Fuzzy Agent-Based Multi-criteria Decision-Making Model for Analyzing Construction Crew Performance

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Abstract

Selecting economically feasible policies for maximizing crew motivation and performance is a multifaceted problem, and each aspect of the process poses considerable unique challenges for construction practitioners. Fuzzy agent-based modeling (FABM) addresses some of the challenges of predicting crew performance (e.g., it accounts for both subjective uncertainties and crew dynamics), but strategy selection is a decision-making problem that is also compounded by expert disagreements, insufficient information, and differing stakeholder priorities. This paper proposes a methodology for integrating multi-criteria decision-making (MCDM) with fuzzy agent-based modeling (FABM) to develop a decision support model that simulates the complex relationships and social interactions between crews and crew members for use in decision-making. This model also accounts for dynamic construction environments and captures the subjective factors that influence crew motivation and performance. The contributions of this paper are twofold. First, it proposes a methodology that will help improve decision-making processes in construction by expanding the scope of MCDM through integration with FABM. Second, it develops a fuzzy agent-based multi-criteria decision-making model that helps construction practitioners adopt economically feasible strategies for improving the motivation and performance of construction crews. Furthermore, the proposed methodology can be adapted to several construction problems to help decision makers prioritize and select from several strategies intended to improve different crew performance measures.

Author keywords: Fuzzy agent-based modeling; multi-criteria decision-making; construction; crew performance; fuzzy logic

Introduction

Agent-based modeling (ABM), a technique for simulating or modeling systems that considers the emergent behaviors and interactions of several "agents" (e.g., crew members, supervisors, etc.) with each other and the environment, is a useful tool for exploring the potential outcomes of multiple scenarios. In the complex environment of construction decision-making, ABM allows practitioners to explore multiple simulations and reach an appropriate "decision space," which is a set of options (i.e., scenarios) that are at the disposal of decision makers (Klein et al. 2009). However, ABM does not account for all the challenges decision makers face in the construction industry, such as changing contexts and subjective uncertainty. Raoufi and Fayek (2018c) therefore developed fuzzy agent-based modeling (FABM), which integrates fuzzy logic with agent-based models, making it possible to address construction-related problems that are highly dynamic and involve subjective uncertainties. After applying FABM to a problem, the decision maker still has to evaluate the consequences of each scenario and make a selection. When a problem involves only one single criterion, the choice is straightforward as the decision maker simply needs to choose the scenario with the highest preference rating. However, when scenarios with multiple criteria are involved, considerations related to the weights of criteria, preference dependence, and conflicts among criteria complicate the problem and more sophisticated methods must be used (Tzeng and Huang 2011). One such method is multi-criteria decision-making (MCDM), which is capable of evaluating alternative scenarios in terms of several criteria (i.e., objectives) while accounting for experts' preferences (Shahdany and Roozbahani 2016).

In a motivation-related context, the problem of selecting strategies to improve crew motivation and performance can be considered a multi-criteria decision-making problem that involves experts (i.e., stakeholders who are responsible for the success of the project). Because construction is a dynamic process that is influenced by different factors, selecting the right strategy is a combination of a simulation problem and a decision-making problem. The decision-making component focuses on improving a performance measure by processing several alternatives and considering objectives (e.g., cost and schedule) while selecting variables for use in the simulation. The simulation aspect of the problem is the analysis of input measurements to produce an output for a given performance measure, such as crew performance. A comprehensive model needs to simulate the crew performance output and incorporate the assessment of several variations of inputs (i.e., parameters) and crew performance outputs for use in selecting the right strategy (i.e., combination of specified inputs).

To address both the decision-making and simulation aspects of the strategy selection problem, an approach is required that incorporates an MCDM model with a simulation technique that uses fuzzy logic principles (i.e., FABM). The MCDM model incorporates the multiple, sometimes conflicting opinions of experts and FABM simulates the subjective and dynamic nature of construction problems, enabling practitioners to select effective strategies for improving a given performance measure (e.g., crew motivation or crew performance). However, even though MCDM and ABM have been used extensively in construction as standalone techniques, there is a gap in the literature on incorporating MCDM with FABM. This paper develops a methodology for integrating MCDM and FABM and illustrates the methodology with an analysis of a real-world case study of improving construction crew motivation and performance.

The paper is organized as follows: A literature review of MCDM in construction is presented, followed by a literature review of ABM, its applications in construction, and its use and limitations in decision-making. Next, a methodology for integrating FABM and MCDM into a fuzzy agent-based decision-making (FABM-MCDM) model is proposed. A case study on crew motivation and performance is then used to illustrate the model. Finally, conclusions and recommendations for future research are presented.

Literature Review

Multi-criteria Decision-Making

Decision-making is a critical aspect of construction-related processes (e.g., policy making, budgeting, risk and safety, planning and scheduling, bidding and tendering, productivity and performance, etc.). These processes usually require that several criteria be analyzed before a decision is made, usually in an environment of differing stakeholder priorities, insufficient information, and expert disagreements. MCDM is an analytic method that assesses the advantages and disadvantages of different alternatives based on a set of multiple criteria (Pirdashti et al. 2009).

