A Framework for Modeling Construction Organizational Competencies and Performance

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ABSTRACT

The variables that characterize construction organizational competencies are both quantitative and qualitative in nature, and thus require measurement methods and modeling techniques that can handle both variable types. Models that are capable of relating organizational competencies to performance provide a critical advantage in the identification of target areas leading to improved performance. This paper proposes a framework to develop a fuzzy hybrid model for mapping organizational competencies to performance. To achieve these objectives, different fuzzy modeling techniques, such as fuzzy rule-based (FRB) systems and fuzzy neural networks (FNNs) are explored. This study highlights research gaps related to organizational competency and performance studies in developing models at the organization level. The proposed framework outlines modeling procedures that enable the integration of fuzzy modeling techniques with other approaches that exhibit learning capabilities. The proposed model captures organizational competencies as input by using various competency evaluation criteria, and provides organizational performance as an output using multiple performance metrics. Finally, the model assists researchers and industry practitioners in evaluating the competencies of construction organizations and in analyzing their impact on organizational performance.

INTRODUCTION

The construction industry is dynamic, and it is becoming increasingly more complex due to uncertainties in technology, budgets, and development processes (Chan and Chan 2004). Furthermore, the construction industry has been criticized for its underperformance compared to other industries, resulting from inefficiency and ineffectiveness (Radujković et al. 2010). Many recent studies place strong emphasis on the importance of adopting effective strategies and performance measurement methods to improve the competitiveness of the construction industry (Horta et al. 2012). The evaluation of organizational competencies has also received significant attention by past researchers, based on its importance in organizational effectiveness, competitiveness, and profitability (Omar and Fayek 2016). It is also vital for construction organizations to explore new approaches for assessing and enhancing their competencies in order to achieve better performance and competitiveness (Giel and Issa 2016).

Organizational competencies and performance

In general, competencies may be defined as “combinations of motives, traits, self-concepts, attitudes or values, content knowledge or cognitive behavioral skills; any individual characteristic that can be reliably measured or counted and that can be shown to differentiate superior from average performers” (Chouhan and Srivastava 2014). Janjua et al. (2012) argue that "multidimensional" and "multicultural" constructs of competencies create problems in establishing a precise definition; as a result, it is common to see a variety of definitions for competency in the literature (Chouhan and Srivastava 2014). Organizational competencies are often thought to simply be employee skills, rather than the overall cross-company core competencies that drive integrated business execution and management alignment (Edgar and Lockwood 2008). Edgar and Lockwood (2008) stress that organizational competencies must be larger than the capabilities held by individuals within an organization. Likewise, Rosas et al. (2011) maintain that organizational competency is the behavioral ability of an organization to perform activities, tasks, or processes aimed at achieving a specified number of outcomes (i.e., performance). Studies on organizational competencies clearly indicate that analyses must capture the performance of the organization as a whole (Edgar and Lockwood 2008; Subramanian et al. 2009). Tiruneh and Fayek (2017) propose a working definition of organizational competency as "an integrated combination of resources, particular set of skills, necessary information, technologies, and the right corporate culture that enable an organization to achieve its corporate goals, competitive advantage, and superior performance."

The term "performance" has been of particular interest in the construction industry, although its interpretation may vary among practitioners (Georgy et al. 2005). Performance is such a complex process that no single factor can be used to predict or evaluate it (Poveda and Fayek 2009). Georgy et al. (2005) claim that performance may imply several dimensions, including effectiveness, efficiency, quality, productivity, quality of work life, innovation, and profitability. Rambe et al. (2015) agree that the performance of an organization relates to the efficiency and effectiveness with which it carries out its tasks in the process of providing products and services. One major challenge is to be able to estimate or predict performance in measurable terms such that it can be used for budgeting and control activities (Georgy et al. 2005; Lin and Shen 2007). An organization's performance depends greatly on its people and their competencies (Chung and Wu 2011), and measuring and improving performance has always been an important endeavor for construction practitioners (Georgy et al. 2005; Lin and Shen 2007). A review of the literature indicates that construction research has largely been focused on establishing performance measurement frameworks for construction companies (Deng and Smyth 2014). For example, Yu et al. (2007) developed a model to measure and compare performance of construction companies based on company-level key performance indicators (KPIs). That being said, many previous studies in the literature do not capture overall organizational competency and performance. Additionally, most competency models do not encompass the dynamic and complex nature of organizations. Such studies consider either individual- and/or project-level competencies and attributes, but fail to frame them at the organization level.

