Fuzzy Monte Carlo Agent-Based Simulation of Construction Crew Performance

Mohammad RAOUFI[1], Ph.D., A.M.ASCE and Aminah Robinson FAYEK[2], Ph.D., P.Eng., M.ASCE (corresponding author)

Abstract

The use of agent-based modeling (ABM) in the analysis of construction processes and practices has increased significantly in the past decade. However, the developed models are not able to address both random and subjective uncertainties that exist in many construction processes and practices. Monte Carlo simulation is able to account for random uncertainty, and fuzzy logic is able to account for the subjective uncertainty that exists in model variables and relationships. In this paper, a methodology for the development of fuzzy Monte Carlo agent-based models in construction is provided, and its application is illustrated through the development of a model of construction crew performance. This paper makes three contributions: first, it expands ABM's scope of applicability by showing how to model both random and subjective uncertainty in ABM; second, it provides a novel methodology for integrating fuzzy logic and Monte Carlo simulation in ABM, which allows for the development of fuzzy Monte Carlo agent-based models in construction; and third, it illustrates a fuzzy Monte Carlo agent-based simulation of construction crew performance, which improves the assessment of crew performance by considering both random and subjective uncertainties in model variables.

[1] Postdoctoral fellow, Department of Civil & Environmental Engineering, 7-385 Donadeo Innovation Centre for Engineering, 9211 116 St NW, University of Alberta, Edmonton AB T6G 1H9, Canada.

[2] Director of the Construction Innovation Centre, Tier 1 Canada Research Chair in Fuzzy Hybrid Decision Support Systems for Construction, NSERC Industrial Research Chair in Strategic Construction Modeling and Delivery, Ledcor Professor in Construction Engineering, Professor, Department of Civil & Environmental Engineering, 7-232 Donadeo Innovation Centre for Engineering, 9211 116 St NW, University of Alberta, Edmonton AB T6G 1H9, Canada.

Author keywords: Fuzzy Monte Carlo simulation; Agent-based simulation; Construction; Fuzzy logic; Monte Carlo simulation; Crew performance

Introduction

Crew performance is influenced not only by the environment in which construction activities occur, but also by crew motivation, which has largely been overlooked in construction research. However, construction researchers have faced challenges in identifying the effect of motivational factors and situational/contextual factors on crew performance. These difficulties are due to the uniqueness and dynamism of the construction environment and the fact that motivational and situational/contextual factors include both random and subjective uncertainties.

To overcome these difficulties, two methodological approaches, agent-based modeling (ABM) and fuzzy logic, have been applied and integrated to develop a model of construction crew motivation and performance (Raoufi and Fayek 2018c). ABM is a good solution for handling complex systems of interacting agents and is therefore suitable for modeling construction crew behavior. ABM can handle complexities that arise from the interactions of system components; however, many systems—especially those comprising human behavior and social relationships—also include subjective uncertainties, which are not accounted for in ABM. Fuzzy logic, on the other hand, is able to deal with subjective uncertainty. Therefore, integrating these two techniques is advantageous for modeling behavioral and social systems, such as construction crew motivation and performance.

In construction research, ABM has recently been used to model complex systems of interacting agents. Agents have their own type (e.g., crew members), attributes (e.g., age), behaviors (e.g., counterproductive behavior), and behavioral rules. ABM can model the interactions between agents, the interactions of agents and the environment, and the learning processes of agents over time. Therefore, it is a suitable modeling technique for modeling the components of a complex system comprised of interacting agents. ABM can also 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 and Macal 2007). However, ABM alone is not able to model both the random and the subjective uncertainty that exist in construction projects.

Construction projects are performed in an environment characterized by uncertainty. Weather conditions, material delivery, equipment breakdown, and crew availability are a few examples of factors that exhibit uncertainty. Uncertainty in construction has traditionally been treated as a random phenomenon, often requiring sufficient historical project data for effective modeling. When approaching uncertainty from this vantage point, researchers frequently rely on the use of classical techniques, such as Monte Carlo simulation, for experimentation with probabilistic data (AbouRizk 2010). The use of Monte Carlo simulation in the three major simulation modeling techniques (i.e., discrete event simulation, system dynamics, and ABM) increases their capability of addressing random uncertainty in simulation modeling (Raoufi et al. 2018).

In construction, it is often the case that numerical project data are not available in sufficient quantity or may not meet the quality standards required for effective modeling. Due to the uniqueness of each project, collected data may not be completely reflective of new project contexts. In addition to random uncertainty, much uncertainty in construction stems from the use of approximate reasoning and linguistically expressed expert knowledge, which is based on subjective assessments rather than numerical data; such knowledge is often not formally documented in construction. Classical analysis techniques, which are based on the precise manipulation of numerical data, are incapable of capturing human thought processes and decision-making (Zadeh 2015). Fuzzy logic plays an important role in addressing subjective uncertainty; thus, the integration of fuzzy logic with other methods such as optimization (e.g., evolutionary models and particle swarm optimization), machine learning (e.g., artificial neural networks and clustering), multi-criteria decision-making (e.g., AHP, TOPSIS, and VIKOR), and simulation (e.g., Monte Carlo simulation, discrete event simulation, system dynamics, and ABM) has been used in construction research (Gerami Seresht et al. 2018).

Agent-based models in construction address random uncertainty through the use of Monte Carlo simulation, while fuzzy agent-based models in construction address subjective uncertainty in model variables and relationships. The ability to account for both random and subjective uncertainty will help with the creation of more accurate predictive models in construction. However, existing ABM in construction is not able to address both random and subjective uncertainties that exist in many construction processes and practices. Therefore, the objective of this paper is to expand ABM's scope of applicability in construction by enabling ABM to simulate both random and subjective uncertainty. To achieve this objective, this paper integrates fuzzy logic and Monte Carlo simulation in ABM and proposes a methodology for performing fuzzy Monte Carlo agent-based simulations in construction. The proposed methodology accounts not only for the random uncertainty in construction variables (e.g., contact rate of crews), but also the subjective uncertainty involved in construction variables (e.g., crew motivation) and relationships (e.g., the relationship between crew motivation and performance). The methodology is illustrated through a case study that models the behavior of construction crews based on the factors affecting crew performance (e.g., crew motivation) and predicts the performance levels of crews.

This paper is structured as follows. First, a literature review of ABM in construction is presented. Past research that addresses uncertainties in agent-based models in construction is also reviewed and discussed. Second, a methodology for the development of fuzzy Monte Carlo agent-based models in construction is provided. Third, a fuzzy Monte Carlo agent-based model of construction crew performance is developed to illustrate the proposed methodology and show the application of fuzzy Monte Carlo ABM in construction.

Literature Review of ABM in Construction

Different simulation techniques are used in construction, such as discrete event simulation, system dynamics, and ABM (Raoufi et al. 2016). Within the study of these simulation techniques, research on ABM is rapidly growing, and there have been numerous published studies on ABM in the last several years. These studies cover a wide range of applications of ABM in construction, such as dispute resolution (Ren and Anumba 2003; El-Adaway and Kandil 2010), productivity (Watkins et al. 2009), supply chain management (Anumba et al. 2002), human resource management (Ahn and Lee 2014), contracting and bidding (Asgari et al. 2016), risk (Farshchian and Heravi 2018), safety (Awwad et al. 2017; Choi and Lee 2017), disaster management (Eid and El-adaway 2017), energy (Azar and Ansari 2017), labor motivation and performance (Raoufi and Fayek 2018c), and modeling earthmoving operations (Jabri and Zayed 2017).

ABM was used to model and improve the efficiency of construction claims negotiation (Ren and Anumba 2003). El-Adaway and Kandil (2010) created a multi-agent system for construction dispute resolution to generate legal arguments based on historical data of precedent construction disputes. Space congestion and its effect on labor productivity in construction sites has been modeled using ABM to help assess the impact of space congestion on labor productivity (Watkins et al. 2009). Within the context of urban infrastructure management, Osman (2012) used ABM to model the complex interactions between infrastructure users, infrastructure assets, system operators, and politicians. ABM has also been used in the modeling of social interactions among construction personnel, as well as in the development of organizational policies to improve human resources management (Ahn and Lee 2014). Asgari et al. (2016) modeled the bidding process of contractors using ABM to analyze the effect of different risk attitudes of contractors on project markups. Seo et al. (2016) used ABM to assess the impact of workers' muscle fatigue on construction operations. To improve planning of construction projects, ABM has been used to model construction processes such as earthmoving operations (Jabri and Zayed 2017). Another application of ABM was in the study of production control policies in residential building construction (Ben-Alon and Sacks 2017). ABM has also been used to study the construction safety climate by modeling the interactions among project stakeholders (Awwad et al. 2017). Disaster management has been another area of application of ABM in construction; for example, it was recently used in the development of a decision-making model for disaster recovery of communities (Eid and El-adaway 2017). Ben-Alon and Sacks (2017) simulated crews' workflow on construction sites using ABM. ABM has also been implemented in order to improve energy consumption, for example by using ABM when modeling the energy-saving potential of commercial buildings (Azar and Ansari 2017). Choi and Lee (2017) used ABM to analyze the impact of safety management policies on construction workers' safety behavior. ABM has also been used in portfolio management to assess the effect of budget allocation on project progress and to reduce risks related to time, cost, and revenue in an owner's portfolio of construction projects (Farshchian and Heravi 2018). In high-rise building construction, ABM has been used to analyze the performance of lift systems (Jung et al. 2017, 2018). A decision-making agent-based approach allowed the needs of multisector stakeholders to be taken into account when managing a budget for sustainable disaster recovery (Eid and El-adaway 2017). Most past research on ABM addresses either random uncertainty or subjective uncertainty but is unable to address both simultaneously in an agent-based model.

