Hybrid Fuzzy Monte Carlo Agent-Based Modeling of Workforce Motivation and Performance in Construction

Abstract

Purpose: This paper covers the development of a methodology for hybrid fuzzy Monte Carlo agent-based simulation (FMCABS) and its implementation on a parametric study of construction crew performance.

Design/methodology/approach: The developed methodology uses fuzzy logic, Monte Carlo simulation, and agent-based modeling to simulate the behavior of construction crews and predict their performance. Both random and subjective uncertainties are considered in model variables.

Findings: The developed methodology was implemented on a real case involving the parametric study of construction crew performance to assess its applicability and suitability for this context.

Research limitations/implications: This parametric study demonstrates a practical application for the hybrid FMCABS methodology. Though findings from this study are limited to the context of construction crew motivation and performance, the applicability of the developed methodology extends beyond the construction domain.

Practical implications: This research will help construction practitioners to predict and improve crew performance by taking into account both random and subjective uncertainties.

Social implications: This research will advance construction modeling by allowing for the assessment of social interactions among crews and their effects on crew performance.

Originality/value: The developed hybrid FMCABS methodology represents an original contribution, as it allows agent-based models to simultaneously process all types of variables (i.e., deterministic, random, and subjective) in the same simulation experiment, while accounting for

interactions among different agents. In addition, the developed methodology is implemented in a novel and extensive parametric study of construction crew performance.

Keywords: Hybrid simulation; agent-based modeling; Monte Carlo simulation; fuzzy logic; construction; motivation; crew performance

Paper type: Research paper

Introduction

Construction simulation is the process of developing and executing computer-based models of construction systems (e.g., construction processes and project management practices) to understand their underlying behaviors (AbouRizk, 2010). Simulation methods, such as agent-based modeling (ABM), system dynamics (SD), discrete event simulation (DES), and Monte Carlo simulation, have been used to solve construction problems. Each of these simulation methods offers its own unique capabilities in modeling construction systems (Raoufi et al., 2016). However, models based on one simulation method alone have limitations, primarily due to their inability to capture all aspects of complex construction systems.

Hybrid simulation (i.e., integration of two or more simulation methods) offers the potential to combine the strengths of multiple methods. Recently, simulation researchers have made efforts to leverage the advantages of hybrid simulation to develop hybrid simulation frameworks for modeling dynamic and complex construction systems. Although these frameworks and models are suitable for the simulation of construction systems, this research is still in its early stages of development, and there are research gaps that need to be filled in the area of hybrid simulation. The applicability of current hybrid simulation frameworks needs to be tested and expanded for different types of construction applications. In addition, in order to improve the modeling of construction systems, hybrid simulation frameworks and models must be advanced to allow the assessment of different types of variables simultaneously. To address this gap, this paper provides an innovative hybrid fuzzy Monte Carlo agent-based simulation (FMCABS) methodology that allows for the assessment of both random and subjective uncertainties in the same simulation environment.

One of the main contributions of this paper is the extension of a hybrid FMCABS methodology, which allows agent-based models to simultaneously process all types of variables (i.e., deterministic, random, and subjective) in the same simulation experiment, while accounting for interactions between different agents. Previous research on construction crew performance focused either on a single experiment, or on a scenario-based analysis using limited simulation runs and limited variations of model parameters. Thus, a major contribution of this paper beyond existing work, in particular Raoufi and Fayek (2020), is the implementation of the developed methodology in a novel and extensive parametric study of construction crew performance.

Literature review of existing hybrid simulation research

Models based on one simulation method alone have limitations in the assessment of construction systems, primarily due to their inability to capture different types of variables: deterministic (i.e., crisp), random (i.e., stochastic), and subjective (i.e., fuzzy) and relationships (e.g., agent interactions) simultaneously. Hybrid simulation was developed to address the limitations of the one-simulation method by enabling integration with other methods. However, the term hybrid simulation has been used in existing literature to define a range of different models, such as simulation models that incorporate both continuous and discrete variables (e.g., system dynamics–discrete event simulation (SD-DES) models) (Nasirzadeh et al., 2008), models integrating two or more simulation methods (e.g., agent-based modeling–system dynamics (ABM-SD) models) (Nasirzadeh et al., 2018), models integrating simulation with fuzzy logic (Gerami

Seresht et al., 2018; Raoufi et al., 2018;), and models integrating simulation with other analytical methods (e.g., simulation integrated with optimization) (Brailsford et al., 2019).

Hybrid simulation models of system dynamics and discrete event simulation

One major area of hybrid simulation research has focused on developing SD-DES frameworks, methodologies, and models. SD is a simulation method used for modeling the dynamic behavior of complex systems that involve interdependent components with time-varying interactions, as well as multiple feedback processes (Nasirzadeh et al., 2008). DES is a simulation method used for modeling systems where changes occur at discrete points in time. DES is an appropriate method for modeling process-type systems (e.g., earthmoving operations), in which several activities are executed in a sequence and for a number of repetitions.

Two fundamental differences between DES and SD make the integration of these two methods difficult. Firstly, DES has discrete state changes, while SD has continuous state changes. Secondly, DES models a system as a network of queues and activities, while SD models a system as a network of stocks and flows. Due to these differences, many early hybrid SD-DES simulation packages and models relied more heavily on either SD or DES, with the addition of very limited features from the other method (Brailsford et al., 2019; Chatha and Weston, 2006).

Recently, better methodologies have been proposed for the development of hybrid DES and SD models, which address the aforementioned challenges. Helal et al. (2007) proposed a hybrid SD-DES methodology to simulate manufacturing enterprise systems, while maintaining the integrity of the two simulation methods and not allowing one to dominate the other. Alvanchi et al. (2011) proposed a hybrid SD-DES architecture that controls the interaction between the SD and DES models to prevent the overloading of hybrid models caused by excessive calculations. Another hybrid modelling framework was proposed by Moradi et al. (2015), which combines SD and DES to simulate the continuous and operational variables affecting the performance of construction projects. A hybrid SD-DES framework was also developed by Hwang et al. (2016) for immediate facility restoration planning after a catastrophic disaster. Finally, Morgan et al. (2017) provided a framework to compare the features of various SD-DES frameworks, such as form and frequency of interactions in the hybrid SD-DES model.

Hybrid simulation models using ABM

Although the literature on hybrid SD-DES simulation is extensive, there are very few studies that focus on integration of ABM with other simulation methods. Mahdavi and Hastak (2004) developed a hybrid ABM–SD model, which uses SD modules built within the agents of an ABM module to quantify the effect of adaptive bidding strategies. Their hybrid ABM-SD model enables the comparison of bidding strategies by utilizing regular and adaptive agents. Lorenz and Jost (2006) compared simulation techniques and emphasized the need to develop hybrid approaches that use DES, SD, and ABM. They developed an initial concept idea for an orientation framework that aligns purpose, object characteristics, and methodology for choosing and/or integrating DES, SD, and ABM. However, Lorenz and Jost (2006) did not propose a methodology or model for hybridization of any of these simulation methods. Djanatliev and German (2013) developed a hybrid simulation methodology, which uses SD to generate agents dynamically from an SD model, and then uses the generated agents in an ABM-DES hybrid model for modeling the effects of medical products on agents in hospitals. Although the authors used SD, ABM, and DES methods in their work, they only used the output of the SD model as the input for their ABM-DES hybrid model. Nasirzadeh et al. (2018) developed a hybrid SD-ABM framework, which was then used by Khanzadi et al. (2018) to develop a labor productivity model.