Objectives and contributions

This paper propose a framework to develop a fuzzy hybrid model capable of predicting organizational performance using organizational competencies as an input. A fuzzy logic-based model is suitable for capturing uncertainty and challenging complex systems; however, such models lack learning capabilities. Modeling techniques that demonstrate strong learning capabilities, yet are not able to handle uncertainty and complex variables can be integrated with fuzzy logic to complement each other and create fuzzy hybrid models. An intelligent fuzzy hybrid model with predictive capabilities is vital for the construction industry, where uncertainties in variables and decisions are common. Therefore, the objectives of this paper are to explore fuzzy hybrid modeling techniques, and to propose a fuzzy hybrid modeling framework to represent organizational competency and performance.

OVERVIEW OF COMPETENCY AND PERFORMANCE FUZZY MODELS

Fuzzy set theory and fuzzy logic

Many variables and decisions in construction involve uncertainties, which can be attributed to subjective judgement, linguistic expression, numerical approximations, and imprecise measurements (Dissanayake and Fayek 2008). Given the dynamic and complex nature of construction environments, these uncertainties pose significant challenges to developing a realistic model of organizational competencies and performance. Fuzzy set theory provides a strict mathematical framework to address such uncertainty conceptually and algorithmically (Pedrycz and Gomide 2007; Zimmermann 2010; Pedrycz 2013). Fuzzy set theory uses linguistic variables and membership functions with varying grades to model the uncertainty inherent in natural language (Zimmermann 2010; Chan et al. 2009). A fuzzy set has elements with varying degrees of membership, where partial membership is possible, unlike Bolean values of 0 (non-membership) and 1 (full-membership) (Pedrycz and Gomide 2007; Yeung et al. 2012; Pedrycz 2013). Fuzzy logic is a superset of Boolean conventional logic that has been expanded to handle the concept of partial truth, which entails the existence of true values between "completely true" and "completely false" (Chan et al. 2009).

Fuzzy modeling techniques for competency and performance

Competency-based multidimensional conceptual models have been proposed to predict the performance of project managers (Dainty et al. 2005). Neuro-fuzzy models have also been developed to predict the performance of engineers and design professionals (Georgy et al. 2005). More recently, Omar and Fayek (2016) developed a fuzzy neural network (FNN) to model project competency and performance. Likewise, Predicting organizational performance helps to identify weak organizational processes and practices in order to improve performance and profitability (Georgy et al. 2005; Elwakil et al. 2009). However, due to the diversity and complexity of construction organizations, it is more difficult to achieve or maintain a scientific strategy to measure current success (Elwakil et al. 2009). Georgy et al. (2005) utilized neuro-fuzzy models as a plausible approach for estimating or predicting engineering performance. FNNs offer the learning capabilities of artificial neural networks (ANNs), while maintaining the flexibility in variable description of fuzzy-based modeling.

MODELING FRAMEWORK FOR ORGANIZATIONAL COMPETENCIES AND PERFORMANCE

Tiruneh and Fayek (2017) proposed a conceptual model that maps construction organizational competencies to performance. This paper proposes a fuzzy hybrid model to be developed using organizational competencies as the input and organizational performance as the output. Fuzzy rule-based (FRB) models, FNNs, and other neuro-fuzzy modeling techniques will be explored. The fuzzy hybrid model that best provides a comprehensive representation of construction organizational competencies and maps them to organizational performance will be selected. This intelligent fuzzy hybrid model will help to predict organizational performance and to identify competencies requiring improvement.

Organizational competency and performance model architecture

Building on the conceptual model proposed by Tiruneh and Fayek (2017), this paper further incorporates a fuzzy hybrid model component. The fuzzy hybrid model architecture, which consists of the model itself, and input and output decoding components, is shown in Figure 1. Detailed lists of inputs (organizational competencies and context and industry variables) and outputs (organizational performance) are presented in Tiruneh and Fayek (2017). Input encoding involves developing and optimizing fuzzy membership functions for each variable in order to transform input variables into a compatible processing format. The fuzzy hybrid model is composed of either FRB systems or FNNs. The output decoding determines the crisp (representative) number of output variables by applying different defuzzification techniques. The components of the model are described briefly in the following sections.

