CSCE Annual Conference
Growing with youth – Croître avec les jeunes

Laval (Greater Montreal)
June 12 - 15, 2019

FRAMEWORK TO ESTABLISH THE RELATIONSHIP BETWEEN FACTORS INFLUENCING CONSTRUCTION PRODUCTIVITY USING FUZZY INTERPRETIVE STRUCTURAL MODELING

Yisshak Gebretekle[1], Nima Gerami Seresht[2], and Aminah Robinson Fayek[3,4]
[1] University of Alberta
[2] University of Alberta
[3] University of Alberta
[4] aminah.robinson@ualberta.ca

Abstract: Construction project productivity is affected by numerous factors that range from the micro level (i.e., activity, crew, and project levels) to the macro level (i.e., organizational, provincial, national, and global levels) and that may have either a direct or an indirect effect. Predictive models commonly map a set of inputs (i.e., influencing factors) to construction productivity but ignore the interrelationships between those different factors. The factors that influence construction productivity are, however, rarely independent from each other, and changes in certain factors may cause changes in other factors. It is therefore necessary to consider the interactions between factors in order to develop more comprehensive predictive models. This is a challenging problem due to the subjective uncertainties associated with the interactions between factors influencing construction productivity. In order to address these uncertainties, this paper combines fuzzy logic with the interpretive structural modeling (ISM) technique to create a fuzzy ISM approach for identifying the interrelationships between the factors that influence construction productivity. The proposed approach will assist in specifying the direction and degree of influence of the relationships between these factors, and it is also capable of categorizing factors based on their level of influence and dependency on other factors.

1 INTRODUCTION

The construction industry employs approximately seven percent of the world's working-age population and is one of the largest sectors of the world's economy, with $10 trillion spent on construction-related goods and services every year (Barbosa et al. 2017). On large-scale construction projects around the globe, improvements in project management and technological innovation can increase the chance of project success. Since construction productivity is an important factor in the profitability of construction projects, it is one of the most frequently used performance indicators for assessing the success of construction projects. Accordingly, productivity is a well-researched topic in the construction industry (Yi and Chan 2014). Construction activities, depending on the resource that drives their productivity, can be categorized as either labour-intensive or equipment-intensive. Extensive research has been conducted on the construction productivity of labour-intensive activities (Dai 2006; Jarkas and Bitar 2012; Tsehayae and Fayek 2014; Tsehayae and Fayek 2016; Yi and Chan 2014), and a handful of research papers have recently been published on the productivity of equipment-intensive activities (Ok and Sinha 2006; Goodrum et al. 2010; Gerami Seresht and Fayek 2018). The contributions of these papers include a critical review of previous works, a comprehensive list of factors influencing construction productivity, and an exploration of how these factors are used to predict productivity at the activity or project level. Predictive models developed for construction productivity commonly map a set of inputs (i.e., influencing factors) to construction productivity, but these models often ignore the interrelationships between those factors. Since each construction project works as a system, it can be argued that any influencing factor within the system has both an individual impact on construction productivity and an impact on other factors within the system. Therefore, it is necessary to account for the interactions of factors influencing construction productivity in order to develop a comprehensive productivity model.

The challenge in identifying the interrelationships between the factors that influence construction productivity lies in the uncertainty of each factor's strength of impact and its direction of influence. To address these uncertainties, this paper proposes a fuzzy interpretive structural modeling (fuzzy ISM) technique. ISM is an effective approach that is widely used to identify the relationships between different variables by creating a comprehensive systematic model of directly and indirectly related factors (Khatwani et al. 2015). The integration of ISM with fuzzy sets allows decision makers the flexibility to determine the level of influence of one factor over another. This is achieved by describing the degree of influence between two factors using a set of linguistic terms (e.g., low, medium, high), each of which represents an uncertain range of values from [0, 1], rather than the binary values of 0 and 1 that are used in ISM to represent the non-existence and existence, respectively, of a relationship.

The remainder of this paper is structured as follows: Section 2 presents a literature review of ISM and fuzzy logic; Section 3 illustrates the methodology for combining the two techniques to capture the relationships between the factors that influence construction productivity; Section 4 presents an application of the proposed methodology for the identification of relationships between a subset of those factors, which has been extracted from an illustrative data set; and Section 5 presents conclusions and future research directions.