A study by Zardari et al. (2015) classifies MCDM approaches as elementary methods, unique synthesis criterion methods, or outranking methods. Elementary methods involve no computational requirements; they are simple and best suited for problems involving a single decision maker who is choosing between very few alternatives. These methods can also fall under the category "non-compensatory decision-making," which is when the positive attributes of an alternative cannot compensate for the negative attributes of another alternative; in such situations, the alternatives are quickly evaluated with minimal effort and an acceptable loss of accuracy. For example, pros and cons analysis, max-min and min-max methods, the lexicographic method, and elimination by aspect belong to this category. The unique synthesis approach entails aggregating varying points of view into a single function that will be optimized. This approach is based on the use of utility functions that can be applied to transfer the raw performance values of alternatives, in terms of diverse criteria, to a common dimensionless scale, usually in the interval [0,1]. Some examples include the simple multi-attribute rating technique (SMART), multi-attribute utility theory (MAUT), the technique for order of preference by similarity to ideal solution (TOPSIS), multi-attribute value theory (MAVT) and the analytic hierarchy process (AHP). The use of utility maximization and the selection of the alternative(s) with the highest value can make the unique synthesis approach a compensatory method. In compensatory methods, the positive (i.e., equal or higher) value of one attribute can compensate for the negative value of another attribute (Lee and Anderson 2009). Outranking synthesis methods, the third category, involve developing an outranking relationship that represents the preferences of the decision maker using available information. When the nature of decision-making does not allow compensatory relationships to be established for use as parameters, or if the decision maker has a preference structure of a non-compensatory nature (Vetschera and Almeida 2012), outranking methods can be effectively used to good effect. Some of the methods in this category introduce discrimination (e.g., indifference or preference) thresholds at each criterion level to locally model the decision maker's preference. Examples include ELimination and Choice Expressing REality (ELECTRE) and the preference ranking organization method for enrichment evaluation (PROMETHEE).

Modeling MCDM problems using different techniques is likely to produce different results, and ease of applicability and accuracy must be considered when choosing which technique to use to solve the problem. The popularity of the AHP in the areas of engineering, management, economics, and sociology stems from its ease of use, its flexibility to integrate both qualitative and quantitative properties, the extensive literature on the topic, and its ability to deal with tangible and intangible criteria (Lee 2014). Sabzi and King (2015) evaluated six popular outranking methods using the same decision matrix to simulate the MCDM process for flood management: simple additive weights (SAW), comprehensive programming (CP), TOPSIS, AHP, ELECTRE and VIKOR. Because of the AHP's aforementioned qualities, Sabzi and King (2015) chose to use this method to process information in the decision matrix and perform multiple pairwise comparisons of alternatives in terms of criteria.

Agent-Based Modeling

Since the first construction-related ABM models were developed in the early 2000s, the application of ABM in construction has increased significantly in areas such as supply chain management, claims management, infrastructure management, equipment management, bidding strategies, procurement, site safety, and workers' behavior (Jabri and Zayed 2017). Eid and El-adaway (2017) presented a decision-making framework that used ABM to capture a host community's ever-changing recovery process in the aftermath of a natural disaster. Some researchers have proposed methods of integrating ABM and other models. Ben-Alon and Sacks (2017) proposed a hybrid model of ABM and building information modeling (BIM) to better study production systems in construction that can capture the motivation and behavior of individual crews and workers, as well as their interactions within a physical and process environment; this is difficult to accomplish with other simulation methods (e.g., discrete event simulation). Cheng et al. (2018) integrated ABM and BIM to simulate accidents on offshore oil and gas platforms to evaluate and improve evacuation planning. Xiao et al. (2018) used ABM to study, from economic and ecological perspectives, the impact of water demand management on the behaviors of different municipal and industrial users. Raoufi and Fayek (2018c) advanced the application of FABM approaches to handle uncertainties related to construction when measuring crew motivation and performance.

ABM can be directly used for decision-making when the decision-making elements have been explicitly modeled (Bernhardt et al. 2007) and the mechanisms of the decision-making of agents (i.e., individuals) have been properly explained (Lee 2014). For example, Eid and El-adaway (2018) proposed a holistic sustainable disaster recovery approach using a decision-making framework that employs ABM; Wang (2013) used ABM in the design of a collaborative decision-making process to improve congestion and delays in air traffic; and Yang et al. (2009) applied ABM in a decision support system for inventory management. However, for some problem contexts (e.g., improving crew performance) where proposed strategies for output improvement differ based on company objectives and experts' assessments and where the selection of alternatives has to be weighed in terms of multiple, sometimes conflicting criteria, using ABM alone can become computationally demanding. In these cases, focusing on ABM's ability to carry out simulations with different parameters, boundaries, and constraints and combining the model with proven decision-making tools can help produce a more applicable model. The work of Marzouk and Mohamed (2018) reflects such an approach, as they integrated simulation results from ABM and BIM into an MCDM model to evaluate the evacuation performance of buildings under different scenarios in case of fire emergency. However, detailed studies on incorporating the subjective nature of construction environments into ABM and using those models to evaluate several scenarios for use in decision-making are lacking. Incorporating a decision-making tool into ABM, specifically FABM, can therefore prove useful as it enables scenario analysis and decision-making to improve performance measures for several types of construction problems.

