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EVALUATION OF HETEROGENEOUS LEVELS OF EXPERTISE IN EXPERT RISK ASSESSMENT IN CONSTRUCTION

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Abstract: The construction risk assessment and management process often involves heterogeneous group of experts with various levels of expertise who must collectively make decisions and reach a common solution. However, real-life decision making involves a great deal of uncertainty and subjectivity. To address these challenges, this paper explores the application of fuzzy logic in contexts involving multi-criteria group decision making (MCGDM) problems. The approach discussed in this paper describes the sub-processes necessary for aggregating the opinions of a heterogeneous group of experts in order to achieve one unique, representative problem solution. An extensive review of existing literature was conducted to explore a variety of construction risk assessment expertise criteria, and finally a comprehensive list of criteria for assessing experts' expertise levels was compiled in order to assign experts' importance weights. In the course of this study, a comparative analysis of methods for assigning weights to experts was developed and a new weight assigning model using fuzzy analytical hierarchy processes (FAHP) was proposed. In order to assist researchers and practitioners investigating construction risk MCGDM problems in heterogeneous settings, this paper main contributions are: (1) eliminating the need of a moderator during the aggregation process; (2) presenting a clear and consistent set of criteria that can be used to rate experts' levels of expertise in risk management; and (3) proposing an innovative expertise weight assigning method (i.e. FAHP) in risk management. In the future, this research will be extended by integrating the weight assigning model outlined in this study into the fuzzy aggregation process.

1 INTRODUCTION

Whenever there is little knowledge or high uncertainty surrounding an area being investigated, such as evaluating and managing risks on construction projects, researchers must rely on the input of experts (Baker et al. 2006). Groups involved in MCGDM can be classified as either homogenous or heterogeneous; this classification is based on each individual's degree of importance, or rather, their expertise in the context of the problem being evaluated. If the opinions of all experts are considered to be equally important, the group is considered homogenous; otherwise, it is identified as a heterogeneous group (Herrera-Viedma et al. 2014).

In construction risk assessment and management, groups of experts with different levels of expertise are involved at various stages of the project lifecycle to make decisions and reach a common solution. Structured aggregation methods are instrumental in risk management processes in order to aggregate individual opinions and achieve a collective assessment. The aggregation of experts' opinions in the construction risk assessment group decision-making process can be employed for applications such as risk and response strategy identification and prioritization, assessment of the probability of occurrence and impact of risk and opportunity events, and selection of the best risk contingency response strategies.

The standard metric used in the literature to differentiate heterogeneous experts assigns importance weights to experts based on their qualification attributes relative to the subject being discussed. Therefore, in the construction risk field, importance weights can be used to determine each expert's level of influence on the final decision being made (Perez et al. 2011). In other words, in construction risk MCGDM problems, the aggregation of the opinions of a heterogeneous group of experts involves assigning an importance weight to each expert involved in the decision-making process in order to combine all the experts' opinions into one unique, representative value. In most approaches for aggregating the opinion of a heterogeneous group of experts, weights are commonly assigned to the experts by the moderator. Moreover, such approaches often do not employ a method for assigning weights that is based on experts' qualification attributes (Herrera-Viedma et al. 2014). Therefore, there is a lack of clear and structured methods to assign importance weights to experts' opinions based on specific field assessment criteria. The objectives of this paper are as follows: (1) addressing the subjectivity and possible biases involved in the assignment of importance weights to experts by eliminating the moderator figure; (2) presenting a clear and consistent list of criteria to assess expert's levels of risk management expertise; (3) and conducting a detailed and extensive review of previous weight assigning models to justify the need for an innovative, clear, and structured weight assigning model (i.e. FAHP) in construction engineering.

The first section of this paper discusses previous research on the qualification attributes of construction risk experts; this section also analyzes existing methods in the literature for assigning weights to experts' opinions. In the second section, research gaps are addressed by proposing an innovative weight assigning method based on a clear and consistent set of criteria that can be used to rate the levels of expertise of group members participating in MCGDM problems. Finally, conclusions are drawn and future research directions are recommended.

2 BACKGROUND

2.1 Literature review of qualification criteria to assess experts' levels of expertise

Even though there is limited consensus regarding the definition of an expert, an individual's expertise should not be evaluated based on whom each person is; instead, expertise should be evaluated on the basis of qualification attributes that each individual possesses (Baker et al. 2006). Thus, it is essential to create a list of attributes (i.e., assessment criteria) to evaluate and calculate each expert's level of expertise.