Hybrid simulation research gaps

A review of existing literature indicates that research on hybrid simulation, which integrates ABM with other simulation methods is in its early stages of development, as compared to hybrid simulation methodologies and models that integrate SD and DES. Hybrid ABM research has recently gained more attention, including the integration of ABM with DES and SD (Nasirzadeh et al., 2018). The current hybrid simulation models provide more powerful simulation tools, but most of these hybrid models only process deterministic and random variables. Therefore, there is a need to advance research on hybrid ABM simulation and its applications by allowing all types of variables to be processed in the same hybrid ABM. This paper bridges the gap in hybrid ABM simulation research by integrating ABM with Monte Carlo simulation and fuzzy logic, developing a methodology for hybrid fuzzy Monte Carlo ABM, and implementing the developed methodology in a real construction case. The developed methodology and its application enables the assessment of all three types of variables in the same hybrid ABM.

Fuzzy Monte Carlo simulation method

In simulation modeling, uncertainty has traditionally been represented by random variables, which are in turn determined by probability density functions (PDFs) based on probability theory. Therefore, in many previous ABM studies related to the construction domain, the use of PDFs and Monte Carlo simulation for experimentation with random variables enabled the handling of random uncertainty in ABM.

Figure 1 shows the Monte Carlo simulation method. In this model, the histogram provided for the output variable Y is based on the PDFs of the input variables X_1, X_2, and X_3.

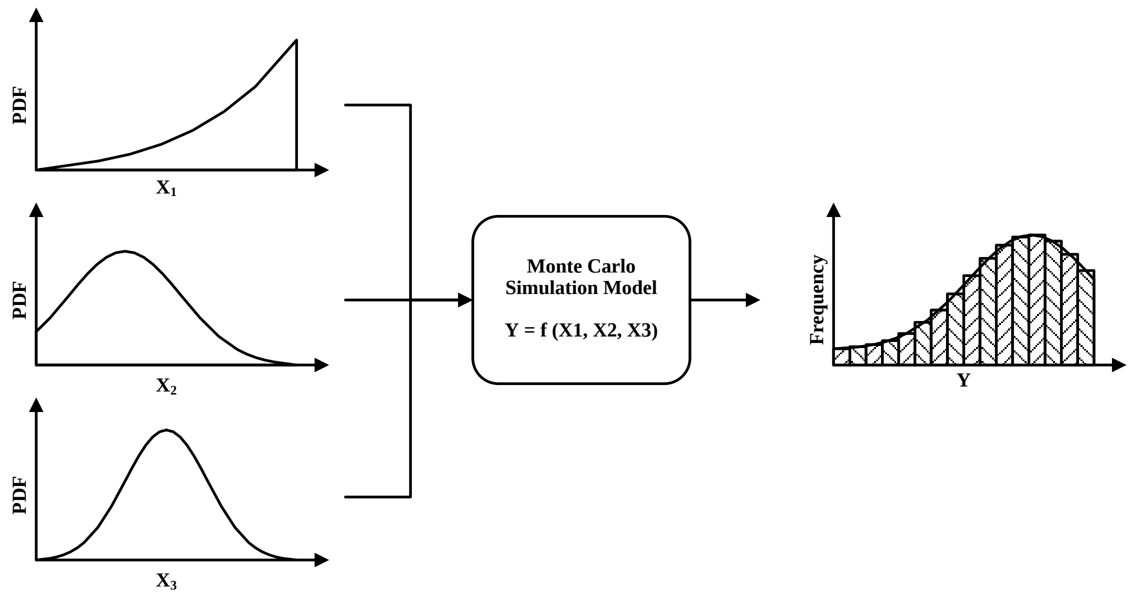

Figure 1. Monte Carlo simulation method.

However, probability theory and PDFs only address random uncertainty, but not the subjective uncertainty associated with the vagueness of subjective information. Subjective uncertainty may arise from the subjective assessment of precise variables by humans (e.g., high temperature); from variables that are not precisely measurable or defined by deterministic or random values (e.g., crew motivation); or from relationships that cannot be precisely represented either by mathematical formulae or regression equations (e.g., the relationship between crew motivation and crew performance). Thus, there was a need to develop a hybrid methodology in ABM that allows handling of both types of uncertainties in construction contexts. Zadeh (2015) introduced fuzzy set theory to handle subjective uncertainty. In addition, research by Raoufi and Fayek (2020) demonstrates how to integrate fuzzy logic and Monte Carlo simulation in ABM. This fuzzy Monte Carlo simulation methodology uses a combination of probability theory and fuzzy set theory to simultaneously handle random and subjective uncertainties in the same construction model. Figure 2 shows the simulation method and the three different types of input variables that a fuzzy Monte Carlo simulation model can handle. Deterministic variables D_1 and D_2 were identified, based on their exact value in the fuzzy Monte Carlo simulation model. Random variables X_1 and X_2 were determined using PDFs, and subjective variables Z_1 and Z_2 were determined using membership functions.

