Fuzzy Agent-based Modeling of Construction Crew Motivation and Performance

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Abstract

Recently, agent-based modeling (ABM) has been used to model construction processes and practices because it is capable of handling some of the complexities that arise from the interactions of system components. However, ABM alone cannot take into account the subjective uncertainty that exists in many construction systems. In this paper, a methodology for the development of fuzzy agent-based models in construction is provided, and its application is illustrated using a case study modeling construction crew motivation and performance. This paper makes three contributions: first, it expands ABM's scope of applicability by integrating it with fuzzy logic to create fuzzy agent-based modeling (FABM) in construction, which can handle both probabilistic and subjective uncertainty; second, it provides a novel methodology for developing fuzzy agent-based models, allowing for the development of new models to assess construction processes and practices; and third, it develops a fuzzy agent-based model of construction crew motivation and performance, which improves the assessments of performance by considering not only the interactions of crews in the project, but also the subjective uncertainty in model variables.

Author keywords: Fuzzy agent-based modeling; Agent-based modeling; Fuzzy logic; Construction; Motivation; Worker behavior; Performance

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Introduction

Agent-based modeling (ABM), a modeling technique that is relatively new to the field of construction research, has been used to model complex systems of interacting agents. Agents are discrete entities that are classified by type (e.g., crew members), with each type having its own individual attributes (e.g., age, years of experience) and behaviors (e.g., counterproductive behavior). Each type of agent can have its own unique set of behavioral rules. In ABM, agents are autonomous; they are able to learn from previous experience; they interact, either proactively or reactively, with other agents in an environment; and they act based on their behavioral rules. There are several advantages to using ABM for modeling complex construction systems containing active agents (e.g., construction crews or project units). For example, ABM can predict the overall behavior of the system by modeling the behavior of system agents, even when there is no existing information about overall system behavior (North & Macal 2007); ABM is capable of examining the interactions of agents with each other and with their environment (Reynolds 1999); ABM reveals the effect of agents' diversity on the dynamic behavior of the system (Macal 2010); and ABM models the dynamic properties of a complex system comprised of interacting agents (Scholl 2001).

There are some gaps in the research on the use of ABM in the construction domain, especially when the problem under investigation involves subjective variables or when numerical data are not available in sufficient quantity and quality for modeling purposes. Traditionally, ABM addresses probabilistic uncertainty in variables (e.g., probabilistic distributions for agent attributes) and the system's relationships (e.g., mathematical formulas or regression equations for agent behavioral rules and interactions). In current agent-based models, variables are usually defined by deterministic values or probabilistic distributions. Relationships in current agent-based models are usually defined by mathematical formulae, regression equations, symbolic relationships, and algorithms. However, ABM alone is not able to address variables' subjective uncertainty, nor is it able to account for system relationships that involve subjective uncertainty (Raoufi et al. 2016). For example, to accurately model construction crew behavior, models must consider subjective uncertainty due to the subjective nature of some factors affecting workers' behavior. A worker's self-efficacy (i.e., perception of his or her ability to transform his or her efforts into a desired outcome) is one such factor that cannot easily be assigned a numerical value. For example, when asked to evaluate his or her self-efficacy, a worker is asked to provide a judgment reflecting his or her perception of his or her own ability. People are usually unable to assign a numerical value for their perception of their own abilities (e.g., "I have 80% self-efficacy" or "My level of commitment is 60%"). Instead, they prefer to use linguistic terms (e.g., "I have *high* self-efficacy" or "My level of commitment is *very low*"). In many other similar situations, in order to define such variables, subjective terms such as *high* and *low* are used by experts (e.g., a worker's supervisor may provide a judgment about the workers' commitment). Therefore, in order to model construction crew behavior, a model should be able to handle the subjective uncertainty that exists in the variables and in the relationships of the system. Fuzzy logic techniques, on the other hand, can deal with subjective uncertainty (Zadeh 2015); therefore, fuzzy logic can be used to incorporate subjective terms into an agent-based model.

To expand ABM's scope of applicability in construction, this research integrates fuzzy logic with ABM and proposes a methodology for developing fuzzy agent-based modeling (FABM) in construction. The proposed methodology accounts for the complexity of interactions among construction agents (e.g., construction crews) and the subjective uncertainty involved in construction variables (e.g., crew motivation) and relationships (e.g., the relationship between crew motivation and performance). FABM is capable of modeling the subjective variables of linguistically expressed attributes of human agents; it can be used when sufficient numerical data are not available for probabilistic distribution fitting; and it can define the subjective behavioral rules of agents.

This paper is structured as follows. First, a literature review of the applications of ABM in construction research is presented and limitations in current ABM research are discussed. Second, an FABM methodology is presented that explains how to integrate fuzzy logic with ABM and how to develop fuzzy agent-based models. Third, a case study is presented that illustrates the proposed methodology and shows the application of FABM in construction by developing a fuzzy agent-based model of construction crew motivation and performance. Finally, the developed model is verified and validated based on the collected field data.

Literature Review

Applications of agent-based modeling in construction

Past research in construction used ABM to define the behavioral characteristics of various types of construction agents and to observe or aggregate the global behavior of a construction system. The first models of ABM in construction research were developed in early 2000. Anumba et al. (2002) described the potential of using ABM in the collaborative design of steel structures. ABM was then applied in supply chain management. Tah (2005) presented an agent-based model of supply chain networks. ABM was also used to develop a framework of construction supply chain coordination (Xue et al. 2005). In the model developed by Xue et al. (2005), the agents were the members of the designer, owner, and general contractor firms; while the agent interactions were the flow of information or funds. Although past applications of ABM in construction were very limited, the trend is changing, and more applications have been introduced in recent literature. Watkins et al. (2009) applied ABM to model space congestion and its effect on labor productivity in construction sites. The traffic flow of construction equipment was also modeled using ABM to help assess the impact of traffic congestion on project duration (Kim and Kim 2010). ABM was also used to model the complex interactions between infrastructure users, infrastructure assets, system operators, and politicians that occur within the context of urban infrastructure management. (Osman 2012).

Recently, the application of ABM has not only increased sharply in number in construction research, but it is also expanding to areas of research that have not previously explored the use of ABM. Ahn et al. (2013) modeled social interactions among construction personnel using ABM. ABM was also implemented in the development of organizational policies to better manage human resources (Ahn and Lee 2014). The impact of workers' muscle fatigue on construction operations was modeled using ABM (Seo et al. 2016). ABM has also been recently used for simulating the bidding process of contractors with different risk attitudes in determining markups (Asgari et al. 2016). Ben-Alon and Sacks (2017) used ABM to study production control policies in residential building construction. ABM has been used to model earthmoving operations in order to help contractors with planning (Jabri and Zayed 2017). Eid and El-adaway (2017) used ABM to develop a decision-making framework for disaster recovery of the community residents. ABM has also been used to simulate crews' workflow in construction sites (Ben-Alon and Sacks 2017). Awwad et al. (2017) used ABM to study construction safety climate by modeling the interactions among project stakeholders. One of the most recent trends in applications of ABM in construction is modeling the energy-saving potential of commercial buildings (Azar and Ansari 2017; Azar and Menassa 2016).

Limitations of current ABM use in construction

In traditional agent-based models, agents are defined by deterministic or probabilistic attributes. Agents in the real world, however, have subjective attributes and behavioral rules. To better represent the real components of human attributes and behaviors, FABM incorporates fuzzy agents that observe fuzzy variables and then decide how to act based on fuzzy rules. Although ABM research is developing rapidly in the construction domain, there are two major limitations in the current literature on ABM in construction. The first limitation is related to the subjective variables that exist in construction systems. For example, motivation is a subjective variable and assigning a numerical value (e.g., a percentage for crew commitment) is not a good representation of that factor. Instead, subjective variables are better represented with linguistic terms (e.g., *low* motivation).

The second limitation is related to the uncertainty that exists in agent behavioral rules. In a construction system, where the workers are the agents of an agent-based model, the behavioral rules of the workers in the system often include subjective uncertainty. Current agent-based models are limited in their ability to model agent behavioral rules that include subjective terms because they either use mathematical formulas based on past research or statistical regression equations based on collected field data (Papadopoulos 2016). Both mathematical formulas and regression equations can address probabilistic uncertainty using Monte Carlo simulation, but they do not address subjective uncertainty. For example, a rule for a crew agent behavior expressed by an expert in natural language (e.g., "if the crew motivation is *high* and the work-setting conditions are *good*, then the crew performance is *high*") can be better represented with a fuzzy rule than with a mathematical formula or a regression equation.

Interest in FABM has been increasing in many areas, such as computing science, robotics, manufacturing, control, and the social sciences (Ostrosi, Fougères & Ferney 2012; Fougères 2013). In the construction domain, however, there is a gap in the literature about FABM that needs to be addressed. This paper addresses that gap by presenting a methodology for FABM and implementing the proposed methodology to model construction crew motivation and performance.

Fuzzy Agent-Based Modeling Methodology

The proposed methodology for developing a fuzzy agent-based model has five steps: (1) determine the fuzzy agent-based model architecture; (2) define the basic structure of agents (i.e., agent attributes and behaviors); (3) define agent interactions; (4) define agent behavioral rules; and (5) perform the simulation experiment. The following sections describe each of these steps.

Determine the fuzzy agent-based model architecture

The first step is to determine the architecture of the fuzzy agent-based model. The fuzzy agent-based model architecture has two major processing components for data analysis: the fuzzy component and the ABM component. Figure 1 shows the architecture of the fuzzy agent-based model in detail. The fuzzy component has two parts: fuzzy clustering and a fuzzy inference system. Fuzzy clustering is used to develop fuzzy sets and fuzzy rules based on collected field data. The output of fuzzy clustering is then used for the development of a fuzzy inference system. The fuzzy inference system receives simulation run time input variables from the agent-based model and delivers the predicted output variable. The ABM component has two parts: the simulation main environment and the agent classes. The simulation main environment is responsible for defining the model parameters, creating agents, running the simulation methods (i.e., Java functions), contacting the fuzzy inference system at simulation run time, and simulating defined scenarios. Agent classes are used to define the attributes and behaviors of each agent in the model.