Existing definitions in the literature related to the classification of expert judgement take into consideration the following attributes: knowledge, experience, ability to influence policy, educational background, professional reputation, status among his/her peers, years of professional experience, own self-appraisal of relative competency in different areas, and where appropriate, publication record (Hoffmann et al. 2007). All these characteristics form criteria that endorse an expert's relevance and credibility in their own field of expertise. However, most qualification attributes used to assess an expert's levels of expertise are qualitative in nature. In order to ensure less subjectivity in assessing expertise in a specific field, there is a need for greater transparency in the criteria used for classifying experts (Cornelissen et al. 2003).

In construction risk assessment, the levels of expertise possessed by experts involved in the decision-making process substantially influences the decisions being made (Wan and Yuan 2011). However, in the literature, there is no definite list of qualification attributes that can be used to classify the decision maker's risk assessment expertise (Wan and Yuan 2011). Therefore, this paper proposes a comprehensive list of criteria to assess experts' levels of expertise in risk assessment MCGDM problems (Section 3.1).

2.2 Comparative analysis of previous methods for assigning weights to heterogeneous groups of experts

According to previous research, importance weights can be assigned to experts in several different ways: (1) a moderator or manager subjectively assigns weights directly to the experts (Herrera-Viedma et al. 2014); (2) the weights are determined by comparing the consistency of the experts in stating their preferences (Herrera-Viedma et al. 2014); (3) a fuzzy expert system (FES) is adopted to determine the weights, based on essential qualification attributes (Elbarkouky et al. 2014); (4) a multi-attribute utility function (MAUF) is used to determine a weight for each expert, based on the expert utility values and relative weight of experience measures (Awad and Fayek 2012a); and (5) the analytical hierarchy process (AHP) is used to derive weights by considering the set of attributes related to decision makers' levels of expertise (Omar and Fayek 2016).

The first method relies on a moderator to assign importance weights to experts; although it is a fast and easy method, it is highly subjective and is prone to human error and bias. In the second method, weights are determined based on the consistency of any given expert in providing information, with more weight being assigned to the most consistent experts. This method is only limited to the consensus-reaching process and requires several rounds of discussion and more computational efforts (Herrera-Viedma et al. 2014). Furthermore, during the consensus-reaching process, a discordant expert may feel obliged to change his/her preferences significantly to attain the required level of agreement among all participants. Therefore, these two methods have limitations that do not make them suitable to assign importance weights to experts in construction risk assessment MCGDM problems.

The method of developing a fuzzy expert system (FES) to determine the importance weight factor for each expert has advantages and disadvantages. The main advantage of the FES model is that it is easy access to knowledge, since natural language terms can be used as descriptors for the input and output variables of the system. However, the first and most impactful disadvantage is that in any fuzzy expert system, the number of rules generated in the model exponentially increases according to the number of inputs; as a result, it is very difficult to establish rules when dealing with complex problems. Moreover, one of the main challenges of using FES, as stated in the literature, is the process of constructing membership functions, which leads to longer computational times (ElBarkouky and Fayek 2010b). Furthermore, the FES is a context-oriented system (Awad and Fayek 2012c). There is a need for a specific methodology for systematic tuning of the FES knowledge base in order to increase the accuracy of the system (Awad and Fayek 2012b). For these reasons, the use of FES is also considered inappropriate for assigning weights of importance to experts' opinions in construction risk MCGDM.

The method of multi-attribute utility functions (MAUF) has the benefit of being effective in resolving MCGDM problems when decision makers need to consider their preferences regarding multiple criteria for making the final decision (Awad and Fayek 2012b). However, the MAUF method involves developing utility functions for each input criteria in the model, and thus it can only effectively assess models with a limited number of input criteria. In addition, the MAUF has been previously applied as a step in the consensus-reaching process, and the same obstacles that occur during consensus reaching also hinder the use of the MAUF as a weight assigning model for construction risk assessment.

