# **Fuzzy Logic Application to the Assessment of BIM Benefits**

Sangwook Lee, Ph.D. University of Wisconsin-Platteville Platteville, WI

Building information modeling has been applied widely in the areas of architecture, engineering, and construction. The more accurate representation of 3-dimensional project models has changed traditional production processes significantly, and impacted on the life-cycle of construction projects from planning to maintenance. The computer technology has been studied and applied to various areas in construction for the purpose of generating high-quality drawings, taking off material quantities, detecting collision or interference, or improving facility management. This paper mainly focuses on the development of a decision-making model to be able to quantify the benefits of building information modeling by using a fuzzy AHP method. This method allows decision makers to choose flexible scales generated by fuzzy membership functions, while deterministic values are used in the traditional AHP. The process to calculate priority weights is presented in detail with a practical example.

Key Words: Building information modeling, Fuzzy AHP, Decision-making model

## Introduction

Building information modeling (BIM) has been applied widely in the areas of architecture, engineering, and construction. The accurate representation of 3-dimensional project models created significant changes to traditional production processes, and impacted on the whole life-cycle of construction projects, i.e. planning, design, construction, operation and maintenance of facilities. BIM application started in some projects in early 2000s to help architects and engineers develop building designs. But, it is now extended to various areas in construction such as cost estimating, clash detection, energy analysis, structural analysis, or jobsite safety (Volk et al., 2014). BIM demonstrated a new paradigm for the better communication between project players, i.e. owners, architects, engineers, general contractors, and subcontractors. The major players collaborate more effectively and accurately through a virtual model created by BIM. As a construction model is being created, they are able to refine it instantly and generate more precise one that was impossible in the traditional process.

A building information model can be used for various purposes (Azhar, 2011). It can be applied to enhance visualization by generating high-quality 3-dimensional renderings, generate shop drawings to show building systems in details, take off material quantities once a building model is completed, detect collision or interference between building systems, and improve facility management for maintenance operations, space planning, or building renovations. As collaboration between multi-disciplinary areas is studied more, the BIM can be combined with other technologies such as laser scanning or drones to enhance coordination and communication (Blackmon, Kim, & Taylor, 2018).

This paper aims at a study of BIM benefits from previous studies and the development of a decision-making model to quantify the benefits by using a fuzzy AHP (Analytic Hierarchy Process) method. A practical example is illustrated to show the process. The fuzzy AHP was recently developed by mixing the principles of a traditional AHP with a fuzzy set theory. One of main reasons for the need of the new approach is that the traditional AHP may not be effective when dealing with uncertainty as a decision maker has to choose a deterministic value from a fundamental scale of 1 to 9. The fuzzy AHP method allows decision makers to work with more flexible scales by

using fuzzy membership functions and linguistic variables, e.g. very good or average, to reflect the uncertainty (Soroor et al., 2012).

## **Fuzzy AHP Approach**

A fuzzy AHP approach was developed from a fuzzy set theory first introduced by Zadeh (1965). He developed the theory to represent ambiguity that cannot be explained by a usual mathematical sense of terms, e.g. "the group of tall people." It has been known that the fuzzy set theory is quite effective when handling problems in which there are no sharp boundaries and precise numbers. Furthermore, fuzzy numbers are not like rigid mathematical terms and equations, but are close to human natural language.

A fuzzy set is different from a crisp set. Fuzzy numbers can be any real number in the interval [0, 1] by fuzzy membership functions, whereas crisp sets only allow either 0 or 1. As the fuzzy number is close to one, the degree of membership of the number is higher. In many applications, triangular fuzzy numbers (TFNs) were used due to their computational simplicity and ability to promote representation and information processing in a fuzzy environment (Khazaeni et al., 2012). A triangular fuzzy number,  $\tilde{A}$ , on R can be denoted as (l, m, u), and its membership function can be defined as follows.

$$\mu_{\tilde{A}(x)} = \begin{cases} 0, \ x \le l \\ \frac{x-l}{m-l}, \ l \le x \le m \\ \frac{x-u}{m-u}, \ m \le x \le u \\ 0, \ otherwise \end{cases}$$
(1)

When there are two triangular fuzzy numbers,  $\tilde{A} = (a_1, a_2, a_3)$  and  $\tilde{B} = (b_1, b_2, b_3)$ , their operational laws are as follows.