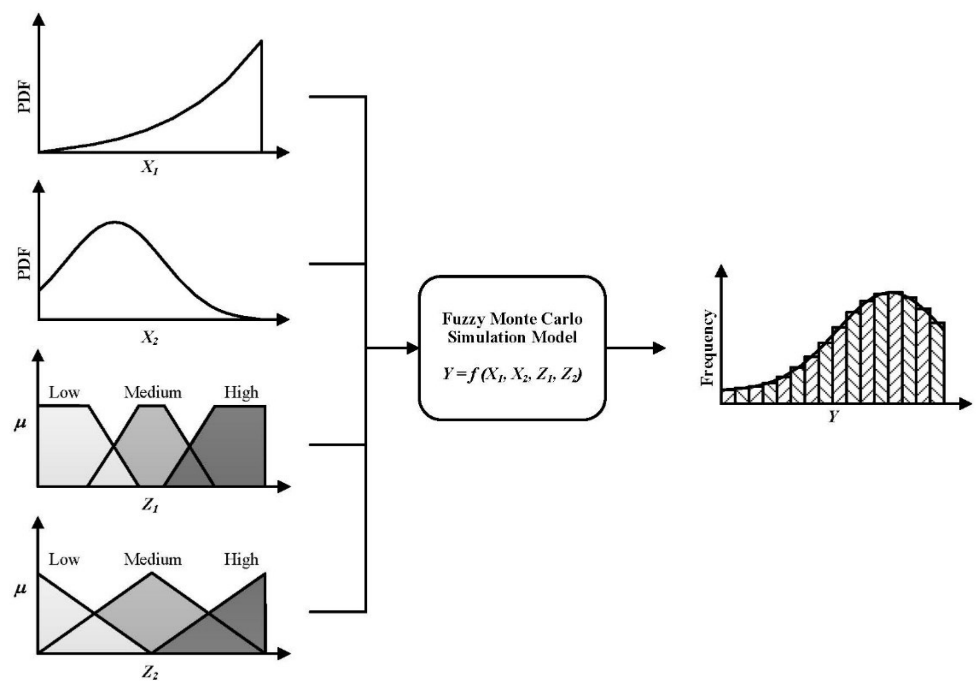

Figure 1. Fuzzy agent-based model architecture.

Define the basic structure of agents: agent attributes and behaviors

The second step is to define the basic structure of agents, including the types of attributes and behaviors of each agent in the model. Agent unified modeling language (AUML), an extension of the unified modeling language (UML), is used to represent agents (Azar and Ansari 2017; Huget 2003). Figure 2 shows a sample of the basic structure of agents.

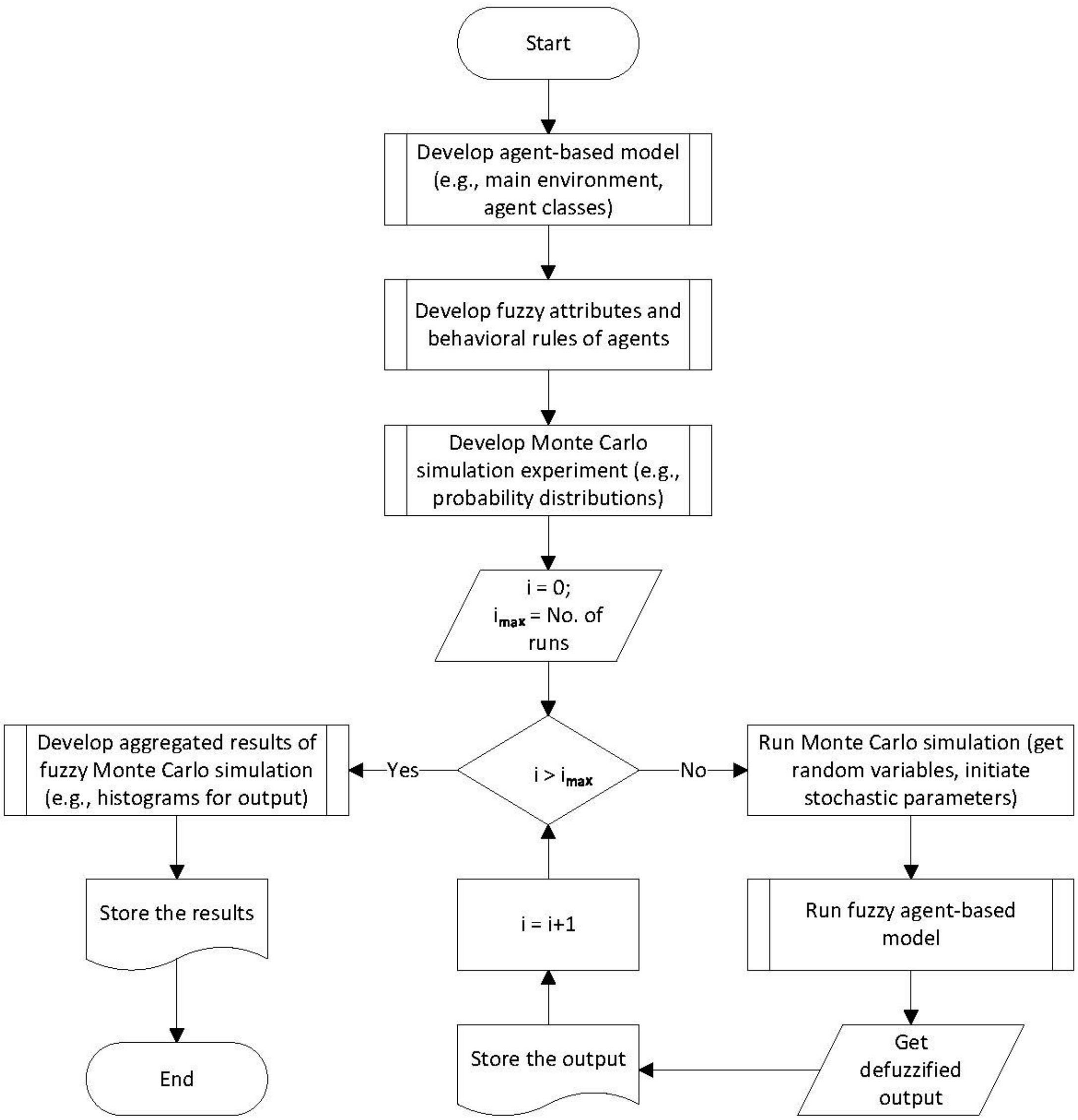

Figure 2. AUML diagram of the basic structure of agents.

Each attribute of each agent needs to be defined. Current agent-based models in construction define agent attributes using probabilistic or deterministic variables. Deterministic variables are either set by the user or defined based on collected field data, while probabilistic variables are determined by curve fitting using statistical distributions based on the available field data (Azar and Ansari 2017). There are, however, subjective variables in the system that also need to be defined.

To model subjective variables, fuzzy sets need to be constructed using one of two available types of methods. The first type includes expert-driven approaches such as horizontal, vertical, pairwise comparison, intuition, inference, and exemplification methods. The second type includes data-driven approaches such as fuzzy machine learning techniques (e.g., fuzzy clustering). Fuzzy C-means (FCM) clustering is one of the most commonly used methods of fuzzy clustering (Bezdek 2013). FCM clustering is a machine learning technique in which each data point belongs to each cluster with a membership ranging from zero to one (Tsehayae and Fayek 2016). In this paper, FCM clustering is used to develop fuzzy sets of agent attributes. Fuzzy sets representing linguistic terms are defined by membership functions, which represent the degree to which a data point (e.g., motivation score) representing a variable (e.g., crew motivation) belongs to a fuzzy set (e.g., *low* motivation). Gaussian membership functions have been recommended for both the input and output variables in various construction applications (Tsehayae and Fayek 2016; Siraj et al. 2016). They have been used in this research because of their continuity and smoothness, and they are suitable for optimization as they have only two parameters (i.e., the modal value representing the typical value and standard deviation representing the spread). To define fuzzy sets, the Gaussian membership function is defined using Equation 1.

$$A = e^{-[\frac{(x-\mu)^2}{2\sigma^2}]} \quad (1)$$

where x represents the value of the variable in the universe of discourse, A represents the membership function for a linguistic term, μ is the modal value, and σ is the standard deviation.

Define agent interactions

The third step is to define agent interactions, following similar approaches to those used in ABM. In ABM, agent interaction can be defined as static or dynamic. Static interactions do not depend on other agents or the state of the system, but dynamic interactions depend on the state of the system and other agents' states at each point in time. Past research has shown that human agents have mostly dynamic interactions (Azar and Ansari 2017; Ben-Alon and Sacks 2017). This is due to the fact that agent attributes or behaviors change based on feedback received from observing the behavior of other agents. However, there are some agents that do not change their attributes or behaviors when interacting with other agents. Such an agent is called a zealot (i.e., an agent with static interaction) in ABM literature. In this research, agents with both static and dynamic interactions are considered in FABM.

Mathematical formulas are often used to define the interactions of agents in ABM. Equation 2 is a type of interaction equation commonly used in past research to represent the interactions of agents (Azar and Ansari 2017). Equation 2 is developed based on the models of behavior dynamics, which are obtained from different sources (Azar and Ansari 2017; Mobilia et al. 2007; Hegselmann and Krause 2002; Deffuant et al. 2002). This formula is used when the agents change their behavior following their interactions with other agents. Past research has shown that human agents have mostly dynamic interactions (Azar and Ansari 2017; Ben-Alon and Sacks 2017). This formula is used to calculate the attribute of an agent at a time step based on both the attribute of the agent at a previous time step and the attributes of other agents at a previous time step. Equation 2 is applicable when there are dynamic interactions of agents, and some agents change their attributes based on the attributes of other agents. For example, when a construction crew observes the motivation of other crews it may change its own motivation based on the level of motivation of the other crews. In such a case, Equation 2 can be used to represent the interactions of construction crews.

$$Att_i^t = (1 - Z \times S) \times Att_i^{t-1} + (Z \times S) \times \frac{\sum_{j=1}^{N} Att_j^{t-1}}{N} \tag{2}$$

where *t* and *t-1* refer to current and previous simulation time steps, *i* and *j* are agent indices, *Att* refers to the attribute of an agent, *Z* refers to the type of agent that changes its attribute based on the observation of the attributes of other agents, S refers to susceptibility (i.e., the probability that an interaction leads to a change in the attribute of an agent), and N refers to the number of other agents interacting with agent i. Similar mathematical formulas can be used in FABM to define the interactions of different agents.