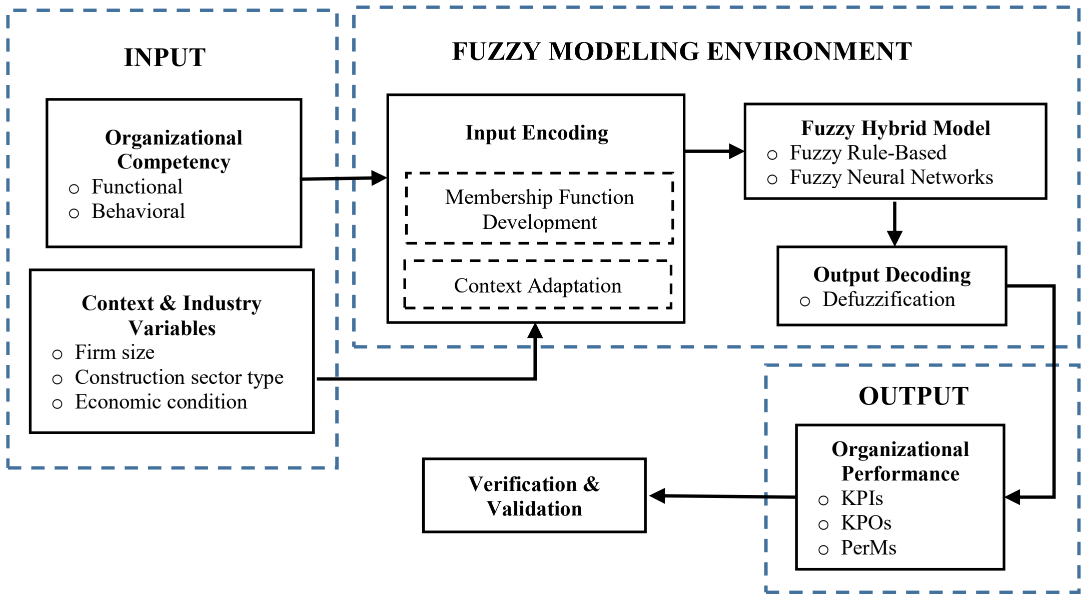

Figure 1. Architecture of proposed fuzzy hybrid model for organizational competencies and performance.

Input encoding

Input encoding involves transforming model input variables into membership functions that can be processed in the fuzzy hybrid model. These processes, including membership function development and context adaptation, are presented below.

Membership function development

A membership function maps a universal set of objects, $\boldsymbol{X}$ to the unit interval [0,1] (Pedrycz 2013). Fuzzy membership functions enable us to perform quantitative calculations (i.e., fuzzy arithmetic operations), natural language computations, and linguistic approximation in fuzzy decision making. The degrees of membership of an element representing a given concept are expressed by its membership function (Yeung et al. 2012). Membership functions can take different functional forms; hence, the form of the membership functions should be reflective of the problem for which fuzzy sets are being constructed (Pedrycz 2013). Additionally, the membership functions should reflect the perception (semantics) of the concept to be represented, the level of detail intended to be captured, and the context in which the fuzzy sets are going to be used (Pedrycz and Gomide 2007; Pedrycz 2013).

The modeling process begins with the development of membership functions for competency measures and performance indicator metrics. There are two main categories of approaches (i.e., expert-driven and data-driven approaches) for determining membership functions (Dissanayake and Fayek 2008; Pedrycz and Gomide 2007; Poveda and Fayek 2009; Pedrycz 2013). The expert-driven method captures the domain knowledge and opinions of experts. Experts are asked to evaluate the degree to which an element belongs to a certain concept. Responses from the experts are then aggregated to determine the membership grades for all elements represented within the universe of discourse. In contrast, the data-driven approach considers experimental data whose global characteristics become realized in the form and parameters of the membership functions. The pairwise comparison is a representative example of an expert-driven method, while fuzzy clustering is the most common data-driven method of membership function estimation (Pedrycz and Gomide 2007; Pedrycz 2013). Yeung et al. (2012) presents four approaches for establishing fuzzy membership functions: horizontal, vertical, pairwise comparison, and probabilistic. However, these approaches can also be generalized into the aforementioned expert-driven (horizontal, vertical, and pairwise comparison approaches) and data-driven (probabilistic approaches) categories. A combination of both types of membership function development techniques will be investigated and applied. Once the membership functions are developed, context adaptation, described next, will be performed using context and industry variables in order to account for differences among construction organizations.