In traditional agent-based models, uncertainty has been represented by the probability density function (PDF) or the cumulative density function (CDF) based on probability theory. Both PDFs and CDFs are able to represent random uncertainty within the parameters of a simulation model. To observe the effect of random uncertainty represented by the PDF or CDF, Monte Carlo simulation is a very common approach used by agent-based modelers. In Monte Carlo simulation, model parameters are considered to be random variables described in terms of PDFs. Simulation experiments are performed by running the agent-based model multiple times, wherein model parameters are randomly selected from the associated PDFs. The results of Monte Carlo simulation in ABM are usually represented by histograms of output parameters of the agent-based model. Thus, Monte Carlo simulation in ABM provides the opportunity to model random uncertainty in construction modeling. However, probability theory and PDFs address only random uncertainty, not the subjective uncertainty associated with vague and imprecise information.

Recently, fuzzy agent-based modeling (FABM) was introduced in simulation modeling in an attempt to model the subjective uncertainty that exists in the attributes and behavioral rules of real-world agents (Raoufi and Fayek 2018c). FABM incorporates fuzzy agents that observe fuzzy variables and then decide how to act based on fuzzy rules. There are two types of subjective uncertainty that FABM currently handles. The first type of subjective uncertainty exists in the variables that represent the attributes of real-world agents. Motivation is an example of a subjective variable for agents. For these type of variables, assigning a linguistic term (e.g., *low* motivation) represents the variable better than assigning a numerical value (e.g., a percentage for crew motivation). The second type of subjective uncertainty exists in agent behavioral rules. An example of a behavioral rule is "if working conditions are *favorable* and the level of motivation of crew is *high*, then the level of performance of crew is *high*."

Both Monte Carlo agent-based simulation and FABM have already been used in construction modeling, with one technique addressing random uncertainty and the other addressing subjective uncertainty. However, a combination of Monte Carlo simulation and FABM to address both random and subjective uncertainty in the same model has not yet been investigated in construction modeling. This paper fills this gap in construction modeling by developing a model capable of performing fuzzy Monte Carlo agent-based simulation, which is able to handle both types of uncertainty in one model.

Fuzzy Monte Carlo Simulation

Fuzzy Monte Carlo simulation uses a combination of probability theory and fuzzy set theory to handle random uncertainty and subjective uncertainty in construction modeling. Fig. 1 shows the types of variables that fuzzy Monte Carlo simulation processes. In Fig. 1, the histogram provided for the output variable Y is based on the PDFs of the random variables X_1, X_2 and the membership functions of the subjective variables Z_1, Z_2. There are two major challenges to performing a fuzzy Monte Carlo simulation: (1) defining model variables and (2) obtaining the output of the model.

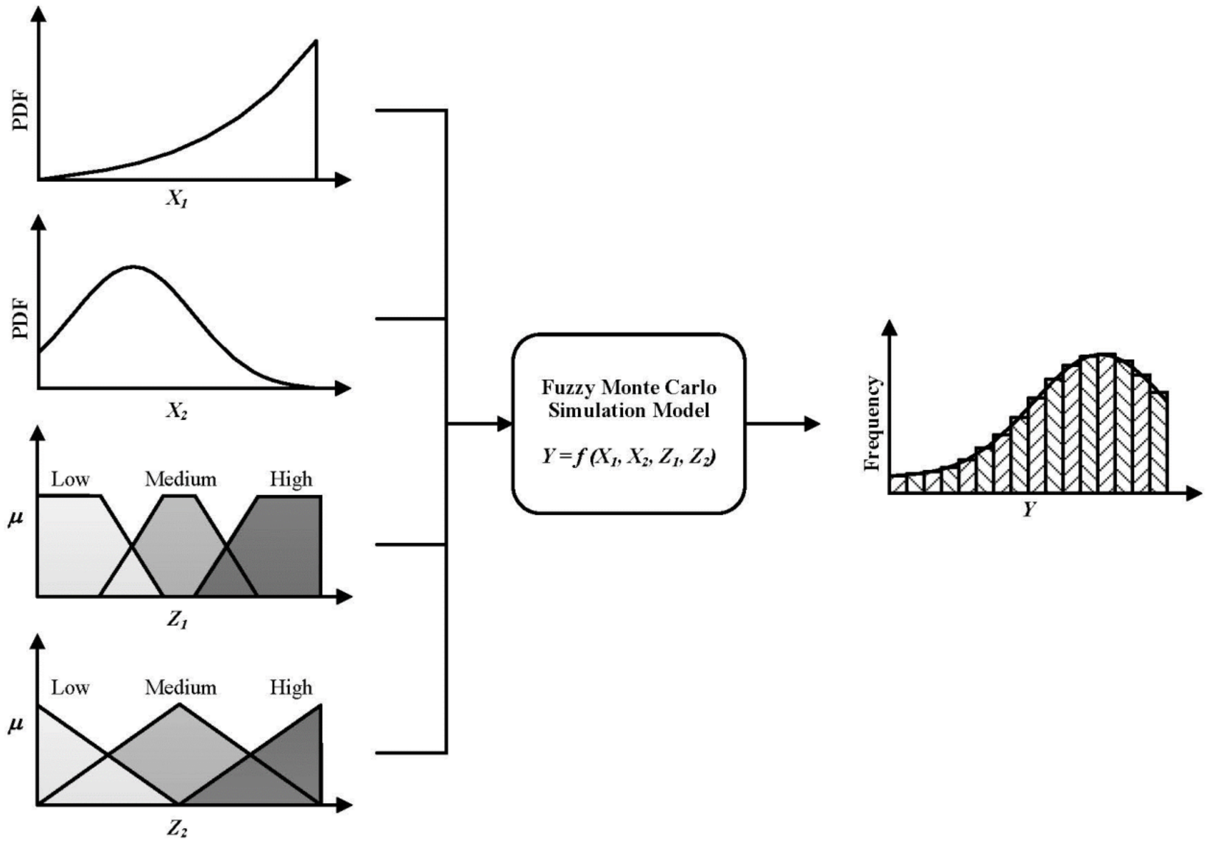

Fig. 1. Types of variables in fuzzy Monte Carlo simulation.

The first challenge is to define both the random variables and the fuzzy variables of the model, which is done using probability theory and fuzzy set theory. Variability in the random variables is defined using PDFs, and the uncertainty associated with the subjective variables is defined using fuzzy membership functions. For the random variables, the PDFs can be defined by fitting distributions over the collected field data. For the subjective variables, fuzzy membership functions, which assign each element a membership degree between 0 (no membership) and 1 (full membership), are defined based on expert judgment or collected field data (Fayek and Lourenzutti 2018).

The second challenge requires that the model's output be analyzed based on multiple runs of the model. Each run represents a random selection of random variables using their PDFs. Thus, the generalized output based on all runs incorporates random uncertainty. Each run, on the other hand, is the simulation of a fuzzy agent-based model based on both fuzzy and non-fuzzy variables (i.e., deterministic variables and selected random samples of random variables). Thus, each individual run incorporates subjective uncertainty. Depending on the type of output of the fuzzy agent-based model (i.e., a fuzzy variable or a deterministic variable), the final output of the fuzzy Monte Carlo simulation is a fuzzy random variable or a deterministic variable. When the output of the fuzzy agent-based model is a fuzzy variable, each run of the fuzzy Monte Carlo simulation results in a fuzzy output. Then, the aggregation of outputs of all runs of the fuzzy Monte Carlo simulation is a fuzzy random variable (Sadeghi et al. 2010). When the output of the model is a crisp variable, then the defuzzified values of the output of the fuzzy agent-based model are used to compare the output of each run to the actual output. Thus, each run of fuzzy Monte Carlo simulation results in a crisp output, and the aggregation of the outputs of all runs of the fuzzy Monte Carlo simulation is a histogram that shows the frequency with which each output value is observed over all simulation runs.