Fuzzy Agent-Based Multi-criteria Decision-Making Model Development

When working to improve construction crew motivation and performance, practitioners must be able to both simulate the subjectivity and dynamism of the problem and select the strategy that will best satisfy a given set of objectives. An appropriate tool must therefore be developed that can handle subjective variables in simulation with the use of fuzzy logic concepts, capture dynamism with the use of dynamic modeling tools such as ABM, and process several simulation outputs in order to select solutions targeted to improve chosen criteria with the use of MCDM. This section presents a methodology for integrating FABM with MCDM to develop such a model. The data set and initial simulation model (i.e., FABM) were obtained from Raoufi and Fayek (2018c) and expanded to enable the development of the integrated model. The fuzzy agent-based–multi-criteria decision-making model (FABM-MCDM) has two major components, as highlighted in Fig. 1. The first component is the MCDM analysis, in which the AHP is used to rank alternatives, which are the inputs to the model. The second component is the FABM technique, in which a parametric study is applied to rank scenarios according to their outputs, which are performance measures (i.e., task performance, contextual performance, and counterproductive behavior). These two components of the FABM-MCDM model are described in the following section.

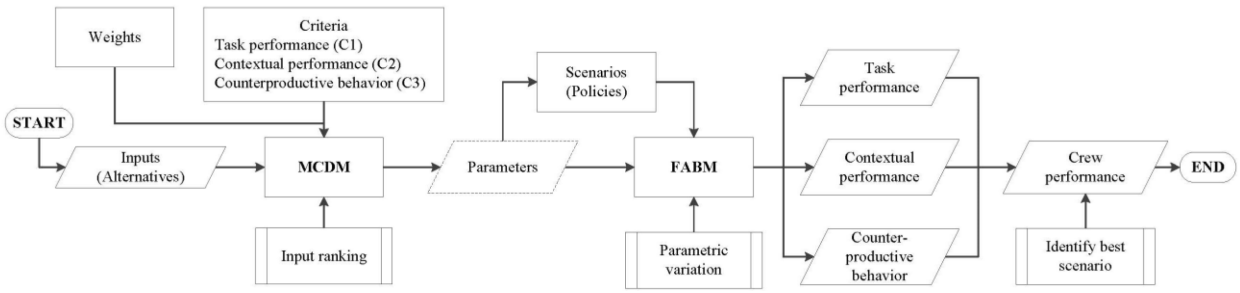

Fig. 1. FABM-MCDM model.

Multi-criteria Decision-Making Model Component

The purpose of the MCDM component in the FABM-MCDM is to rank the inputs of the model according to their influence on the outputs. Inputs with a significant influence on crew performance will be ranked and used as parameters for the model's second component (i.e., FABM).

The inputs, shown in Table 1, are labeled "alternatives" (Alt.). Since the AHP was adopted for this study, pairwise comparisons are used to rank the alternatives according to their importance for three criteria (i.e., task performance [C1], contextual performance [C2], and counterproductive behavior [C3]). At the same time, pairwise comparisons will also be used to weight the criteria, as the importance of each criterion depends on the project context. The importance levels of the three criteria (AHP Level 1) are aggregated to form the goal of the hierarchical structure (i.e., crew performance), as shown in Fig. 2. The sub-criteria (AHP Level 2) inform the experts who are completing the pairwise comparison decision matrix as to what metrics are used to produce each of the performance measurements at Level 1. This allows experts to give emphasis to the performance metrics that are more relevant to their project when performing the pairwise comparisons for the criteria matrix.

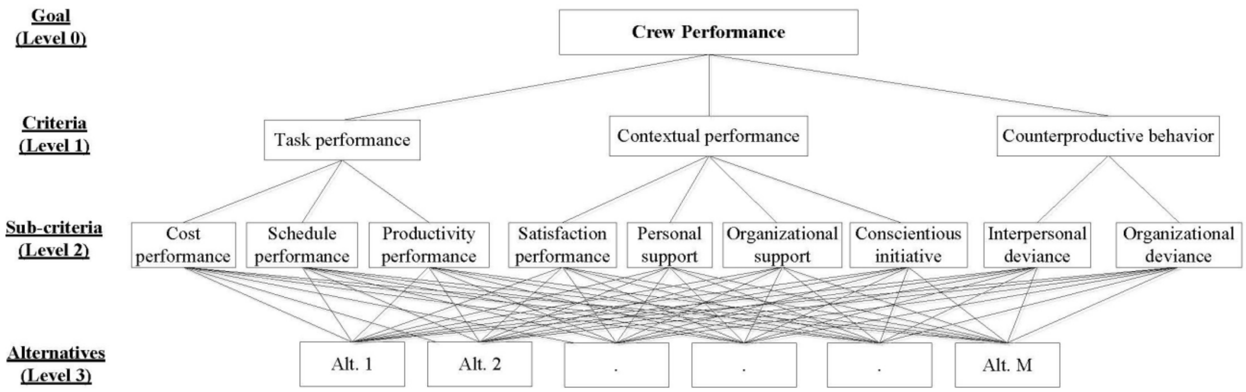

Fig. 2. Hierarchical structure of crew performance.