2 LITREATURE REVIEW

2.1 Interpretive Structural Modeling (ISM)

ISM, first introduced by Warfield (1974), is a well-established methodology for identifying the relationships between the different variables of a dataset, which is developed to define a problem (e.g., construction productivity) in a given domain (e.g., construction management). The existence of a relationship between variables is presented in the form of binary numbers, where 0 stands for the non-existence and 1 stands for the existence of the relationship. ISM represents the relationships between variables using either (1) a digraph (i.e., a directed graph), which is a set of elements connected by arrows, or (2) a matrix (Hwang and Lin 1987). Thus, the ISM technique models the overall structure of a real-world system in an abstract way by establishing the interrelationships between its different components, from which the complex patterns of system behavior stem. It can be also considered a modeling technique, since the specific relationships and overall structure are portrayed in a digraph model (Attri, Dev, and Sharma 2013).

In spite of the capabilities of the ISM technique, it is challenging to use ISM to establish the interrelationships between the factors influencing construction productivity due to the uncertain nature of such relationships. More specifically, due to the subjective uncertainty of the factors that influence construction productivity, it is difficult to predict the magnitude of their impact on one another using binary values. Hence, the standard binary values used in the ISM technique may not be appropriate for measuring the interactions between these factors. Therefore, in this paper, fuzzy logic is hybridized with the ISM modeling technique to overcome this limitation.

2.2 Fuzzy ISM

The relationships that exist between the variables that define a problem in a given domain can be inherently uncertain, making it challenging to assign crisp numerical values to the magnitudes of those relationships. The concept of fuzzy logic was introduced to ISM to improve its ability to handle such uncertainties. Fuzzy logic is an appropriate technique for addressing the uncertain nature of the relationships between productivity factors, which are defined based on the subjective judgment of experts. First addressed by Zadeh (1965), fuzzy set theory, on which fuzzy logic is based, allows for a generalization of classical set theory that makes it possible to model complicated, uncertain, and ill-defined systems (Chan, Chan, and Yeung 2009). Fuzzy sets with non-sharp boundaries are typically able to use "linguistic variables and membership functions with varying grades to model uncertainty inherent in natural language" (Chan, Chan, and Yeung 2009).

Although fuzzy logic and ISM are both well-established concepts, the implementation of fuzzy ISM is a relatively new occurrence. Khatwani et al. (2015) used fuzzy ISM to determine the interrelationships between the different criteria taken into consideration when selecting vendors. By introducing fuzzy logic to ISM, it was possible to determine the degree of influence of one criterion over another. Bhosale and Kant (2016) used a methodology integrating fuzzy logic and ISM to inspect the interrelationships between supply chain knowledge flow enablers (SCKFEs). The ISM methodology analyzed the interactions between the SCKFEs, and fuzzy cross-impact matrix multiplication applied to classification (MICMAC) analysis was employed to obtain insights into the dependencies among the SCKFEs. Dube and Gawande (2015) used a fuzzy ISM-based methodology to identify the barriers to implementing a green supply chain and to understand their mutual relationships. Chaudhuri et al. (2016) proposed a fuzzy ISM-based methodology to identify the various risk drivers that affect a food processing supply chain and to map how those risk drivers propagate risks through the supply chain. Through the concept of fuzzy logic, the methodology proposed by Chaudhuri et al. (2016) can help to clarify the interrelationships between supply chain risks and between those risks and performance measures. Applications of fuzzy ISM-based approaches in construction management studies are even more recent. Etemadinia and Tavakolan (2016) and Tavakolan and Etemadinia (2017) used the fuzzy weighted ISM approach to establish a network of risk factor interactions on construction projects. Their work provided the necessary means for exploring the influence of a risk factor on project success and its dependence on others factors. In addition, it identified the key factors that drive the management of project risks and ranked the factors based on their degree of influence on project success.

Although the capacity of a fuzzy ISM approach to identify the interrelationships between different factors of a system has been proven in previous research, there is no study implementing such an approach to model the interrelationships between factors affecting productivity. This paper aims to address that knowledge gap. In order to implement the fuzzy ISM approach, a set of fuzzy membership functions needs to be defined to represent the different levels of influence between the factors affecting construction productivity. In this paper, fuzzy triangular membership functions are used because according to Pedrycz and Gomide (2007), these membership functions are one of the most common membership functions in engineering applications. The triangular membership function is defined by a lower limit *a*, an upper limit *c,* and the core value *b*, where $a \le b \le c$, to represent linguistic variables. The points *a*, *b*, and *c* represent the x coordinates of the three vertices of the triangular membership function ($\mu_A(x)$) in a fuzzy set *A*. A triangular fuzzy number *A* is shown as a triplet (a, b, c) in Figure 1.