Fuzzy Monte Carlo Agent-Based Modeling Methodology

The challenge in developing a methodology for fuzzy Monte Carlo ABM lies in processing both random and fuzzy variables in one model. The output is a function of both random variables represented by probabilistic distributions and fuzzy variables represented by fuzzy membership functions. Past research, in most cases, transformed one type of uncertainty to the other type before starting the simulation experiments (Sadeghi et al. 2010). For example, Wonneberger et al. (1995) and Dubois et al. (2004) transformed possibility (e.g., fuzzy membership functions) to probability (e.g., probability distribution) which resulted in a stochastic model with only random variables. However, the transformation of either probability to possibility or possibility to probability is not recommended as each theory only addresses one type of uncertainty. Sadeghi et al. (2010) implemented a hybrid approach for fuzzy Monte Carlo simulation for risk assessment that uses both fuzzy variables and random variables in the simulation without transforming one type into the other. In their approach, they generated a number of sample sets from probability distributions, ran the simulation based off each sample set, and finally aggregated the results of the runs in the form of fuzzy random variables. Similar to Sadeghi et al. (2010), this paper proposes a methodology for fuzzy Monte Carlo ABM that uses both random and fuzzy variables in the same model.

The proposed methodology for fuzzy Monte Carlo ABM has three steps: (1) development of the agent-based model; (2) development of the fuzzy attributes and behavioral rules of agents; and (3) development of the Monte Carlo simulation experiments. Fig. 2 shows the flow chart for the fuzzy Monte Carlo ABM methodology.

The first step of the methodology is the development of the agent-based model, which includes the main environment and agent classes. The main environment includes model parameters, agent populations, and connections to other models (e.g., a fuzzy model for agent behavior). The agent classes include agent attributes, agent behavioral rules, state variables, and state charts. There are several steps for developing an agent-based model. First, the architecture of the agent-based model is determined. This includes determining the type of agents, agent attributes, and agent behaviors, as well as the input and output variables of the agent-based model. Second, the basic structure of the agents (i.e., agent attributes and behaviors) is defined. The attributes and behaviors of each agent are identified. Then, the type of attributes (e.g., deterministic, stochastic, or fuzzy) of each

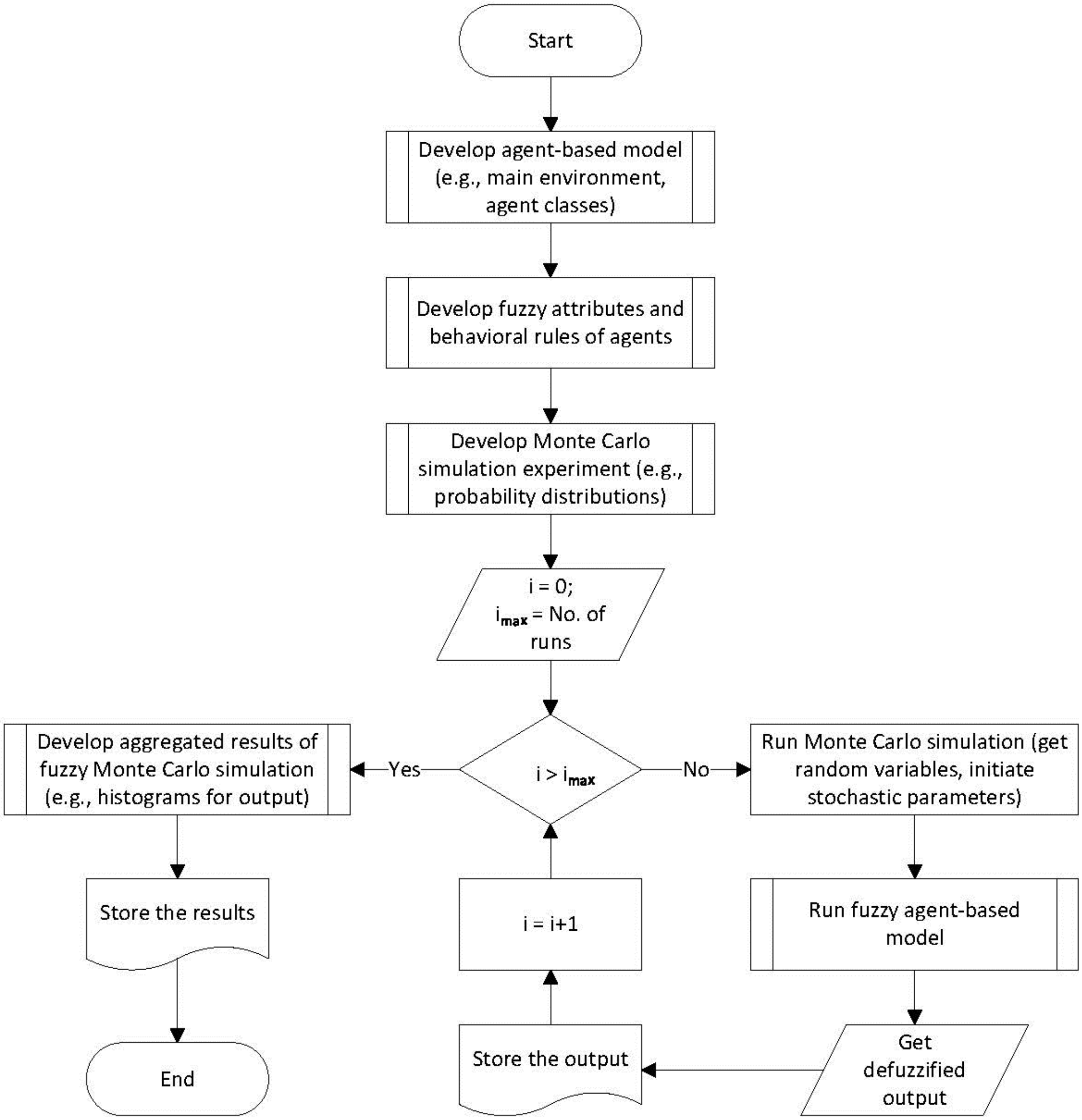

Fig. 2. Fuzzy Monte Carlo ABM methodology.

agent and the type of behavior (e.g., mathematical formula or fuzzy relationship) of each agent are defined. Third, agent interactions are defined. The questions of how the interactions occur and what happens based on each interaction are answered. The method of modeling the interactions is defined (e.g., random interaction, mathematical formula, regression model, or fuzzy model). Fourth, agent behavioral rules are defined (e.g., conditional rules, mathematical formula, regression model, or fuzzy rules).

The second step of the methodology is the development of fuzzy attributes and behavioral rules of agents. Fuzzy attributes and fuzzy behavioral rules are added to the agent-based model to address subjective uncertainty related to the subjective variables (e.g., fuzzy attributes of agents) and subjective relationships (e.g., fuzzy behavioral rules) in the model. First, the fuzzy membership functions of subjective variables, which represent the fuzzy attributes of agents, are defined. Several methods can be used to define membership functions: horizontal and vertical methods, pairwise comparison, statistical methods, and methods based on clustering (Fayek and Lourenzutti 2018). In this paper, fuzzy C-means (FCM) clustering, a commonly used machine learning technique, is applied to define the fuzzy membership functions using collected data. FCM clustering assumes the membership of a data point to more than one cluster with different degrees of membership ranging from 0 to 1 (Bezdek 2013). Second, to represent the fuzzy behavioral rules of agents, a fuzzy inference system is developed based on the rules and membership functions generated from collected data using FCM clustering. FCM clustering is also a common method of determining fuzzy rules from data (Fayek and Lourenzutti 2018). In this paper, FCM clustering is used to define fuzzy rules from field data that will be used in the fuzzy inference system, which represents the behavioral rules of agents. Third, the defined fuzzy membership functions and fuzzy inference system are incorporated into the agent-based model. Raoufi and Fayek (2018c) demonstrated a methodology to incorporate fuzzy membership functions and a fuzzy inference system into an agent-based model to represent the attributes and behaviors of construction crew agents.

The third step of the methodology is the development of Monte Carlo simulation experiments. Monte Carlo simulation is based on running a model many times, where each run is initiated based on generated random variates of each stochastic input variable. Each run of Monte Carlo simulation results in a random outcome of each output variable. Thus, in cases where the agent-based model has stochastic variables, the model parameters associated with those variables are defined by probability distributions. To define probability distributions for stochastic variables, data-driven approaches (e.g., distribution fitting to available data) are used when sufficient data are available, and expert-driven approaches (e.g., defining distribution parameters based on experts' inputs on range, mean, or other estimations of distribution parameters) are used when sufficient data are not available. In this paper, probability distributions for stochastic parameters are defined using field data (i.e., data-driven approaches). Then, fuzzy Monte Carlo agent-based simulation is performed to allow the assessment of both probabilistic and subjective variables simultaneously in the same model. Since some of the inputs of the model are random and some are fuzzy, the outputs of the fuzzy Monte Carlo agent-based simulation experiments incorporate both random and subjective uncertainties.

Fuzzy Monte Carlo Agent-Based Model of Construction Crew Performance

In this section, a fuzzy Monte Carlo agent-based model of construction crew performance is developed to show how to model both random and subjective uncertainty in an agent-based model representing a real construction case. The goal is to develop an agent-based model to enable the analysis of various types of variables in the model (i.e., deterministic, stochastic, and fuzzy variables). Fig. 3 shows the overall scheme of the fuzzy Monte Carlo agent-based model of construction crew performance. The methodology used in this section can be applied to other agent-based models in construction and makes them capable of handling both random and subjective uncertainty.