The classical AHP approach provides a logical and comprehensive framework for structuring MCGDM problems in the following areas: representing and quantifying elements, relating overall goals to elements, and evaluating alternative solutions to the problem (Zhang 2010). AHP is a structured, yet flexible approach based on a powerful methodology that can be integrated with almost any group decision-support system (Dyer and Forman 1992). Previous applications of AHP include selecting the best alternative problem solution, ranking alternative solutions, and determining the merit of the members of a set of alternatives (i.e., prioritization) (Zhang 2010). Considering the literature (Medsker et al. 1995, Yang 1995, Lee et al. 2001) on expert knowledge acquisition methods, such as the Delĥi method, consensus decision making, and brainstorming sessions, the AHP presents a straightforward format for information elicitation that is capable of using focus group sessions to obtain the pairwise comparison matrices. The classical AHP approach has also been used for assigning weights to experts in MCGDM problems as a part of an AHP model, or in a subsidiary AHP model constructed for assessing experts' levels of expertise (Dyer and Forman 1992, Saaty 1980). However, one of the main limitations of the classical AHP model is its inability to resolve the uncertainty and imprecision associated with mapping experts' opinions onto crisp numbers (Li and Zou 2011). In order to simulate actual human judgment in FAHP, Buckley (1985) extended Saaty's (1980) importance rating scale so that experts can use fuzzy numbers as ratios in the pairwise comparison matrices in place of classical AHP crisp ratios (Li and Zou 2011); as a result, the fuzzy pairwise comparison matrices were developed to address the vague and uncertain value of human opinion (Li and Zou 2011). Since construction risk assessment and management usually involves significant uncertainty and subjectivity, this paper proposes the use of the FAHP method (Section 3.2) to better capture experts' opinions.

3 A PROCESS FOR ASSIGNING IMPORTANCE WEIGHTS TO HETEOGENEOUS GROUPS OF EXPERTS IN CONSTRUCTION RISK ASSESSMENT MCDGM PROBLEMS

3.1 A clear and consistent set of criteria for assessing experts' levels of expertise in construction risk assessment

In this research, a preliminary list of criteria to assess experts' levels of expertise in risk assessment was developed, based on a review of previous literature (Figure 1). The assessment criteria are organized into seven "criteria" categories that each contains three to seven sub-criteria attributes. Quantitative criteria are measured using numerical scales, while qualitative criteria are measured using predetermined rating scales. For brevity, only a few of the criteria depicted in Figure 1 are discussed. For example, the "experience" quantitative criterion, which is used to assess level of expertise, comprises the following five sub-criteria: (1) "total years of experience" (i.e., the number of years the expert has been working in his/her discipline); (2) "diversity of experience" (i.e., the number of different companies the expert worked for); (3) "relevant experience" (i.e., the number of years the expert has been working in risk management); (4) "applied experience" (i.e., the number of projects in which the expert performed risk management tasks); and (5) "supervisory experience" (i.e., the number of employees supervised by the expert). All quantitative sub-criteria in Figure 1 are measured using numerical scales.

An example of a qualitative criterion among the list provided in Figure 1 is "reputation". The "reputation" criterion includes the following five sub-criteria: (1) "social acclamation" (i.e., the a number of participants that indicate one specific participant expert as being the most relevant expert in risk management); (2) "willingness to participate in the survey" (i.e., the quality of responses provided by a participating expert); (3) "professional reputation" (i.e., the expert's level of credibility, based on consistency and reasonableness (i.e., use of engineering judgement) in previous decisions); (4) "enthusiasm and willingness" (i.e., the expert's level of enthusiasm and willingness in performing risk management tasks in his/her current company); and (5) "level of risk conservativeness", (i.e., an expert's tendency to be conservative in their risk assessment practices). All qualitative sub-criteria in Figure 1 are measured using the predetermined rating scale shown in Table 1. The Likert scale includes an odd number of values in order to allow decision makers to select a neutral rating (Hartley 2014, Johnson and Morgan 2016).

Table 1: Predetermined rating scale for experts' "reputation"

Predetermined Rating Scale	Description of References Variables of Predetermined Rating Scale
1	*Very poor* consistency and *very poor* reasonableness of previous decisions
2	*Poor* consistency and *poor* reasonableness of previous decisions
3	*Average* consistency and *average* reasonableness of previous decisions
4	*Good* consistency and *good* reasonableness of previous decisions
5	*Very good* consistency and *very good* reasonableness of previous decisions