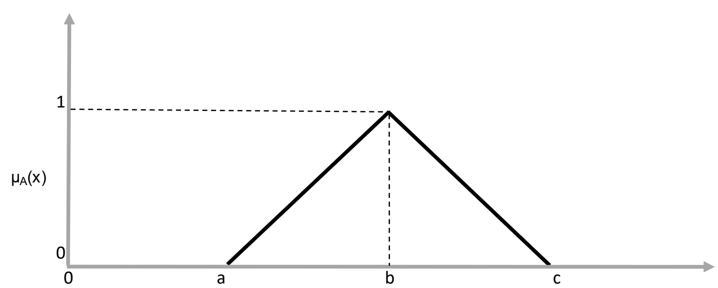

Figure 1: Fuzzy number with triangular membership function

The membership function $\mu_A(x)$ is defined by Equation 1.

$$[1]\ \mu_A(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & x > c \end{cases}$$

3 PROPOSED FRAMEWORK FOR EVALUATING RELATIONSHIPS BETWEEN FACTORS INFLUENCING CONSTRUCTION PRODUCTIVITY

The proposed framework establishes the direction and degree of influence between factors influencing productivity. In addition, it distinguishes between direct and inverse types of causal relationships. The methodology is depicted in Figure 2, and the details of the steps involved are discussed in Section 3.1.