Context adaptation

Context adaptation helps to calibrate membership functions through scaling functions/operators to adjust the universe of discourse of input and output variables, which in turn modifies the core, support, and shape of the fuzzy sets. The scaling function adapts the partitions (i.e., membership functions that define the input or output variables) by mapping the normalized universe of discourse to a context-adapted universe of discourse. The distribution and shape of the fuzzy set is then modified (Pedrycz et al. 1997; Botta et al. 2009). Industry and context variables, including size of firm, construction sector type, and economic/market conditions, will be incorporated for the purpose of context adaptation in order to capture the variability of construction organizations. Moreover, context adaptation helps to optimize accuracy and interpretability; it also does not change the number of linguistic terms (or variables), and it maintains their semantic ordering to achieve interpretability (Botta et al. 2009). Context adaptation can be performed using either linear and/or non-linear mapping (Pedrycz et al. 1997; Botta et al. 2009). Different context adaptation approaches will be explored to select the most suitable method for practical applications in the construction industry.

Model development

Fuzzy logic is a powerful modeling technique designed to handle natural language and approximate reasoning; moreover, it is able to process linguistic inputs to provide outputs or decisions (Pedrycz 2013; Senouci et al. 2014; Haidar 2016). The application of fuzzy techniques has been gaining popularity in construction management research over the past decade (Chan et al. 2009; Sadeghi et al. 2016; Zhao et al. 2016). Some of the major applications of fuzzy techniques in construction research include modeling construction labor productivity (Tsehayae and Fayek 2016), project competency and performance (Omar and Fayek 2016), and risk management (Zhao et al. 2016); decision making and evaluation/assessment for contractor selection (Xia et al. 2011); and integrating fuzzy logic with discrete event simulation for construction projects to improve simulation time in modeling uncertainty (Sadeghi et al. 2016). Fuzzy techniques refer to all fuzzy concepts, which include fuzzy set theory, fuzzy logic, and fuzzy hybrid techniques. Fuzzy hybrid techniques combine fuzzy set theory/fuzzy logic with other techniques, such as FNNs, neuro-fuzzy models, fuzzy reasoning, fuzzy expert systems, fuzzy analysis, and fuzzy clustering (Rey et al. 2017; Shihabudheen and Pillai 2017). Once the membership functions of the variables are determined, they can be used in a wide variety of fuzzy models to analyze construction organizational competencies and performance. Zimmermann (2010) suggests that fuzzy technology has proven superior to classical approaches in many cases, and it serves as an attractive ‘add-on’ as a tool for modeling and problem solving. Having developed membership functions, the fuzzy hybrid model proposed in this paper will be constructed by establishing either a FRB systems or FNNs to determine the link between inputs (organizational competencies) and outputs (organizational performance), depending on the amount and quality of data available. Figure 1 shows selected fuzzy modeling approaches for modeling organizational competencies and performance.

Fuzzy rule-based (FRB) systems

Fuzzy rules capture relationships among fuzzy variables and provide a mechanism to link linguistic input variables of systems with output variables (Rey et al. 2017). FRB systems come in the form of ‘‘if–then’’ conditional statements (rules). For the rule “if the competency of the organization is medium, then the performance is average”, fuzzy sets represent the linguistic variables as condition and conclusion statements (Kerr-Wilson and Pedrycz 2016; Rey et al. 2017). These rules can capture qualitative concepts and represent the non-linear and complex relationships relevant to a given problem, such as the link between competency and performance. Though FRB systems have been a popular method of knowledge representation (Kerr-Wilson and Pedrycz 2016; Rey et al. 2017), they often exhibit dimensionality issues. Generally, multiple input and multiple output variables gives rise to the curse of dimensionality (Ahmad and Pedrycz 2012). The dimensionality problem can be addressed by reducing the constructed fuzzy rules, as well as by reducing the number of variables representing the concept. This reduction can be realized by removing redundant fuzzy rules through the use of fuzzy similarity/equality (Pedrycz and Gomide 2007; Ahmad and Pedrycz 2012). For the FRB component of the fuzzy hybrid model in Figure 1, the condition encompasses the membership functions developed for organizational competencies, and the conclusion encompasses the membership functions developed for organizational performance. FRB systems establish the competency-performance link for construction organizations and incorporate industry and context variables (i.e., firm size, construction sector type, and economic condition).