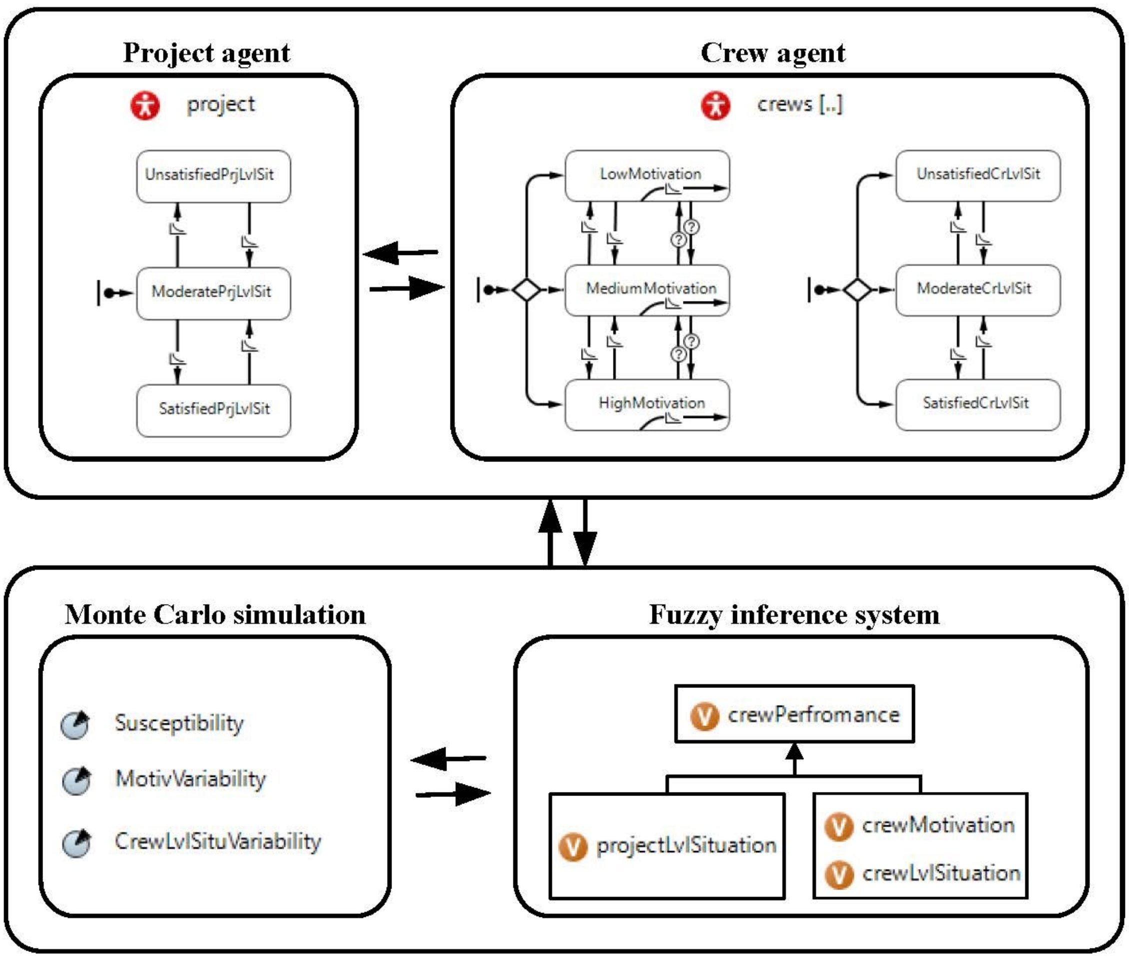

Fig. 3. Overall scheme of fuzzy Monte Carlo agent-based model.

Application of the Fuzzy Monte Carlo Agent-Based Model

In construction, crew performance is influenced by both crew motivation and the working environment. Therefore, this paper assesses crew performance based on the motivational attributes of crew agents, as well as the situational/contextual attributes of both crew and project agents. The model simulates the motivation and performance of crews on construction projects to understand the relationship between construction crew motivation, situational/contextual factors, and crew performance. The goal of this paper is to observe the effect of both subjective variables, such as crew motivation, and random variables, such as crew contact rate, on crew performance.

There are many complexities involved in modeling construction crew behavior, such as interactions among crews or interactions with the environment, and this model is able to assess such complexities. Previous studies on crew motivation and performance mostly considered the motivation-performance relationship in a static state without taking into account variations in crew motivation over time. This model, on the other hand, is able to examine the effects of variations in crew motivation and variations in the work environment on crew performance.

Input and Output Variables of the Model

The model accepts three types of input variables: (1) crisp (i.e., deterministic) variables; (2) random (i.e., stochastic) variables; and (3) fuzzy (i.e., subjective) variables. The output of the model is crew performance, which is presented in the form of histograms showing the frequency with which each output value is observed over all simulation runs. Fig. 4 shows the input and output variables of the model.

The types of variables in the model are defined based on past literature as well as collected field data. Based on past research, some variables (e.g., crew motivation) that incorporated subjective uncertainty and subjective variables were a better representation of those variables (Raoufi and Fayek 2018c). The variables that did not incorporate subjective uncertainty were considered either stochastic or deterministic variables. The collected field data were used to define stochastic variables (e.g., susceptibility) when there was random uncertainty in the data. The

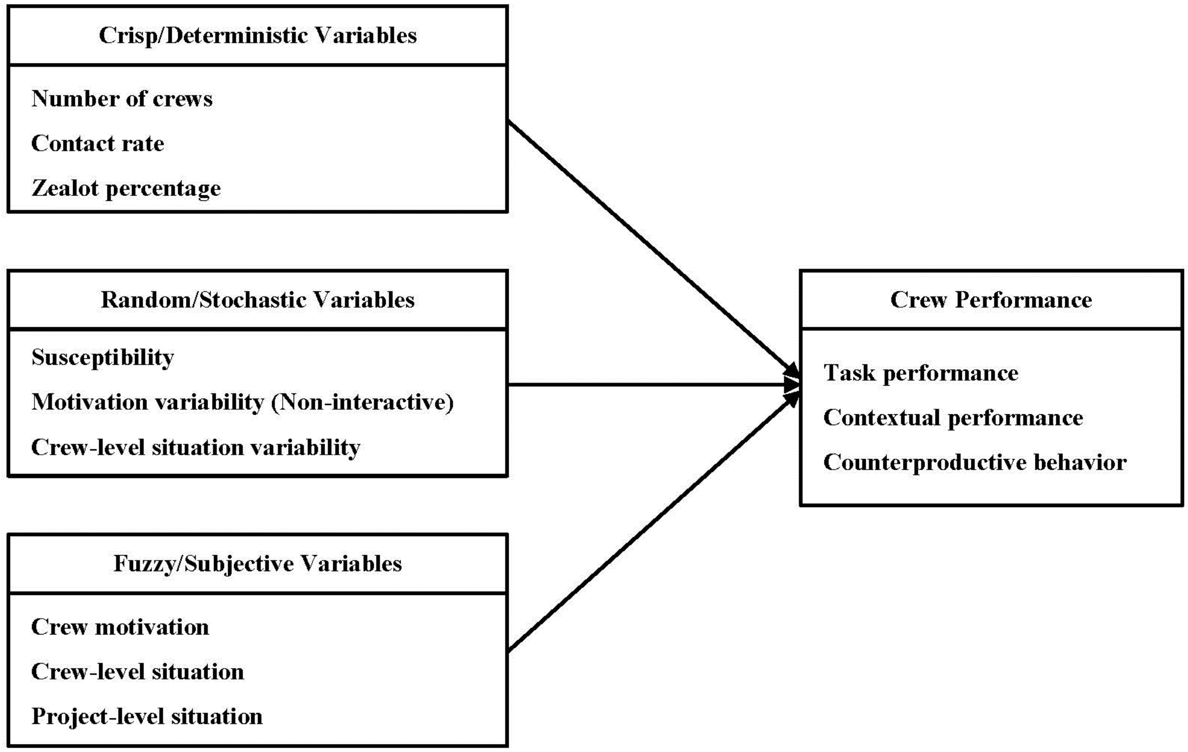

Fig. 4. Input and output variables of the model.

remaining variables (e.g., number of crews) did not show any variability in the collected field data and thus were considered deterministic variables.

In this paper, the selection of variables (i.e., crisp, fuzzy, and random) is based on past research on fuzzy agent-based modeling of construction crew motivation and performance. The selected variables are those showed a significant influence on crew performance based on a sensitivity analysis performed in previous research [see Raoufi and Fayek (2018c) for the results of the sensitivity analysis]. The model's crisp variables are number of crews, contact rate, and zealot percentages. *Number of crews* is the total number of crews working on work packages on the project. *Contact rate* is the number of contacts between crews per simulation time unit. *Zealot percentage* is the percentage of crews that did not show variations in their motivation level in the project.