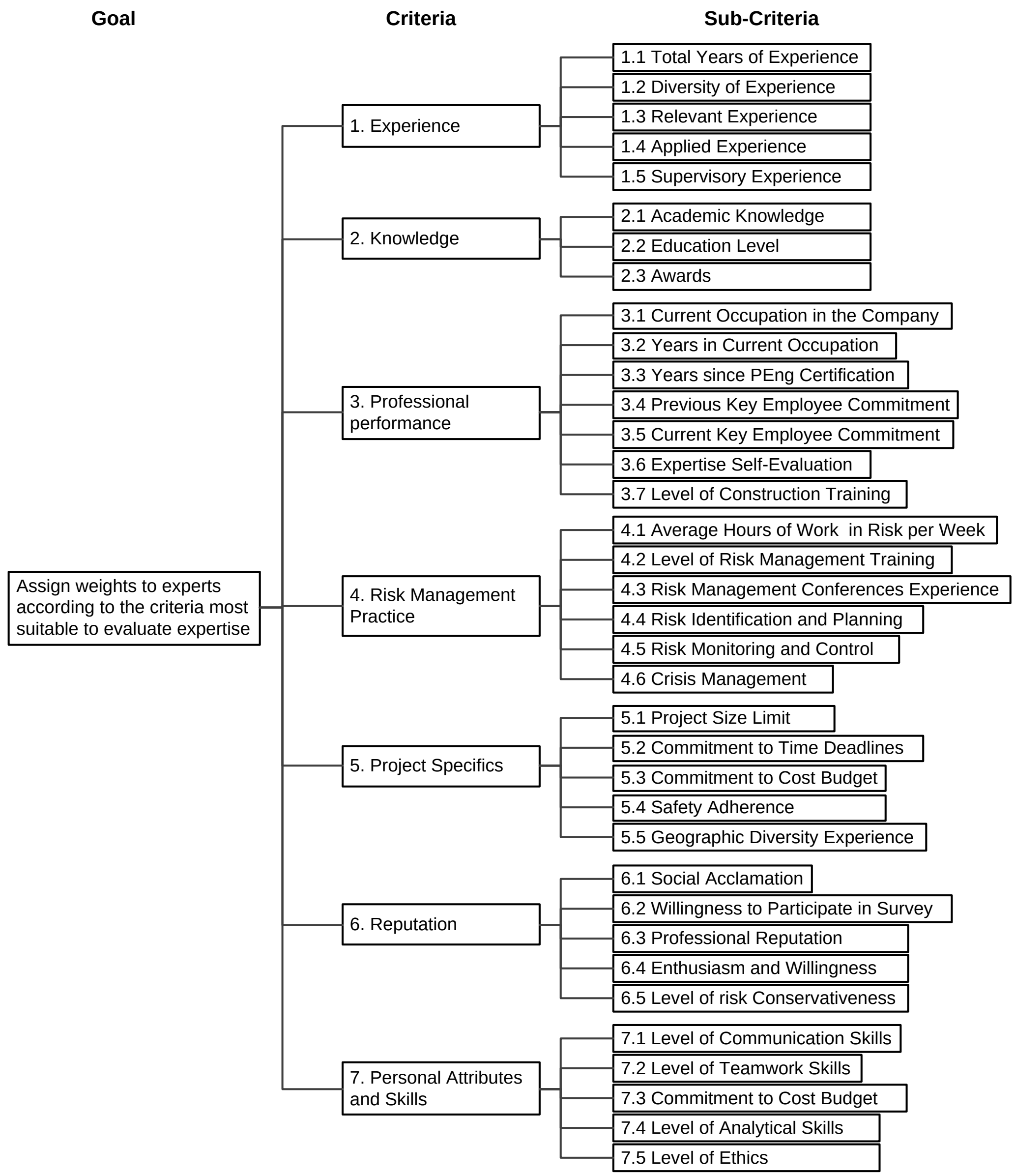

Figure 1: List of criteria to assess experts' levels of expertise in construction risk assessment (decomposed into FAHP hierarchical structure)

3.2 The proposed fuzzy AHP weight assigning method

The method for assigning importance weights to experts' opinions proposed in this research is the fuzzy analytical hierarchy process (FAHP) (Figure 2). One of the main advantages of FAHP is that it allows decision makers to represent their preferences with a reasonable interval, instead of crisp values. These intervals are represented as fuzzy numbers, which allows the FAHP model to better express the overlap of concepts or values being represented by the experts. Triangular fuzzy numbers (TFNs) are adopted in this research, as they are the most widely used form of fuzzy numbers and are easier to construct than other forms (Gohar et al. 2012). TFNs are defined by three real numbers expressed as (l, m, u), where l is the lower limit, m is the most likely value, *and* u is the upper limit (Srichetta and Thurachon 2012).