Define agent behavioral rules: the fuzzy inference system

The fourth step is to define agent behavioral rules, which are how agents decide on their actions based on the history of the system state (i.e., the state of the system at both the current and previous time steps) (Dash, Jennings, and Parkes 2003). Current agent-based models either use mathematical formulas or regression equations to define agent behavioral rules (Papadopoulos 2016). Both these techniques can address probabilistic uncertainty, but they do not account for the subjective uncertainty involved in agent behavioral rules. In order to model behavioral rules in FABM, fuzzy rules need to be defined, which can be done using one of three methods. The first method involves using past literature (e.g., theories of human behavior in literature). This method is useful if there are no data available but there is previous reliable literature regarding the agents' behavioral rules. For example, Ahn and Lee (2014) used social cognitive theory to determine rules for agents' absence behavior. The second method is an expert-driven approach (i.e., using domain expert judgments). This method is useful if sufficient data about the agent's attributes and behavior are not available but there is access to sufficient domain expert knowledge regarding the behavioral rules of agents. The third type of method involves data-driven approaches. If sufficient data regarding the agent's attributes and behaviors are available, data-driven approaches (e.g., fuzzy machine learning techniques) can be used to define agent behavioral rules. Pedrycz (2013) showed how to define fuzzy rules from data using fuzzy machine learning techniques such as FCM clustering. FCM clustering minimizes an objective function representing the sum of squared distances of data instances to cluster centers.

In this research, FCM clustering is used to define agent behavioral rules through the following process. In a system with n input variable (x_i, $i=1,\ldots, n$) and one output variable (y), the input-output data set (z) has $n+1$ dimension. Having N sets of data instances, the data instance k is denoted by Equation 3.

$$\boldsymbol{z}_k = [x_{k1}, x_{k2}, \ldots, x_{kn}, y_k],\ k = 1, \ldots, N \tag{3}$$

where k refers to the data instance, x_{kj} represents the j^{th} input variable for the k^{th} data instance, and y_k represents the output variable for the k^{th} data instance.

The optimization process of FCM clustering results in the development of a partition matrix ($\boldsymbol{U}$) that includes the membership degrees of a data point in each cluster (Pedrycz 2013). The partition matrix ($\boldsymbol{U}$) is denoted by Equations 4 and 5.

$$\boldsymbol{U} = [u_{st}],\ s = 1, \ldots, c,\ \ t = 1, \ldots, N \tag{4}$$

$$u_{st} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|z_t - v_s\|}{\|z_t - v_j\|}\right)^{2/m-1}},\ s = 1, \ldots, c,\ \ t = 1, \ldots, N \tag{5}$$

where s refers to the cluster, t refers to the input-output variable, z_t represents the data instance t, and v_s represents the s^{th} prototype.

Using the input-output dataset, FCM clustering clusters the input-output dataset into c number of clusters. For each cluster, FCM clustering defines a prototype (cluster center), which is denoted by Equations 6 and 7.

$$\boldsymbol{V} = [v_{ij}],\ i = 1, \ldots, c,\ \ j = 1, \ldots, N \tag{6}$$

$$v_{st} = \frac{\sum_{k=1}^{N} u_{ik}^{m} z_{kt}}{\sum_{k=1}^{N} u_{ik}^{m}},\ s = 1, \ldots, c,\ \ t = 1, \ldots, N \tag{7}$$

Each cluster represents a fuzzy rule; thus, FCM clustering results in the development of c number of fuzzy rules in the form of "If X is A_j then y is B_j". In this research, FCM clustering is used to develop fuzzy rules of crew behavior based on collected field data.

The behavioral rules of agents can be the same or different depending on the problem under study. For example, multiple fuzzy inference systems can be defined for different types of agents in a model or even among the population of one type of agent. Therefore, the proposed methodology is not limited in terms of the number of fuzzy inference systems that represent agent behavioral rules.

Perform the simulation experiment

The final step in the FABM methodology is to perform the simulation experiment. The fuzzy agent-based model is built by connecting the ABM component and the fuzzy component at simulation run time. The ABM component is developed in Anylogic®, which is a simulation software based on the Java environment that allows the user the flexibility of adding custom Java codes in different parts of the model (e.g., simulation main, object classes). The fuzzy component is developed in MATLAB®, which allows programming. Java programming in the Anylogic® environment is used to connect the ABM and fuzzy components. The connection of the ABM and fuzzy components was done through Java programming in the Anylogic® environment by developing a MATLAB® controller class. The developed MATLAB® controller class calls and uses the MATLAB® control library and returns the proxies required for connection of ABM and fuzzy components. Programming in MATLAB® is also used to perform fuzzy clustering, define fuzzy membership functions for variables, define fuzzy behavioral rules of agents, and develop the fuzzy inference system. The fuzzy agent-based model runs the simulation experiments by executing the simulation methods (i.e., the Java functions) in ABM. Data about agent attributes are sent to the fuzzy inference system in MATLAB® at simulation run time. Next, data about the agent behaviors are calculated using the fuzzy inference system in MATLAB® and sent to the agent-based model in AnyLogic®. The simulation experiments include fuzzy agents who will act in the simulation environment based on their fuzzy behavioral rules. The collective actions of fuzzy agents in the simulation environment will then provide the outputs of the fuzzy agent-based model. In the following sections, a case study is presented to illustrate the proposed FABM methodology.

Case Study: FABM Model of Construction Crew Motivation and Performance

The construction industry is made up of complex processes that involve many individuals and crews working together and interacting over long periods. In order to effectively manage construction projects, it is important to be able to assess crew performance (e.g., task performance, contextual performance, and counterproductive behavior). Crew performance is influenced by many factors, including crew motivation and the situations in which crews perform their tasks. Thus, one challenge to assessing crew performance is how to model the attributes and behaviors of crews; another challenge is how to model the situation in which the tasks are performed. In addition, the interactions of crew members with each other and with the environment (i.e., the situation in which crew perform their tasks) must also be modeled.

Both motivational factors and situational/contextual factors affect crew performance. Figure 3 shows the proposed model of the relationship between motivational factors, situational/contextual factors, and crew performance. Motivational factors are antecedent to crew motivation, which is the predictor variable in the model. Situational/contextual factors are potential moderators of the relationship between crew motivation and performance. Crew performance is the dependent variable in the model. The motivational factors are efficacy (Bandura 1977; Hannah et al. 2016), commitment/engagement (Meyer and Allen 1991; Cesário and Chambel 2017), identification (Ashforth and Mael 1989; Lin et al. 2016), and cohesion (Beal et al. 2003; Chiniara and Bentein 2017), each of which operates at both individual and crew levels. The crew-level situation and the project-level situation represent situational/contextual factors, which might also affect the relationship between crew motivation and performance. It is therefore important to take into account situational/contextual factors when studying the effect of motivation on crew performance. In this research, situational/contextual factors at both the crew level (i.e., the crew-level situation) and the project level (i.e., the project-level situation) are accounted for in the model. The crew-level situation has three categories: task-related (e.g. task design), labor-related (e.g., the functional skills of the crew), and foreman-related (e.g., leadership skills). The project-level situation has five categories: project characteristics (e.g., work shifts), management-related factors (e.g., project management practices), work-setting conditions (e.g., weather conditions), resources (e.g., tools, equipment, material), and safety precautions (e.g., safety training). Crew performance metrics are divided into three categories: task performance, contextual performance, and counterproductive behavior.

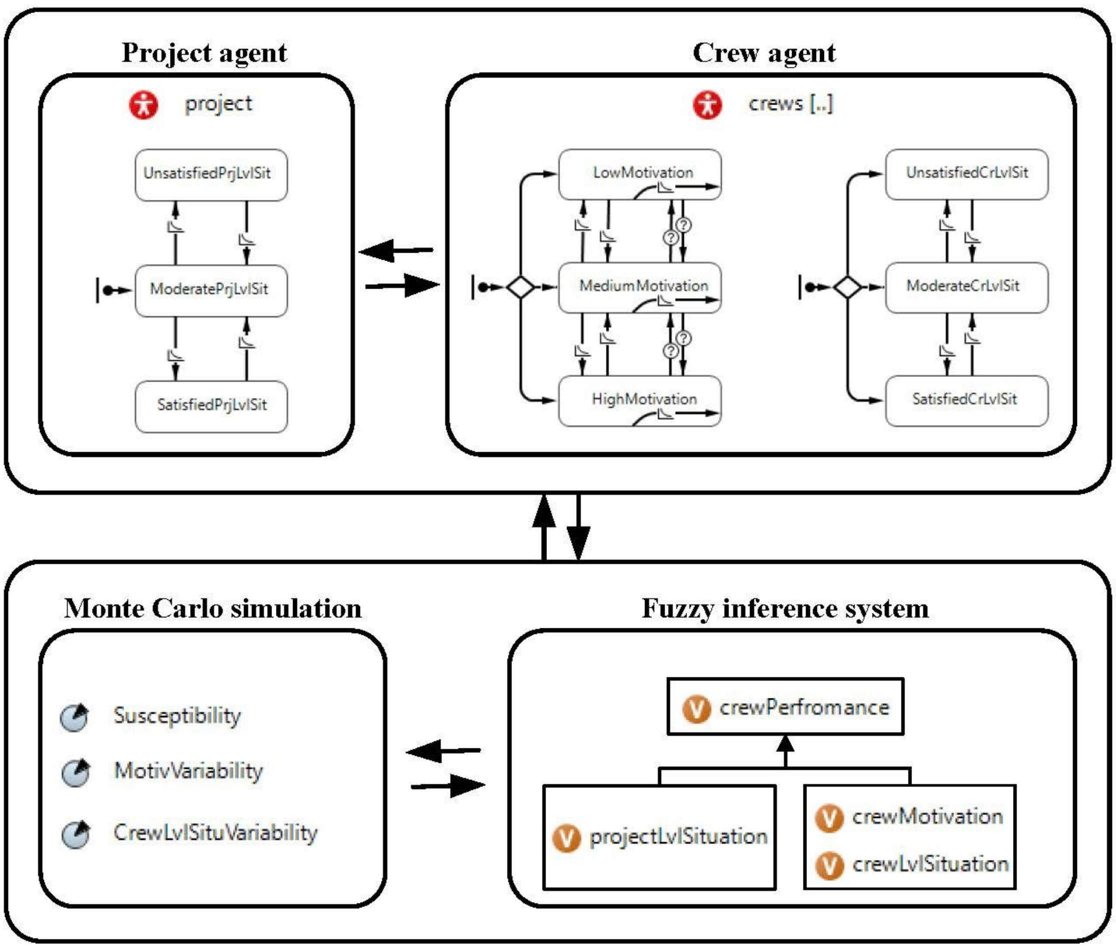

Figure 3. Conceptual model of the case study.