The model's random variables are susceptibility, non-interactive motivation variability, and crew-level situation variability. *Susceptibility* is the probability that an interaction leads to change in crew motivation. *Non-interactive motivation variability* is the rate of change in the crew motivation level without contact with other crews. *Crew-level situation variability* is the rate of change in crew-level situation states per simulation time unit.

The model's fuzzy variables are the attributes of the crew agent related to crew motivation and the situation in which crews are performing their tasks, as well as the attributes of a project agent related to the situation in which the project is executed. Crew motivation is defined based on four motivational factors: 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). Situational/contextual factors, the factors related to the working environment, are defined at the crew level and the project level. The crew-level situation accounts for task-related factors (e.g., task repetition), labor-related factors (e.g., the behavioral skills of the crew), and foreman-related factors (e.g., performance monitoring). The project-level situation has five categories: project characteristics (e.g., project type), management-related factors (e.g., communication), work-setting conditions (e.g., congestion), resources (e.g., equipment availability), and safety precautions (e.g., safety training). A total of 129 situational/contextual factors are used in this study [see Raoufi and Fayek (2018a) for a complete list of situational/contextual factors of this study].

Crew performance is the output of the model and is defined based on three metrics: task performance (i.e., cost, schedule, change, quality, safety, productivity, and satisfaction), contextual performance (i.e., personal support, organizational support, and conscientious initiative), and counterproductive behavior (i.e., interpersonal deviance and organizational deviance). Crew performance is calculated as the mean of the crew performance metrics (i.e., task performance, contextual performance, and counterproductive behavior). To calculate crew performance metrics, each crew performance metric (i.e., task performance, contextual performance, and counterproductive behavior) is calculated based on the mean of its metrics subcategories. For example, task performance is calculated as the mean of the following metrics subcategories: cost performance, schedule performance, change performance, quality performance, safety performance, productivity performance, and satisfaction performance. A total of 55 key performance indicators (KPIs) are used in this study to define crew performance metrics subcategories. In this research, normalized KPIs are used in the calculation of crew performance metrics subcategories. Thus, crew performance metrics range between 0 (undesirable value) and 1 (desirable value) [see Raoufi and Fayek (2018b) for a complete list of KPIs of this study].

Data Source

In this paper, data regarding crew motivational factors, situational/contextual factors, and crew performance metrics are based on collected field data from an industrial construction project. The project was located in Canada and included 54 craftspeople working on 79 work packages. The data are based on three months of the project's timeline and cover all nine crews who worked on construction work packages on the project. Table 1 shows the characteristics of the project and data collected.

Table 1. Project and data characteristics

Project and data characteristics	Value	Description
Project type	Industrial project	Oil & Gas
Number of crews on project	9 crews	8 excavation/backfilling (EB) 1 sandblasting/coating (SC)
Number of crews participating in field data collection	9 crews	7 crews (6 EB and 1 SC), motivational and situational/contextual data collected 9 crews (8 EB and 1 SC), performance data collected
Number of work packages on the projects	79 work packages	
Number of work packages investigated during field data collection	79 work packages	79 work packages, company data collected 17 work packages, visited and field data collected

Motivational factors and situational/contextual factors were based on different data collection sources, such as interviews with crew members, foremen, field supervisors, and project managers; observations by data collectors on the work packages of the project; extracted data from project documents such as project safety logs; and external databases such as a government database for weather data. Crew performance data were based on actual project documents (e.g., time sheets, score cards, safety logs, change order logs, inspection test plans, schedule updates, tender documents, and cost estimates) with a total of 612 task performance data points. Contextual performance and counterproductive behavior data were based on multiple-source interviews with crew members and foremen with a total of 153 data points. A sample of a data collection form for situational/contextual factors is provided in the appendix.

Development of the Agent-Based Model

The agents in this model are project and crew agents; therefore, two agent classes are developed in the model. The first class is the project agent class which is developed to model construction projects where construction crews are working. Project ID, initial project-level situation, and current project-level situation are attributes of the project agent class, and update the project-level situation is the defined Java method of the project agent class. Project-level situation attributes are defined to model situational/contextual factors at the project level.

The second class is the crew agent class, which is developed to model construction crews. Crew ID, initial crew motivation, current crew motivation, initial crew-level situation, and current crew-level situation are the attributes of the crew agent class. Calculate interactions, update crew motivation, update the crew-level situation, connect to the fuzzy inference system, and calculate crew performance are the defined Java methods of the crew agent class. Crew motivation attributes are defined to model motivational factors (i.e., efficacy, commitment/engagement, identification, and cohesion) at both the individual and crew levels. Crew-level situation attributes are defined to model situational/contextual factors at the crew level.

State charts are developed in the model to update state variables representing agent attributes. A state chart in the project agent class is used to represent the attribute "the situation at the project level" for each project during the simulation experiments. This state chart is responsible for updating the current project-level situation. Two state charts in the crew agent class are also used: (1) a state chart to represent the attribute of "the situation at the crew level" for each crew during the simulation experiments and (2) a state chart to represent the attribute of "crew motivation" for each crew during the simulation experiments.

In this model, the mathematical equation shown in Equation 1 is used to represent the effect of the interactions of crew agents on the level of motivation of a crew. Based on Equation 1, the level of motivation of a crew agent is calculated based on the level of motivation of that crew and the level of motivation of other crews in the project.

$$M_i^t = (1 - Z \times C \times S) \times M_i^{t-1} + (Z \times C \times S) \times \frac{\sum_{j=1}^{N} M_j^{t-1}}{N}, \tag{1}$$

where t and $t-1$ refer to the current and the previous simulation time steps, i and j are crew indices, M refers to crew motivation, Z refers to the type of crew agent (i.e., zealot or not zealot agent), C refers to crew agent contact rate (i.e., the rate that crew agents contact each other over the simulation time unit), 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.

Z takes two binary values 0 and 1. Z is 0 when the crew agent is a zealot and never changes its motivation when interacting with others, and Z is 1 when the crew agent is not a zealot and may change its motivation when interacting with others. C is 0 when there is no contact between crews; when there is contact between crews, C takes positive real numbers. S takes real numbers between 0 and 1. S is 0 when there is no susceptibility, and S is 1 when there is full susceptibility. The values of S between 0 and 1 indicate how much the interacting crew agents affect the motivation level of crew agent i.

Development of Fuzzy Attributes and Behavioral Rules of Agents

Fuzzy membership functions are defined in the model for subjective variables, and a fuzzy inference system is defined to represent subjective relationships in the model (Raoufi and Fayek 2018c). In this research, crew behavioral rules (i.e., how crews perform based on their level of motivation and the project environment) are developed by applying FCM clustering on the collected field data. Then, a fuzzy inference system, a Mamdani fuzzy rule-based model, is constructed using the identified fuzzy rules. The fuzzy inference system has three inputs (i.e., crew motivation, crew-level situation, and project-level situation) and one output (i.e., crew performance) and uses Gaussian membership functions as suggested and implemented by Raoufi and Fayek (2018c). MATLAB is used to perform FCM clustering on the collected field data and fuzzy rules and membership function parameters are defined. For example, one of the fuzzy rules is "If crew motivation is *very low*, and the crew-level situation is *unsatisfied*, and the project-level situation is *unsatisfied,* then crew performance is *very low*." *Very low* motivation is represented by a Gaussian membership function with μ=0.7192 and σ=0.0550; *unsatisfied* crew-level situation is represented by a Gaussian membership function with μ=0.6426 and σ=0.0472; *unsatisfied* project-level situation is represented by a Gaussian membership function with μ=0.6013 and σ=0.0849; and *very low* crew performance is represented by a Gaussian membership function with μ=0.6957 and σ=0.0392. Table 2 show the fuzzy rules of the fuzzy inference system.

Table 2. Fuzzy rules of fuzzy inference system

Rule number	Crew motivation	Crew-level situation	Project-level situation	Crew performance
Rule 1	Low	Satisfied	Slightly satisfied	Medium
Rule 2	Medium	Slightly unsatisfied	Moderate	Low
Rule 3	High	Slightly satisfied	Slightly unsatisfied	Very High
Rule 4	Very High	Moderate	Satisfied	High
Rule 5	Very Low	Unsatisfied	Unsatisfied	Very Low

Development of Monte Carlo Simulation Experiments

Monte Carlo simulation is a technique that uses random sampling to simulate a model representing a real system. A large number of random samplings of the model's stochastic input parameters are used to provide a large number of random samples of the model output (Thomopoulos 2013). Thus, Monte Carlo simulation allows for the observation of variations in model parameters, such as variations in susceptibility, and the effect of these variations on the output of the model (e.g., overall crew performance). In this paper, the Monte Carlo simulation experiments include initiating the simulation runs based on generated random variates of the attributes of construction crews and the situations in which the crews are performing. Crews interact in the simulation environment, which allows changes in their attributes (e.g., motivation) and thus changes in their behavior (e.g., improving their performance). Following numerous iterations of the model, the collective actions of all crews in the simulation environment will then provide the outputs of the model.

