Fuzzy Similarity Consensus Model for Early Alignment of Construction Project Teams on the Extent of Their Roles and Responsibilities

Mohamed M. G. Elbarkouky[1] and Aminah Robinson Fayek, M.ASCE[2]

Abstract: A fuzzy similarity consensus (FSC) model is presented for alignment of construction project owner and contractor project teams to their roles and responsibilities, identifying and reducing fundamental problems of conflicts, duplication, and gaps in roles and responsibilities as early as the project initiation stage. The model achieves its objective by incorporating consensus and quality of construction project teams in aggregating their opinions to decide on the party responsible for every standard task of a construction project. The roles and responsibilities of the owner and contractors are described to different extents using seven linguistic terms defined by triangular membership functions and constructed using a three-step Delphi approach, which allows experts to develop common understanding of the meaning of the terms by determining their overlap on a fuzzy linguistic scale. A modified similarity aggregation method (SAM) aggregates experts' opinions in a linguistic framework using a consensus weight factor for each expert that is based on the similarity of his or her opinion relative to the other experts to ensure that the experts' final decision is a result of common agreement. A fuzzy expert system (FES) determines an importance weight factor, representing expert quality for each expert; opinions are aggregated using this factor and the consensus weight factor. The FSC model contributes to the construction industry by solving a fundamental problem for project owners who want to identify and reduce potential conflicts between their project teams on the extent of their roles and responsibilities prior to the construction stage. Also, the FSC model provides an improvement over previous consensus-based approaches, which rely on a subjective assessment of experts' important weights in aggregating their opinions, and it modifies the SAM to adapt it to a linguistic environment. **DOI: 10.1061/(ASCE)CO.1943-7862.0000310.**

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Introduction and Problem Statement

Construction projects are unique; even similar construction projects will have different characteristics, contract types, and delivery systems (PMI 2008). Project management (PM) and construction management (CM) tasks handled by project owners as opposed to their contractors vary from project to project, which can impact a project's success (Bennett 2003). The allocation of responsibilities among the owner and its contractors, which may vary even for projects executed using the same delivery system, can be affected by several factors, such as confidentiality of the company's business, owner risks, schedule delays, change orders, level of communication within a project, and contract claims (Oyetunji and Anderson 2006; Kramer 2004). Project teams have difficulty evaluating these factors and agreeing on their responsibilities; owner organizations usually depend on expert judgment and on construction industry standards in deciding their responsibilities based on the selected project delivery system. Key managers of two large project owner organizations in Canada described one common problem: agreement on roles and responsibilities in a project. Common agreement in the decisions of project teams ensures their early alignment on the roles and responsibilities of the owner versus its contractors, minimizing the risk of duplication or gaps in project task allocation.

Distinctions and uncertainties may affect decision-making processes in the construction industry, especially in determining roles and responsibilities of project teams in a given project delivery system (Karamouz and Mostafavi 2010). Decision makers therefore often rely on expert opinions when making decisions (Tam et al. 2002). According to Predd et al. (2008), two major problems may affect the decision-making process: extracting meaningful information from a group of experts, and combining the experts' subjective opinions by resolving disagreements.

Objectives

This paper therefore presents construction project owners with a tool for early alignment between project owner versus contractor project teams on the extent of their roles and responsibilities for any predetermined set of tasks in a given project delivery system. A fuzzy similarity consensus (FSC) model was developed to aggregate the opinions of project teams using fuzzy logic (Zadeh 1965), which allowed project teams to express themselves linguistically, aggregate their subjective assessments in a linguistic frame-

[1]Ph.D., P.Eng., PMP, Voice Construction Ltd., 7545 52nd Street, Edmonton, AB, Canada T6B 2G2; formerly, Dept. of Civil and Environmental Engineering, Univ. of Alberta, Edmonton, AB, Canada T6G 2W2. E-mail: elbarkou@ualberta.ca

[2]Professor, NSERC Associate Industrial Research Chair, Ledcor Professor in Construction Engineering, Dept. of Civil and Environmental Engineering, Univ. of Alberta, Edmonton, AB, Canada T6G 2W2 (corresponding author). E-mail: aminah.robinson@ualberta.ca

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work, and account for imprecision in decisions about roles and responsibilities of project teams. The FSC model provides a flexible methodology based on expert judgment and fuzzy consensus aggregation to assist a construction project owner and its contractors and ensure that the project teams' decision on the extent of their roles and responsibilities is the result of common agreement. It allows for classification of the quality of experts in the decision-making process by defining an importance weight factor for each expert, and can be used to weight his or her response during aggregation. Finally, the FSC model is implemented on a case study of a large oil and gas construction project owner in Canada that wanted to define the extent of its roles and responsibilities versus those of its contractors in a customized project delivery system.

Literature Review

Simple statistical-based approaches, such as linear averaging, are successful in aggregating expert judgment (Clemen and Winkler 1999; Genest and Zidek 1986). However, linear averaging breaks down if opinions are incoherent or inconsistent (Predd et al. 2008). Linear averaging then centers on an erroneous mean rather than the true value (Reagan-Cirincione and Rohrbaught 1992). Neither linear averaging nor complex statistical-based approaches such as the coherent approximation principle (CAP) (Osherson and Vardi 2006) or the scalable algorithm of aggregation (SAA) (Predd et al. 2008) can aggregate opinions in a linguistic framework (Chen et al. 2006), where fuzzy logic excels (Herrera et al. 1996).