The pairwise comparisons are computed based on a scale of 1–7 (Saaty 2008). Discrete values between 1 and 7 are used to score the relative importance of alternatives in terms of each criterion, and the relative importance of each criterion to overall crew performance. The scores represent the following importance levels: 1 = equal importance, 3 = moderate importance, 5 = strong importance, and 7 = very strong importance; and values in between (2, 4, and 6) are compromises. For example, a score of A_{ij} ($=A_i/A_j$) indicates the relative importance of alternative *i* when it is

Table 1. Inputs for the FABM model.

Alt.	Inputs	Range	Description
1	Number of crews	Z+	Number of crews in the project
2	Contact rate	[0-3]	Number of times there is contact between crews per simulation time unit
3	Zealot percentage	[0,1]	Percentage of zealots in the project
4	Susceptibility	[0,1]	Probability that an interaction leads to change in motivation
5	Non-interactive motivation variability	[0,1]	The rate of change in motivation level without contact with other agents
6	Initial motivation states of crews	[0,1]	Percentages of crews in each motivation state at the start of the simulation
7	Initial state of crew-level situation	String: "unsatisfied", "satisfied"	Percentages of crews in each crew-level situation state at the start of the simulation
8	Initial state of project-level situation	String: "unsatisfied", "medium", "satisfied"	String parameter representing initial state of the project-level situation

9	Crew-level situation variability	R+	Rate of change in crew-level situation states per simulation time unit
10	Project-level situation variability	R+	Rate of change in project-level situation states per simulation time unit

compared with another alternative *j* in terms of criterion *C*. The rest of this section presents the ranking procedure for inputs; weights are also given to each criterion based on the same procedure. Each alternative matrix is a pairwise comparison of the inputs in terms of a single criterion. Eq. (1) shows the pairwise matrix, where *m* alternatives are compared in terms of a criterion.

$$\begin{array}{c} \\ Alternative\ Matrix\ (A) = \end{array} \begin{array}{c} \\ A_1 \\ A_2 \\ . \\ A_m \end{array} \overset{\begin{array}{cccc} A_1 & A_2 & . & A_m \end{array}}{\begin{bmatrix} \frac{A_1}{A_1} & \frac{A_1}{A_2} & . & \frac{A_1}{A_m} \\ \frac{A_2}{A_1} & \frac{A_2}{A_2} & . & \frac{A_2}{A_m} \\ . & . & . & . \\ \frac{A_m}{A_1} & \frac{A_m}{A_2} & . & \frac{A_m}{A_m} \end{bmatrix}} \quad (1)$$

After the pairwise matrix is formed for each criterion, the next step is to calculate the reciprocal matrix [R], which satisfies the following three properties (Saaty 1990): reflexivity (r_{ii} = 1), reciprocity ($r_{ij} = 1/r_{ji}$), and transitivity ($r_{ik} = r_{ij} * r_{jk}$). This matrix will be used to solve the eigenvalue problem shown in Eq. (2), where E is the eigenvector and λ_{max} is the corresponding maximum eigenvalue.

$$[R] = \begin{bmatrix} \frac{A_1}{A_1} & \frac{A_1}{A_2} & . & \frac{A_1}{A_m} \\ \frac{A_2}{A_1} & \frac{A_2}{A_2} & . & \frac{A_2}{A_m} \\ . & . & . & . \\ \frac{A_m}{A_1} & \frac{A_m}{A_2} & . & \frac{A_m}{A_m} \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ . \\ . \\ A_m \end{bmatrix} = \lambda_{max} * E \quad (2)$$

The resulting consistency index must be checked using Eq. (3), and it must be less than 0.1 for the normalized eigenvector values to be used as weights for the criteria and alternatives (Saaty 1980). The consistency index is a measurement of the consistency of the performed comparisons throughout all alternatives. For example, if alternative A1 is more important than A2, and alternative A2 is more important than A3, then alternative A1 needs to be more important than A3 in a consistent reciprocal matrix.

$$\nu = \frac{\lambda_{max} - m}{m-1} \quad (3)$$

where ν is the consistency index, λ_{max} is the maximum eigenvalue for the reciprocal matrix R, and *m* is the number of alternatives.