To develop Monte Carlo simulation experiments, data collected about agent attributes are used to define the model's initial conditions and to perform the simulation experiments. First, collected data are used to define probability distributions for all model parameters associated with stochastic variables.

The model has three stochastic parameters: susceptibility, non-interactive motivation variability, and crew-level situation variability. The typical probability distribution candidates for continuous random variables, such as uniform, normal, exponential, lognormal, gamma, beta, and Wiebull, are fitted to data. Beta distributions are fitted better than others to the collected field data, and the resulting beta distributions are used to initiate the Monte Carlo simulation. The beta distribution is a continuous distribution that has both upper and lower finite bounds, which makes it suitable when the data are bounded on both upper and lower ends. The resulting beta distributions for susceptibility, non-interactive motivation variability, and crew-level situation variability are shown in Table 3. Second, the initial parameters for initiating the fuzzy Monte Carlo agent-based simulation are set as shown in Table 3. Third, the number of iterations is set to 1000, and the simulation experiments are executed. Finally, histograms of crew performance data are developed to provide the results of fuzzy Monte Carlo agent-based simulation.

Table 3. Initial parameters for fuzzy Monte Carlo agent-based simulation

Parameter	Range of values	Initial value for simulation experiments (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	Percentage of zealots in the project
Susceptibility	[0,1]	Beta (0.2276, 2.1886, 0.0, 0.4286)	Probability that an interaction leads to a change in motivation
Non-interactive motivation variability	[0,1]	Beta (0.1538, 13.846, 0.0, 0.2888)	Rate of change in motivation level without contact with 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	$\mathbb{R}^+$	Beta (0.3127, 9.6465, 0.0, 0.1429)	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

In this paper, the model is developed and simulated using AnyLogic©, a simulation software based on the Java environment, and connected to a fuzzy inference model developed in MATLAB. AnyLogic© is used for development of the agent-based model as well as development of the Monte Carlo simulation experiments. MATLAB is used for the development of fuzzy attributes and behavioral rules of agents.

Results and Discussion

The results of fuzzy Monte Carlo agent-based simulation of construction crew performance for 1000 iterations are provided in the histograms shown in Figs. 5–7. Fig. 5 shows the 3D (i.e., three-dimensional) histogram of the simulation experiments, which provides the frequency with which a single value of crew performance was observed during each day of the project. For example, for day 10 and a crew performance of 0.730, the frequency is 0, which indicates that over the performed 1000 simulation runs, a crew performance of 0.730 was never observed on day 10. Higher numbers of frequency in Fig. 5 are related to higher numbers of observing a crew performance in the simulation experiments. Fig. 5 provides the probability of observing a crew performance value on a certain day, and the cross sections of this figure over the day's axis are 2D (i.e., two-dimensional) histograms that can be used to fit the PDFs of crew performance associated with that day of the project. Having the PDF of crew performance on each day of the project allows for planning of resources (e.g., crews) for a certain day of the project.

Fig. 6 shows the 3D histogram of the simulation experiments from the top. It shows the possible ranges (i.e., minimum and maximum) of crew performance on each day over the project timeline. The 3D histograms in Figs. 5 and 6 provide a good understanding of crew performance variations over the project timeline. Thus, they can be used in project scheduling, resource allocation, and decision-making on when and how to improve crew performance.

Fig. 7 shows the 2D histogram of the simulation experiments. The frequency of each category of crew performance is shown in this histogram. Fig. 7 shows that the crew performance categories 0.790-0.795 and 0.795-0.800 occur more frequently during the project, with a frequency of 0.186 (i.e., 18.6%). Fig. 7 also shows that the histogram is left-skewed. Considering the fact that at simulation start time, crew performance was 0.780, this left-skewed histogram indicates an improvement in crew performance over the timeline of the project. This improvement in performance occurred due to the interaction of crews in the simulation environment and the effect of crew interactions on crew motivation and performance, as shown in Equation 1. It should also be noted that the skewness is also toward lower values of crew performance. In other words, the categories of higher crew performance have higher frequencies than the categories of lower crew performance. This observation is in agreement with the findings of Raoufi and Fayek (2018c) that the positive interactions of crews lead to improved crew performance.

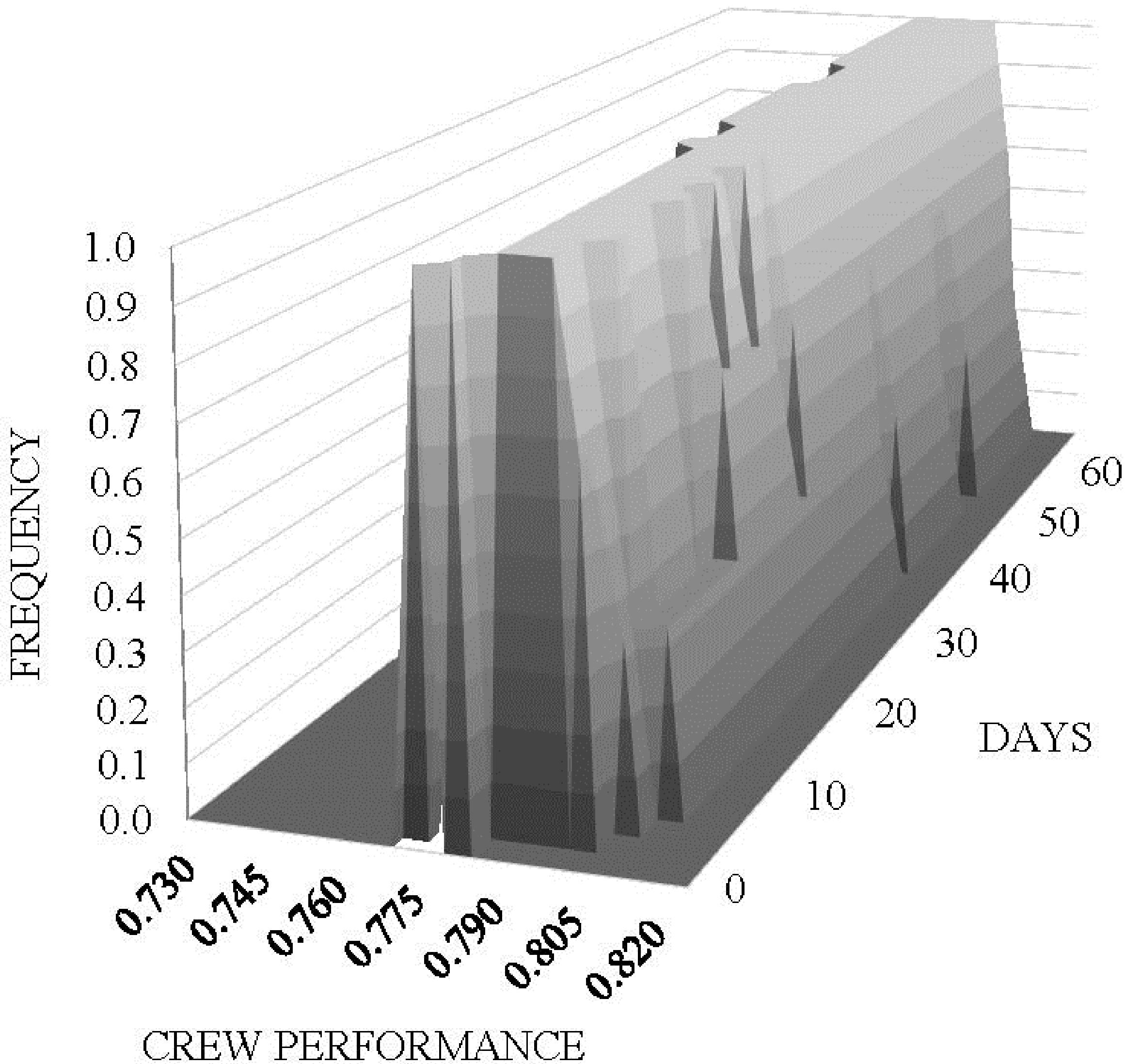

Fig. 5. 3D histogram of the simulation experiments.