Fuzzy logic is more flexible for group decision-making in a linguistic framework, since the linguistic judgments of human beings are often vague (Herrera and Herrera-Viedma 2000); several studies investigated fuzzy logic-based consensus approaches for aggregating opinions in a linguistic framework (Kuncheva and Krishnapuram 1996; Bardossy et al. 1993; Ishikawa et al. 1993). Herrera et al. (1996) proposed the use of fuzzy preference relations (Blin 1974) to aggregate fuzzy opinions and measure expert consensus and introduced a scale of certainty expressions (numerically or linguistically assessed) to experts to describe their degree of certainty in preferring one alternative over another, similar to Saaty's (1980) analytical hierarchy process (AHP). Fuzzy preference relations can be applied in a linguistic framework to measure experts' consensus on a given opinion (Herrera and Herrera-Viedma 2000) but most techniques are iterative and may require several consensus rounds between experts before aggregation. A more robust approach is required to aggregate linguistic judgments that still ensures that the aggregated decision is a result of common agreement; it should also reduce or eliminate the effect of inconsistent judgments among experts in the aggregated decision. Fuzzy similarity measures (Zwick et al. 1987) provide a solution.

Fuzzy similarity measures classify similar elements or distinguish between similar groups of individual decisions—numerical or linguistic—to ensure that their aggregated opinion is a result of common agreement (Rezaei et al. 2006) and use mathematical models (Hsu and Chen 1996; Rezaei et al. 2006) or optimization algorithms (Lee 2002) to aggregate individual fuzzy opinions into a group fuzzy consensus opinion. Hsu and Chen (1996) proposed a similarity aggregation method (SAM) to aggregate fuzzy opinions under group decision-making. SAM uses a simple algorithm based on fuzzy arithmetic and similarity agreement, and can aggregate numerical forecasts provided by experts using fuzzy numbers by computing a consensus weight factor for each expert based on the similarity of their opinions. A similarity measure function (Zwick et al. 1987) was used to calculate the degrees of similarity between experts' opinions based on areas of overlap of their fuzzy numbers. Hsu and Chen (1996) assumed numerical importance weight factors to incorporate experts' credibility in decision-making. A simple aggregation equation aggregated experts' opinions using their combined consensus and importance weight factors. The SAM ensures that the aggregated decision is a result of common agreement, because the experts whose opinions are far from the common opinion of the group of experts will receive lower consensus weight factors in the aggregation algorithm.

The SAM is a simple, practical approach to the problem at hand. First, it uses a flexible aggregation algorithm that can be modified to aggregate the overlapping meanings of experts' linguistic assessments of the different parties' roles and responsibilities. Second, it ensures that the aggregated opinion is based on common agreement between experts, ensuring early alignment of project teams on the roles and responsibilities of the owner versus those of its contractors. Third, it incorporates the importance weights of experts in the aggregation equation; these weights can be computed using a stand-alone model.

To apply SAM to the problem at hand, a standard fuzzy linguistic scale, or standard membership functions (MFs), must be developed to represent experts' linguistic assessments. Second, the SAM needs a method to determine the MFs' distance from the aggregated opinion of experts on the standard fuzzy linguistic scale. Finally, Hsu and Chen's (1996) work did not define a clear methodology for the determination of the expert weighting. An FSC model addressing the limitations of the SAM for the aggregation of experts' linguistic assessments of roles and responsibilities in a given project delivery system has been developed.

Methodology and Model Development

This section describes the five main steps of the methodology and development of the FSC model (Fig. 1). First, a standard fuzzy linguistic rating scale is created; on which project teams define different extents of the roles and responsibilities of the project owner versus those of its contractors. Second, project teams' opinions are collected regarding the extent of the roles and responsibilities of the owner versus its contractors on a predetermined set of tasks using the linguistic terms that are defined in step one. Third, a stand-alone fuzzy expert system (FES) is created, to determine an importance weight factor for each expert in the decision-making process. Fourth, the SAM (Hsu and Chen 1996) is applied to aggregate the opinions of experts by combining each expert's importance weight factor (output of the FES) with his or her consensus weight factor in the SAM; this produces a fuzzy number, depicted on the fuzzy linguistic scale. Fifth, the Euclidean distance measure function (Heilpern 1997) is used to determine the best linguistic term for the aggregated fuzzy number (output of the SAM algorithm) in a linguistic framework. The linguistic term whose MF has the minimum Euclidean distance to the aggregated fuzzy number describes the final extent of the roles and responsibilities of the project owner versus its contractors for a given task. Based on the aggregated extent of responsibility, the task is classified under one of three responsibility task lists: the owner's, contractors', or shared responsibility task list. Each step in developing the FSC model is described in detail in the following sections.

Creating the Fuzzy Linguistic Rating Scale

To create the fuzzy linguistic rating scale, the universe of discourse and the number of linguistic terms forming the scale defining the degrees of responsibility of the owner versus its contractors had to be determined. The cardinality of the linguistic term set must be small enough to avoid unnecessary precision, but rich enough to