After the consistency index is checked and found to be within the threshold, the resulting eigenvector (E_1, $E_2 \ldots E_m$) is normalized for use as the final weight for the corresponding value of each alternative. The steps in Eqs. (2) and (3) are performed for all three criteria (i.e., C1, C2, and C3). The criteria are also weighted using the same procedure, but instead of an alternative matrix, as shown in Eq. (1), there will be a criteria matrix, where the weight of each criterion is obtained by performing a pairwise comparison and applying the AHP procedure described in this section. The final ranking for each alternative is produced by using a weighted sum to aggregate the scores of each alternative for each criterion. For *m* alternatives and *n* criteria, the final ranking is obtained by sorting the scores of the *m* alternatives, which are determined using Eq. (4), in descending order.

$$For\ \ i = 1, m\text{: } Score\ (Alt_i) = \sum_{j=1}^{n} E_{ij} * C_j \quad where,\ j = 1, n \qquad (4)$$

where E_{ij} is the weight of alternative *i* with respect to criterion *j*, and C_j is the weight of criterion j.

The output of the MCDM model is a ranking of all the alternatives (i.e., inputs) proposed by the experts. The ranking is then used to support the formulation of meaningful strategies that aim to improve crew performance.

Fuzzy Agent-Based Modeling Component

The FABM component of the FABM-MCDM is the integration of fuzzy logic and ABM in MATLAB and AnyLogic, respectively. FABM simulates the effects of a combination of inputs (see Table 1) on three criteria (i.e., task performance, contextual performance, and counterproductive behavior). The main outputs of this model are variations in task performance, contextual performance, and counterproductive behavior over the lifetime of the project.

Parametric variation is used in the proposed model because it can effectively simulate varying sets of input combinations to obtain scenario analysis results. The main objective of the parametric study is to reduce the number of experimental analyses that need to be performed to achieve the target result, which is the best performance measure. This is done by simulating a combination of input intervals for the input variables of the model at every run, rather than using single values of inputs. Instead of having to simulate every possible set of input combinations, which may require infinite runs, scenarios are built by specifying ranges for each input and then performing analyses for all possible combinations within range. The results of FABM simulation are outputs of proposed scenarios as functions of task performance, contextual performance, and counterproductive behavior. The proposed scenarios are then ranked according to their effect on crew performance values.

Case Study

The following case study illustrates the FABM-MCDM process using the analysis procedure presented in the proposed model. Crew performance is defined as a function of three performance metrics, namely task performance, contextual performance, and counterproductive behavior.

First, the alternatives listed in Table 1 are ranked according to the questionnaire shown in Table 2. These rankings are performed in terms of all three criteria. The criteria are weighted according to the questionnaire shown in Table 3. After obtaining the weight for each alternative in terms of each criterion, as well as the weight of each criterion, a weighted average aggregation is performed on each alternative to obtain the overall score in terms of crew performance, as shown in Eq. (4). For example, for alternative 1 (number of crews), the overall score is:

$$Score\ (Alt_1) = \sum_{j=1}^{n} E_{1j} * C_j\ ; \quad where\ n = 3 \qquad (4)$$

$$= E_{11}C_1 + \ E_{12}C_3 + \ E_{13}C_3$$

where E_{11}, E_{12}, and E_{13} are the weights of alternative 1 in terms of criteria 1, 2, and 3, respectively, and C_1, C_2, and C_3 are the weights of criteria 1, 2, and 3, respectively. The data for the pairwise matrix can be obtained by following the procedure outlined in the methodology and responding to the questionnaire surveys shown in Table 2 and Table 3, which are used for ranking alternatives and criteria, respectively.

The resulting pairwise matrix of alternatives for task performance is shown in Fig. 3, and it is used to rank the input variables as part of the MCDM process. In this paper, the pairwise matrix for alternatives with respect to the task performance criterion is based on hypothetical data used to illustrate the methodology. The alternative matrix (A) is calculated using Eq. (1) and the resulting pairwise matrix of alternatives is shown in Fig. 3. This pairwise matrix has also been used for the contextual performance and counterproductive behavior criteria matrices.

Table 2. Questionnaire for ranking alternatives.

	-7	-5	-3	1	3	5	7	
Number of crews								Zealot percentage
								Contact rate
								Susceptibility
								Non-interactive motivation variability
								Initial motivation states of crews
								Initial state of crew-level situation
								Initial state of project-level situation
								Crew-level situation variability

To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "number of crews" parameter to each of the parameters listed on the right, using the scale above.		
Zealot percentage		Contact rate
		Susceptibility
		Non-interactive motivation variability
		Initial motivation states of crews
		Initial state of crew-level situation
		Initial state of project-level situation
		Crew-level situation variability
To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "zealot percentage" parameter to each of the parameters listed on the right, using the scale above.		
Contact rate		Susceptibility
		Non-interactive motivation variability
		Initial motivation states of crews
		Initial state of crew-level situation
		Initial state of project-level situation
		Crew-level situation variability
To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "contact rate" parameter to each of the parameters listed on the right, using the scale above.		
Susceptibility		Non-interactive motivation variability
		Initial motivation states of crews
		Initial state of crew-level situation
		Initial state of project-level situation
		Crew-level situation variability
To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "susceptibility" parameter to each of the parameters listed on the right, using the scale above.		
Non-interactive motivation variability		Initial motivation states of crews
		Initial state of crew-level situation
		Initial state of project-level situation
		Crew-level situation variability