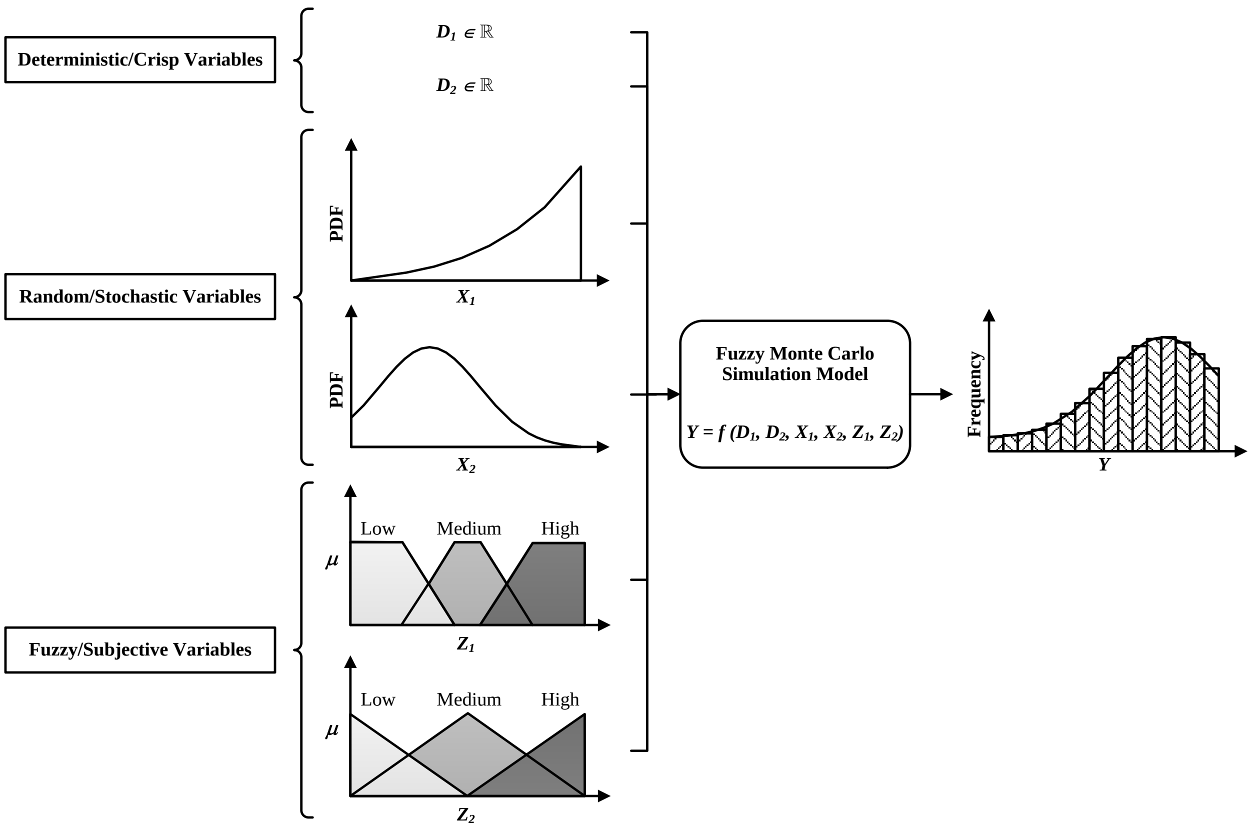

Figure 2. Fuzzy Monte Carlo simulation method.

In Figure 2, the output of the fuzzy Monte Carlo simulation model Y is represented by a histogram, which was generated using D_1, D_2, X_1, X_2, Z_1, and Z_2. The final output of the fuzzy Monte Carlo agent-based simulation depends on the type of output of the fuzzy agent-based model (i.e., a subjective variable or a deterministic variable). When the output of the fuzzy agent-based model is a subjective variable, the output of fuzzy Monte Carlo agent-based model is a fuzzy random variable. When the output of the fuzzy agent-based model is a crisp variable, the output of fuzzy Monte Carlo agent-based model is a histogram that shows the frequency with which each output value was observed over all simulation runs. The present research used the above fuzzy Monte Carlo simulation method in order to develop a hybrid FMCABS methodology, which was then implemented on a parametric study of construction crew performance.

Methodology for hybrid fuzzy Monte Carlo agent-based simulation

Defining the types of variables for the hybrid fuzzy Monte Carlo agent-based simulation model

Three types of variables were defined in the hybrid FMCABS model discussed in this paper: deterministic variables; random variables; and subjective variables. The types of variables in a hybrid FMCABS model should be defined based on past literature and/or actual field data (if available).

The subjective variables in a hybrid FMCABS model should also be defined. Any variables that are not precisely measurable or defined by deterministic or random values involve subjective uncertainty (e.g., crew motivation), and should be considered as subjective variables. All subjective variables should be determined by membership functions using previous research or actual field data. The remaining variables that do not incorporate subjective uncertainty are either random (e.g., susceptibility, meaning the probability that interaction among crews leads to changes in crew motivation) or deterministic variables (e.g., crew size). Those variables that involve random uncertainty are random variables and should be determined by probability density functions (PDFs) using previous research or actual field data. Variables that do not show any uncertainty (e.g., crew size) are deterministic and are specified by numeric values. In the present research, variables (i.e., deterministic, random, and subjective) were selected based on actual field data.

Developing the main simulation environment

Simulation model parameters and methods were defined in the main simulation environment. Agent type and population were the model parameters. In addition, the following methods were defined: agent creation; contacting the fuzzy inference system at simulation run time; simulation methods (e.g., Java functions) for running experiments; and methods for obtaining and representing the results of simulations.

Defining the characteristics of each agent class

Agent classes were used to model different type of agents in the system. The hybrid FMCABS model can include several classes of agents. Each agent class has its own unique characteristics, including attributes, behaviors, and interactions. The next sections discuss how to determine the characteristics of agent classes.

Determining agent attributes

Each agent can have different attributes (e.g., crew size), which need to be defined by different types of variables (e.g., deterministic, random, or subjective) in the hybrid FMCABS model. All of these variables are determined using actual field data when field data are available. If field data are not available, they can be determined using previous research or expert judgement. In the case that none of these sources are available, variables can be hypothetically defined by the user to experiment with different simulation scenarios.

Probabilistic variables are mostly determined by curve fitting using statistical distributions that are based on available field data (Raoufi and Fayek, 2018c; Azar and Ansari, 2017). Subjective variables are defined by membership functions using one of two available types of methods: expert-driven or data-driven methods. Expert-driven methods include horizontal, vertical, pairwise comparison, intuition, inference, and exemplification methods (Fayek and Lourenzutti, 2018).

Data-driven methods include fuzzy machine learning techniques (e.g., fuzzy clustering). Fuzzy C-means (FCM) clustering is a machine learning technique, where each data point belongs to each cluster and is defined by a membership value ranging from zero to one (Bezdek, 2013).

In this paper, FCM clustering was used to develop the membership functions of subjective variables. Membership functions, which are shown as linguistic terms, express the degree to which a data point representing a subjective variable (e.g., crew motivation) belongs to a fuzzy set (e.g., low motivation). Gaussian membership functions were used to represent the subjective variables of agents, as they are continuous and smooth functions, and are suitable for optimization. The Gaussian membership function is shown below in Equation 1.

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

where x represents the value of the subjective variable, A represents the membership function for a linguistic term, μ is the modal value, and σ is the standard deviation. The modal value and standard deviation of each membership function were determined using FCM clustering (Pedrycz 2013; Raoufi and Fayek 2018c).

Determining agent behavioral rules

The type of behavior of each agent needs to be defined by agent behavioral rules, which are mathematical representatives of what agents decide to do, based on the state of the system at both current and previous time steps (Dash et al., 2003). Several methods have been used to define agent behavioral rules. For example, behavioral rules may be defined from simple rules using mathematical formula, or from conditional rules to more complex rules using regression models or fuzzy relationships.

In some of the previous research on ABM, agent behavioral rules were defined using mathematical formulae and regression equations (Papadopoulos, 2016). Both of these methods are useful in ABM models when the system involves random uncertainty, but they are not equipped for handling subjective uncertainty. In order to model agent behavioral rules in a system that involves subjective uncertainty, fuzzy rules must be defined to represent agent behavior. Several methods have been suggested for defining fuzzy rules in this context. Ahn and Lee (2015) used past literature on theories of human behavior to determine rules for agents' absence behavior. This method is useful if there are no data available but there is reliable literature. Garro and Russo (2010) developed an expert-oriented methodology for agent-based modeling; they used an expert-driven approach (i.e., using domain expert judgment) to define agent behavioral rules. This approach is limited, as it relies heavily on human judgment, but it is useful when there is lack of actual data and there is access to a sufficient sample of domain experts. Cui and Hastak (2006) developed an agent-based learning model for bidding decision making, which used system dynamics to model the learning process of agents in order to improve the performance of bidding decisions. Recently, data-driven approaches (e.g., fuzzy machine learning techniques) have been introduced to define agent behavioral rules. Data-driven approaches use actual data to generate agent-behavioral rules. Raoufi and Fayek (2018c) described a set of methodological steps for generating fuzzy rules, which represent agent behavioral rules in a system, using fuzzy clustering (e.g., FCM clustering). FCM clustering minimizes an objective function, which represents the sum of squared distances of data instances to cluster centers. In this paper, FCM clustering was used to define agent behavioral rules of construction crews from collected field data, as well as the membership functions representing agent attributes.