In the proposed model, the primary list of factors was derived from existing research in both construction and non-construction domains. First, a motivation expert with 30 years of experience in business and industrial psychology provided his expertise regarding the initial list of motivational factors. This initial list of factors was then presented in a workshop to 10 construction experts involved in projects in Canada. These experts had an average of 15 years of experience, and they represented different types of construction organizations (e.g., owners, contractors, and labor unions); they also held various positions in their organizations (e.g., senior management, project management, human resources representative, and labor relations representative). The experts reviewed the list and proposed additional factors they thought might affect construction crew motivation and performance. They reached a consensus on the proposed additional factors, and the primary list of factors was updated to include the additional factors. This process allowed for the development of a comprehensive list of factors that not only takes into account the literature in construction and non-construction domains, but that also captures the opinions of both motivation and construction experts. In this research, 78 situational/contextual factors at the project-level were identified, such as project characteristics—work shifts, management-related—project management practices, work-setting conditions—weather conditions, and resource—material. In addition, 51 situational/contextual factors at the crew level were identified, such as task-related—task design, labor-related—crew functional skills, and foreman-related—leadership skills. Table 1 shows a sample of situational/contextual factors and their measures.

Furthermore, a total of 12 different crew performance metrics categories, consisting of 55 KPIs, were identified from previous research (Raoufi and Fayek 2018). Task performance consists of seven categories: cost performance, schedule performance, change performance, quality performance, safety performance, productivity performance, and satisfaction performance. Contextual performance consists of three categories: personal support, organizational support, and conscientious initiative. Counterproductive behavior consists of two categories: interpersonal deviance and organizational deviance. Each category of crew performance metrics has several KPIs. Table 2 shows the crew performance metrics and a sample of KPIs.

Data collection was performed in a construction company actively involved in industrial projects in Canada. Field data were collected on crew motivational factors, situational/contextual

Table 1. Sample of situational/contextual factors and their measures.

Factor category	Factor sub-category	Factor	Scale of measure	Sub-factors	Range of values
Task-related	▪ Task characteristics	Task type	Categorical		1. Civil 2. Mechanical 3. Electrical 4. Instrumentation
		Task repetition	Percentage (% of identical tasks in work package over total tasks in work package)		[0%, 100%]
	▪ Task design	Visibility of outcome	Five-point rating scale		(1) Very low to (5) Very high
Labor-related	▪ Crew properties	Crew size	Integer		$\mathbb{Z}^+$
Foreman-related	▪ Foreman characteristics	Foreman knowledge	Five-point rating scale		(1) Very poor to (5) Very good
	▪ Foreman functional skills	Performance monitoring	Five-point rating scale		(1) Very poor to (5) Very good
		Communication	Five-point rating scale		(1) Very poor to (5) Very good
	▪ Foreman behavioral skills	Goal setting	Five-point rating scale	• Goal clarity • Goal specificity • Goal difficulty	(1) Very poor to (5) Very good
		Working relationship	Five-point rating scale		(1) Extremely ineffective to (5) Extremely effective
		Building trust	Five-point rating scale		(1) Very low to (5) Very high
Management-related	▪ Project and construction management practices	Project time management	Five-point rating scale	• Work breakdown structure (WBS) • Project schedule • Resource requirements	(1) Very poor to (5) Very good
		Project cost management	Five-point rating scale	• Project cost estimates • Project budget • Project cash flow	(1) Very poor to (5) Very good
Work-setting conditions	▪ Site general facilities	Location of facilities	Real number (average distance, m)		$\mathbb{R}^+$
	▪ Working area conditions	Congestion	Real Number (number of people per 100 square meter in working area)		$\mathbb{R}^+$

Table 2. Crew performance metrics and sample of KPIs.

Crew performance metrics	Crew performance metrics category	Sample KPI[a]	KPI formula	KPI threshold
Task performance	Cost performance indicators	Work package cost growth	$\frac{(actual\ total\ work\ package\ cost - total\ work\ package\ estimated\ cost\ at\ tender\ stage)}{total\ work\ package\ estimated\ cost\ at\ tender\ stage}$	<0 Desirable value =0 Planned value >0 Undesirable value
	Schedule performance indicators	Work package schedule growth	$\frac{(actual\ work\ package\ duration - estimated\ work\ package\ duration\ at\ tender\ stage)}{estimated\ work\ package\ duration\ at\ tender\ stage}$	<0 Desirable value =0 Planned value >0 Undesirable value
	Change performance indicators	Total change cost factor	$\frac{total\ cost\ of\ scope\ changes\ in\ work\ package}{actual\ total\ work\ package\ cost}$	=0 Desirable value >0 Undesirable value
	Quality performance indicators	Work package rework cost factor	$\frac{total\ direct\ cost\ of\ work\ package\ rework}{actual\ work\ package\ direct\ cost}$	=0 Desirable value >0 Undesirable value
	Safety performance indicators	Lost time rate	$\frac{amount\ of\ lost\ time\ to\ incidents\ in\ work\ package,\ in\ hours}{100\ man - hours\ worked}$	=0 Desirable value >0 Undesirable value
	Productivity performance indicators	Work package productivity factor (physical work)	$\frac{actual\ direct\ man - hours\ worked\ in\ work\ package}{actual\ installed\ quantity\ in\ work\ package}$	Lower values are more desirable.
	Satisfaction performance indicators	Overall performance satisfaction	*Rating of client satisfaction from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied*	=7 Desirable value =1 Undesirable value
Contextual performance	Personal support	Helping	*Rating of frequency of engagement in this behavior from 1 to 7 with 1 being never and 7 being consistently.*	=7 Desirable value =1 Undesirable value
	Organizational support	Representing	*Rating of frequency of engagement in this behavior from 1 to 7 with 1 being never and 7 being consistently.*	=7 Desirable value =1 Undesirable value
	Conscientious initiative	Persistence	*Rating of frequency of engagement in this behavior from 1 to 7 with 1 being never and 7 being consistently.*	=7 Desirable value =1 Undesirable value
Counterproductive behavior	Interpersonal deviance	Inappropriate verbal actions	*Rating of frequency of engagement in this behavior from 1 to 7 with 1 being never and 7 being consistently.*	=1 Desirable value =7 Undesirable value
	Organizational deviance	Poor attendance	*Rating of frequency of engagement in this behavior from 1 to 7 with 1 being never and 7 being consistently.*	=1 Desirable value =7 Undesirable value

[a] There are several KPIs in each crew performance metrics category but the table shows only one KPI as a sample.

factors, and crew performance metrics over the three-month timeline of an industrial construction project. All nine crews working on the work packages in the project participated in the data collection. Crew performance metrics were collected for all nine crews and for all 79 work packages of the project. Motivational factors and situational/contextual factors were collected for all nine crews and for 17 work packages out of 79. The collected field data related to the 17 work packages were used for field data analysis because they included the full set of variables (i.e., motivational factors, situational/contextual factors, and crew performance metrics).

The sources of data collection for motivational and situational/contextual factors were interviews with project personnel, including crew members, foremen, field supervisors, and project managers; observations by data collectors on the work packages of the project; project databases and documents such as project safety logs; and external sources such as government databases (e.g., databases for weather data). For task performance, actual project documents (e.g., time sheets, score cards, safety logs, change order logs, inspection test plans, schedule updates, tender documents, and cost estimates) were used to extract available crew performance data. Key performance indicators (KPIs) related to task performance were calculated for all crews. For KPIs related to contextual performance and counterproductive behavior, multiple-source data collection was utilized, which accounts for both self-evaluation and supervisor evaluation. Statistical analysis was also performed on the collected field data to identify the strength and direction of the relationships between the variables in the proposed model, as well as the key moderators of the relationship between crew motivation and performance (Raoufi and Fayek 2018).

In this case study, a simulation model of construction crew motivation and performance is developed that describes the relationship between crew motivation, project situation, and crew performance using FABM. The goal is to develop a fuzzy agent-based model that accounts for diversity in the level of crew motivation, the change of crew motivation over time, and changes in the situation in which crews are performing. The model can thus calculate crew performance in a way that reflects the dynamic aspects of crew motivation and the project environment. Furthermore, the model accounts for agent interactions and the variations in agent attributes and behaviors that are based on interactions with other agents.

Construction crew Motivation and Performance Model Architecture

The fuzzy agent-based model of construction crew motivation and performance includes five components: simulation main environment, project agent class, crew agent class, fuzzy clustering, and the fuzzy inference system. At the simulation run time, the components of the developed FABM send and receive processing information (i.e., agent run time variables and states) to each other and calculate crew performance based on model parameters, agent state history, and the project situation state history. The simulation main environment is responsible for defining model parameters, creating project and crew agents, running the simulation methods (e.g., calculating statistics on crew populations), and contacting the fuzzy inference system at simulation run time. The project agent class is for simulating the situation at the project level, while the crew agent class is for simulating crew motivation and situation at the crew level. The model's inputs are parameters in the simulation main environment, attributes of the project agent (e.g., the situation at the project level), and attributes of the crew agent (e.g., crew motivation, the situation at the crew level). The output of the model is crew performance.