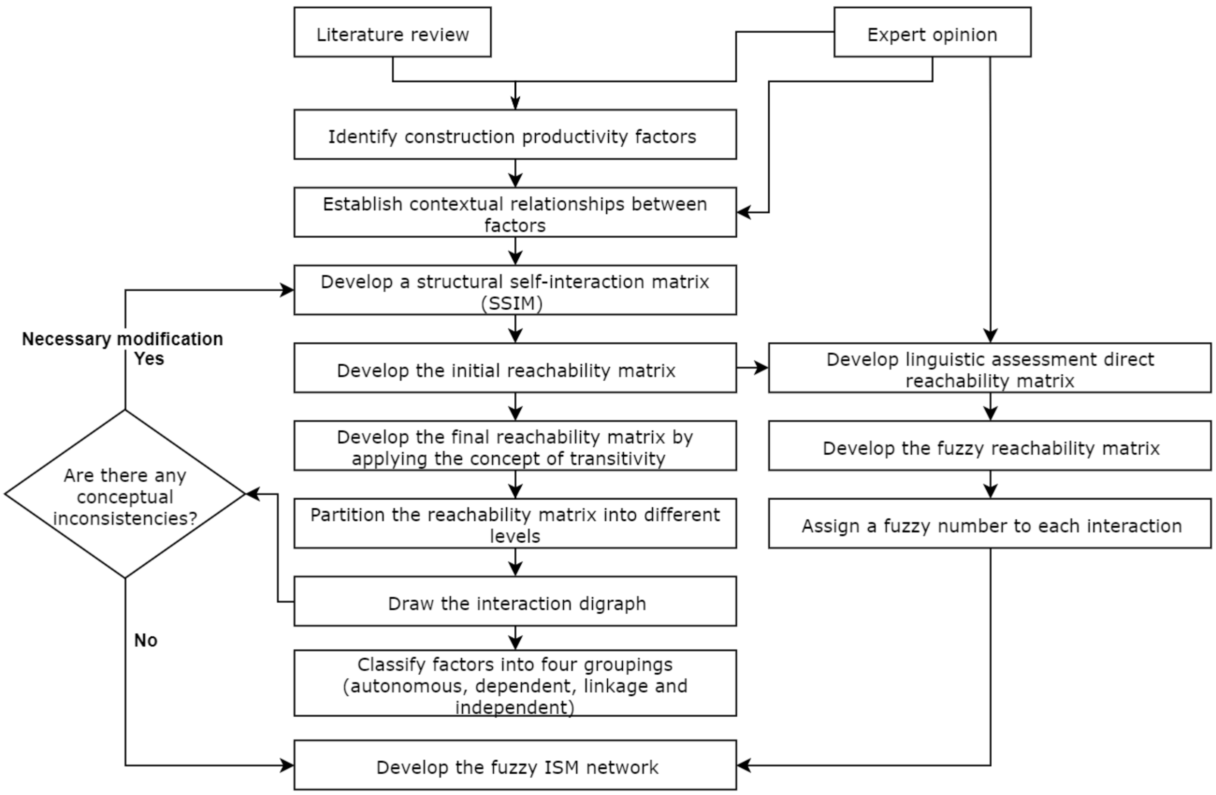

Figure 2: Flow chart for the integrated fuzzy ISM methodology

3.1 Methodology for Identifying Interrelationships between the Factors Influencing Productivity

Step 1. Identify factors:

Identify the factors that affect the productivity of a construction activity and categorize the factors based on their source (e.g., foreman-related factors, location-related factors, etc.) (Gerami Seresht and Fayek 2018). The factors that influence construction productivity are identified through a literature review and validated by expert knowledge using surveys or focus groups.

Step 2. Establish directional relationships between factors and develop a structural self-interaction matrix:

To analyze factors, a directional relationship of the *influence* type is chosen. This means that one factor influences another factor. For this purpose, experts should be surveyed to identify the directional relationships between any given pair of factors. The survey collects the experts' knowledge of:

- The direction of the relationship between two factors using the four designated symbols V, A, X, and O, where V stands for the relation from factor *i* to factor *j* (i.e., factor *i* will influence factor *j*); A stands for the relation from factor *j* to factor *i* (i.e., factor *i* will be influenced by factor *j*); X stands for relations in both directions (i.e., factors *i* and *j* will influence each other); and O stands for no relation between the factors (i.e., factors *i* and *j* are unrelated).

- The type of relationship between the factors as *direct* or *inverse*. A direct relationship implies that as factor *i* increases, factor *j* also increases, and an inverse relationship implies that as factor *i* increases, factor *j* decreases.
- The degree of influence of one factor on the other using five linguistic terms: *very low*, *low*, *medium*, *high*, and *very high*.

Based on the directional relationships, the structural self-interaction matrix (SSIM) is developed. The elements of the SSIM represent the relationships between the different factors, which are determined by the four symbols V, A, X, and O. The symbols indicate whether or not a relationship exists between two factors and, if a relationship does exist, what its direction is.

Step 3. Develop a reachability matrix:

By transforming the information of each cell of the SSIM (i.e., V, A, X, and O) into binary values (i.e., 0 or 1), an initial reachability matrix is obtained. This establishes a link between factors for the final fuzzy ISM network. The link does not represent the degree of influence between the factors. The rules for this transformation are (Attri, Dev, and Sharma 2013):

a) If the (*i*, *j*) entry in the SSIM is V, then the (*i*, *j*) entry in the reachability matrix is 1 and the (*j*, *i*) entry is 0.
b) If the (*i*, *j*) entry in the SSIM is A, then the (*i*, *j*) entry in the matrix is 0 and the (*j*, *i*) entry is 1.
c) If the (*i*, *j*) entry in the SSIM is X, then the (*i*, *j*) entry in the matrix is 1 and the (*j*, *i*) entry is also 1.
d) If the (*i*, *j*) entry in the SSIM is O, then the (*i*, *j*) entry in the matrix is 0 and the (*j*, *i*) entry is also 0.

Thereafter, the concept of transitivity is applied, some of the cells of the initial reachability matrices are adjusted for, and the final reachability matrix is obtained. The transitivity of the relationships is a basic assumption made in the ISM method which indicates that if element X is related to element Y, and element Y is related to element Z, then element X is necessarily related to element Z.

Step 4. Partition the reachability matrix into different levels:

Level partitions are made to determine the factors' hierarchy, which helps to establish the levels of the driving factors within the productivity model. In other words, it forms a structure starting from the most independent factor to the most dependent factor in the model. The levels are partitioned from the final reachability matrix by first forming the reachability set and the antecedent set for each productivity factor. The reachability set includes the factor itself and all other factors that it influences, and the antecedent set includes the factor itself and all other factors that it is influenced by. Then, the intersection set is formed from these two sets for all factors. The intersection is the set of elements common to both the reachability set and the antecedent set of the same factor. Next, the factors for which the reachability set and the intersection set are equal are assigned as the top-level factors in the ISM hierarchy. The top-level factors are then removed from the set and the reachability and intersection sets are recalculated for all remaining factors. The process is repeated to ascertain the elements in the next level of the hierarchy. The identified levels aid in building the final model of fuzzy ISM. This process is repeated until the ISM hierarchy level of each factor is determined.