To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "non-interactive motivation variability" parameter to each of the parameters listed on the right, using the scale above.		
Initial state of crew-level situation		Initial state of project-level situation
		Crew-level situation variability
To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "initial motivation states of crews" parameter to each of the parameters listed on the right, using the scale above.		
Initial state of project-level situation		Crew-level situation variability
To rank the alternatives presented in Table 1 in terms of their contribution to the task performance objective, compare the "initial state of project-level situation" parameter to each of the parameters listed on the right, using the scale above.		

Table 3. Questionnaire for ranking criteria.

	-7	-5	-3	1	3	5	7	
Task performance								Contextual performance
								Counterproductive behavior
To rank the alternatives presented in Table 1 in terms of their contribution to the crew performance objective, compare the "task performance" criterion to each of the criteria listed on the right, using the scale above.								
Contextual performance								Counterproductive behavior
To rank the alternatives presented in Table 1 in terms of their contribution to the crew performance objective, compare the "contextual performance" criterion to each of the criteria listed on the right, using the scale above.								

Number of crews	1	1/5	1/5	1	1	1/7	1	1/5	1	1
Contact rate	5	1	3	5	5	1/3	5	3	5	5
Zealot percentage	5	1/3	1	3	5	1/3	3	1	3	3
Susceptibility	1	1/5	1/3	1	1	1/7	1/3	1/3	1/3	1/3
Non-interactive motivation variability	1	1/5	1/5	1	1	1/7	1/3	1/3	1/3	1/3
Initial motivation states of crews	7	3	3	7	7	1	5	3	5	5
Initial states of crew-level situations	1	1/5	1/3	3	3	1/5	1	3	1	1
Initial states of project-level situations	5	1/3	1	3	3	1/3	1/3	1	1	1
Crew-level situation variability	1	1/5	1/3	3	3	1/5	1	1	1	1
Project-level situation variability	1	1/5	1/3	3	3	1/5	1	1	1	1

Fig. 3. Pairwise matrix of alternatives [a].

Next, Eq. (2) is applied to get the eigenvector and Eq. (3) is applied to get the consistency index. This is done separately for each criterion. The consistency index is calculated and found to be 0.082, which conforms with the maximum consistency index requirement of 0.1. The normalized eigenvector, which is used as weights for the alternatives, is calculated using Eq. (2). Finally, Eq. (4) is applied to obtain the weights for each alternative, which are shown in Table 4.

As shown in Table 4, the highest-ranked alternatives (i.e., those with a significant contribution to the crew performance output) are alternatives 6, 2, 3, and 8. These inputs are used to propose scenarios and study their contributions to task performance, contextual performance, and counterproductive behavior. Proposed scenarios can differ according to the kinds of policies experts intend to implement to improve performance output (e.g., depending on their available budget, time, and resources), which are reflected in the weights experts assign to each alternative. Table 5 shows crew motivation and performance improvement strategies that companies can adopt and the associated values (i.e., ranges) for the input parameters used in the FABM simulation.

The ranges of the selected inputs (i.e., parameters) are used in the FABM simulation for parametric variation. The remaining inputs are also used in the simulation, but they will have fixed values that are based on data specific to the project. Scenarios that are built based on the selected parameters (see Table 5) are used as inputs for the parametric variation, and are shown in Table 6.

Keeping "initial state of project level situation" "satisfied" in the simulation, 27 (3*3*3) scenarios are simulated in the FABM for every criterion. Each scenario is labeled according to the initial values of contact rate, initial high-motivation states of crews, and zealot percentage. For example, scenario 1 is labeled "LLL," which indicates low contact rate, low initial high-motivation states of crews, and low zealot percentage. Results are based on mean performance, computed at every time step (i.e., daily), and taking the value of the project's last day.

Table 4. Weights for alternatives.

Alternative	1	2	3	4	5	6	7	8	9	10
Weight	0.128	0.698	0.303	0.093	0.093	1.000	0.263	0.303	0.190	0.190

Table 5. Proposed company strategies.

Parameter	Strategy	Range	
Contact rate	Promoting interactions among crew members through interactive site orientations, safety meetings, and daily meetings	[0-1]	Low
		[1-2]	Medium
		[2-3]	High
Zealot percentage	Inclusion of crew members with a high level of experience whose motivation will not be affected by their environment; increasing the efficacy of crew members (at the individual level) through training	[0-0.33]	Low
		[0.33-0.66]	Medium
		[0.66-1]	High
Initial motivation states of highly motivated crews	Increasing commitment (engagement) at the individual and crew levels by improving relationships, belongingness, and communication between crews and crew members through team building activities; proposing incentives such as bonuses and vacation pay	[0-1]	Low
		[1-2]	Medium
		[2-3]	High
Initial state of project-level situation	Improving work/job conditions on the project by making resources readily available, such as quality equipment and other materials	"Satisfactory"	
		"Unsatisfactory"	

Table 6. Inputs used for parametric variation.