Basic structure of agents: attributes and behaviors of crew and project agents

To define project and crew agents' attributes and behaviors, fuzzy sets for agent attributes and behaviors are constructed based on FCM clustering, as discussed in the FABM methodology section.

Project agent class

The project agent class represents construction projects in which construction crews are performing their tasks. The attributes of the project agent class are defined as project ID, initial project-level situation, and current project-level situation. The behaviors of the project agent class are: update the project-level situation, which is defined by Java methods (i.e., Java functions), and state charts in the AnyLogic® agent class template. Figure 4 shows the developed project agent class in AnyLogic®.

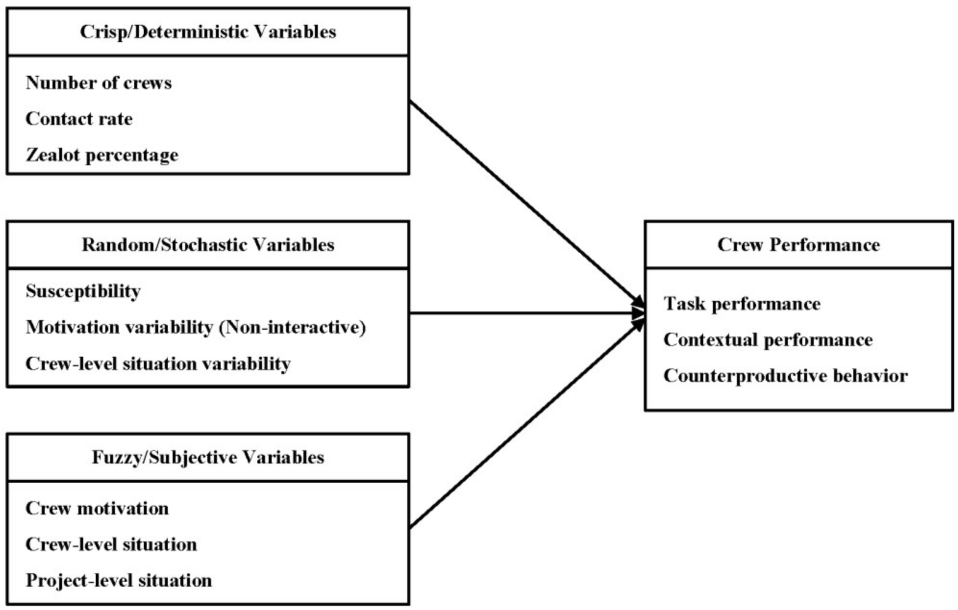

Figure 4. Project agent class in AnyLogic®.

A project ID is assigned to distinguish different projects in the model. However, in this case study, just one project with several construction crews is simulated, since the goal is to simulate different crews in a project environment rather than the different projects of an organization. Project-level situation attributes are variables representing situational/contextual factors at the project level. In this case study, based on the analysis that was performed on the collected field data, two factors among the situational/contextual factors at the project level were shown to have a significant effect on the relationship between crew motivation and performance: project time management and project cost management (Raoufi and Fayek 2018). The project-level situation attribute is calculated as the mean of the normalized project time management and project cost management to ensure equal weighting between different project-level situational contextual factors and to prevent bias (i.e., the effect of difference in the identified range of values for each situational/contextual factor on the calculated crew-level situation). Normalization was done by dividing each situational/contextual factor by its maximum value, to achieve a value between 0 (undesirable value) and 1 (desirable value).

Crew agent class

The crew agent class represents construction crews that are performing their tasks in a construction project. The attributes of the crew agent class are crew ID, initial crew motivation, current crew motivation, initial crew-level situation, and current crew-level situation. The behaviors of the crew agent class are: calculate interactions, update crew motivation, update the crew-level situation, connect to the fuzzy inference system, and calculate crew performance. The behaviors are defined either through Java methods or directly through state charts in the AnyLogic® agent class template. Figure 5 shows the developed crew agent class in AnyLogic®.

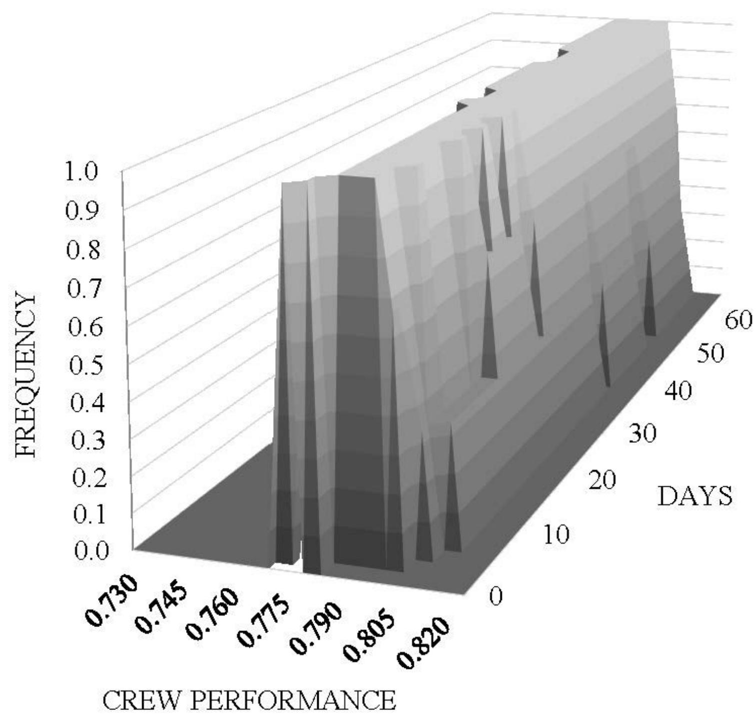

Figure 5. Crew agent class in AnyLogic®.

A crew ID is assigned to distinguish different crews in the model. Crews are generated in the model based on the initial number of crews that the user defines before each simulation experiment. Crew motivation attributes, either initial or current crew motivation, are variables representing motivational factors (i.e., efficacy, commitment/engagement, identification, and cohesion) at both the individual and crew levels. Crew motivation is calculated as the mean of normalized motivational factors. An equal weight is given to motivational factors in order to avoid any uninformed assumptions about which motivational factor influences crew motivation the most. Crew-level situation attributes, at either the initial or current project-level situation, are variables representing situational/contextual factors at the crew level. Based on the analysis that was performed on the collected field data, 12 of the situational/contextual factors at the crew level were shown to have a significant effect on the relationship between crew motivation and performance: task type, task repetition, visibility of outcome, crew size, foreman knowledge, performance monitoring, communication, goal setting, working relationship, building trust, location of facilities, and congestion (Raoufi and Fayek 2018). The crew-level situation attribute is calculated as the mean of the normalized values of the 12 identified factors to ensure equal weighting between different situational/contextual factors at the crew level and to prevent bias (i.e., the effect of difference in the identified range of values for each situation/contextual factor on the calculated crew-level situation). Normalization was done by dividing each situational/contextual factor by its maximum value, to achieve a value between 0 (undesirable value) and 1 (desirable value).

Crew interactions

The collected field data suggests that crew motivation changed over time, implying the possibility of dynamic interactions of crew agents. Equation 8 is used to represent variations in crew motivation based on the interactions of crew agents. The level of motivation of crew agents is calculated using Equation 8 and is based on the level of motivation of that crew and the level of motivation of other crews in the project.

$$CM_i^t = (1 - Z \times S) \times CM_i^{t-1} + (Z \times S) \times \frac{\sum_{j=1}^{N} CM_j^{t-1}}{N} \quad (8)$$

where *t* and *t-1* refer to the current and the previous simulation time steps, *i* and *j* are crew indices, *CM* refers to crew motivation, *Z* refers to the type of crew agent that changes motivation based on observing the motivation of other agents, *S* refers to susceptibility (i.e., the probability that an interaction leads to change of motivation level), and *N* refers to the number of other crew agents that are interacting with crew *i*.

A crew that interacts with other crews may or may not change its motivation based on the motivation of other crews. *Z* has two states: 0 (i.e., the crew agent is a zealot and never changes its motivation when interacting with others) and 1 (i.e., the crew agent is not a zealot and may change its motivation when interacting with others). *S* enables the model to consider the probability that an interaction leads to a change in the level of motivation of a crew agent. *S* takes values between 0 (i.e., no susceptibility) and 1 (i.e., full susceptibility), which indicates how much the interacting crew agents affect the motivation level of crew agent *i*.

Equation 8 calculates the motivation level of a crew agent *i* when the interaction of that crew agent with other crew agents happens. However, crews are not always in contact with each other. Therefore, the extension of Equation 8, which considers agent contact rate, is developed as Equation 9.

$$CM_i^t = (1 - Z \times CR \times S) \times CM_i^{t-1} + (Z \times CR \times S) \times \frac{\sum_{j=1}^{N} CM_j^{t-1}}{N} \tag{9}$$

where *CR* refers to crew agent contact rate (i.e., the rate that crew agents contact each other over the simulation time unit).

Crew behavioral rules

Individual and group performance has long been viewed as a function of both capability/ability and motivation (Campbell, 1990; Wildman et al. 2011). Therefore, when studying crew performance, it is important to consider not only motivational factors but also situational/contextual factors (i.e., the factors related to the situation in which the tasks are performed). A number of situational/contextual factors have been investigated in past research on motivation (Cox et al. 2006; Raoufi and Fayek 2018; Šajeva 2007; Wang et al. 2016). Past research has also shown that the presence of situational/contextual factors will help or hinder the effect of crew motivation on crew performance (Raoufi and fayek 2018). Therefore, in addition to motivational factors, it is important to include the situational/contextual factors when defining crew behavioral rules.