$$\widetilde{A} \oplus \widetilde{B} = (a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$$
(2)

$$\widetilde{A} \otimes \widetilde{B} = (a_1, a_2, a_3) \otimes (b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3)$$
(3)

$$\tilde{A}^{-1} = (1/a_3, 1/a_2, 1/a_1) \tag{4}$$

$$\lambda \otimes \widetilde{A} = \lambda \otimes (a_1, a_2, a_3) = (\lambda a_1, \lambda a_2, \lambda a_3) \ (\lambda > 0, \lambda \in R)$$
(5)

Figure 1 shows two triangular fuzzy numbers,  $\tilde{A}$  and  $\tilde{B}$ , to illustrate the operations of fuzzy numbers. The fuzzy number of  $\tilde{A}$  can be represented as (1, 2, 3) and the fuzzy number of  $\tilde{B}$  can be expressed as (2, 3, 4).



Figure 1: Triangular Fuzzy Numbers

#### **Development of Decision Hierarchy**

A decision hierarchy has to be developed by identifying decision variables as it is needed in the traditional AHP method. The hierarchy can consist of three levels in general, i.e. a goal, criteria, and alternatives. A goal or an objective is placed at the top level, and criteria are located just below the goal level. Alternatives are placed at the bottom. Figure 2 presents a decision hierarchy developed with four criteria or factors. They were selected from previous studies that explained some main benefits of BIM (Azhar, 2011; Volk et al., 2014; Carmona & Irwin, 2007). The selected factors are as follows:

• Better production quality (C1): Product data are all digitized to obtain accurate dimensions. It is relatively simple to generate shop drawings for various building systems.

• Improved collaboration (C2): Major project players such as architects, owner, and general contractors can communicate each other more effectively, while improving collaboration between them.

• More accurate representation and visualization (C3): More accurate 3-dimensional project models can be created relatively quickly with little additional effort.

• Improved safety (C4): BIM modeling can be utilized for better safety planning and hazard identification on a job site.

There are various ways to apply a fuzzy AHP method to calculate priority weights, and the weight results could be different depending on specific variables you choose. Lee (2015) showed the analysis of four different approaches by varying fuzzy fundamental scales and weight aggregations. The study identified a method that produced the most comparable results with the traditional AHP method. This study followed the recommendation of the previous study when selecting a fuzzy fundamental scale and a weight aggregation. Table 1 presents a fuzzy fundamental scale for pair-wise comparisons. In group decision making with z experts, the aggregation of multiple weights can be made as follows. Table 2 shows fuzzy pairwise comparisons made by multiple decision makers, i.e. three decision makers involved in this example, by using the fuzzy fundamental scale.

$$Lw_{ij} = \frac{1}{Z} \sum_{z=1}^{Z} Lw_{ijz}, Mw_{ij} = \frac{1}{Z} \sum_{z=1}^{Z} Mw_{ijz}, Uw_{ij} = \frac{1}{Z} \sum_{z=1}^{Z} Uw_{ijz},$$
(6)



Figure 2: Decision Hierarchy for the Determination of BIM Benefits

Table 1

## Fuzzy Fundamental Scale

Linguistic Term	Fuzzy Number	Triangular Fuzzy Scale	Reciprocal Fuzzy Scale
Equally important	ĩ	(1, 1, 1)	(1, 1, 1)
Intermediate value	ĩ	(1, 2, 4)	(1/4, 1/2, 1)
Moderately important	ĩ	(1, 3, 5)	(1/5, 1/3, 1)
Intermediate value	<del>Ĩ</del>	(2, 4, 6)	(1/6, 1/4, 1/2)
Strongly important	5	(3, 5, 7)	(1/7, 1/5, 1/3)
Intermediate value	õ	(4, 6, 8)	(1/8, 1/6, 1/4)
Very strongly important	ĩ	(5, 7, 9)	(1/9, 1/7, 1/5)
Intermediate value	Ĩ	(6, 8, 9)	(1/9, 1/8, 1/6)
Extremely important	<u> </u> 9	(7, 9, 9)	(1/9, 1/9, 1/7)