Step 5. Draw the interaction digraph and ISM model:

Factors and their interdependencies are represented in terms of nodes and arrows. If there is a relationship between factors *i* and *j*, this is shown by an arrow that points from node *i* to node *j* or vice versa, based on the SSIM. These graphs are called directed graphs or digraphs. Once the ISM-based digraph is constructed, it should be reviewed to check for consistency with the established directional relationship (step 2) and make any necessary modifications.

Step 6. Develop a linguistic assessment direct reachability matrix:

Based on the collected expert knowledge about the degree of influence of one factor over the other factors (referring to step 2), the binary values of the relationship matrices that represent the existence and non-existence of relationships are replaced with the triangular fuzzy numbers (TFNs) representing the degree of influence of one factor over another factor (Bhosale and Kant 2016). The linguistic terms representing the degree of influence and their corresponding triangular fuzzy membership functions are adopted from Tavakolan and Etemadinia (2017) and Khatwani et al. (2015) (Table 1 and Figure 3).

Table 1: Linguistic terms for the degree of influence

Linguistic Term	Triangular Fuzzy Number (TFN)
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]

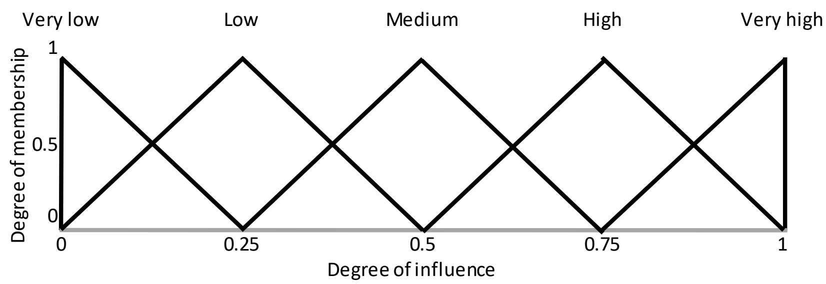

Figure 3: Triangular fuzzy numbers for linguistic terms

To this end, the SSIM is converted into a fuzzy reachability matrix by replacing the binary values with the fuzzy numbers that represent the strength of the relationships.

Step 7. Assign a fuzzy number to each interaction:
Each expert's opinion regarding the degree of influence of each relationship is transformed to a TFN according to Table 1 (see step 6). To assign a single fuzzy number for each interaction, the average of the fuzzy numbers is calculated.

Step 8. Classify factors into four categories:
The driving power and dependence power for each factor are determined so the factors can be classified into four groups. The driving power accounts for the total number of factors a given factor influences, and the dependence power accounts for the total number of factors that influence a given factor. The driving power of a factor is derived by summing all the values of the final reachability matrix (step 3) in its corresponding row; its dependence power is determined by summing all the values of the matrix in its corresponding column. Based on their driving power and dependence power, factors are classified into four groups (Tavakolan and Etemadinia 2017):

- **Autonomous factors**: These factors have a weak driving power and a weak dependence power, which means they have the lowest number of links with other factors in the established fuzzy ISM model.
- **Linkage factors**: These factors have a strong driving power as well as a strong dependence power. In other words, they have the largest number of links of both *influencing* and *influenced by* factor types. These factors are considered unstable because any action directed toward or exerted on these factors will have a subsequent influence on a number of factors. These changes in the remaining factors are in return reflected back on themselves.
- **Dependent factors**: These factors have a weak driving power but a strong dependence power. They have the least effect on the other factors.
- **Independent factors**: These factors have a strong driving power but a weak dependence power. They have the most effect on the other factors.

4 APPLICATION OF THE PROPOSED FRAMEWORK

This section presents an example of how the proposed framework can be used to establish the interrelationships between a subset of seven location-related factors that influence productivity. The factors were identified by Gerami Seresht and Fayek (2018), and the interrelationships were established through the eight steps presented in Section 3.1.

Step 1. Factor identification: The seven location-related factors selected in this example are spaciousness of working area (PF1), site restrictions (PF2), soil type (PF3), soil moisture (PF4), groundwater level (PF5), underground facilities (PF6), and hauling/delivery distance (PF7).