The behavioral rules of crew agents in previous agent-based models in construction do not consider the situational/contextual factors and the crew motivational factors together. In this case study, the purpose of simulation is to predict crew performance. Thus, the behavioral rules of the agents are a function of both crew motivation and situational/contextual factors. Using a fuzzy inference system is proposed in the fuzzy agent-based methodology section to address the subjective uncertainty in the subjective variables and in relationships of the model. Following the proposed methodology, FCM clustering is applied on the collected field data to develop fuzzy rules to represent crew behavioral rules (i.e., how crews perform based on their level of motivation and the project environment). The identified fuzzy rules are then used to construct a fuzzy inference system. A Mamdani fuzzy rule-based model, which is one of the most widely used architectures in fuzzy modeling, is selected to build the fuzzy inference system (Pedrycz 2013). Mamdani fuzzy rule-based models provide an output as fuzzy sets that can be defuzzified to obtain a crisp output and that can be used in the agent-based model at the simulation run time. Gaussian membership functions are used because of their advantages, which are that they have full coverage (i.e., non-zero values at all points), they possess interpretability, and they are suitable for optimization (Tsehayae and Fayek 2016).

MATLAB® is used to perform FCM clustering and to build a Mamdani fuzzy rule-based model. It is advantageous to limit the number of input variables and the number of linguistic terms in order to have a fuzzy inference system with good interpretability (Tsehayae and Fayek 2016; Gacto et al. 2011). In this paper, crew motivation and crew-level situation and project-level situation are the three input variables and crew performance is the output variable of the fuzzy inference system. The results of the FCM clustering performed in MATLAB® on the collected field data are the defined fuzzy rules and membership function parameters, which are presented in Table 3.

Table 3 shows the parameters for fuzzy membership functions for each input and output variable of the model. For example, *low* motivation is represented by a Gaussian membership function as described in Equation 1 where μ=0.8543 and σ=0.0349. Five fuzzy rules are shown in Table 3. For example, fuzzy rule 1 is "If crew motivation is *low*, and the crew-level situation is s*atisfied*, and the project-level situation is *slightly satisfied,* then crew performance is *medium*."

Simulation Experiment and Results

After building the fuzzy agent-based model, the next step is to perform the simulation experiment. Performing the simulation experiment allows for the observation of variations in model variables, such as variations in crew motivation, crew-level situation, project-level situation, and crew performance. The initial conditions (e.g., the model parameters) are defined based on the collected field data. For example, the project under study had 9 crews, of which 4 were at a state of *high* motivation at the beginning of the project (i.e., 42.86% in *HighMotivated* state). Table 4 shows the parameters of the fuzzy agent-based model that need to be defined in order to perform a simulation experiment. In the second column of Table 4, the possible range of values for each parameter in the model is presented. The range of values can be used for sensitivity analysis and scenario building. For example, the simulation experiment can be run under new initial conditions (usually hypothetical initial conditions) and the possible outcomes observed. The third column of Table 4 shows the initial values for the simulation experiment. These initial values were obtained from the collected field data for the project under study, and they were used in the simulation experiment in the case study.

Table 3. Fuzzy inference system rules and membership function parameters.

Variable	Rule 1		Rule 2		Rule 3		Rule 4		Rule 5	
	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ
Crew motivation	Low		Medium		High		Very High		Very Low	
	0.0349	0.8543	0.0312	0.8806	0.0205	0.9240	0.0325	0.9258	0.0550	0.7192
Crew-level situation	Satisfied		Slightly unsatisfied		Slightly satisfied		Moderate		Unsatisfied	
	0.0252	0.8054	0.0166	0.7322	0.0290	0.7899	0.0199	0.7516	0.0472	0.6426
Project-level situation	Slightly satisfied		Moderate		Slightly unsatisfied		Satisfied		Unsatisfied	
	0.0478	0.9954	0.0618	0.8092	0.0871	0.6021	0.0470	0.9979	0.0849	0.6013
Crew performance	Medium		Low		Very High		High		Very Low	
	0.0106	0.8071	0.0108	0.8055	0.0080	0.8198	0.0168	0.8172	0.0392	0.6957

Table 4. Fuzzy agent-based model parameters.

Parameter	Range of Values	Initial Value for Simulation Experiment (Based on Collected Field Data)	Description
Number of crews	$\mathbb{Z}^+$	9	Number of crews in the project
Contact rate	$\mathbb{R}^+$	1.00000	Number of contacts between crews per simulation time unit
Zealot percentage	[0,1]	0.28570	The percentage of zealots in the project
Susceptibility	[0,1]	0.09419	The probability that an interaction leads to change in motivation
Non-interactive motivation variability	[0,1]	0.01098	The rate of change in motivation-level without contact to other agents
Initial motivation states of crews	[0,1]	0.28570 for "*low*" 0.42860 for "*high*"	Percentages of crews in each motivation state at the start of the simulation. The percentage for "*medium*" is calculated by the model after the user defines percentages for "*low*" and "*high*".
Initial states of crew-level situation	[0,1]	0.14260 for "*unsatisfied* crew-level situation" 0.00000 for "*satisfied* crew-level situation"	Percentages of crews in each crew-level situation state at the start of the simulation. The percentage for "*medium* crew-level situation" is calculated by the model after the user defines percentages for "*unsatisfied* crew-level situation" and "*satisfied* crew-level situation".
Initial state of project-level situation	String	"*medium* project-level situation"	String parameter representing initial states of the project-level situation such as "*unsatisfied*", "*medium*", and "*satisfied*".
Crew-level situation variability	$\mathbb{R}^+$	0.03139	Rate of change in crew-level situation states per simulation time unit
Project-level situation variability	$\mathbb{R}^+$	0.03333	Rate of change in project-level situation states per simulation time unit

There are nine crews in the simulation experiment, each of which has a different level of motivation and performs tasks in different crew-level situations. Field data were collected over 68 days of the project under study; therefore, the simulation finish time is 68 days for the simulation experiment. The behavior of the system was then observed over the simulation run time and the statistics regarding model variables were collected. Time plots for crew motivation, crew-level situation, and crew performance for all crews are provided in the crew agent class. Time plots for the project-level situation are provided in the project class. In the main simulation environment, time plots for the motivation states of crews, the crew-level situation states of crews, the project-level situation, the average motivation of all crews, the average crew-level situation of all crews, and the average performance of all crews in the project is provided. Figure 6 shows a summary of the results of the model experimentation obtained from the simulation main environment for all crews in the project. The results related to each agent are also visible in the agent class, as shown previously in Figures 4 and 5 for one of the crews in the same simulation experiment.

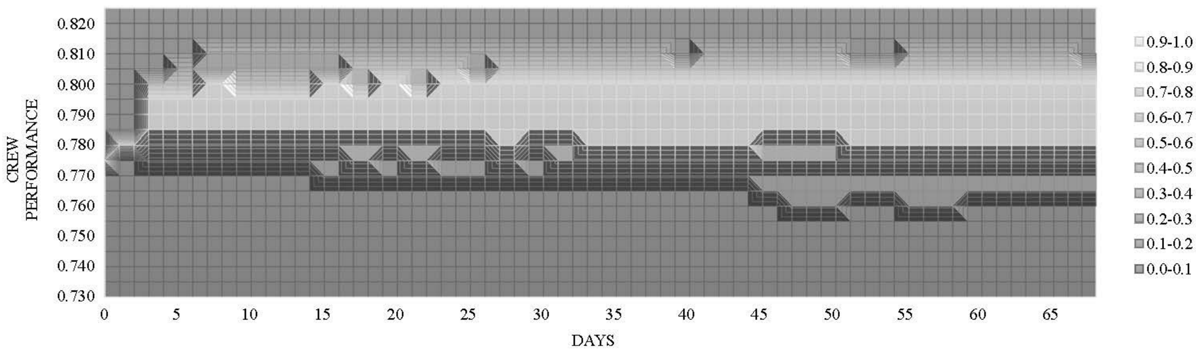

Figure 6. FABM simulation experimentation results.

In Figure 6, the time plot for the motivation states of crews shows the number of crews in each motivation state (*LowMotivated*, *MediumMotivated*, and *HighMotivated*) over the simulation run time. Of the nine crews generated at the start of the simulation, four crews were in a *MediumMotivated* state, three crews were in a *HighMotivated* state, and two crews were in a *LowMotivated* state. Therefore, at the start of the simulation, the number of crews in *HighMotivated* state was more than the number of crews in *LowMotivated* state. Since the initial number of high-motivated crews was more than the initial number of low-motivated crews, the crew interactions were in favor of changing the motivation of low-motivated crews to higher motivation levels (e.g., medium-motivated crews). The time plot of motivation states of crews shows that over time, some low-motivated crews changed to medium-motivated crews. This is due to the interactions of the crews. The plot of average motivation of all crews over time shows that there was an increasing trend regarding the motivation of crews. As Figure 6 presents the aggregated results of all crews, it is also possible to examine this trend in the change in motivation of each crew separately in the time plots that exist in the crew class. For example, in Figure 5, the time plot for crew motivation shows a gradual increase in the overall motivation of a crew over time, demonstrating how the interaction of crews affected the motivation of the crew in the project over time. The areas with a sharp drop or increase in motivation are due to non-interactive motivation variability in crew motivation.

In Figure 6, time plots of crew-level situation states of crews, the project-level situation, and the average crew-level situation of all crews are presented. The time plot of the average performance of all crews shows the average performance of all crews at each time step. The performance of each crew agent is calculated in the model using a fuzzy inference system based on crew motivation, crew-level situation, and project-level situation. As shown in Figure 6, the developed fuzzy agent-based model is able to account for the diversity of crews, crew interactions, variations of crew motivation over time, and variations in the situation in which crews are performing. Thus, the calculated crew performance reflects the dynamic aspects of crew motivation and project situation.

The fuzzy agent-based model of construction crew motivation and performance has some practical applications in construction. For example, based on the above discussion on the results of the model, the developed fuzzy agent-based model is able to account for the diversity of crews, crew interactions, variations in crew motivation over time, and variations in the situation in which crews are performing their work. The results also show that the fuzzy agent-based model is able to predict the performance of construction crews in the project by taking into account not only the complexities related to agent interactions, but also the subjective uncertainty involved in the construction system. These capabilities of the fuzzy agent-based model can be used during project planning (e.g., by analyzing the effect of system parameters on crew performance to identify the required resources, such as the required number of crews to be recruited to work on the planned work packages), project execution (e.g., to predict and monitor overall crew performance during the execution of the project), project monitoring and control (e.g., to experiment with new scenarios when facing a change in the project situation during project execution in order to take timely corrective actions).