Table 2

Criteria	C1	C2	C3	C4
C1	(1, 1, 1)	(1/5, 1/3, 1)	(1/5, 1/3, 1)	(1, 1, 1)
		(1/5, 1/3, 1)	(1/5, 1/3, 1)	(1, 1, 1)
		(1/7, 1/5, 1/3)	(1/6, 1/4, 1/2)	(1, 3, 5)
C2	(1, 3, 5)	(1, 1, 1)	(1, 1, 1)	(3, 5, 7)
	(1, 3, 5)		(1, 1, 1)	(3, 5, 7)
	(3, 5, 7)		(1, 3, 5)	(2, 4, 6)
C3	(1, 3, 5)	(1, 1, 1)	(1, 1, 1)	(1, 3, 5)
	(1, 3, 5)	(1, 1, 1)		(1, 3, 5)
	(2, 4, 6)	(1/5, 1/3, 1)		(1, 1, 1)
C4	(1, 1, 1)	(1/7, 1/5, 1/3)	(1/5, 1/3, 1)	(1, 1, 1)
	(1, 1, 1)	(1/7, 1/5, 1/3)	(1/5, 1/3, 1)	
	(1/5, 1/3, 1)	(1/6, 1/4, 1/2)	(1, 1, 1)	

## Fuzzy Pairwise Comparison Matrix with Three Decision Makers

## **Calculation of Priority Weights**

The procedure of the fuzzy AHP method proposed by Chang (1996) is explained in this section with an example of pair-wise comparison. Let  $X = \{x_1, x_2, ..., x_n\}$  be an object set, and  $U = \{u_1, u_2, ..., u_m\}$  be a goal set. An extent analysis for each goal is performed to each object. Therefore, *m* extent analysis values for each object can be obtained, with the following signs:  $M_{gi}^1, M_{gi}^2, M_{gi}^3, ..., M_{gi}^m$  (j = 1, 2, ..., m and i = 1, 2, ..., n). All extent analysis

values are triangular fuzzy numbers.

Then, the value of fuzzy synthetic extent with respect to the *i*th object can be defined as follows.

$$S_{i} = \frac{\sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}}{\sum_{j=1}^{m} M_{gi}^{j}}$$
(7)

Step 2 is to calculate the degree of possibility between two fuzzy synthetic extent values. The degree of possibility of  $S_2 = (l_2, m_2, u_2) \ge S_1 = (l_1, m_1, u_1)$  can be calculated as:

$$V(S_{2} \ge S_{1}) = hgt (S_{2} \cap S_{1}) = \mu(d)$$

$$= \begin{cases} = 1, if \ m_{2} \ge m_{1} \\ = 0, if \ l_{1} \ge u_{2} \\ = \frac{l_{1} - u_{2}}{(m_{2} - u_{2}) - (m_{1} - l_{1})}, \text{ otherwise} \end{cases}$$
(8)

Where, *d* is the ordinate of highest intersection point **D** between two fuzzy numbers. To compare  $S_1$  and  $S_2$ , we need to calculate both values,  $V(S_2 \ge S_1)$  and  $V(S_1 \ge S_2)$ .

Step 3: The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers can be defined as follows.

$$V(S \ge S_1, S_2, ..., S_k) = V[(S \ge S_1) \text{ and } (S \ge S_2) \text{ and } ... \text{ and } (S \ge S_k)] = \min V(S \ge S_i) \ (i = 1, 2, ..., k)$$
(9)

Step 4: Assume that  $d'(C_i) = \min V(S_i \ge S_k)$  for k = 1, 2, ..., n  $(i \ne k)$ Then, the weight vector is given by

$$W' = (d'(C_1), d'(C_2), ..., d'(C_n))^T$$
(10)  
Where,  $C_i (i = 1, 2, ..., n)$ 

Step 5: The normalized weight vector needs to be obtained through normalization.  $W = (d(C_1), d(C_2), ..., d(C_n))^T$ (11)

To calculate priority weights, fuzzy numbers evaluated by multiple experts have to be aggregated by Equation (6). Table 3 shows a resulting pairwise comparison matrix by the weight aggregation method. Then, the value of fuzzy synthetic extent with respect to *i*th object can be computed by Equation (7). Then, the degree of possibility (V values) can be calculated by Equation (8). Table 4 shows the degree of possibility values. Then, priority weights can be obtained by using Equation (10).