TFNs are used in FAHP to form fuzzy judgment matrices, which correspond to the crisp value matrices in classical AHP. Table 2 represents one of the common fuzzy linguistic scales that are employed for the pairwise comparisons in this research (Tian and Yan 2013, Chang 1996). According to Chang (1996), for the fuzzy comparison matrix to be consistent, the fuzzy numbers to the left and right of the matrix's diagonal have to be reciprocal, just as in classical AHP. Chang (1996) uses the fuzzy inverse formula (Equation 1) to represent the reciprocal TFNs.

[1] $(l, m, u)^{-1} = \left(1/u, 1/m, 1/l\right)$

Table 2: Linguistic scales for relative importance ratings (adapted from Demirel et al. 2008)

Linguistic Scale for Relative Importance	Triangular Fuzzy Scale	Reciprocal of Triangular Fuzzy Scale
Exactly the same	(1,1,1)	(1,1,1)
Approximately the same importance	(1/2,1,3/2)	(2/3,1,2)
Weakly more important	(1,3/2,2)	(1/2,2/3,1)
More important	(3/2,2,5/2)	(2/5,1/2,2/3)
Strongly more important	(2,5/2,3)	(1/3,2/5,1/2)
Absolutely more important	(5/2,3,7/2)	(2/7,1/3,2/5)

The four main FAHP approaches are those developed by Van Laarhoven and Predrycz (1983), Buckley (1985), Chang (1996), and Cheng (1997). Among these approaches, Chang's extent analysis method is the most popular, because it involves considerably simpler computational efforts than the other methods, and it has been successfully applied in many fields (Ding et al. 2008). In summary, Chang's extent analysis approach is based on the degrees of possibility for each criterion in FAHP. After the crisp weights for the criteria are obtained, they are normalized to obtain final criteria weights (Zhang 2010).

The FAHP weight assigning model proposed in this research involves two main processes: (1) developing the FAHP weight assigning model and (2) using the model (Figure 2).