The developed model is based on collected field data from multiple crews in one construction project, but it can be used to assess crew performance in projects with similar contexts. It is also possible to use the model in projects with very different contexts, but the membership functions and fuzzy rules would need to be tuned. To do so, data should be collected from projects in a new context, and the methodology of this paper regarding the development of fuzzy membership functions and fuzzy rules should be followed. Then the fuzzy inference system could be developed with the new fuzzy membership functions and fuzzy rules for projects in the new context. The ABM part of the model would not change in a new context, but a new project would need to be simulated with new initial conditions.

Verification and validation

In construction research, various verification and validation techniques have been developed and used over time, including face validity, internal validity, external validity, and construct validity (Lucko and Rojas 2009). Different methods were implemented in past literature for the verification and validation of simulation models, including agent-based models. Ormerod and Rosewell (2009) defined the methods for verification and validation of agent-based models in the social sciences; Sargent (2013) classified the methods for verification and validation of simulation models; and Lucko and Rojas (2009) reviewed the methods for verification and validation in construction research. In this research, a combination of the methods proposed for verification and validation in construction, the social sciences, and computer science are implemented. The methods applied in this research are the most commonly used according to recent literature on ABM in construction (Azar and Ansari 2017; Azar and Menassa 2012).

To verify the developed fuzzy agent-based model, four steps are followed. First, all mathematical equations are checked to identify and correct any possible errors in the model (Ormerod and Rosewell 2009). Second, a structured walk-through is performed to examine the components of the model, such as the developed Java methods (Sargent 2013). Third, the model is simulated multiple times to check for the replicability of its results (Ormerod and Rosewell 2009). Fourth, both tracing and runtime graphs are used to track changes in the variables of the model during the simulation experiment and to ensure that model components are working as expected (Sargent 2013).

To validate the fuzzy agent-based model, three steps are followed. First, conceptual validity is performed by basing the model on validated motivational concepts from past literature (Sargent 2013). Motivational factors, situational/contextual factors, and crew performance metrics are defined based on past literature in the construction and non-construction domains. Then the identified list of factors is validated by both motivation experts and construction experts. As suggested by Ormerod and Rosewell (2009), the problem to be modeled is fully described, including all model components such as agents, parameters, and simulation time steps. Second, data validity is performed by developing a data collection protocol and following a structured data collection methodology; testing for construct validity and the reliability of the measures used for data collection must also be done (Sargent 2013). Third, operational validity is performed by both subjective approaches (i.e., methods that do not use actual data) and objective approaches (i.e., methods that use actual data) (Sargent 2013). A subjective approach to operational validity is performed using graphical displays such as time plots at simulation run time. Time plots for model variables are presented in all model agents to observe the behavior of different elements of the model. The first objective approach to operational validity is performed using ten-fold cross-validation, an internal validity technique. A ten-fold cross-validation technique is used to check the accuracy of the developed fuzzy agent-based model in predicting the output. To calculate the error terms, mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) are used. MAPE is calculated based on Equation 10, and it is a measure of the differences between predicted values and actual values. RMSPE is calculated based on Equation 11 and provides a quadratic loss function that is similar to the statistical measure of standard deviation of the differences between predicted values and actual values. Both MAPE and RMSPE express errors as a percentage of actual data; thus, they provide a way of judging the differences in the extent of the errors of one model compared to other models developed by different modeling methods and applied in different contexts.

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{AP_i - PP_i}{AP_i}\right|}{n} \times 100 \tag{10}$$

$$RMSPE = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{AP_i - PP_i}{AP_i}\right)^2}{n}} \times 100 \tag{11}$$

where *AP* refers to the actual crew performance, *PP* refers to performance predicted by the fuzzy agent-based model, and *n* is the number of data.

The ten-fold cross-validation technique was performed, and the calculated MAPE was 2.48% and the calculated RMSPE was 0.79%, indicating a very good prediction of crew performance by the developed fuzzy agent-based model. The second objective approach to operational validity is performed using sensitivity analysis.

Sensitivity analysis

Sensitivity analysis is performed on the main parameters of the model (i.e., parameters listed in Table 4) to identify parameters that have a significant effect on the output of the model. Anylogic® is used to perform sensitivity analysis on a selected parameter. First, all other parameters of the model except the selected parameter are fixed at their values in Table 4. Then, the selected parameter for sensitivity analysis is iterated within its defined range and increments. Finally, the variations in the model output are observed on the graphs of average motivation of all crews provided by Anylogic®. Variations in patterns of model output based on variations in a selected parameter indicate a significant influence of that parameter on the model output. For some parameters, there is a clear direction of the influence the parameter on model output. However, for some other parameters, there is no clear direction of the influence, and only changes in output patterns are observed. Table 5 shows the results of the sensitivity analysis performed for the parameters of the model.

Table 5. Sensitivity analysis of model parameters.

Parameter	Range of Values	Increment	Sensitivity Analysis Results[a]	
			Is influence of the parameter on model output significant?	Is direction of influence of the parameter on model output clear?
Number of crews	[5,25]	5	Yes	No
Contact rate	[0.5, 2.5]	0.50	Yes	Yes (higher contact rate results in higher output of the model)
Zealot percentage	[0,1]	0.25	Yes	No
Susceptibility	[0.05,0.20]	0.05	Yes	Yes (higher susceptibility results in higher output of the model)
Non-interactive motivation variability	[0,0.2]	0.05	Yes	Yes (higher non-interactive motivation variability results in lower output of the model)
Initial motivation states of crews	[0,0.6]	0.15 for "*low*" 0.15 for "*high*"	Yes	Yes (higher percentage of high-motivated crews results in higher output of the model)
Initial states of crew-level situation	[0,0.2]	0.05	Yes	No
Initial state of project-level situation	String	{"*low*", "*medium*", "*high*"}	Yes	No
Crew-level situation variability	[0,0.2]	0.05	Yes	No
Project-level situation variability	[0,0.2]	0.05	Yes	No

[a] Model output for sensitivity analysis is the average performance of all crews for the entire project

Here, the results of the sensitivity analysis for one of the parameters of the model (i.e., contact rate) is illustrated. The contact rate as defined in Table 4 is the number of contacts between crews per simulation time unit, which was 1 for in the case study. Sensitivity analysis is performed for contact rate to illustrate the effect of the contact rate on the output of the model. The results of the sensitivity analysis for five values of contact rate (0.5, 1.0, 1.5, 2.0, and 2.5) are provided in Figure 7. The horizontal axis represents project time (in days) and the vertical axis represents the average performance of crews from the project start time. The average performance of crews from the project start time provides a comparison of the performance of all crews in different scenarios (i.e., different contact rates). The range of values for crew performance is between 0 (undesirable value) and 1 (desirable value). The results in Figure 7 indicate that different contact rates between crews results in different performance of the crews. Since the performance values in Figure 7 are related to average performance of crews from the project start time, the performance values related to the last day of the project (68th day) represent the average performance of all crews for the entire project (i.e., from project start time to project finish time). Comparing the plots of different contact rates in Figure 7, it is observed that the average performance of all crews for the entire project (i.e., the values of performance related to the 68th day in Figure 7) is higher for higher contact rates. The lowest 68th day performance value is related to a contact rate of 0.5, and the highest 68th day performance value is related to a contact rate of 2.5. The results indicate that increasing the contact rate of crews will increase the performance of the crew. This is due to the feedback provided to the crews regarding the performance of other crews when they are in contact which each other.

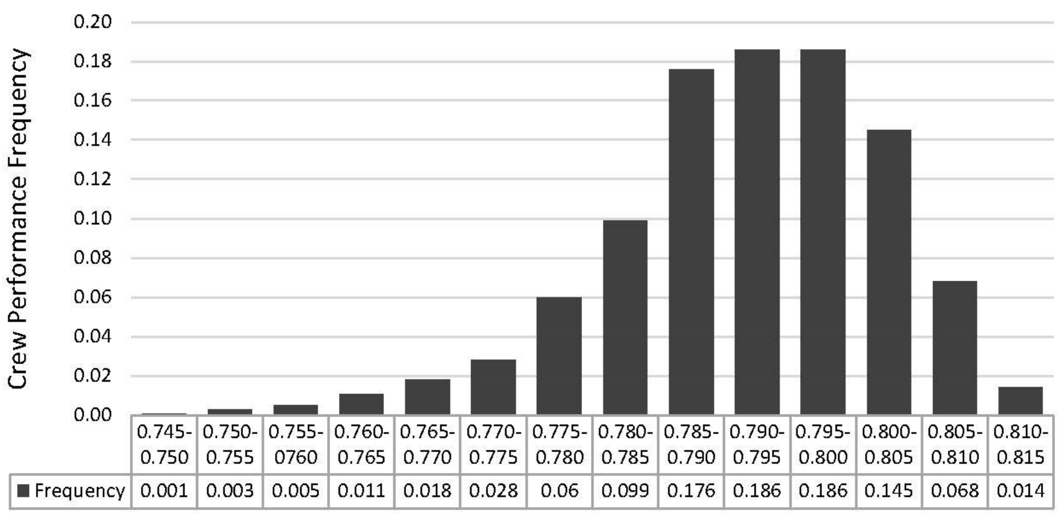

Figure 7. Sensitivity analysis for contact rate.

Similar to the sensitivity analysis related to contact rate, the sensitivity analysis performed for other parameters of the model is summarized in Table 5. The results in Table 5 suggest that contact rate, susceptibility, non-interactive motivation variability, and initial motivation states of crews have a significant influence on the output of the model. Other parameters listed in Table 5 have an influence on the output of the model by changing the pattern of model outputs, yet the direction of their influence is not clear, and they require further data collection and analysis in future research. Although sensitivity analysis is performed for the parameters of this study, future data collection and analysis is needed for additional sensitivity analysis, since the full range of the parameters should be defined based on empirical data from multiple projects.