Step 2. Establish directional relationships between factors and develop the SSIM: Based on the results of pairwise comparisons conducted by four experts, the relationships between the factors are established. Next, the consolidated SSIM and the relationship types are determined as presented in Table 2.

Table 2: Final SSIM and type of relationship

SSIM	PF1	PF2	PF3	PF4	PF5	PF6	PF7	Type of relationship	PF1	PF2	PF3	PF4	PF5	PF6	PF7
PF1		A	A	O	O	A	X	PF1		I	I	N/A	N/A	D	I
PF2			A	O	A	A	V	PF2			I	N/A	D	D	D
PF3				V	O	O	O	PF3				D	N/A	N/A	N/A
PF4					A	O	O	PF4					D	N/A	N/A
PF5						V	O	PF5						I	N/A
PF6							O	PF6							N/A
PF7								PF7							

Step 3. Develop the reachability matrix: In this step, the elements of the SSIM matrix (i.e., V, A, X, and O) are transformed into binary values (i.e., 0 or 1) and the initial reachability matrix is constructed. The final reachability matrix (Table 3) is obtained by applying the concept of transitivity to the initial reachability matrix in order to determine the indirect relationships that exist between factors.

Table 3: Final reachability matrix with driving power and dependence calculation

Final Reachability Matrix	PF1	PF2	PF3	PF4	PF5	PF6	PF7	Driving power
PF1	1	0	0	0	0	0	1	2
PF2	1	1	0	0	0	0	1	3
PF3	1	1	1	1	0	0	1*	5
PF4	0	0	0	1	0	0	0	1
PF5	1*	1	0	1	1	1	1*	6
PF6	1	1	0	0	0	1	1*	4
PF7	1	0	0	0	0	0	1	2
Dependence power	6	4	1	3	1	2	6	23

Step 4. Partition the reachability matrix into different levels: In order to determine the hierarchy of factors and construct the ISM network model, the factors are categorized into different levels using the reachability and antecedent sets. Accordingly, four levels are identified as shown in Figure 4, with PF1, PF4, and PF7 occupying the top level and PF5 occupying the bottom level.

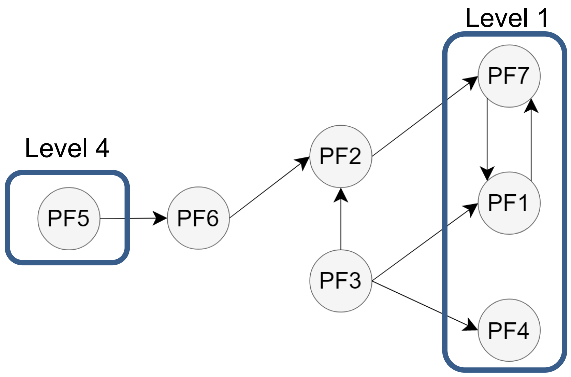

Figure 4: Digraph of the ISM model

Step 5. Draw the interaction digraph and the ISM model: Using the final reachability matrix developed in step 3 and the level partitions developed in step 4, the ISM network digraph is generated, as shown in Figure 4.

Step 6. Develop the linguistic assessment of the direct reachability matrix: In this step, the linguistic terms used by the experts to determine the strength of the relationships between factors are represented by fuzzy numbers (refer to Table 1), and the fuzzy reachability matrix is developed for each expert.

Step 7. Assign a fuzzy number to each interaction: In this step, the five fuzzy reachability matrices developed in the previous step are aggregated by averaging the opinions of the experts regarding the strength of each relationship using fuzzy arithmetic operations. As a result, the aggregated strength of each relationship in the ISM model (Figure 4) is determined by a fuzzy number, as shown in Table 4.

Table 4: Averaged TFNs of each relationship in the fuzzy ISM model

Relationship	Influence Factor (Fuzzy Number)
PF5-► PF6	[0.35, 0.60, 0.80]
PF6-► PF2	[0.65, 0.90, 1.0]
PF2-► PF7	[0.50, 0.75, 0.95]
PF3-► PF2	[045, 0.70, 0.90]
PF3-► PF4	[0.00, 0.05, 0.30]
PF5-► PF6	[0.45, 0.70, 0.90]
PF1◄-► PF7	[0.15, 0.40, 0.65]

Step 8. Classify factors into four categories: Based on the driving power and dependence power of each factor, as computed in step 3 (refer to Table 3), the factors are classified into four categories (i.e., autonomous, linkage, dependent, or independent). The driving–dependence power diagram is plotted to show the grouping of these factors in Figure 5. The break lines forming the four grouping quadrants are established by computing the break point coordinates, which are the average of the driving power and the average of the dependence power.