Parameters			
Contact rate	Initial high-motivation states of crews	Zealot percentage	Initial state of project-level situation
Low	Low	Low	"Satisfied"
Medium	Medium	Medium	
High	High	High	

Results and Discussion

This section discusses the results of the FABM-MCDM process and analysis based on the different scenarios. The 27 policies, which are a combination of three ranges of inputs (i.e., low, medium, and high), have been arranged to better capture the relationships between performance measures and variations of contact rate, initial high-motivation states of crews, and zealot percentage. The effects of variations in each input on the different performance measures (i.e., task performance, contextual performance, counterproductive behavior, and crew performance) were studied systematically by keeping one input constant while varying the others. For example, to see the results of variations in contact rate, contact rate is kept constant for the different values of initial high-motivation states of crews and zealot percentage. Thus, it is easy to observe when contact rate changes from low to medium to high while all other combinations of inputs are exhausted for each range of contact rate. For variations based on contact rate, scenarios 1–9 show the results of low contact rate and all other possible values of initial high-motivation states of crews and zealot percentage. Scenarios 10–18 and 19–27 show the results of medium and high contact rate values, respectively, while varying the other inputs. Linear graphs of the performance values are made by grouping the results of each set of nine scenarios, where each line traces the values for low, medium, and high values of contact rate. All results have been presented in this manner.

Variations Based on Contact Rate

The results in the category "contact rate" show the variations in performance measures (i.e., task performance, contextual performance, counterproductive behavior, and crew performance) based on contact rate. The results are tabulated in Table 7. As shown in Fig. 4, a general trend of increasing crew performance can be seen as the contact rate increases. This increase becomes more pronounced for medium and high values of initial high-motivation states. For low values of the other parameters, the increase in contact rate did not have any effect. Hence, strategies intended to increase crew performance by increasing contact rate have to also include an increase in either of the other two parameters. An improvement to the crew performance recorded when all parameters are low (i.e., scenario 1) can be obtained by adopting scenario 7 (LHL), scenario 17 (MHM), or scenario 27 (HHH). All three scenarios indicate the need to keep the levels of initial high-motivation states of crews higher. The choice of the scenario to be used as a strategy then depends on the amount of improvement needed and the contextual situations (e.g., financial capability, time available, etc.) decision makers face when implementing a strategy. The effects of input parameter variations on task performance, contextual performance, counterproductive behavior, and crew performance are shown in Figs. 5a–5d, respectively.

Table 7. Performance values based on contact rate.

Scenario	Label	Task Performance	Contextual Performance	Counterproductive behavior	Crew Performance
1	LLL	0.819	0.752	0.760	0.777
2	LLM	0.819	0.752	0.760	0.777
3	LLH	0.820	0.754	0.760	0.778
4	LML	0.819	0.761	0.767	0.782
5	LMM	0.819	0.762	0.768	0.783
6	LMH	0.820	0.762	0.768	0.783
7	LHL	0.819	0.770	0.777	0.789
8	LHM	0.819	0.770	0.777	0.789
9	LHH	0.820	0.770	0.775	0.788
10	MLL	0.819	0.752	0.760	0.777
11	MLM	0.820	0.752	0.760	0.777
12	MLH	0.820	0.753	0.760	0.778
13	MML	0.819	0.760	0.766	0.782
14	MMM	0.820	0.762	0.767	0.783
15	MMH	0.820	0.762	0.770	0.784
16	MHL	0.819	0.770	0.779	0.789
17	MHM	0.820	0.770	0.779	0.790
18	MHH	0.820	0.770	0.779	0.790
19	HLL	0.819	0.752	0.760	0.777
20	HLM	0.820	0.753	0.760	0.778
21	HLH	0.820	0.753	0.760	0.778
22	HML	0.820	0.761	0.767	0.783
23	HMM	0.820	0.762	0.768	0.783
24	HMH	0.820	0.762	0.770	0.784
25	HHL	0.820	0.771	0.779	0.790
26	HHM	0.820	0.772	0.779	0.790
27	HHH	0.820	0.772	0.780	0.791