Determining agent interactions and learning

Agent interactions describe how interactions occur and what happens after each interaction between agents. Interactions are either static or dynamic. Dynamic interactions depend on the state of other agents or the system at any point in time, while static interactions do not. When agents are humans, their interactions are mostly dynamic, due to the feedback they receive from other agents (e.g., observing the behavior of others) and the environment (e.g., observing changes in the environment) (Azar and Ansari, 2017; Ben-Alon and Sacks, 2017). This change in the behavior of agents based on the feedback received from the environment or other agents is a learning process, as described by Cui and Hastak (2006). However, there are some agents (i.e., zealot agents) that have static interactions and do not change their attributes or behavior following interactions with others.

Different methods have been used to define agent interactions and agent learning, such as using random interactions, mathematical formulae, regression models, and system dynamics models. When agents are humans, their interactions are mostly dynamic, and their learning process can be represented by mathematical formulae (Azar and Ansari, 2017; Ben-Alon and Sacks, 2017) or system dynamics models (Cui and Hastak 2006). Models of behavior dynamics of humans are also often used to define mathematical formulae for agent interactions in cases where agents learning includes changing their behavior following interactions (Azar and Ansari, 2017; Mobilia et al., 2007; Hegselmann and Krause, 2002; Deffuant et al., 2000). Mathematical formulae for agent interactions and learning are used to calculate the attributes of an agent at a time step, based on both that agent's attributes at previous time steps, as well as the attributes of other agents at previous time steps. System dynamics for agent learning is used to define a learning loop whereby agents record other agents' attributes, environment states, and actions of other agents (Cui and Hastak 2006). Then agent behavior is defined based on the feedback the agent receives from other agents and the environment.

In the present research, the mathematical equation developed by Raoufi and Fayek (2018c) shown in Equation 1 was used to represent the effect of the interactions of crew agents on the level of motivation of a crew and represents a learning process among crews. 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 on 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 *i* and *j* are crew indices, *t* and *t-1* refer to the current and the previous simulation time steps, *M* refers to crew motivation, *Z* refers to the type of agent (i.e., zealot or non-zealot agent), *C* refers to crew agent contact rate (i.e., the rate at which crew agents contact each other over the simulation time unit), *S* refers to susceptibility (i.e., the probability that an interaction leads to change in 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 agent is a zealot and never changes their motivation following interactions with others, and *Z* is 1 when the crew agent is not a zealot and may change their motivation after 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 value of *S* indicates how much the interacting crew agents affect the motivation level of crew agent *i*.

Application of the hybrid fuzzy Monte Carlo agent-based simulation model

To demonstrate the applicability and suitability of the proposed hybrid FMCABS methodology, it was implemented on a parametric study of construction crew performance on a real industrial project. The hybrid FMCABS model of construction crew motivation and performance developed by Raoufi and Fayek (2020) was extended in this paper to determine the effects of variations in model parameters on crew performance. The connection between MATLAB and AnyLogic was enhanced to allow parallel simulation, which in turn led to faster simulation and an increase in the number of iterations compared to previous studies. The analysis performed in this paper is novel, as previous research on crew performance either used a single experiment (Raoufi and Fayek, 2020), or compared scenarios based on a limited number of simulation runs and limited variations of model parameters (Kedir et al., 2020). Figure 3 shows the hybrid FMCABS model for the parametric study of construction crew performance.

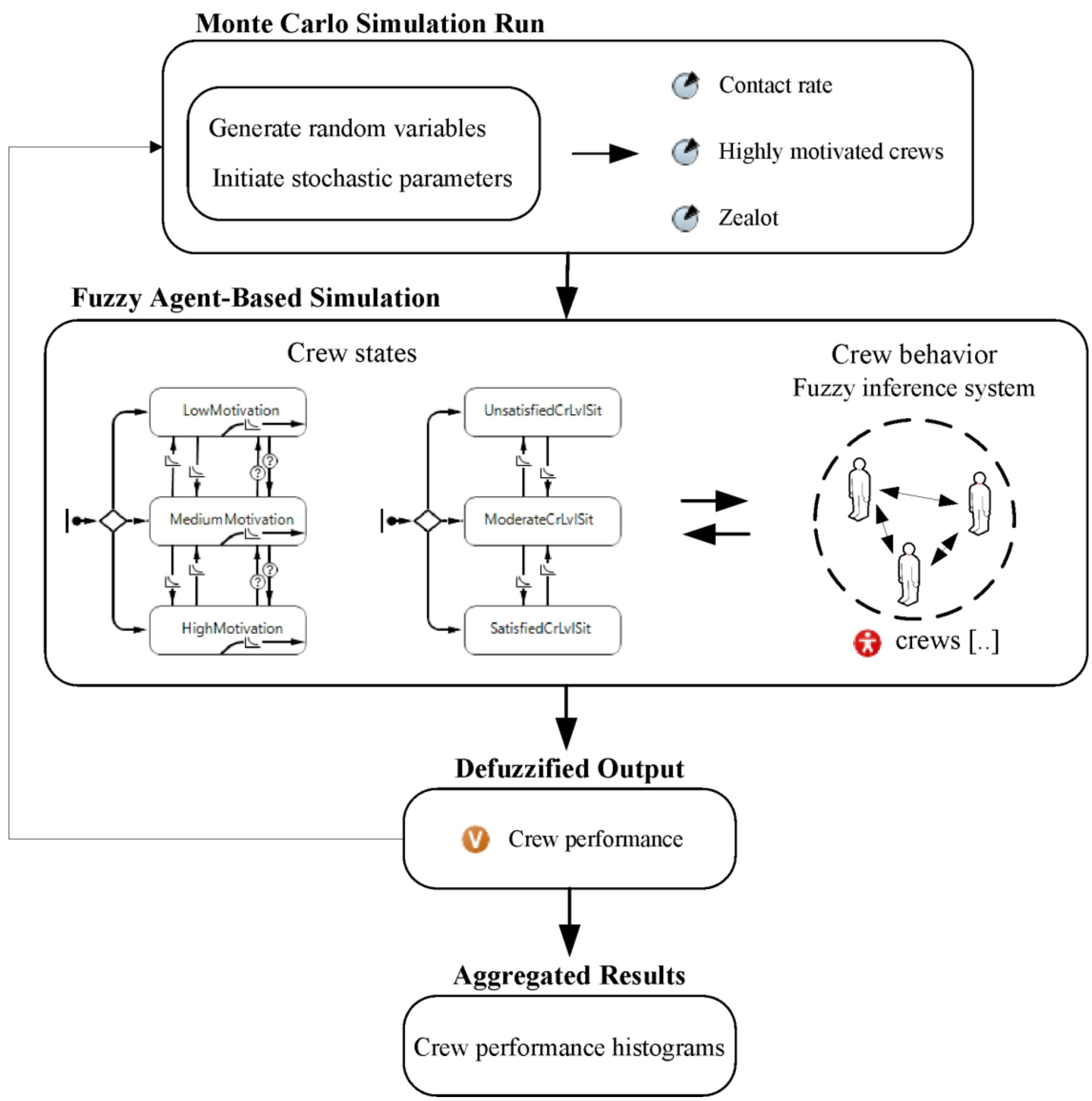

Figure 3. Hybrid FMCABS model for parametric study of construction crew performance.