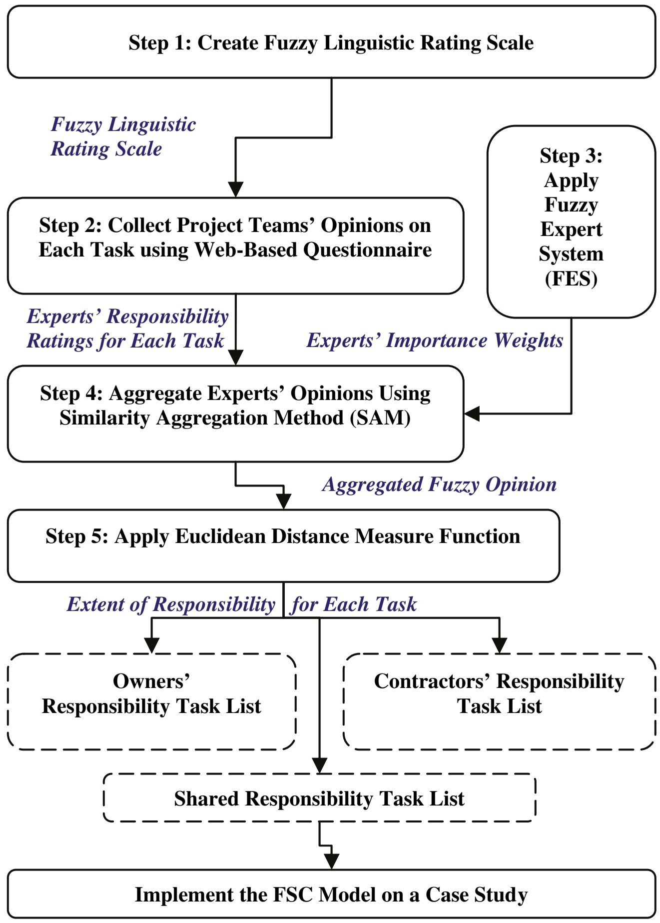

Fig. 1. Steps in developing fuzzy similarity consensus model

allow discriminating assessments (Herrera and Herrera-Viedma 2000). Typical cardinality values are odd in number, preferably 7 or 9; the midterm value represents an average assessment and the other terms are placed symmetrically around it (Bonissone and Decker 1986). These cardinality values conform to Miller's (1956) observation that human beings can reasonably assess seven simultaneous alternatives.

Using these guidelines, five key experts of a large oil and gas construction project owner organization defined seven linguistic terms for the degrees of responsibility of the owner versus those of its contractors. The universe of discourse of the rating scale ranged from 1—no responsibility—to 7—sole responsibility of the owner (Table 1). Experts were then asked to construct the membership functions (MFs) of the linguistic terms using a three-step Delphi approach conducted in three rounds (Saaty 1980), developing consensus on the linguistic terms.

The first round solicited generic opinions regarding the preliminary shapes of the MFs from 20 experts of the owner organization and its contractors, with 5 to 20 years of experience, kept anonymous to avoid bias (Hyun et al. 2008). For simplicity, we assumed a triangular MF, with a peak at the numerical rating of its respective linguistic term. The experts were asked, "what are the ranges of elements (x_i) that may represent this linguistic term on the scale—please circle as many answers as applicable." This resulted in 18 different responses, each with different shapes of the fuzzy linguistic terms on the scale based on the different ranges of elements chosen. In round two, the proposed 18 fuzzy scales were sent back to each expert with additional information: two simple rules for defining relevance. The rules were (1) the membership functions should have some symmetry because the scale is reciprocal, and (2) the membership functions should have certain degrees of overlap to represent the overlap between their linguistic meanings. Experts were otherwise free to change the shapes of their membership functions and compare the responses. The results were categorized into nine different responses from 14 experts, and showed more convergence in opinions.

Before round three, the frequency of responses on each side (leg) of each triangular fuzzy number was determined. In round three, nine experts from the first two rounds' participants were shown the round two results in a meeting that included all nine experts. The experts assessed each MF's correspondence with its linguistic term by voting on the support (i.e., range) of each side of the term's triangular MF in several rounds, until consensus was reached on a single fuzzy scale. In each round, those with differing opinions were asked to reconsider or provide support. One persistently conflicting expert's opinions were disregarded. This process produced the final fuzzy linguistic rating scale (Fig. 2), used to collect the responses of project teams on the extent of the owner's roles and responsibilities versus that of its contractors on any predetermined set of tasks.

Collecting Project Teams' Opinions Using Web-Based Questionnaire

To collect the opinion of project teams regarding the extent of their roles and responsibilities, a Web-based questionnaire was prepared

Table 1. Description of Linguistic Terms Forming Fuzzy Linguistic Rating Scale

Rating	Linguistic term	Description
1	No responsibility	Project owner is not responsible for carrying out the task. The owner may be consulted based on the contractor's sole discretion.
2	Limited involvement	Project owner is not responsible for carrying out the task. Minor input is required from the owner to enable the contractor to perform the task.
3	Active involvement	Project owner is not responsible for carrying out the task. The owner must be involved in all task-related discussions and provide considerable input.
4	Shared equally	Both parties carry out the task with equal levels of involvement.
5	Significant involvement	Project owner is responsible for carrying out the task. The contracor must be involved in all task-related discussions and provide considerable input.
6	Principal responsibility	Project owner is responsible for carrying out the task. Minor input is required from the contractor to enable the owner to perform the task.
7	Sole responsibility	Project owner is fully responsible for carrying out the task. The contractor may be consulted based on the owner's sole discretion.

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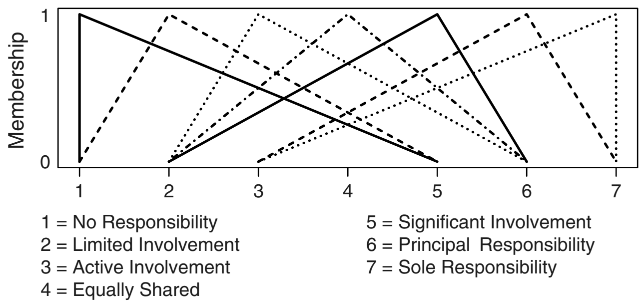

Fig. 2. Finalized fuzzy scale after consensus reaching

using a commercially available Web-based survey tool, the seven linguistic terms that were created in step one, and a general methodology of data collection applicable to any participating organization. First, multiple choice questions addressing characteristics of the projects and project team members were developed, providing information on individual experts, such as years of experience and role in the company. These questions were helpful in collecting the attributes of the input variables to the FES to calculate individual experts' importance weights (step 3). Second, the predetermined tasks the project team members would rate were categorized into standard work processes to facilitate grouping of tasks based on the in-house work processes of the participating owner organization. The question for each task was in the form of, "to what extent would you rate the roles and responsibilities of the owner versus that of its contractors?" The project team members chose from definitions of the seven linguistic terms (Table 1). The data collected was analyzed using the modified SAM, as will be explained in steps four and five.