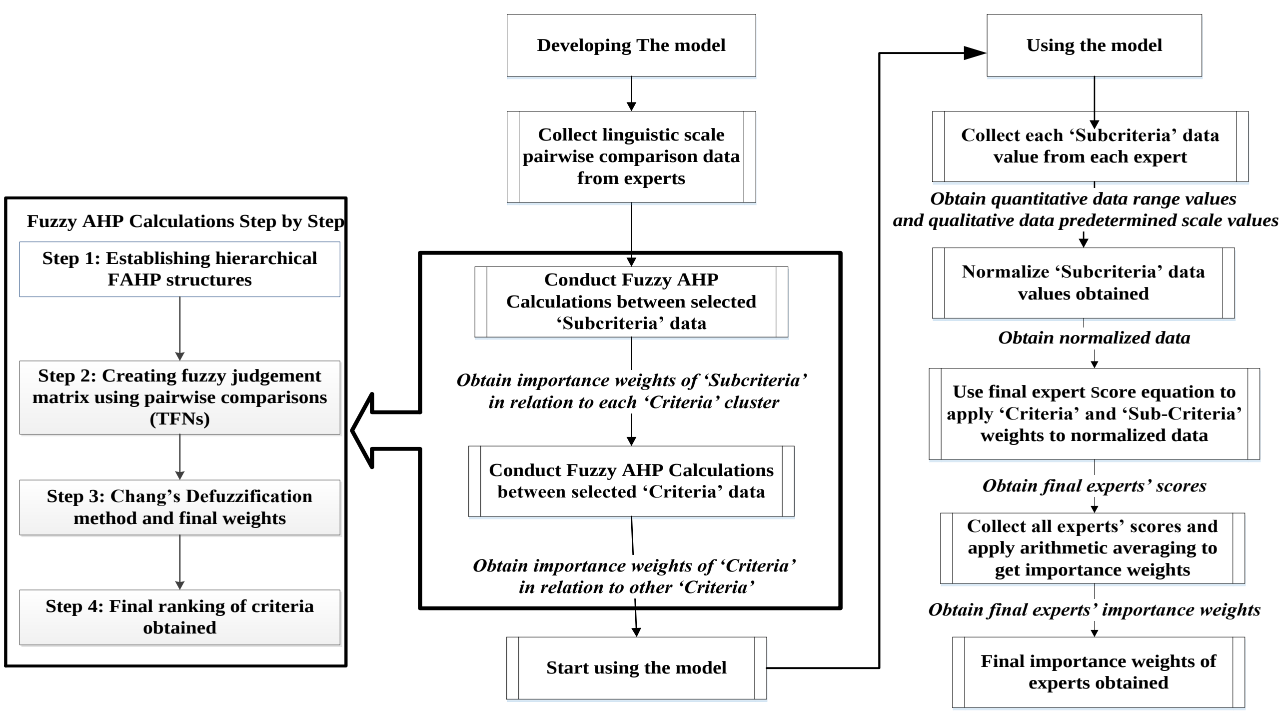

Figure 2: Proposed FAHP weight assigning model

The basic procedure to develop the FAHP model (Figure 2) is as follows (Srichetta and Thurachon 2012):

1. Decompose the MCGDM problem into a structured hierarchy, with the goal at the top and the criteria and sub-criteria below (Figure 1).

2. Create fuzzy pairwise comparison matrices. In this step, the decision maker uses the fuzzy linguistic scale (Table 2) to assess the rating score for each pair of sub-criteria or criteria. Therefore, the fuzzy pairwise comparison matrix (Equation 2) is constructed where the element $\tilde{a}_{ij}$ inside the matrix is interpreted as the degree of importance of the *i*[th] criterion over the *j*[th] criterion.

[2] $$\tilde{A} = \left[\tilde{a}_{ij}\right] = \begin{bmatrix} (1,1,1) & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \vdots & (1,1,1) & \ddots & \vdots \\ 1/\tilde{a}_{n1} & 1/\tilde{a}_{n2} & \cdots & (1,1,1) \end{bmatrix}$$

Where $\tilde{A}$ represents the fuzzy pairwise comparison matrix of *n* criteria and each $\tilde{a}_{ij}$ element represents a triangular fuzzy number.

3. After the two FAHP pairwise comparisons have been completed for the two hierarchy levels (i.e., criteria and sub-criteria), Chang's (1996) approach is used to determine the final weights for each criterion and cub-criterion listed in Figure 1. The step-by-step FAHP approach is as follows (Srichetta and Thurachon 2012):

   a. Compute the value of the fuzzy synthetic extent $\widetilde{S_I}$ with respect to the i^{th} criterion by applying the algebraic operations of summation and multiplication to the TFNs as follows (Equation 3):

[3] $$\tilde{S} = \begin{bmatrix} \tilde{s}_1 \\ \vdots \\ \tilde{s}_n \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{n} \tilde{a}_{1j} \otimes \left(\sum_{j=1}^{n} \tilde{a}_{1j}\right)^{-1} \\ \vdots \\ \sum_{j=1}^{n} \tilde{a}_{nj} \otimes \left(\sum_{j=1}^{n} \tilde{a}_{nj}\right)^{-1} \end{bmatrix} = \begin{bmatrix} \left(\sum_{j=1}^{n} l_{1j}, \sum_{j=1}^{n} m_{1j}, \sum_{j=1}^{n} u_{1j}\right) \otimes \left(\frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} u_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} m_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} l_{kj}}\right) \\ \vdots \\ \left(\sum_{j=1}^{n} l_{nj}, \sum_{j=1}^{n} m_{nj}, \sum_{j=1}^{n} u_{nj}\right) \otimes \left(\frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} u_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} m_{kj}}, \frac{1}{\sum_{k=1}^{n}\sum_{j=1}^{n} l_{kj}}\right) \end{bmatrix}$$

   b. Then, based on the fuzzy synthetic extent values, the non-fuzzy values that represent the relative preference of one criterion over others must be calculated. Therefore, it is necessary to compute the degree of possibility in order to approximate the fuzzy priorities in the pairwise comparison matrices. In order to find the degree of possibility for $\tilde{s}_2 = (l_2, m_2, u_2) \geq \tilde{s}_1 = (l_1, m_1, u_1)$, apply Equation 4 and Equation 5 as follows:

[4] $$V(\tilde{s}_1 \geq \tilde{s}_2) = \begin{cases} 1, if\ m_2 \geq m_1 \\ 0, if\ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, otherwise \end{cases}$$