The developed FMCABS model and the parametric study of construction crew performance were based on the actual field data that were previously collected from an industrial project located in Alberta, Canada. Different sources were used to collect data: interviews surveys with project personnel, including crew members, foremen, and project managers (Raoufi and Fayek, 2018a); project documents, such as time sheets, score cards, inspection test plans, schedule updates, tender documents, and cost estimates; project databases, such as safety logs and change order logs; observations on the work packages of the project by data collectors; and external databases, such as a databases for weather data (Raoufi and Fayek, 2018b).

The input variables of the hybrid FMCABS model included deterministic variables (e.g., number of crews, contact rate, and zealot percentage); random variables (e.g., susceptibility, motivation variability, and crew-level situation variability); and subjective variables (e.g., crew motivation, crew-level situation, and project-level situation).

Crew motivation was determined based on four motivational factors: efficacy (Hannah et al., 2016; Bandura, 1977), commitment/engagement (Cesário and Chambel, 2017; Meyer and Allen, 1991), identification (Lin et al., 2017; Ashforth and Mael, 1989), and cohesion (Chiniara and Bentein, 2018; Beal et al., 2003).

The crew-level situation and the project-level situation represent factors related to the working environment. Actual field data on the crew-level situation were collected from three categories: task-related factors (e.g. task design), labor-related factors (e.g., the functional skills of the crew), and foreman-related factors (e.g., leadership skills). Actual field data on the project-level situation were collected from 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, and materials), and safety precautions (e.g., safety training).

Crew motivation, the crew-level situation, and the project-level situation all affect crew performance, the latter of which is the output of the hybrid FMCABS model. Crew performance was defined by 55 key performance indicators (KPIs) across three performance metrics, namely task performance, contextual performance, and counterproductive behavior. Table 1 shows the crew performance metrics and their KPI categories.

Table 1. Crew performance metrics and KPI categories

Crew performance metrics	KPI category
Task performance	Cost performance indicators
	Schedule performance indicators
	Change performance indicators
	Quality performance indicators
	Safety performance indicators
	Productivity performance indicators
	Satisfaction performance indicators
Contextual performance	Personal support
	Organizational support
	Conscientious initiative
Counterproductive behavior	Interpersonal deviance
	Organizational deviance

The developed hybrid FMCABS model is able to process different types of input variables (i.e., deterministic, random, and subjective) and analyze the effect of variations in model parameters on construction crew performance. In this paper, the hybrid FMCABS model was used to perform a parametric study of construction crew performance, which determined the effect of crew contact rates, the initial percentage of highly motivated crews, and the percentage of zealots in the project on crew performance.

Parametric study of crew performance

Three simulation parameters that showed significant influence on crew performance were selected for this parametric study, based on past research performed by Raoufi and Fayek (2018c):

contact rate (i.e., the number of interactions between crews per simulation time unit), the initial percentage of highly motivated crews (i.e., the percentage of crews in a high-motivation state at the start of the simulation), and zealot percentage (i.e., the percentage of crews that do not change their motivation following interactions with other agents).

Anylogic and MATLAB were used to perform the parametric study on the selected parameters of the FMCABS model. The parametric study involved the performance of multiple simulation experiments for each selected parameter (i.e., 26 simulation experiments for contact rate, 11 simulation experiments for initial percentage of highly motivated crews, and 11 simulation experiments for zealot percentage), where each simulation experiment included 1000 simulation runs. This configuration produced to a total of 48,000 simulation runs during the parametric study.

To perform the simulation experiment, several steps were followed. First, all parameters of the FMCABS model were set at their actual values based on field data. Table 2 shows the actual values of all parameters of the FMCABS model.

Second, for each simulation experiment, one of the selected parameters was incrementally adjusted in value across its defined range. For example, in the first simulation experiment, all parameters were set at their actual values shown on Table 2, except contact rate, which was set at 0. In the second simulation experiment, all parameters were set to their actual values, while contact rate was set to 0.1. This increment in contact rate continued until all 26 possible values of contact rate from 0 to 2.5 were explored for simulation experiments 1 to 26. Then, during the next 11 simulation experiments (i.e., experiments 27–37), contact rate and other simulation parameters were set at their actual values, and the initial percentage of highly motivated crews was incremented by a value of 0.1 across a range from 0 to 1. In the last 11 experiments (i.e., experiments 38–48), zealot percentage was incremented by a value of 0.1 across a range from

Table 2. Actual values for initial parameters of the FMCABS model

FMCABS Model Parameters	Unit	Actual value (Based on collected field data)	Selected parameters for parametric study		
			Experiment No.	Range of Values	Increment
Contact rate	$\mathbb{R}^+$	1.0000	1-26	[0,2.5]	0.1
The initial percentage of highly motivated crews	[0,1]	0.4286	27-37	[0,1]	0.1
Zealot percentage	[0,1]	0.2857	38-48	[0,1]	0.1
Number of crews	$\mathbb{Z}^+$	9			
Susceptibility	[0,1]	Beta (0.2276, 2.1886, 0.0000, 0.4286)			
Non-interactive motivation variability	[0,1]	Beta (0.1538, 13.8460, 0.0000, 0.2888)			
The initial percentage of low motivated crews	[0,1]	0.2857			
Initial states of crew-level situation	[0,1]	0.1426 for "*unsatisfied* crew-level situation" 0.0000 for "*satisfied* crew-level situation"			
Initial state of project-level situation	String	"*medium* project-level situation"			
Crew-level situation variability	$\mathbb{R}^+$	Beta (0.3127, 9.6465, 0.0000, 0.1429)			
Project-level situation variability	$\mathbb{R}^+$	0.0333			

0 to 1 in each simulation experiment. Table 2 also shows the range of values and increments for the selected parameters in the parametric study of the FMCABS model.

Third, each simulation experiment was run separately for 1000 runs to determine the output of the FMCABS model for each value of the selected parameters. Finally, a histogram of the average crew performance of all crews on the project based on 1000 simulation runs was generated.

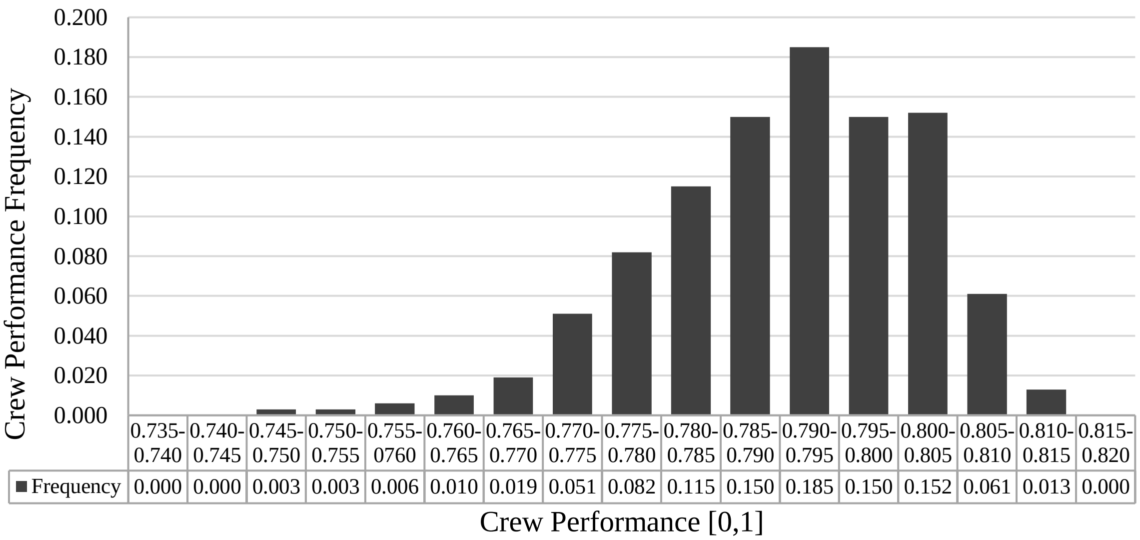

Figure 4. FMCABS model output for simulation experiment 32 (1000 runs).