Calculating Experts' Importance Weights Using FES

In this step, a stand-alone FES was developed to incorporate the quality of experts in the decision-making process with an importance weight factor based on an expert's attributes: years and diversity of experience, role and years in role in the company, and enthusiasm and willingness to participate. Use of the FES in the FSC model is an improvement over previous consensus-based approaches, which rely on a subjective assessment of experts' importance weights in aggregating their opinions.

FESs provide a method of representing qualitative data and describing input variables using natural language. The FES used in this paper was built in two stages using FuzzyTECH software, which is composed of a model interface, a knowledge base, and an inference engine. The first stage was to develop the components of the knowledge base: fuzzy if-then rules that connect the inputs to the output, and a method that defines membership functions. Both the input and output variables are described by linguistic terms defined by membership functions (MFs). The second stage was to develop the inference engine, which fuzzifies the input, performs fuzzy operations on the rules, and defuzzifies the output.

Five key decision makers in the owner organization, each with over 15 years of experience in oil and gas construction, participated in several interviews and a questionnaire to define the input variables. The interviews resulted in five input variables and an output variable, as well as the linguistic terms that describe each variable, which were defined on a seven-point scale. The first input factor, years of experience, indicates construction industry experience. This factor affects experts' understanding of the construction project as a whole and the advantages and disadvantages of different project delivery systems, as well as awareness of their requirements and ranges from less than one year to more than 20 years of experience. It is described by three MFs (small, medium, and large). The second input factor, diversity of experience, determines an expert's experience in working with various owner and contractor organizations, increasing an opinion's importance if the expert has previous experience in working in both organizations. It is described by three MFs (low, medium, and high). The third input factor, role in the company, indicates managerial skill level, and affects an expert's judgment regarding appropriate roles and responsibilities in a given project delivery system and ability to interpret and categorize the tasks to be rated under each work process; it ranges from project lead to general manager and is described by three MFs (low, medium, and high). The fourth input factor, years in role, determines an expert's managerial experience, complementing the factor role in the company, so that a rating provided by a more senior manager in his or her role has significant reliability; it ranges from less than one year to more than 20 years of experience and is described by three MFs (small, medium, and large). The last input factor is, enthusiasm and willingness, and indicates the potential to evaluate roles and responsibilities, helps assess the validity of responses, and is described by three MFs (low, medium, and high).

The output variable of the FES is described as an importance weight factor (w_i) of each expert. The elements of the output variable are continuous on the universe of discourse with a range of 0 to 1. It is represented by five MFs, as agreed upon with the experts: very low, low, medium, high, and very high.

The questionnaire that was used to collect data on the input and output variables also helped the experts in ranking the input variables in terms of their influence on the output variable, facilitating the creation of the knowledge base of fuzzy if-then rules in the FuzzyTECH software. The knowledge base in the FuzzyTECH software consists of fuzzy if-then rules in the form of: If A is low and B is high then C is medium, where A and B are the input variables, C is the output variable, and low, high, and medium are examples of the linguistics terms describing each variable. The rule base was created for the FES using data obtained from the questionnaire, in which respondents rated the five input variables on a scale of 1 to 7 in terms of their influence on the output variable, where 1 means extremely low influence, 4 means medium influence, and 7 means extremely high influence. The ratings of 2, 3, 5, and 6 represent symmetrical intermediate values on the scale.

The linguistic terms used for the rating were generated by the FuzzyTECH software based on the influence of the input variables on the output. Two hundred forty-three rules (3^5) were implemented in the FES based on all available combinations of linguistic terms comprising the five input variables (each represented by three membership functions). The average rating of experts for each input variable was then used to determine the output of a given rule for a given set of inputs by accounting for the relative influence of the input variables on the output. For example, if years of experience is large and diversity of experience is high and role in the company is high and years in role is small and enthusiasm and willingness is low, then importance weight factor is high. The output variable is high because years of experience and diversity of experience were rated by experts to be of very high influence and high influence on the output factor, respectively, while role in the company, years in role, and enthusiasm and willingness were each rated by experts to be of medium influence on the output factor. If the years in role were large and enthusiasm and willingness were high, and the other three input variables remained constant, the output would be very high, as all input variables would be represented by their maximum linguistic terms.

The MFs of the input and output variables were then constructed. First, the modified horizontal approach was used to determine preliminary nonuniform shapes of the MFs representing their

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linguistic terms (Marsh 2008). Then, the MFs were transformed to fit standard triangular or trapezoidal shapes. The supports and shapes of each linguistic term were determined based on a simple questionnaire from the same five key experts, asking, "what are the ranges of elements (x_i) that may represent this linguistic term on the scale—please circle as many answers as applicable," for each term. The replies were counted in terms of frequencies of responses [$P(x_i)$] to the total number of responses (N) for every element x_i to calculate its membership value [$A(x_i)$], resulting in the preliminary nonuniform shapes of each MF. The finalized standard shapes of the MFs that best fit the nonuniform shapes were determined using the least sum of errors calculation. The sum of errors was calculated between the membership values [$A(x_i)$] of the elements (x_i), composing the nonuniform shapes and their relevant elements in each proposed standard shape. The elements of the standard shape with the least sum of errors to those of the nonuniform shape were considered the best fit for the data.