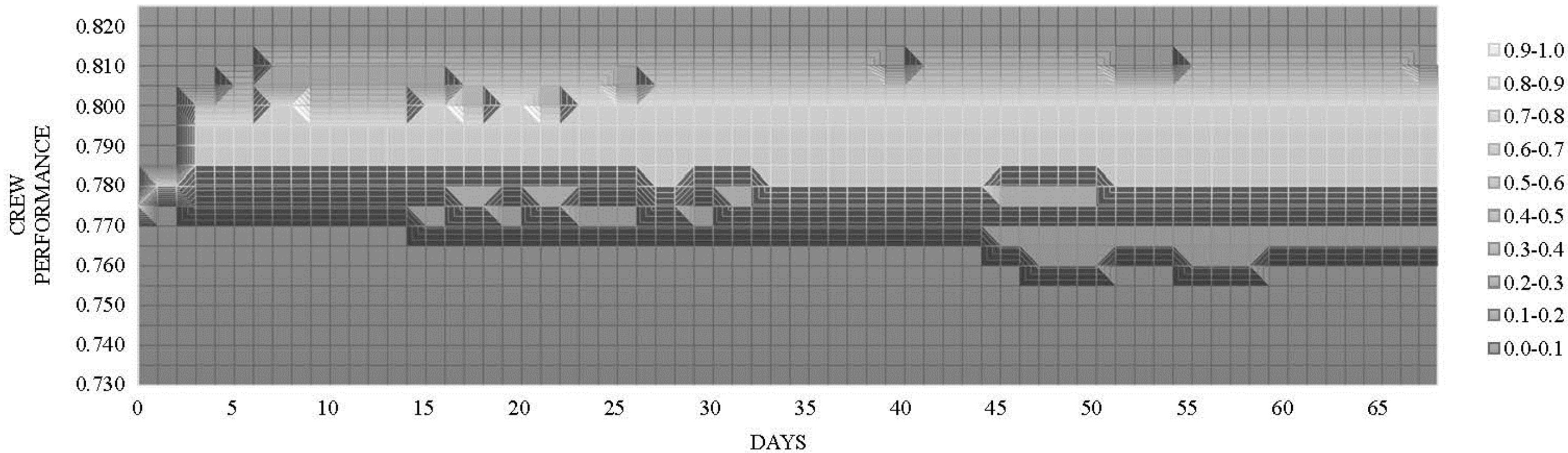

Fig. 6. 3D histogram of the simulation experiments (top view)

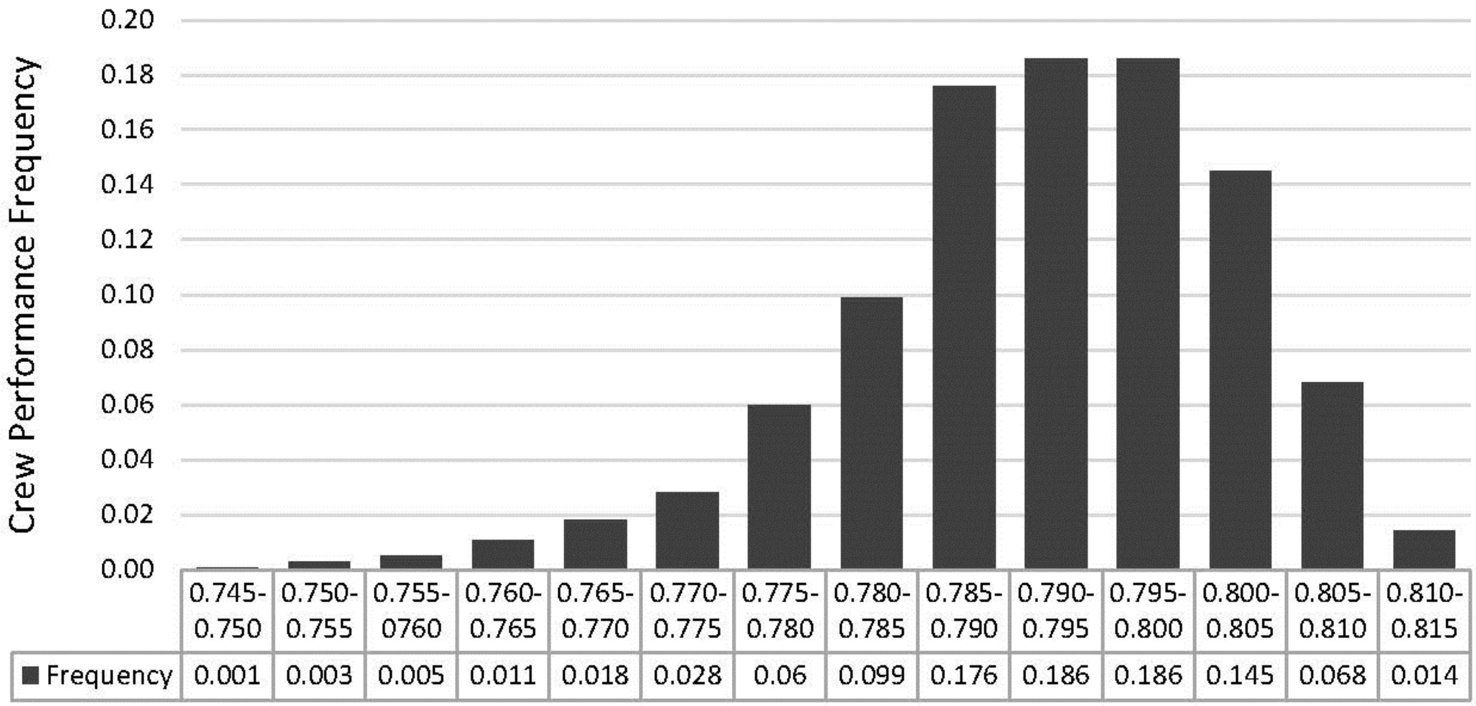

Fig. 7. 2D Histogram of the simulation experiments

Some of the practical applications of the developed model of construction crew motivation and performance are: (1) to analyze the influence of subjective and random variables on crew performance; (2) to identify the resources (e.g., number of crews) required to best execute work packages; (3) to predict the progress of the project during project execution; (4) to monitor project progress and observe the effect of changes in the project situation on crew performance; and (5) to experiment with changes to the project situation to improve crew performance based on the results of scenario analysis.

Validation of the Fuzzy Monte Carlo Agent-Based Model

To validate the fuzzy Monte Carlo agent-based model, three steps need to be followed: conceptual validity, data validity, and operational validity. In this research, the first two steps (i.e., conceptual validity and data validity) have previously been performed (Raoufi and Fayek 2018a, 2018b, 2018c). First, conceptual validity was performed by basing the model on validated motivational concepts from past literature (Sargent 2013). Motivational factors, situational/contextual factors, and crew performance metrics were defined based on past literature in the construction and nonconstruction domains. Then, the identified list of factors was validated by both motivation experts and construction experts (Raoufi and Fayek 2018a). Second, data validity was performed as suggested by Sargent (2013) by developing a data collection protocol, following a structured data collection methodology, and testing for construct validity and the reliability of the measures (Raoufi and Fayek 2018b). Third, the operational validity of the fuzzy agent-based model was performed using (1) sensitivity analysis and (2) tenfold cross-validation (Raoufi and Fayek 2018c). The sensitivity analysis performed for the parameters of the model suggested that contact rate, susceptibility, non-interactive motivation variability, and initial motivation states of crews had a significant influence on the output of the model. The tenfold cross-validation technique suggested a good accuracy of the developed fuzzy agent-based model in predicting crew performance. The calculated mean absolute percentage error was 2.48%, and the calculated root mean square percentage error was 0.79%, indicating a very good prediction of crew performance by the developed fuzzy agent-based model.

Both sensitivity analysis and cross-validation are internal validity techniques used to test for operational validity. There are other operational validity techniques (i.e., external validity techniques) that can be performed when validated models exist for the problem under study. External validity compares the results of a model with previously validated models to discuss the predictive ability of the new model compared to the previously validated models. In this paper, the predictive ability of the fuzzy Monte Carlo agent-based model for the prediction of crew performance is compared to the predictive ability of the fuzzy agent-based model by Raoufi and Fayek (2018c) to test the external validity of the fuzzy Monte Carlo agent-based model. This allows the researchers to see if the fuzzy Monte Carlo agent-based model provides better predictions of crew performance than the fuzzy agent-based model. Table 4 shows the result of the external validity test in the form of absolute percentage errors in predicting overall crew performance for each method compared to the actual field data.

Table 4. External validity test (error in predicting overall crew performance)

Method	Overall crew performance	Absolute percentage error (APE) in predicting overall crew performance
Actual field data	0.7992	—
Fuzzy agent-based model	0.7896	1.21%
Fuzzy Monte Carlo agent-based model (1000 runs)	0.7902	1.13%

The results in Table 4 indicate that the fuzzy Monte Carlo agent-based model provides a better prediction of overall crew performance than the fuzzy agent-based model. This paper provides a fuzzy Monte Carlo agent-based model of construction crew performance based on data from a real construction project. More projects need to be investigated to improve the external validity of this model and to expand the scope of applicability of the developed methodology.

Conclusions and Future Research

In this paper, a methodology for the development of fuzzy Monte Carlo agent-based models in construction is provided in an attempt to close the gap in ABM regarding the ability to assess both random and subjective uncertainty. The methodology is then tested using collected field data from a real construction project, and fuzzy Monte Carlo agent-based simulation of construction crew motivation performance is performed. The developed fuzzy Monte Carlo agent-based simulation model simulates the performance of crews using deterministic input variables such as number of crews, stochastic input variables such as susceptibility, and subjective inputs such as crew motivation. This paper demonstrates that the developed methodology is able to expand the applicability of fuzzy agent-based models by addressing random uncertainty in addition to the subjective uncertainties that exist in many construction systems. The fuzzy Monte Carlo agent-based model is then validated based on collected field data. The results show that the fuzzy Monte Carlo agent-based model of construction crew motivation and performance provides more accurate predictions on crew performance than the fuzzy agent-based model. Thus, the developed methodology helps in the creation of more accurate predictive models in construction.