Figure 4 shows the model output for simulation experiment 32, where the initial percentage of highly motivated crews was 0.5000 and all other parameters were set at their actual values. The frequency of each category of crew performance is shown in this histogram. Figure 4 demonstrates that in this simulation experiment, the crew performance category of 0.790–0.795 occurred more frequently during the project, with a frequency of 0.185 (i.e., 18.5%). Other simulation experiments were performed to observe the effect of variations in FMCABS model parameters on crew performance. A sample of this comparison is shown in Figure 5.

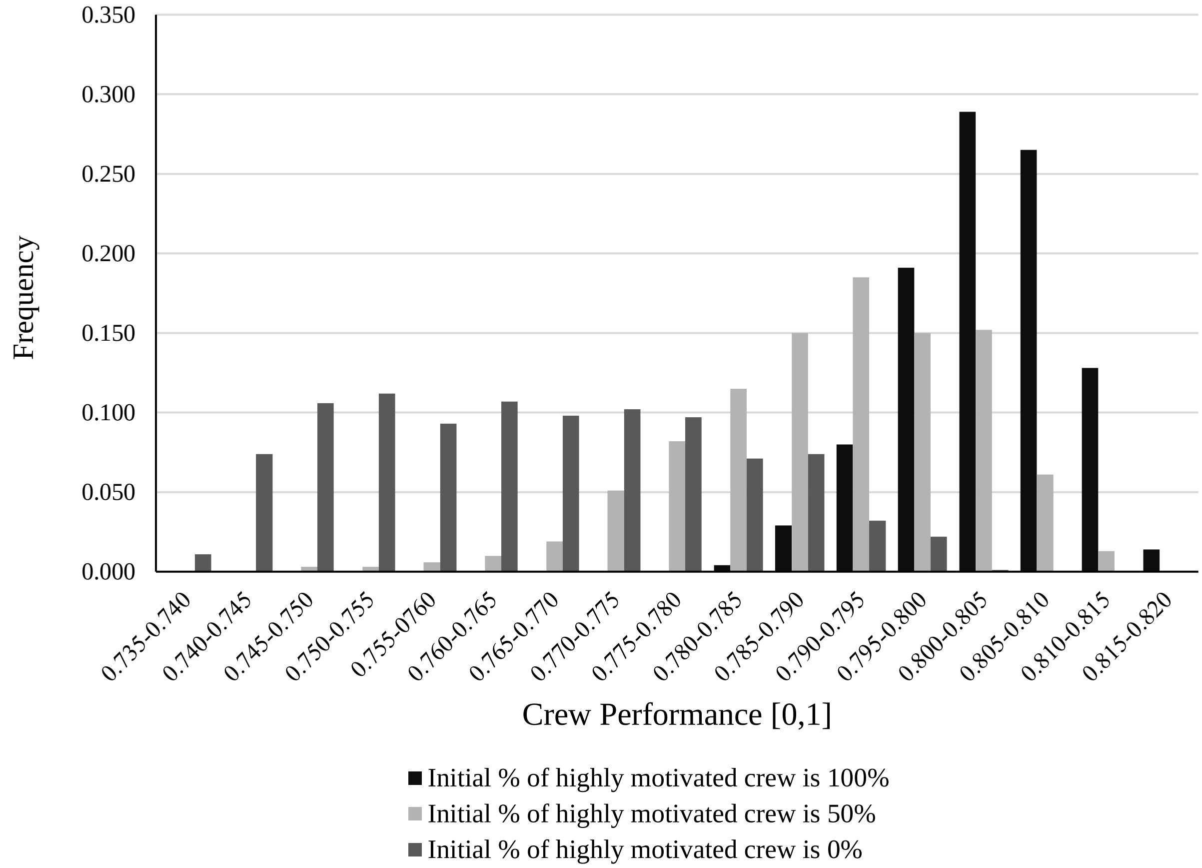

Figure 5. Comparison of three simulation experiments.

Figure 5 shows the results of three different simulation experiments, where the initial percentage of highly motivated crews in the project was 100%, 50%, and 0%. An increase in the initial percentage of highly motivated crews resulted in higher crew performance on the project, which is in agreement with the results of past studies on construction crew motivation (Kedir et al., 2020). The present study represents a more extensive analysis of the effects of contact rate, initial percentage of highly motivated crews, and zealot percentages, as compared to previous studies of crew motivation and performance.

Figure 6 shows the results of 26 simulation experiments, which were performed to determine the effect of variations in contact rate on crew performance. As shown in Figure 6, an increase in contact rate resulted in an increase in crew performance. Linear and polynomial trendlines were also fitted to the results of the simulation experiments. The linear regression model had an R-squared value of 0.7730, while the polynomial regression model (order 2) had an R-squared value of 0.8409. Both R-squared values were substantial (i.e., more than 0.75), indicating a good fit to the results of simulation experiments (Hair et al. 2016). The regression coefficient for contact rate in the linear regression model was 0.0007, indicating that there was a significant positive relationship between contact rate and crew performance.