 $d'(C_1) = \min(0.3191, 0.5385, 1.0) = 0.3191$   $d'(C_2) = \min(1.0, 1.0, 1.0) = 1.0$   $d'(C_3) = \min(1.0, 0.7971, 1.0) = 0.7971$  $d'(C_4) = \min(0.8824, 0.1053, 0.3333) = 0.1053$ 

As a result, priority weights form a vector of  $W' = (0.3191, 1.0, 0.7971, 0.1053)^T$ . This vector goes through a normalization process to make the sum of weights equal to one. Lastly, final priority weights can be calculated as  $W = (0.1437, 0.4501, 0.3588, 0.0474)^T$ . Based on the results, C2 has the highest weight of 0.4501, and C4 has the lowest value of 0.0474.

## Table 3

#### **Fuzzy Pairwise Comparison Matrix**

Criteria	C1	C2	С3	C4
C1	(1, 1, 1)	(0.18, 0.29, 0.78)	(0.19, 0.31, 0.83)	(1, 1.67, 2.33)
<b>C2</b>	(1.67, 3.67, 5.67)	(1, 1, 1)	(1, 1.67, 2.33)	(2.67, 4.67, 6.67)
<b>C3</b>	(1.33, 3.33, 5.33)	(0.73, 0.78, 1)	(1, 1, 1)	(1, 2.33, 3.67)
C4	(0.73, 0.78, 1)	(0.15, 0.22, 0.39)	(0.47, 0.56, 1)	(1, 1, 1)

Table 4

## **Degree of Possibility**

V	$S_I$	$S_2$	$S_{3}$	<b>S</b> 4
V( <i>S</i> <sup><i>1</i></sup> ≥)		0.3191	0.5385	1.0
$V(S_2 \ge)$	1.0		1.0	1.0
V( <i>S</i> ₃≥)	1.0	0.7971		1.0
V(S₄≥)	0.8824	0.1053	0.3333	

#### Conclusions

This research paper presented the development of a decision-making model to assess the benefits of BIM by using a fuzzy AHP method. As the fuzzy AHP method is based on a fuzzy set theory, fuzzy membership functions need to be developed to utilize fuzzy flexible scales. Triangular fuzzy numbers were used in this paper since they were used

popularly in the previous studies. A decision hierarchy with four criteria was developed to illustrate the calculation of priority weights. The process to calculate priority weights was presented in detail. This kind of decision-making model can be utilized in construction industry in many cases. For example, we can evaluate the benefits of BIM in an objective quantitative way or compare the benefits of BIM between multiple projects by using the model so that we can apply BIM modeling to a project with highest benefits. Also, the model can be integrated with cost information so that a benefits-cost analysis can be made, while enhancing the efficiency of BIM usage. For further study, a more sophisticated decision hierarchy needs to be developed by selecting more-related factors in the model. Also, the inputs from a construction industry need to be obtained to check out the validity and workability of the developed model.

## References

Azhar, S. (2011). Building Information Modeling (BIM): Trends, Benefits, Risks, and Challenges for the AEC Industry, *Leadership and Management in Engineering*, 11, 241-252.

Blackmon, T., Kim, J., & Taylor, M. (2018). Factors hindering the incorporation of virtual design and construction services into construction management firms in the Southeastern United States, 54<sup>th</sup> ASC Annual International Conference Proceedings, Minneapolis, MN.

Carmona, J. & Irwin, K. (2007). BIM: Who, What, How and Why. Building Operating Management, <u>http://www.facilitiesnet.com/software/article/BIM-who-what-how-and-why-7546</u> (August 30, 2018).

Chang, D. Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research*, 95, 649-655.

Khazaeni, G., Khanzadi, M., & Afshar, A. (2012). Fuzzy adaptive decision making model for selection balanced risk allocation. *International Journal of Project Management*, 30, 511-522.

Lee, S. (2015). Determination of Priority Weights under Multiattribute Decision-making Situations: AHP versus Fuzzy AHP. *Journal of Construction Engineering and Management*, 141(2), 05014015. Soroor, J., Tarokh, M. J., & Abedzadeh, M. (2012). Automated bid ranking for decentralized coordination of construction logistics. *Automation in Construction*, 24, 111-119.

Volk, R., Stengel, J. & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings – Literature review and future needs. *Automation in Construction*, 38, 109-127.

Zadeh, L. A. (1965). Fuzzy sets. Information and Control 8, 338-353.