The second stage in developing the FES was to develop the inference engine by determining the fuzzy operators, implication method, and defuzzification method. The best inference system was chosen using the variation in the system outputs for a sample group of experts, whose attributes were collected for this purpose. The system configuration that showed the highest variation in the experts' importance weights on the range of 0–1 was selected, because the actual input values of the experts' attributes varied widely. For the selected system, the minimum (MIN) t-norm fuzzy operator (corresponding with linguistic AND) is used for combining the input variables, the product (PROD) t-norm is used for rule implication, and the maximum (MAX) s-norm is used for rule aggregation. The center of maxima (CoM) defuzzification method provides a crisp importance weight value for each expert. Output importance weights (w_i) are then normalized into a relative importance weight factor (W_i) [Eq. (1)], where n is the number of experts participating in the survey and W_i ranges from 0–1.

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{1}$$

Applying the SAM to Aggregate Experts' Opinions

In this step, the SAM algorithm (Hsu and Chen 1996) is used to aggregate experts' opinions. Assume, for a given task, that three experts E_1, E_2, and E_3 selected their fuzzy ratings R_1, R_2, and R_3 from the fuzzy linguistic rating scale (Fig. 2) as illustrated in part (a) of Table 2. The membership functions that describe the experts' fuzzy ratings are represented by the fuzzy triplets (r_1, r_2, r_3) [part (b) of Table 2], based on the shapes and supports of the standard membership functions that describe the seven fuzzy ratings Y_k, where k ranges from 1–7 on the fuzzy linguistic rating scale (Fig. 2). The standard fuzzy ratings Y_k help the experts to determine the extent of the roles and responsibilities for each task according to their respective linguistic terms.

Table 2. Numerical Calculations of Fuzzy Similarity Consensus Model

		Expert 1	Expert 2	Expert 3
(a) Rating		Principal responsibility	Principal responsibility	No responsibility
(b) Fuzzy triplets	r_1	3	3	1
	r_2	6	6	1
	r_3	7	7	5
(c) Agreement matrix	Expert 1	1.00	1.00	0.08
	Expert 2	1.00	1.00	0.08
	Expert 3	0.08	0.08	1.00
(d) Consensus calculation	$A(E_i)$	0.54	0.54	0.08
	RAD_i	0.47	0.47	0.06
	W_i	0.400	0.400	0.435
	CDC_i	0.435	0.435	0.130

Note: R = (2.74 5.35 6.74); owner's principal responsibility.

The SAM algorithm first calculates the agreement degree $S(R_i, R_j)$ between the fuzzy ratings selected by each expert pair. The agreement degree is the intersection area of the ratings divided by the bounding area, as shown in Eq. (2), where μR_i and μR_j = relevant membership degrees of every element (x) of the fuzzy ratings selected by the two experts on the scale

$$S(R_i, R_j) = \frac{\int_x (\min\{\mu R_i(x), \mu R_j(x)\}) dx}{\int_x (\max\{\mu R_i(x), \mu R_j(x)\}) dx} \tag{2}$$

For example, based on the membership functions' shapes (Fig. 2), the intersecting area between the fuzzy ratings of experts 1 and 2 is calculated as 1.0 because they selected the same fuzzy ratings from the fuzzy scale (both selected the linguistic term principal responsibility). The total bounded area is also equal to 1.0, so their agreement degree is $S(R_1, R_2) = 1.0$. However, the area of intersection of the triangular shapes of the fuzzy ratings selected by experts 1 and 3 is calculated as 0.29, while the total area bounded by their fuzzy ratings on the fuzzy linguistic rating scale is 3.71. This means that their agreement degree $S(R_1, R_3) = (0.29)/(3.71) = 0.08$ and $S(R_2, R_3) = 0.08$. An agreement matrix (AM) [part (c) of Table 2] is constructed for each task and stores the calculated agreement degrees between expert pairs.

The SAM algorithm then computes a relative agreement degree (RAD_i) for every expert: his or her consensus weight factor among the group [Eq. (3)], where $A(E_i)$ is the average level of agreement of an expert with other experts, and is calculated by dividing the sum of his or her agreement degrees with other experts by ($n-1$) number of experts.

$$\mathrm{RAD}_i = \frac{A(E_i)}{\sum_{i=1}^{n} A(E_i)} \tag{3}$$

In the previous example, $A(E_1) = A(E_2) = (1 + 0.08)/2 = 0.54$, $A(E_3) = (0.08 + 0.08)/2 = 0.08$. Thus, $\mathrm{RAD}_1 = \mathrm{RAD}_2 = (0.54)/(0.54 + 0.54 + 0.08) = 0.47$. Using the same equation, $\mathrm{RAD}_3 = (0.08)/(0.54 + 0.54 + 0.08) = 0.06$.

The SAM algorithm computes a consensus degree coefficient (CDC_i) combining the relative importance weight factor (W_i) (step 3) for every expert with his or her RAD_i in a single equation. A modifier (β) is used to either emphasize W_i, if β is set to 1, or RAD_i, if β is set to 0, for every expert before aggregating the opinions into a single fuzzy number (R) [Eq. (4)].

$$\mathrm{CDC}_i = \beta * W_i + (1 - \beta) * RAD_i \tag{4}$$

For the CDC_i calculation of experts 1, 2, and 3, assume that their relative importance weight factors W_i are determined using the FES to be 0.40, 0.40, and 0.20, respectively. By assuming equal emphasis of the three experts' consensus weight factors and their importance weight factors, a modifier $\beta = 0.5$ is selected. Thus, $\mathrm{CDC}_1 = \mathrm{CDC}_2 = (0.50 \times 0.40) + (0.50 \times 0.47) = 0.435$ and $\mathrm{CDC}_3 = (0.50 \times 0.20) + (0.50 \times 0.06) = 0.130$. Note that the total CDC sums to 1.000.