Fuzzy neural networks (FNNs)

FNNs are fuzzy set-driven models that use logic processing units known as fuzzy neurons (Pedrycz and Gomide 2007). FNNs incorporate fuzzy principles into the architecture of ANNs (Georgy et al. 2005; Pedrycz and Gomide 2007). While ANNs can model the complexity of relationships in the studied domain, fuzzy modeling addresses the imprecision in the domain description (Georgy et al. 2005). Moreover, fuzzy hybrid techniques, such as neuro-fuzzy systems and FNNs, can be more widely applied because they can better tackle problems in construction that fuzzy sets/fuzzy logic alone may not be suitable for (Pedrycz and Gomide 2007; Shihabudheen and Pillai 2017). Therefore, FNNs are known to be robust in solving problems involving complex and nonlinear relationships, as well as in dealing with situations where the process cannot be explicitly represented in mathematical or statistical terms (Chan et al. 2009; Shihabudheen and Pillai 2017). The inputs and outputs for the FNN model in Figure 1 are the organizational competencies and organizational performance metrics, respectively. A fuzzy FNN model will be trained and tested based on the data available to analyze the impact of organizational competencies and performance.

Output decoding

The outputs of the fuzzy hybrid model are fuzzy numbers, representing organizational performance indicator metrics. Therefore, output decoding helps to determine crisp values of output variables through the application of defuzzification techniques. Defuzzification is the operation of producing a crisp number that adequately represents the fuzzy number. The resulting crisp value generated through defuzzification represents the output possibility distribution (i.e., a fuzzy output that constitutes a multi-modal membership function) (Zhao et al. 2013). Different defuzzification methods, such as center of area (centroid), bisector, maxima method (middle of maxima, largest of maxima, smallest of maxima, and mean of maxima) will be explored. The impact of different defuzzification methods on the final output will be investigated for implementation in the proposed fuzzy hybrid model.

Model verification and validation

Model verification will be conducted to check the accuracy of the underlying theory and assumptions, test the model integrity, investigate errors, and assess the data collection procedures and the consistency of data (i.e. both input competency measures and output performance indicator metrics). Structural verification on fuzzy rules, AND/OR FNN layers, and the structure of the layers will be performed through a literature review and through expert interviews. Verification will assess how realistic the input–output relations and model structure are. Additionally, the model will be validated to determine how well it reflects real-world operations of organizations by comparing model output with actual organizational data. Different validation techniques (i.e. 70–30 or leave one out) will be implemented, depending on the suitability of available organizational data. Additionally, sensitivity analysis will be conducted to determine whether the model behaves realistically by changing model parameters and by evaluating changes in the behavior of model output. The model will also be validated through assessments made by industry experts.

CONCLUSIONS AND FUTURE RESEARCH

This paper highlights a methodology and framework for developing a fuzzy hybrid model that captures complex organizational practices and processes attributed to competency, and relates them to organizational performance. The framework offers procedures for developing an intelligent fuzzy hybrid model capable of predicting organizational performance using organizational competencies. Furthermore, this paper proposes a fuzzy hybrid model and present its components. The steps described within the framework will support academic and industry practitioners in modeling similar problems. Future research includes investigating the suitability of different fuzzy hybrid modeling techniques to capture the overall aspects of organizational competencies and to establish their relationship to organizational performance. The proposed model will enable the assessment of the impact of organizational competencies on performance. In addition, various context adaptation methods will be explored to account for differences in organizational and industry contexts; which will make it valuable to construction organizations, regardless of their size or sector of operation.

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