This paper makes three contributions. Previous research on ABM in construction addressed either random uncertainty through the use of Monte Carlo simulation or subjective uncertainty through the use of fuzzy logic. This paper incorporates both Monte Carlo simulation and fuzzy logic ABM to simultaneously address both types of uncertainty. Therefore, the first contribution of this paper is to expand ABM's scope of applicability by showing how to model both random and subjective uncertainty in ABM. There are different methodologies for performing fuzzy Monte Carlo simulation in construction modeling; however, there was no methodology in past literature that showed how to develop a fuzzy Monte Carlo agent-based simulation model. Thus, the second contribution of this paper is to provide a novel methodology for integrating fuzzy logic and Monte Carlo simulation in ABM, which allows for the development of fuzzy Monte Carlo agent-based models in construction. Previous simulation models of construction crew motivation and performance used only fuzzy logic, and there was no fuzzy Monte Carlo model of construction crew motivation and performance in past research. Thus, the third contribution of this paper is to develop and illustrate fuzzy Monte Carlo agent-based simulation of construction crew performance, which improves the assessments of crew performance by considering both random and subjective uncertainties in model variables.

In the future, the developed fuzzy Monte Carlo agent-based model will be expanded to simulate various scenarios of different combinations of the input factors affecting construction crew performance in order to identify drivers of performance. For example, a project with different combinations of crew motivation and contact rates would be assessed in order to compare the effect of these factors on the performance of crews.

Construction research on simulation modeling faces considerable challenges when selecting optimum and feasible scenarios for improving crew performance. There is a need in construction research on simulation modeling to develop decision support systems that account for the complex relationships and social interactions between crews and the dynamic construction environment. One of the limitations of the developed fuzzy Monte Carlo agent-based model is the lack of a decision-making process for selecting the best case scenario from a number of feasible scenarios. Such a decision-making process should be able to capture the subjective, deterministic, and probabilistic factors that influence crew performance. Therefore, in future, the fuzzy Monte Carlo agent-based model presented in this paper will be integrated with multi-criteria decision-making to develop a decision support system that allows for the selection of optimum and feasible scenarios for improving crew performance. In this paper, the context in which the data are collected and used is industrial construction. Data from projects in other construction contexts (e.g., commercial construction and building construction) will be collected to expand the scope of applicability of the developed methodology and make fuzzy Monte Carlo agent-based models applicable to other contexts in construction.

Data Availability Statement

All data, models, and code generated or used during the study appear in the submitted article.

Acknowledgments

This research is funded by the Natural Sciences and Engineering Research Council of Canada Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. A. Robinson Fayek. The authors gratefully acknowledge the support and data provided by industry partners and all personnel who participated in this study.

References

AbouRizk, S. (2010). "Role of simulation in construction engineering and management." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000220, 1140–1153.

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.*, 10.1061/(ASCE)CO.1943-7862.0000918, 04014065.

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.

Ashforth, B. E., and Mael, F. (1989). "Social identity theory and the organization." *Acad. Manage. Rev.,* 14(1), 20–39.

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.*, 10.1061/(ASCE)CP.1943-5487.0000612, 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*., 10.1061/(ASCE)CP.1943-5487.0000651, 04017007.

Bandura, A. (1977). "Self-efficacy: toward a unifying theory of behavioral change." *Psychol. Rev.,* 84(2), 191.

Beal, D. J., Cohen, R. R., Burke, M. J., and McLendon, C. L. (2003). "Cohesion and performance in groups: A meta-analytic clarification of construct relations." *J. Appl. Psychol.,* 88(6), 989.

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.

Cesário, F., and Chambel, M. J. (2017). "Linking organizational commitment and work engagement to employee performance." *Knowledge and Process Management*, 24(2), 152–158.

Chiniara, M., and Bentein, K. (2017). “The servant leadership advantage: When perceiving low differentiation in leader-member relationship quality influences team cohesion, team task performance and service OCB.” *The Leadership Quarterly*, 10.1016/j.leaqua.2017.05.002.

Choi, B., and Lee, S. (2017). “An empirically based agent-based model of the sociocognitive process of construction workers’ safety behavior.” *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0001421, 04017102.

Dubois, D., Foulloy, L., Mauris, G., and Prade, H. (2004). “Probability-possibility transformations, triangular fuzzy sets, and probabilistic inequalities.” *Reliab. Comput.*, 10(4), 273–297.

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.*, 10.1061/(ASCE)CP.1943-5487.0000680, 04017030.

El-Adaway, I. H., and Kandil, A. A. (2010). “Multiagent system for construction dispute resolution (MAS-COR).” *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000144, 303–315.

Farshchian, M. M., and Heravi, G. (2018). “Probabilistic assessment of cost, time, and revenue in a portfolio of projects using stochastic agent-based simulation.” *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0001476, 04018028.

Fayek, A. R., and Lourenzutti, R. (2018). “Introduction to fuzzy logic in construction engineering and management.” *Fuzzy hybrid computing in construction engineering and management: Theory and applications*, Emerald Publishing Limited, Bingley, UK, 3–35.

Gerami Seresht, N., Lourenzutti, R., Salah, A., and Fayek, A. Robinson (2018). “Overview of fuzzy hybrid techniques in construction engineering and management.” *Fuzzy hybrid* *computing in construction engineering and management: Theory and applications*, Emerald Publishing Limited, Bingley, UK, 37–107.

Hannah, S. T., Schaubroeck, J. M., and Peng, A. C. (2016). "Transforming followers' value internalization and role self-efficacy: Dual processes promoting performance and peer norm-enforcement." *J. Appl. Psychol.*, 101(2), 252.

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

Jung, M., Park, M., Lee, H., and Chi, S. (2017). "Agent-based lift system simulation model for high-rise building construction projects." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)CP.1943-5487.0000707, 04017064.

Jung, M., Park, M., Lee, H., and Chi, S. (2018). "Multimethod supply chain simulation model for high-rise building construction projects." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)CP.1943-5487.0000751, 04018007.

Lin, C., He, H., Baruch, Y., and Ashforth, B. E. (2016). "The effect of team affective tone on team performance: The roles of team identification and team cooperation." *Hum. Resour. Manage.*, 56(6), 1–22.

Meyer, J. P., and Allen, N. J. (1991). "A three-component conceptualization of organizational commitment." *Hum. Resourc. Manage. R.,* 1(1), 61–89.

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

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

Raoufi, M., and Fayek, A. Robinson (2018a). "Framework for identification of factors affecting construction crew motivation and performance." *J. Constr. Eng. Manage*, 10.1061/(ASCE)CO.1943-7862.0001543, 04018080.

Raoufi, M., and Fayek, A. Robinson (2018b). "Key moderators of the relationship between construction crew motivation and performance." *J. Constr. Eng. Manage*, 10.1061/(ASCE)CO.1943-7862.0001509, 04018047.

Raoufi, M., and Fayek, A. Robinson (2018c). "Fuzzy agent-based modeling of construction crew motivation and performance." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)CP.1943-5487.0000777, 04018035.

Raoufi, M., Gerami Seresht, N., 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.

Raoufi, M., Gerami Seresht, N., Siraj, N. B., and Fayek, A. R. (2018). "Fuzzy simulation techniques in construction engineering and management." *Fuzzy hybrid computing in construction engineering and management: Theory and applications*, Emerald Publishing Limited, Bingley, UK, 149–178.

Ren, Z., Anumba, C. J., and Ugwu, O. O. (2003b). "Multiagent system for construction claims negotiation." *J. Comput. Civ. Eng.*, 10.1061/(ASCE) 0887-3801(2003)17:3(180), 180–188.

Sadeghi, N., Fayek, A. R., and Pedrycz, W. (2010). "Fuzzy Monte Carlo simulation and risk assessment in construction." *Comput-Aided Civ. Inf.*, 25(4), 238–252.

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

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.*, 10.1061/(ASCE)CO.1943-7862.0001182, 04016063.

Thomopoulos, N. T. (2013). *Essentials of Monte Carlo simulation: Statistical methods for building simulation models*. Springer Science & Business Media, New York, NY, 1–90.

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.*, 10.1061/(ASCE)CO.1943-7862.0000022, 657–667.

Wonneberger, S, Kistinger, S, Deckert, A. (1995) Unbiased guess, a concept to cope with fuzzy and random parameters? *European Commission Rep. No. EUR 16199 EN*, Office for Official Publications of the European Communities, Luxembourg.

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

Appendix. Sample data collection form for situational/contextual factors

Factors	Scale of measure	Sub-factors	Range of values
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%]
Crew size	Integer		$\mathbb{Z}^+$
Performance monitoring	Five-point rating scale		(1) Very poor to (5) Very good
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
Project cost management	Five-point rating scale	Project cost estimates Project budget Project cash flow	(1) Very poor to (5) Very good
Location of facilities	Real number (average distance, m)		$\mathbb{R}^+$