The aggregated fuzzy number R for each task is the sum of the multiplication of the CDC_i of each expert by the fuzzy number R_i that represents his or her fuzzy rating [Eq. (5)].

$$R = \sum_{i=1}^{n} (\mathrm{CDC}_i * R_i) \tag{5}$$

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Using the same example, $R = [0.435 \times (3,6,7)] + [0.435 \times (3,6,7)] + [0.130 \times (1,1,5)] = (2.74, 5.35, 6.74)$. The last step is to determine the final extent of the roles and responsibilities for every task by defining the relevant linguistic term that best matches the aggregated fuzzy number R, explained next.

Determining the Final Extent of Responsibility

The Euclidean distance measure, illustrated in its generic form (Heilpern 1997) in Eq. (6), is used to determine the final extent of responsibility for each task by measuring the Euclidean distance between the triplets (r_1, r_2, r_3) of the aggregated fuzzy number R and those of the seven standard fuzzy ratings Y_k on the scale, where $p = 2$ for the Euclidean distance measure function, $n = 3$ because each fuzzy rating is represented by a triplet, r_i is each number forming the triplet of the aggregated fuzzy number R, and y_i is the corresponding number forming the triplet of each of the seven standard fuzzy ratings (Y_k) on the scale

$$d_g(R, Y_k) = \left(1/n \sum_{i=1}^{n} |r_i - y_i|^p\right)^{1/p} \tag{6}$$

The linguistic term that best describes the aggregated fuzzy number (R) is the one defined by the standard fuzzy rating (Y_k) with the minimum distance to the aggregated fuzzy number R on the scale. This term determines the final responsibility for the task (Table 1). The Euclidean distance measure function then calculates the distance of the aggregated fuzzy number R (2.74, 5.35, 6.74) to each of the seven standard fuzzy ratings Y_k. Eq. (7) illustrates a sample calculation of the Euclidean distance between the fuzzy number $R(2.74, 5.35, 6.74)$ and the standard fuzzy rating $Y_7(3,7,7)$ representing the linguistic term sole responsibility:

$$d_g(R, Y_7) = (\{1/3 \times [(2.74 - 3)^2 + (5.35 - 7)^2 + (6.74 - 7]\})^{1/2} = 0.98 \tag{7}$$

Using the same method of calculation, the measure of the Euclidean distances of the fuzzy number $R(2.74, 5.35, 6.74)$ to the standard fuzzy ratings, Y_1 no responsibility, Y_2 limited involvement, Y_3 active involvement, Y_4 equally shared, Y_5 significant involvement, Y_6 principal responsibility, are 2.89, 2.40, 1.74, 0.99, 0.64, and 0.43, respectively. From the previous calculations, the owner organization's final responsibility can be defined by the linguistic term Y_6—principal responsibility, because it has the minimum Euclidean distance to the aggregated fuzzy number $R(2.74, 5.35, 6.74)$. Principal responsibility defines the same responsibility originally selected by experts 1 and 2 to represent their opinion.

The SAM algorithm therefore yields an appropriate aggregated decision entailing common agreement between experts, as the impact of expert 3's inconsistent opinion was minimized in the aggregation algorithm because of his low consensus weight factor of 0.06 compared to the relatively high consensus weight factors of experts 1 and 2 of 0.47 [Eq. (3)]. All tasks are categorized into one of three task lists. From Fig. 2, the fuzzy ratings Y_k with peaks corresponding to the elements (5) significant involvement, (6) principal responsibility, and (7) sole responsibility of the owner indicate that the owner is responsible for the task. The fuzzy ratings (Y_k) of peaks corresponding to the elements (1) no responsibility, (2) limited involvement, and (3) active involvement of the owner indicate that the contractor is the responsible party, because the scale is reciprocal. The fuzzy number with a peak of 4 indicates an equally shared responsibility. The next section illustrates a case study using the FSC.

Model Implementation: Case Study

To demonstrate the applicability and practicality of the model, the FSC model was implemented to assist an owner organization in the oil and gas field in defining its roles and responsibilities versus those of its engineering, procurement, and construction (EPC) contractors in a newly proposed owner-customized project delivery system, the owner managing contractor (OMC). The project owner previously used engineering, procurement, and construction management (EPCM) contractors to manage the construction of its oil and gas projects from the design phase up to the project turnover phase. In the EPCM project delivery system, the owner handled traditional supervision roles; the EPCM contractor executed all contracts and procurement and was compensated on a cost reimbursable basis to perform engineering and management services and manage the EPC and EP companies, general contractors, and subcontractors. The major advantage of this system is that the EPCM contractor has the flexibility to deal with project problems and scope changes by deploying additional resources, without the need to negotiate cost and schedule impacts with the owner (Agnitsch et al. 2001), although project owners may be involved to a limited extent in equipment selection and commercial arrangements with major vendors and subcontractors. However, it has one major disadvantage: the project owner has to assign its major PM and CM functions to the EPCM contractor, which led to conflicts between the various project teams owing to uncontrolled project interfaces. In addition, relying on the EPCM contractors for project management reduced the required PM and CM competencies of the owner organization, which reduced its ability to make project decisions in a timely manner.

To correct the problem, the owner organization undertook a joint venture (JV) with two other owner organizations to deliver their oil and gas construction projects more efficiently using a customized project delivery system. In addition to assuming the roles of a traditional project owner organization, one of the three companies took over the PM and CM roles previously handled by the EPCM contractor. Thus, the traditional owner was assigned the title of owner managing contractor (OMC), which is how the project delivery system got its name. Also, some of the roles of the EPC and EP contractors, such as setting up contracts for bulk purchasing of long lead equipment, were transferred to the OMC, resulting in an OMC project delivery system that is a hybrid of the EPC and CM systems, because of the dual role of the OMC as a project and construction manager as well as an EPC contractor. The OMC differs from the CM project delivery system, because it encourages the owner to rely less on the use of external expertise, such as CM consultants or EPCM contractors, and it allows the sharing of the owner's resources with the EPC contractors in executing the project tasks. The OMC differs from partnering (Chan et al. 2003), as it allows the owner to manage its projects using internal resources for most project functions.