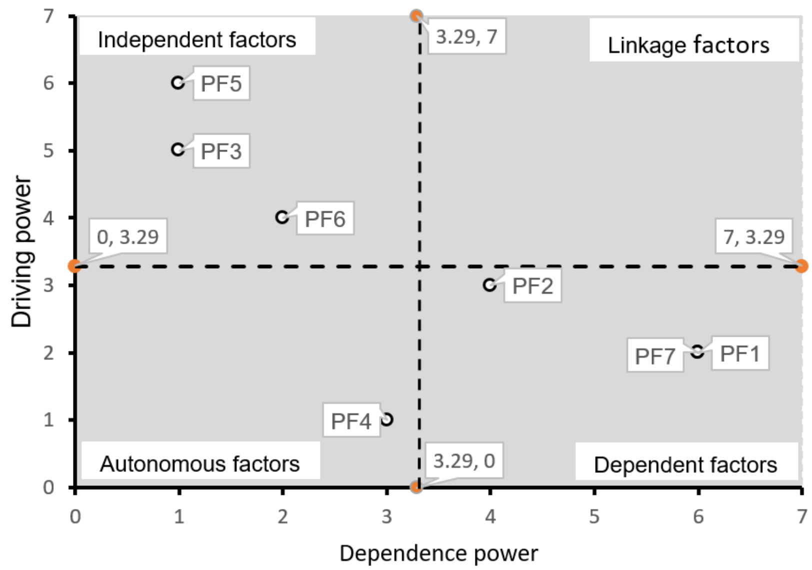

Figure 5: Driving–dependence power diagram

The diagram indicates that soil type (PF3), groundwater level (PF5), and underground facilities (PF6) are the main drivers of the model (independent factors), whereas spaciousness of working area (PF1), site restrictions (PF2), and hauling/delivery distance (PF7) are the most dependent factors. Soil moisture (PF4) is found to be an autonomous factor, and there are no linkage factors (unstable factors).

5 CONCLUSIONS AND FUTURE STEPS

Due to the significance of productivity for the successful delivery of construction projects, construction productivity is one of the most researched topics in the construction domain. Predictive models developed for construction productivity commonly map a set of inputs (i.e., influencing factors) to productivity, but they often ignore the interrelationships between the factors that influence productivity. Since construction projects work as a system, it can be argued that any influencing factor in such a system has an individual impact on construction productivity as well as an impact on the other factors within the system. In this paper, a new framework is introduced to identify the interrelationships between the factors that influence productivity by integrating fuzzy logic with the ISM approach. The use of the ISM approach makes it possible for this framework to be used to identify the interrelationships between the factors that influence productivity, and the use of fuzzy logic allows the user to subjectively determine the degree of influence between any two factors using linguistic terms rather than the binary numbers (1 or 0) used in a conventional ISM approach. Determining the interrelationships between the factors influencing productivity helps construction practitioners identify the most influential factors in their projects and helps researchers develop more accurate predictive models of construction productivity. The proposed framework categorizes the factors influencing productivity based on the level of influence they have on other factors and the level of influence they receive from other factors. This categorization supports the development of predictive models of productivity using the system dynamics technique by identifying the dynamic and auxiliary variables of the system.

In future research, the proposed framework will be used to identify the interrelationships between a comprehensive list of the factors influencing productivity, and the results will be used to develop predictive models of construction productivity at the project level using the fuzzy system dynamics modeling technique.

ACKNOWLEDGMENTS

This research is funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. Aminah Robinson Fayek. The authors gratefully acknowledge the financial support provided by industry partners and NSERC through the Chair.

REFERENCES

Attri, R., Dev, N., and Sharma, V. 2013. Interpretive Structural Modelling (ISM) Approach: An Overview. *Research Journal of Management Sciences*, **2**(2): 3–8.

Bhosale, V.A., and Kant, R. 2016. An Integrated ISM Fuzzy MICMAC Approach for Modelling the Supply Chain Knowledge Flow Enablers. *International Journal of Production Research,* **54**(24): 7374–7399.

