNA measures (*network density* and *in-degree centrality* and *out-degree centrality*) and two MICMAC measures (*dependence power and driving power*). Network density measure is useful for assessing the level of difficulty in managing the risk of project delays. In-degree and out-degree centrality measures are useful for analyzing direct interrelationships, whereas the other two measures are useful for analyzing overall (cumulative) influences. By plotting the values of the last four measures on two diagrams (an *out-in-degree centrality* diagram and a *driving-dependence power* diagram), factors can be categorized into four different groups. Using this categorization and by visualizing the interactions among factors through a constructed network, engineering managers can differentiate between independent and dependent factors and their mutual relationships and thus determine the key factors. Then, a sensitivity analysis can be performed in order to develop remedial strategies for minimizing the risks of delays in future projects.

As expected, the study does have a number of limitations. Firstly, although set within the context of projects known for their evolving and temporal nature (Bakker et al., 2016; Ligthart et al., 2016), no provisions for these project attributes were taken into consideration. Secondly, the developed approach did not consider the possible multi-dimensionality of individual delay factors (see Chipulu et al., 2019). Thirdly, only three measures of SNA (*network density*, *in-degree centrality,* and *out-degree centrality*) were taken into consideration in the developed approach. Therefore, the exploration of other SNA measures might be useful for analyzing interrelationships among factors, or for analyzing them from different perspectives. Arguably, these limitations offer future research directions in order to further refine the developed approach.

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