The intentions of the JV in creating the OMC project delivery system were to better control project activities, reduce complex interfaces between project teams, enhance its PM and CM competencies, and benefit from economies of scale in procuring long lead items on behalf of the EPC and EP companies. These unique roles created a complex environment for construction projects, causing confusion and misunderstanding in the roles and responsibilities of the project team in both the owner's and its EPC constructors' organizations. Thus, the owner organization required a tool to help ensure the early alignment of its project teams on the extent of the roles and responsibilities of the owner versus that of its EPC contractors in the customized OMC project delivery system for a standard set of PM

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and CM tasks. The next section describes the application of the FSC model to solve this problem for the owner organization.

Application of the FSC Model

The authors investigated several standardized project delivery systems to prepare a standard set of PM and CM task lists (Elbarkouky and Fayek 2009). Examples of these delivery systems are design-build (Chan et al. 2005; Bender 2003), EPCM [Construction Owners Association of Alberta (COAA)] (2007), and traditional construction management (CMAA 2002; Bennett 2003). The 30 core competencies of the Construction Industry Institute (CII 1997) and their subtasks provided additional tasks that were added to the lists. Interviews with the owner's personnel, their EPC contractors, and a review of the preliminary OMC model of the owner's organization extended the preliminary task lists.

The final set of lists included 324 PM and CM tasks categorized under 18 work processes (e.g., project initiation, project management, project control, and construction management) based on the structure of the owner organization's projects (Table 3). The task lists were then incorporated into a Web-based questionnaire that solicited the opinion of 52 owner organizations and EPC project managers. Twenty-six owner organizations' project managers and 11 EPC contractor project managers, all with 5 to 20 years of experience, participated in the survey (a 71% response rate). The results of the survey helped project teams define the responsibilities of the owner versus those of its EPC contractors in the new OMC project delivery system using the seven linguistic terms (Table 1), and helped in collecting the five key attributes of the participating experts that represent the input factors to the FES. The importance weights of each of the 37 experts were calculated by the FES based on these attributes (Table 4). The SAM algorithm was then applied to aggregate the 37 experts' linguistic assessments on every task of the 324 tasks. The modifier β of 0.5 was selected by the JV to calculate the CDC in the SAM algorithm. Finally, the Euclidean distance measure function was applied to the aggregated fuzzy number (output of the SAM) to determine the final extent of responsibility of the owner versus its EPCs for each task and classified each task in one of the three responsibility task lists (owner, EPC, and shared responsibility task lists) based on the aggregated extent of responsibility.

Table 3. List of Sample Tasks Categorized under Project Management Work Process

Task description	Work process
Preparing the project's detailed work breakdown structure	Project management
Approving detailed scope statements of work	Project management
Preparing the preliminary project execution plan (PEP)	Project management
Implementing a value improvement practice (VIP)	Project management
Supervising planning and estimation coordination meetings	Project management
Identifying, analyzing, mitigating, and controlling risks	Project management
Establishing clear accountabilities for projects' parties	Project management
Communicating the project control system to all parties	Project management
Monitoring and approving the scope and conceptual designs	Project management
Recruiting operating or ready for operations organization	Project management
Setting initial partnering strategy, if any	Project management
Advising on the contracting strategy, and subcontractors	Project management
Assembling the contractors' project teams	Project management

Analysis of Implementation Results and Model Validation

After applying the FSC model to the 324 standard tasks and analyzing experts' aggregated opinions, 168 tasks were determined to be owner's tasks, 110 were EPC contractors' tasks, and 46 were equally shared tasks. To test the validity of the FSC model in providing an output that satisfies the JV-determined requirements in an OMC project delivery system, the output responsibility results of the model were compared, on a work process basis, to the actual responsibilities for relevant tasks in three successful oil and gas construction projects, ranging in size from \$300 million to over a billion dollars. One of these projects, the largest of the three, was the only project that followed an OMC project delivery system that satisfied the JV's requirements in most of its work processes, and therefore is used in this paper to validate the FSC model. The objective of the comparison was to determine whether the model's recommendations, which are based on the collective decision of the project teams, are aligned with the JV-determined requirements of the OMC project. This comparison also provides the JV with insights on whether its project teams were aligned on their roles and responsibilities in the OMC project. For each work process, the degree of matching of the output responsibilities of the FSC model to the actual responsibilities in the OMC project was calculated as a percentage by dividing the number of tasks with matching (similar) responsibilities by the total number of tasks in this work process.

The project manager of the OMC project was asked via questionnaire to indicate whether each of the 324 tasks on his project

Table 4. Sample FES Output of Importance Weights of Five Experts

	Years of experience	Diversity of experience	Years in role	Enthusiasm and willingness	Role in the company	Relative importance weight
Influence	Very high	High	Medium	Medium	Medium	
Expert 1	> 20	Extremely high	> 20	High	Sr. project manager	0.84
Expert 2	> 20	Average	9–12	High	Sr. project manager	0.71
Expert 3	9–12	Extremely high	9–12	Extremely high	Project director	0.67
Expert 4	9–12	High	9–12	High	Project manager	0.60
Expert 5	5–8	Low	5–8	Average	Project manager	0.46

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was the responsibility of the owner, the contractors, or if it was equally shared; the output responsibility results of the FSC model to those of the actual OMC project were compared on a work process basis. This step determines whether the project teams were aligned on the JV-determined requirements of the OMC project for each work process. In addition, to determine whether the recommendations of the FSC model contribute to the success of each work process in the OMC project, subjective assessments were solicited from the project manager regarding his level of satisfaction for each work process in terms of its success in achieving the JV's desired objectives of the OMC project delivery system. A scale from 1 to 7, ranging from extremely unsatisfactory to extremely satisfactory, was used to collect the level of satisfaction of the project manager for each work process on his project. For each work process that had a level of satisfaction lower than average and a degree of matching less than 65% (cutoff percentage was decided by the JV's key managers), the project manager was asked to subjectively determine if the misalignment of the project teams (degree of matching less than 65%) had an impact on the level of satisfaction of that work process in the project. The project manager was asked to make his assessment on a scale from 1 to 5. A rating of 1 meant that misalignment had a very low impact on the level of satisfaction of a work process. A rating of 5 represented a very high impact, meaning that the low level of satisfaction for a work process was caused by possible conflicts or gaps in responsibility assignments of its tasks because of misalignment of project teams.