Conclusions and Future Research

ABM has previously been used to model construction processes and practices, which are influenced by the complexities that arise from the interaction of agents. However, the application of ABM in construction research has some limitations, as ABM alone can only deal with probabilistic uncertainty, while construction systems also include subjective uncertainty. For example, construction crew motivation and performance involve subjective uncertainty that exist in human behavior and social relationships. To address this limitation and improve the effectiveness of ABM, this paper proposed a methodology for integrating fuzzy logic and ABM. The proposed FABM methodology was then used to develop an FABM model of construction crew motivation and performance that predicts the performance of construction crews using input variables such as crew motivational and situational/contextual variables. The develop FABM methodology was then verified and validated based on collected field data from a company active in various industrial projects in Canada. The developed fuzzy agent-based model is able to account for the diversity of crews, crew interactions, variations in crew motivation over time, and variations in the situation in which crews are performing. The results show that the developed fuzzy agent-based model is able to predict the performance of construction crews in the project by taking into account not only the complexities related to agent interactions, but also the subjective uncertainty involved in the construction system.

This paper makes three contributions. First, it expands the scope of applicability of ABM by integrating fuzzy logic with ABM to create fuzzy agent-based modeling (FABM) in construction, which can handle both probabilistic and subjective uncertainty; second, it provides a novel methodology for developing fuzzy agent-based models, which allows for the development of new models to assess construction processes and practices; and third, it develops a fuzzy agent-based model of construction crew motivation and performance, which improves the assessment of crew performance by accounting for not only the interactions of crews in the project, but also subjective uncertainty in model variables such as crew motivation.

In the future, various scenarios will be developed and simulated, such as a project with different combinations of crew motivation, to compare the performance of crews in different scenarios. Data from more companies will be collected to expand the scope of applicability of the developed FABM methodology and provide models applicable to other contexts in construction. The model will be expanded to the organization level by adding the organization class in order to be able to simulate the different projects of an organization. Monte Carlo simulation will also be performed in order to observe the effect of the probabilistic uncertainty that exists in the construction system. Future research will also investigate the applicability of using a fuzzy rule-based system to define agent interactions in order to address the subjective uncertainty that exist in the interactions among model agents.

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References

Ahn, S., and Lee, S. (2014). “Methodology for Creating Empirically Supported Agent-Based Simulation with Survey Data for Studying Group Behavior of Construction Workers.” *J. Constr. Eng. Manage.*, 141(1), 04014065-1 – 04014065-9.

Ahn, S., Lee, S., and Steel, R. P. (2013). “Construction workers’ perceptions and attitudes toward social norms as predictors of their absence behavior.” *J. Constr. Eng. Manage.*, 140(5).

Anumba, C., Ugwu, O., Newnham, L., and Thorpe, A. (2002). "Collaborative design of structures using intelligent agents." *Autom. Constr.*, 11(1), 89-103.

Asgari, S., Kandil, A., and Odeh, I. (2016). "Optimal Risk Attitude for Construction Contractors in Competitive Bidding Environments." *Construction Research Congress 2016*, 2474-2480.

Awwad, R., Shdid, C. A., and Tayeh, R. (2017). “Agent-based model for simulating construction safety climate in a market environment.” *J. Comput. Civ. Eng.*, 31(1), 05016003.

Azar, E., and Al Ansari, H. (2017). “Multilayer Agent-Based Modeling and Social Network Framework to Evaluate Energy Feedback Methods for Groups of Buildings.” *J. Comput. Civ. Eng.*, 31(4): 04017007, 1-14.

Azar, E., and Menassa, C. C. (2012). “Agent-based modeling of occupants and their impact on energy use in commercial buildings.” *J. Comput. Civ. Eng.*, 26(4), 506-518.

Azar, E., and Menassa, C. C. (2016). “Optimizing the performance of energy-intensive commercial buildings: Occupancy-focused data collection and analysis approach.” *J. Comput. Civ. Eng.*, 30(5), C4015002.

Ben-Alon, L., and Sacks, R. (2017). “Simulating the behavior of trade crews in construction using agents and building information modeling.” *Autom. Constr.*, 74, 12-27.

Bezdek, J. C. (2013). *Pattern recognition with fuzzy objective function algorithms*, Springer Science & Business Media, New York, NY.

Campbell, J. P. (1990). “Modeling the performance prediction problem in industrial and organizational psychology.” In M. D. Dunnette and L. M. Hough, Eds., *Handbook of Industrial and Organizational Psychology* (pp. 687-732). Consulting Psychologists Press, Inc., Palo Alto, CA.

Cox, R. F., Issa, R. R., and Frey, A. (2006). “Proposed subcontractor-based employee motivational model.” *J. Constr. Eng. Manage.*, 132(2), 152-163.

Dash, R. K., Jennings, N. R., and Parkes, D. C. (2003). “Computational-mechanism design: A call to arms.” *Intell. Syst., IEEE*, 18(6), 40-47.

Deffuant, G., Neau, D., Amblard, F., and Weisbuch, G. (2000). "Mixing beliefs among interacting agents." *Adv. Complex Syst.*, 3(1), 87-98.

Eid, M. S., and El-adaway, I. H. (2017). “Integrating the Social Vulnerability of Host Communities and the Objective Functions of Associated Stakeholders during Disaster Recovery Processes Using Agent-Based Modeling.” *J. Comput. Civ. Eng.*, 31(5), 04017030.

Fougères, A. (2013). “A modelling approach based on fuzzy agents.” *ArXiv Preprint arXiv:1302.6442*.

Gacto, M. J., Alcalá, R., and Herrera, F. (2011). “Interpretability of linguistic fuzzy rule-based systems: An overview of interpretability measures.” *Inf. Sci.*, 181(20), 4340-4360.

Hegselmann, R., and Krause, U. (2002). "Opinion dynamics and bounded confidence models, analysis, and simulation." *Artif. Soc. Social Simul.*, 5(3), 1-33.

Huget, M. (2003). “Agent UML class diagrams revisited.” *Agent technologies, infrastructures, tools, and applications for e-services*, Springer, 49-60.

Jabri, A., and Zayed, T. (2017). “Agent-based modeling and simulation of earthmoving operations.” *Autom. Constr.*, 81 210-223.

Kim, K., and Kim, K. J. (2010). "Multi-agent-based simulation system for construction operations with congested flows." *Autom. Constr.*, 19(7), 867-874.

Lucko, G., and Rojas, E. M. (2009). “Research validation: Challenges and opportunities in the construction domain.” *J. Constr. Eng. Manage.*, 136(1), 127-135.

Macal, C. M. (2010). “To agent-based simulation from system dynamics.” *Proceedings of the 2010 Winter Simulation Conference (WSC)*, IEEE, 371-382.

Mobilia, M., Petersen, A., and Redner, S. (2007). "On the role of zealotry in the voter model." *J. Stat. Mech. Theory Exp.*, (8), 1-9.

North, M. J., and Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford University Press.

Ormerod, P., and Rosewell, B. (2009). “Validation and verification of agent-based models in the social sciences.” *Epistemological Aspects of Computer Simulation in the Social Sciences*, 130-140.

Osman, H. (2012). "Agent-based simulation of urban infrastructure asset management activities." *Autom. Constr.*, 28 45-57.

Ostrosi, E., Fougères, A., and Ferney, M. (2012). “Fuzzy agents for product configuration in collaborative and distributed design process.” *Appl. Soft Comput.*, 12(8), 2091-2105.

Pedrycz, W. (2013). *Granular computing: analysis and design of intelligent systems*, CRC press, Boca Raton, FL.

Raoufi, M., and Fayek, A. Robinson (2018). “Key moderators of the relationship between construction crew motivation and performance.” *J. Constr. Eng. Manage*, accepted on January 3, 2018.

Raoufi, M., Seresht, N. G., and Fayek, A. Robinson (2016). “Overview of fuzzy simulation techniques in construction engineering and management.” *Fuzzy Information Processing Society (NAFIPS), 2016 Annual Conference of the North American*, IEEE, 1-6.

Reynolds, C. (1999). “Individual-based models.” *Red3d.Com [Online Article], October, accessed October 2017*. http://www.red3d.com/cwr/ibm.html.

Šajeva, S. (2007). “Identifying factors affecting motivation and loyalty of knowledge workers.” *Econ. Manage.*, 12, 643-652.

Sargent, R. G. (2013). “Verification and validation of simulation models.” *Journal of Simulation*, 7(1), 12-24.

Scholl, H. J. (2001). “Agent-based and system dynamics modeling: a call for cross study and joint research.” System Sciences, 2001. *Proceedings of the 34th Annual Hawaii International Conference on*, IEEE, 8 pp.

Seo, J., Lee, S., and Seo, J. (2016). “Simulation-based assessment of workers’ muscle fatigue and its impact on construction operations.” *J. Constr. Eng. Manage.*, 142(11), 04016063.

Siraj, N. B., Fayek, A. Robinson, and Tsehayae, A. Assefa (2016). “Development and optimization of artificial intelligence-based concrete compressive strength predictive models.” *International Journal of Structural and Civil Engineering Research*, 5(3), 156-167.

Tah, J. H. (2005). "Towards an agent-based construction supply network modelling and simulation platform." *Autom. Constr.*, 14(3), 353-359.

Tsehayae, A. Assefa, and Fayek, A. Robinson (2016). “Developing and optimizing context-specific fuzzy inference system-based construction labor productivity models." *J. Constr. Eng. Manage.*, 142(7), 04016017.

Wang, D., Arditi, D., and Damci, A. (2016). “Construction project managers’ motivators and human values.” *J. Constr. Eng. Manage.*, 143(4), 04016115.

Watkins, M., Mukherjee, A., Onder, N., and Mattila, K. (2009). “Using agent-based modeling to study construction labor productivity as an emergent property of individual and crew interactions.” *J. Constr. Eng. Manage.*, 135(7), 657-667.

Wildman, J. L., Bedwell, W. L., Salas, E., and Smith-Jentsch, K. A. (2011). “Performance measurement at work: A multilevel perspective.” In Zedeck S., Ed., *APA Handbook of industrial and organizational psychology, Vol. 1: Building and developing the organization* (pp. 303-342). American Psychological Association, Washington, DC.

Xue, X., Li, X., Shen, Q., and Wang, Y. (2005). "An agent-based framework for supply chain coordination in construction." *Autom. Constr.*, 14(3), 413-430.

Zadeh, L. A. (2015). “Fuzzy logic—A personal perspective.” *Fuzzy Sets Syst.*, 281, 4-20.