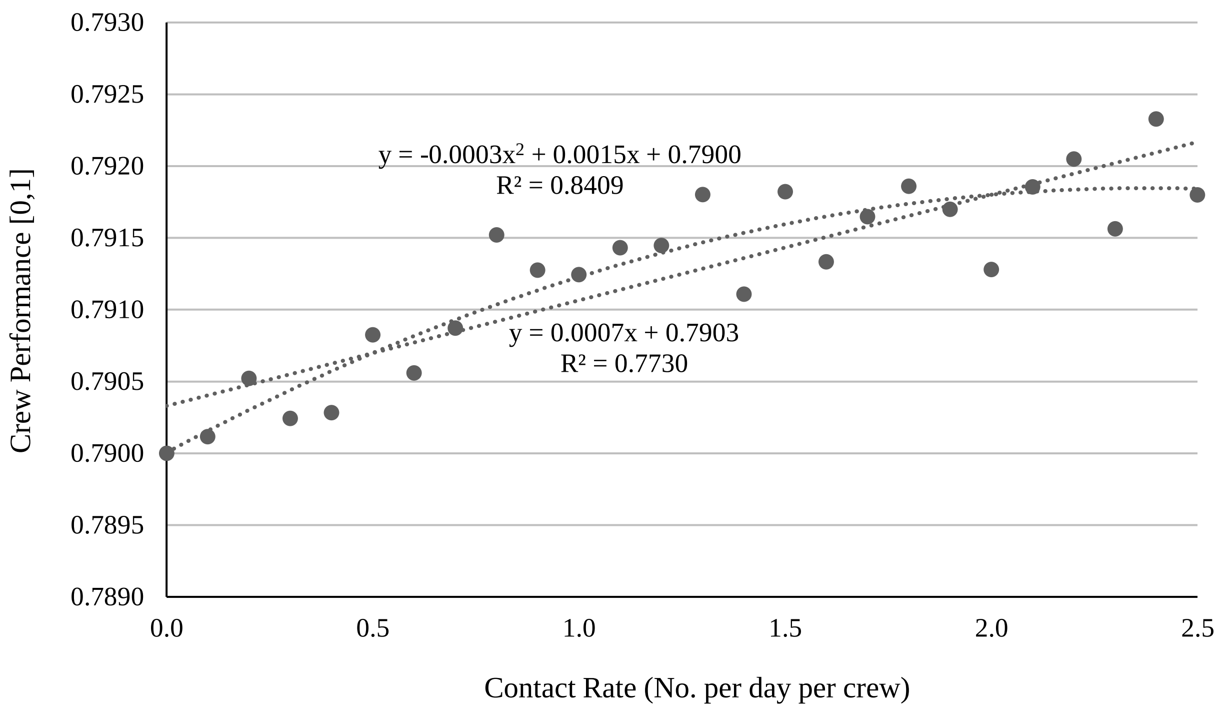

Figure 6. The effect of contact rate on crew performance.

Figure 7 shows the result of 11 simulation experiments, which were performed to determine the effect of the variations in the initial percentage of highly motivated crews on crew performance. In these simulation experiments, the initial percentage of highly motivated crews was incremented by values of 0.1 across a range from 0 to 1. For example, a value of 0.6000 for initial percentage of highly motivated crews indicates that 60% of crews were in a high motivation state at the start of the simulation. The remaining crews were considered to be in a low motivation state at this time. However, during the simulation experiment, the crews interact with each other, which can result in the change of their motivation states. Each crew can have three states of motivation during the simulation experiment: low motivation, medium motivation, and high motivation. As shown in Figure 7, an increase in the initial percentage of highly motivated crews resulted in an increase in crew performance. Linear and polynomial trendlines were also fitted to the results of the simulation experiments. The linear regression model had an R-squared value of 0.9486, while the polynomial regression model (order 2) had an R-squared value of 0.9991. Both R-squared values were substantial (i.e., more than 0.75), indicating a good fit to the results of the simulation experiments (Hair et al., 2016). The regression coefficient for the initial percentage of highly motivated crews in the linear regression model was 0.0392, indicating that there was a significant positive relationship between the initial percentage of highly motivated crews and crew performance. In other words, an increase in the number of highly motivated crews at the start of the project, as compared to crews with low motivation, resulted in higher crew performance on the project overall.

Figure 8 shows the result of 11 simulation experiments, which were performed to determine the effect of variations in zealot percentage on crew performance. In these simulation experiments, zealot percentage was incremented by values of 0.1 across a range from 0 to 1. For example, a value of 0.3000 for zealot percentage indicates that 30% of crews were zealot in nature and never change their motivation when interacting with others. The remaining crews were considered non-zealot, meaning they may change their motivation when interacting with others. As shown in Figure 8, an increase in zealot percentage did not produce a substantial increase in crew performance. Linear and polynomial trendlines were also fitted to the results of the simulation

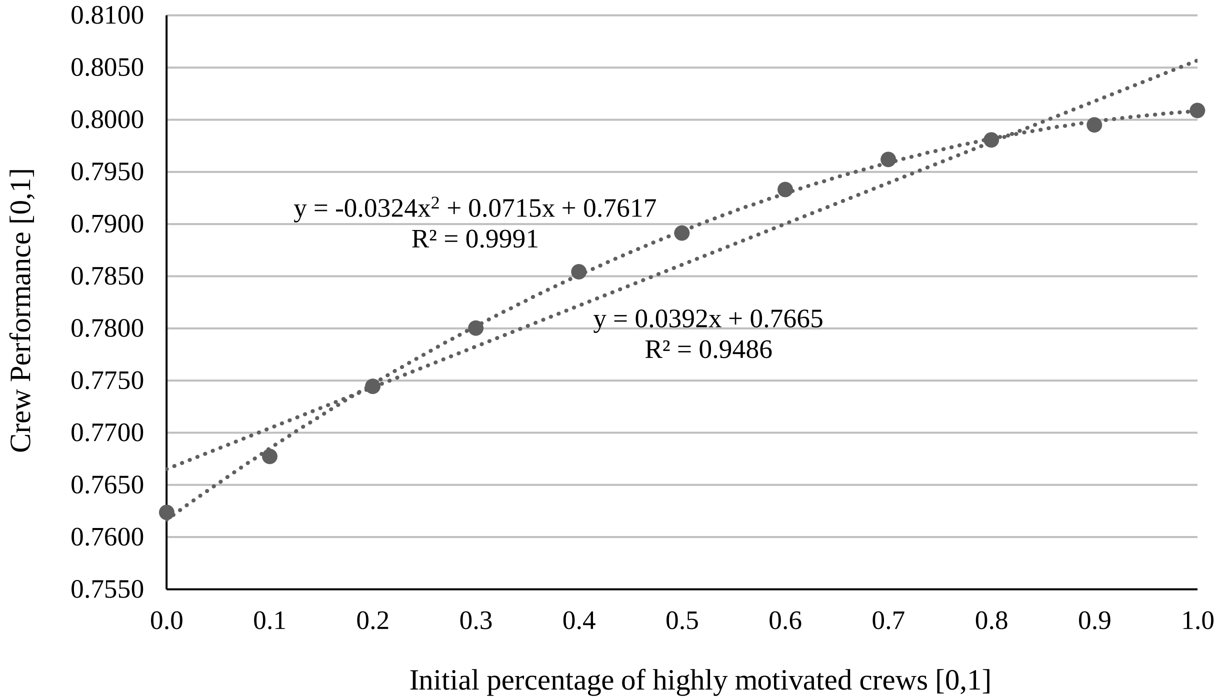

Figure 7. The effect of the initial percentage of highly motivated crews on crew performance.