Barbosa, F., Woetzel, J., Mischke, J., Ribeirinho, M.J., Sridhar, M., Parsons M., Bertram N., and Brown S. 2017. *Reinventing Construction Through a Productivity Revolution*. https://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/reinventing-construction-through-a-productivity-revolution.

Chan, P.C.A., Chan, W.M.D., and Yeung, F.Y.J. 2009. Overview of the Application of “Fuzzy Techniques” in Construction Management Research. *Journal of Management in Engineering*, ASCE, **135**(11): 1241–1252.

Chaudhuri, A., Srivastava, K.S., Srivastava, K.R., and Parveen, Z. 2016. Risk Propagation and its Impact on Performance in Food Processing Supply Chain: A Fuzzy Interpretive Structural Modeling Based Approach. *Journal of Modelling in Management,* **11**(2): 660–693.

Dai, J., Goodrum, P.M., Maloney W.F., and Srinivasan, C. 2006. Latent Structures of the Factors Affecting Construction Labor Productivity. *Journal of Construction Engineering and Management*, ASCE, **135** (5): 397–406.

Dube, S.A., and Gawande, R.R. 2015. Analysis of Green Supply Chain Barriers Using Integrated ISM-Fuzzy MICMAC Approach. *Benchmarking: An International Journal*, **23**(6): 1558–1578.

Etemadinia, H., and Tavakolan, M. 2016. Fuzzy Weighted Interpretive Structural Modeling: A New Method for Risk Path Identification of Infrastructure Projects. *Construction Research Congress 2016*, ASCE, San Juan, Puerto Rico.

Gerami Seresht, N. and Fayek, A.R. 2018. Dynamic Modeling of Multifactor Construction Productivity for Equipment-Intensive Activities. *Journal of Management in Engineering*, ASCE, **144**(9): 04018091.

Goodrum, P.M., Haas, C.T., Caldas, C., Zhai, D., Yeiser, J., and Homm, D. 2010. Model to Predict the Impact of a Technology on Construction Productivity. *Journal of Construction Engineering and Management*. **137**(9): 678–688.

Hwang, C.L., and Lin, M.L. 1987. *Group Decision Making under Multiple Criteria Methods and Applications*. Springer-Verlag, Berlin, Heidelberg, Germany.

Jarkas, A.M., and Bitar, C.G. 2012. Factors Affecting Construction Labor Productivity in Kuwait. *Journal of Construction Engineering and Management*, ASCE, **138**(7): 04016017.

Khatwani, G., Singh, P.S., Trivedi, A., and Chauhan, A. 2015. Fuzzy-TISM: A Fuzzy Extension of TISM for Group Decision Making. *Global Journal of Flexible Systems Management*, **16**(1):97–112.

Ok, S.C., and Sinha, S.K. 2006. Construction Equipment Productivity Estimation Using Artificial Neural Network Model. Construction Management and Economy, **24**(10): 1029–1044.

Pedrycz, W., and Gomide, F. 2007. *Fuzzy Systems Engineering: Toward Human-Centric Computing*. John Wiley & Sons, Inc., New Jersey, NJ, USA.

Tavakolan, M., and Etemadinia H. 2017. Fuzzy Weighted Interpretive Structural Modeling: Improved Method for Identification of Risk Interactions in Construction Projects. *Journal of Management in Engineering*, ASCE, **143**(11): 04017084.

Tsehayae, A.A., and Fayek, A.R. 2014. Identification and Comparative Analysis of Key Parameters Influencing Construction Labour Productivity in Building and Industrial Projects. *Canadian Journal of Civil Engineering*, **41**(10): 878–891.

———. 2016. Developing and Optimizing Context-Specific Fuzzy Inference System-Based Construction Labor Productivity Models. *Journal of Construction Engineering and Management*, ASCE, **142**(7): 04016017.

Warfield, J.N. 1974. Developing Interconnection Matrices in Structural Modeling. *IEEE Transactions on Systems, Man, and Cybernetics*, **SMC-4**(1): 81–87.

Yi, W. and Chan, P.C.A. 2014. Critical Review of Labor Productivity Research in Construction Journals. *Journal of Management in Engineering*, ASCE, **30**(2): 214-225.

Zadeh, L.A. 1965. Fuzzy Sets. *Information and Control*, **8**(3): 338-353.