The degree of possibility for a TFN S_i, to be greater than *n* TFNs S_k, can be given by the use of operation min proposed by Dubois and Prade (1980):

[5] $$V = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} = \begin{bmatrix} minV(\tilde{s}_1 \geq \tilde{s}_k) \\ \vdots \\ minV(\tilde{s}_n \geq \tilde{s}_k) \end{bmatrix}$$

Where, k ∈ $\{1,2,\dots,n\}$ and k ≠ I and *n* is the number of criteria being described previously. Each $[V_1, V_2, \dots V_n]$ value represents the relative non-fuzzy weight of one criterion over the others. However, these weights have to be normalized in order to be analogous to the classical AHP criteria weights.

c. Normalize the weight vector *V* to get the final non-fuzzy normalized weight vector *W* as follows (Eq. 6):

$$[6] \qquad W = \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} v_1 / \sum_{i=1}^{n} v_i \\ \vdots \\ v_n / \sum_{i=1}^{n} v_i \end{bmatrix}$$

The weight values contained in the vector *W* are the final weights for each criterion (i.e. C_i) and sub-criterion (i.e. S_i) in the FAHP model, where the sum of C_i and the sum of S_i are both equal to 1.

Once the values of C_i and S_i are obtained, the model can be used to determine the importance weight of each expert involved in the MCGDM problem using the following steps (Figure 1):

1. Experts provide data input values for each sub-criterion being assessed.
2. Apply a normalization process to ensure all input data ranges from [0–1], according to the maximum and minimum value of the data range for the quantitative sub-criterion obtained, and the qualitative predetermined scale data values.
3. Apply the weights previously obtained for the criteria and sub-criteria (i.e. C_i and S_i, respectively) to calculate each expert's final (ES_j) score using Equation 7.

$$[7] \; ES_j = \sum_{i=1}^{n_C} [C_i * (\sum_{k=1}^{n_S} S_k * I_{k,j})]$$

Where C_i represents the FAHP weight of the first *(i=1)* criterion, $S_k$represents the FAHP weight of the first *(k=1)* sub-criterion, and $I_{k,j}$ represents the normalized data value input by the first *(j=1)* expert assessment. Also, n_c and n_s represent the number of criteria and sub-criteria, which are listed in Figure 1. Finally, after each individual expert score is calculated for the experts in the group, the final importance weight (*IW*) of each expert is calculated using Equation 8. The sum of all experts' final importance weights should be equal to 1.

$$[8] \; IW_j = ES_j / \sum_{j=1}^{n} ES_j$$

Where IW_j represents the final importance weight of the j^{th} expert in the group and n is the number of experts in the group. The final importance weight will be used later on in the aggregation process to differentiate the influence of each expert during construction risk assessment MCGDM problems.

4 CONCLUSIONS AND FUTURE RESEARCH

For construction risk assessment MCGDM problems, the process of aggregating the opinions of experts in a heterogeneous group involves the two sub-processes of assessing experts' levels of expertise and assigning importance weights to experts. In the literature, importance weights are often assigned to experts arbitrarily and subjectively by the moderator. The main gaps in previous research are the lack of a clear and consistent set of criteria to assess experts' levels of expertise, as well as the lack of a clear weight assigning method that is based on selected qualification attributes (i.e. knowledge, experience, reputation, performance, etc.) according to the field of study relevant to the problem (i.e. construction risk assessment). The main contribution of this paper is in addressing these gaps by proposing a FAHP weight assigning model based on a clear and consistent list of criteria for assessing experts' levels of expertise in construction risk assessment. The FAHP weight assigning model provides a logical and comprehensive framework for structuring a MCGDM problem and quantifying its elements. Furthermore, this model addresses the subjectivity and uncertainty characteristic of the construction risk environment by allowing decision makers to represent pairwise comparison matrices using fuzzy linguistic scales.

Future research will explore automation of the FAHP weight assigning model proposed in this paper and its integration with Fuzzy Contingency Determinator© (FCD), a software tool that uses a fuzzy arithmetic procedure to determine construction project contingency (ElBarkouky et al. 2016). This research will facilitate the aggregation of the opinions of experts in a heterogeneous group when conducting risk assessment and contingency determination. In addition, an integrated aggregation framework that supports the FAHP weight assigning model and aggregation methods will be developed. Such a framework will help in comparing and selecting the most appropriate aggregation method to incorporate in risk assessment and management models.

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