Table 5 illustrates the degree of matching and the level of satisfaction on a work process basis in the OMC project. Four processes, regulation compliance, procurement, contracting and operations, and maintenance, showed a high degree of matching (90 to 100%) and had satisfactory or very satisfactory levels of satisfaction. Eight processes (initiation, project management, document management, financial controls, engineering, construction management, ready for operations, and administration) showed an average degree of matching (65 to 75%). Most of these work processes had satisfactory level of satisfaction, except for project management and initiation work processes that had average and very satisfactory levels of satisfaction, respectively. The project manager indicated that none or minor responsibility conflicts took place between the project teams in the execution of all of these work processes, and that they were aligned with the JV-determined requirements of the OMC project delivery system, except for the project management work process, which had considerable conflicts and gaps in responsibilities of the PM teams, and suffered from the unavailability of skilled resources. Two processes, information systems and safety management, showed a low degree of matching of 25% and 35%, respectively, yet both of them were rated as average in terms of level of satisfaction. The project manager indicated that no specific requirements were mentioned by the JV in the OMC project regarding these two processes, which could be a potential cause of misalignment (i.e., low degree of matching); however, there were different EPC contracts in the project with different requirements for these specific processes that were met to an average level of satisfaction. Project controls and organization had unsatisfactory levels of satisfaction and 50 and 20% degrees of matching, respectively. The project manager stated the misalignment of project teams had a very high impact on these processes because of the gaps in responsibilities that were found between the owner and its EPC contractors during the project execution phase.

Table 5. Comparison of FSC Model's Output Responsibilities with Those of an Actual Project

(a) Process	(b) # of Tasks	(c) Matching %	(d) Satisfaction
Operation and maintenance	3	100%	Very satisfactory
Regulation compliance	9	90%	Satisfactory
Procurement	16	90%	Very satisfactory
Contracting	9	90%	Very satisfactory
Initiation	28	70%	Very satisfactory
Financial controls	11	75%	Satisfactory
Engineering	27	75%	Satisfactory
Construction management	18	70%	Satisfactory
Ready for operations	24	70%	Satisfactory
Administration	4	75%	Satisfactory
Document management	9	70%	Satisfactory
project management	58	65%	Average
Quality	20	60%	Average
Change management	8	60%	Average
Project controls	48	50%	Unsatisfactory
Safety management	23	35%	Average
Information systems	4	25%	Average
Organization	5	20%	Unsatisfactory

This analysis indicates that only the work processes that showed a considerably high degree of matching (at least 65%) of the output responsibilities of the FSC model to the actual responsibilities in the OMC project were satisfactory. This result indicates that the model's recommendations, which are based on the collective decision of the project teams, are aligned with the JV-determined requirements of the OMC project. The analysis also indicates that the processes that did not follow the recommendations of the FSC model, such as project controls and organization, did not satisfy the JV-determined requirements of the OMC project. Thus, the FSC model's recommendations are valid. The FSC model also provides the JV with insights on whether its project teams are aligned on their roles and responsibilities in an OMC project and showed the impact of not aligning the project teams in the form of a low level of satisfaction of work processes.

In conclusion, the outputs of the FSC model provide a structure and guidelines toward successful roles and responsibilities task assignment according to the requirements of the OMC project delivery system that entails common agreement between project teams. Although the model helps in determining and reducing responsibility conflicts on the majority of the OMC tasks, the average level of agreement of experts, calculated by the SAM, is low on the tasks that are rated by project teams as equally shared (46 tasks out of 324), which still needs to be further investigated and resolved. The authors are developing a fuzzy consensus preference relations model (Herrera et al. 1996) for resolving conflicts in experts' opinions on tasks with shared responsibility in a consensus-reaching process (Elbarkouky and Fayek 2010).

Conclusions and Contributions

An FSC model is proposed that solves a fundamental problem for construction project owners who need to align their project teams on the extent of their proper roles and responsibilities in any project delivery system. A three-step Delphi consensus approach combined with the modified SAM allows experts to reach common agreement on their proper roles and responsibilities in a linguistic framework, identifying and reducing the gaps and conflicts in responsibilities between their project teams. A FES was developed to incorporate the subjective quality aspects of experts' opinions, improving upon previous consensus approaches that rely on subjective assessments of experts' weights in aggregating their

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opinions. The FSC model modifies an existing fuzzy aggregation approach (SAM) to adapt it to a linguistic framework, and takes into account the subjective opinions of multiple experts in classifying project roles and responsibilities, as well as the quality of experts, to develop a valuable decision-making tool. It yields three responsibility lists that classify project tasks into owner responsibility, contractor responsibility, or shared responsibility. The FSC model was applied to help a Canadian owner organization define its and its EPC contractors' roles and responsibilities in an owner-customized project delivery system, namely the OMC. The authors are investigating the use of fuzzy preference relations to develop a stand-alone fuzzy consensus preference relations model for resolving conflicts in experts' opinions on tasks with shared responsibility.

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