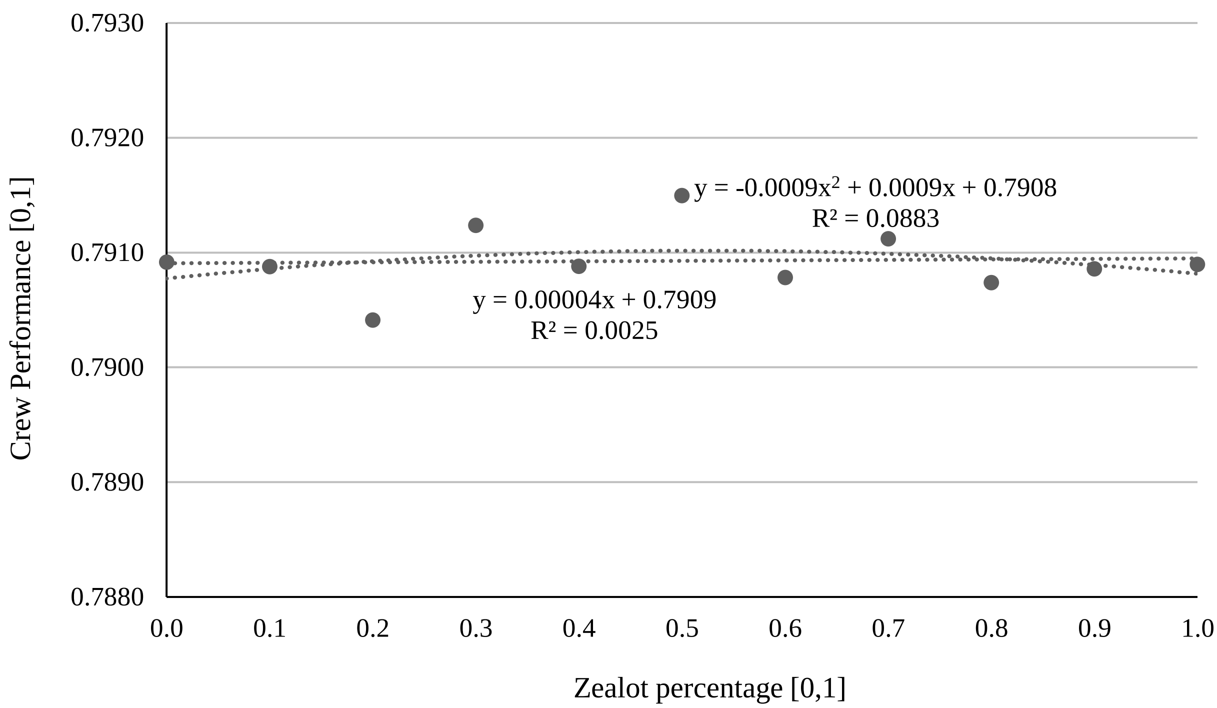

Figure 8. The effect of zealot percentage on crew performance.

experiments. The linear regression model had an R-squared value of 0.0885, while the polynomial regression model (order 2) had an R-squared value of 0.0025. Both R-squared values were not significant (i.e., less than 0.25), indicating a poor fit to the results of the simulation experiments (Hair et al., 2016). Therefore, no significant relationship was observed between zealot percentage and crew performance. Although zealot percentage did not have a significant effect on crew performance in this series of simulations, other studies suggest that in cases where the initial percentage of highly motivated crews is high, zealot percentage can have significant effect of crew performance (Kedir et al., 2020). Not having a direct effect does not indicate that zealot percentage is not an important factor to consider for improving crew performance, as it might moderate (i.e., influence) the relationship of crew motivation to crew performance. Potential moderating effects of zealot percentage on crew performance should be investigated in future studies.

Verification and Validation

This research used a combination of verification and validation methods, as suggested by Lucko and Rojas (2009) for performing face validation, internal validation, external validation, and construct validation for construction research; Ormerod and Rosewell (2009) for verification and validation of agent-based models; and Sargent (2013) for verification and validation of simulation models.

To verify the developed model, four steps were followed. First, all possible errors in the model's mathematical equations were checked, as suggested by Ormerod and Rosewell (2009). Second, all components of the model were examined by performing a structured walk-through, as suggested by Sargent (2013). Third, the replicability of the results of the model was checked by performing multiple simulation runs, as suggested by Ormerod and Rosewell (2009). Fourth, changes in the model variables were traced during the simulation experiment, as suggested Sargent (2013).

To validate the developed model, three steps were followed. First, the model variables (e.g., motivation) were defined based on validated concepts to ensure conceptual validity, as suggested by Ormerod and Rosewell (2009), and the reliability of the measures of the variables were checked to ensure validity of the collected data, as suggested by Sargent (2013). Third, time plots representing graphical displays of model variables were developed for all model agents to ensure operational validity, as suggested by Sargent (2013). Fourth, a sensitivity analysis was performed on model parameters to identify parameters that have a significant effect on crew performance. The sensitivity analysis suggests that crew performance varies due to the variations in contact rate and in initial motivation states of crews, which is consistent with the results presented in Figures 6 and 7.

Discussion

Variations in crew performance were studied, based on the variations in three parameters: contact rate (i.e., number of interactions between crews per simulation time unit), the initial percentage of highly motivated crews (i.e., percentage of crews in a high-motivation state at the start of the simulation), and zealot percentage. The results of the study indicate that there is a significant influence of both contact rate and the initial percentage of highly motivated crews on crew performance. However, there was no direct influence of zealot percentage on crew performance based on the results of the simulation experiments. These results suggest that strategies intended to increase crew performance should emphasize increases in the initial percentages of highly motivated crew and in the contact rate between the crews. In addition, more research is needed to understand potential moderating effects of zealot percentage on crew performance. Findings from this paper suggest that moderation is an important issue to be taken into consideration when the goal is to improve crew performance.

Conclusions and future research

In this paper, a hybrid FMCABS methodology was extended to and implemented on a parametric study of construction crew performance. This methodology allows construction modelers to develop simulation models that are able to account for both subjective and random uncertainties. An FMCABS model of construction crew performance was developed, which integrates fuzzy logic, Monte Carlo simulation, and ABM to simulate crews in construction environments and predict crew performance. The developed hybrid FMCABS model was implemented on a parametric study to assess the effects of contact rate, initial percentage of highly motivated crews, and zealot percentage on crew performance.

One of the main contributions of this paper is the extension of a hybrid FMCABS methodology, which allows agent-based models to simultaneously process all types of variables (i.e., deterministic, random, and subjective) in the same simulation experiment, while accounting for interactions between different agents. Another major contribution of this paper is the implementation of the developed methodology in a novel and extensive parametric study of construction crew performance. Past research on construction crew performance focused either on a single experiment, or on a scenario-based analysis using limited simulation runs and limited variations of model parameters. The hybrid FMCABS model of construction crew performance developed by Raoufi and Fayek (2020) was extended in this paper to determine the effects of variations in model parameters on crew performance. The connection of MATLAB and AnyLogic was enhanced, allowing for parallel simulation and leading to faster simulation.

The results of the parametric study will enable construction practitioners to develop strategies to increase crew performance through emphasizing increases in the initial percentage of highly motivated crews and in the contact rate between crews. The results indicate that the concept of emotional contagion is applicable to the relationship of crew motivation and performance. Emotional contagion is the concept that a person's emotional responses trigger similar responses in other people (Hatfield et al. 1994). To the extent that motivation captures emotional content, it may be assumed that the logic underlying emotional contagion allows for the increase in crew motivation when contacting other highly motivated crews. For instance, a worker with low levels of motivation working in a crew of highly motivated members will become more motivated due to his or her interactions with highly motivated crew members. The results also suggest that the direct effect of zealot percentage on crew performance was not significant in the project under study, but that there is a possibility of a moderating effect of zealot percentage on crew performance. In the future, moderating effects of zealot percentage on crew performance should be investigated. The effect of variations of other model parameters on crew performance can also be studied using the methodology developed in this paper. Though the results of the parametric study are limited to the context of construction crew performance, future research will investigate implementation of the developed FMCABM methodology in other construction research contexts. In the future, more data need to be collected to enable the modeling of emergent behavior of agents, such as the changes in the behavior of crews when faced with drastic changes in their working environment (e.g., changes due to the COVID-19 pandemic).

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