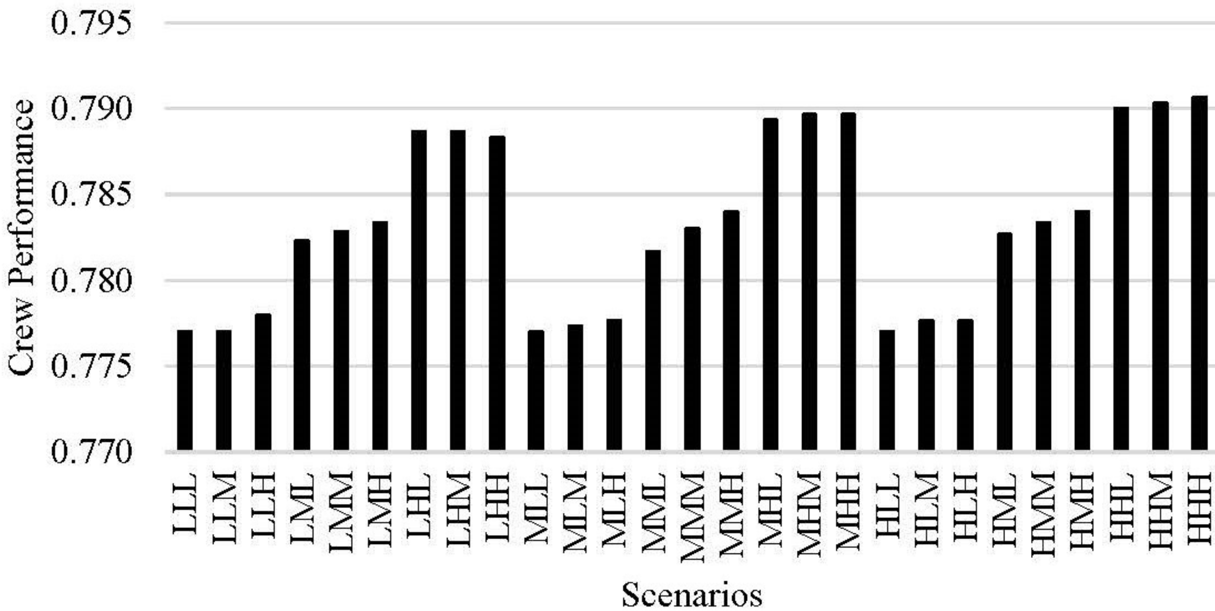

Fig. 4. Crew performance results based on contact rate.

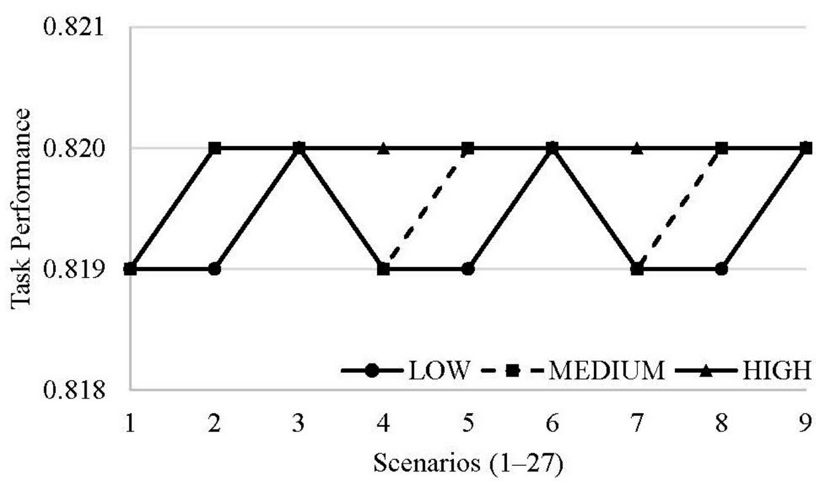

Fig. 5a. Task performance based on contact rate.

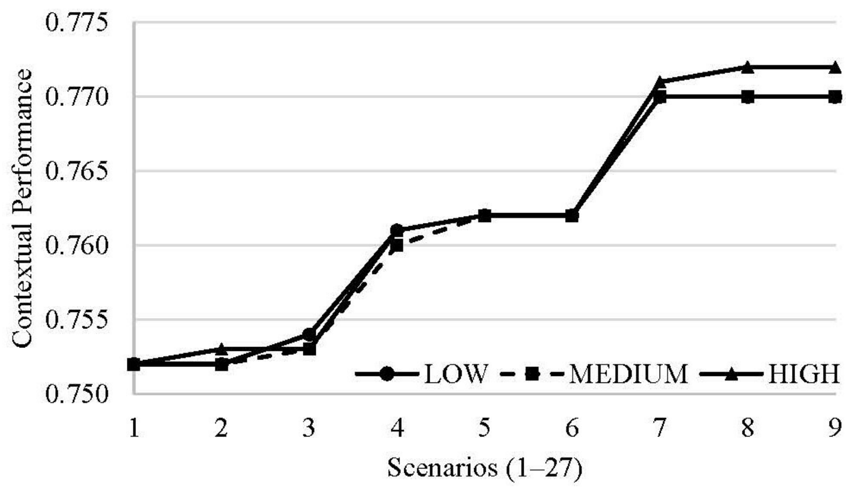

Fig. 5b. Contextual performance based on contact rate.

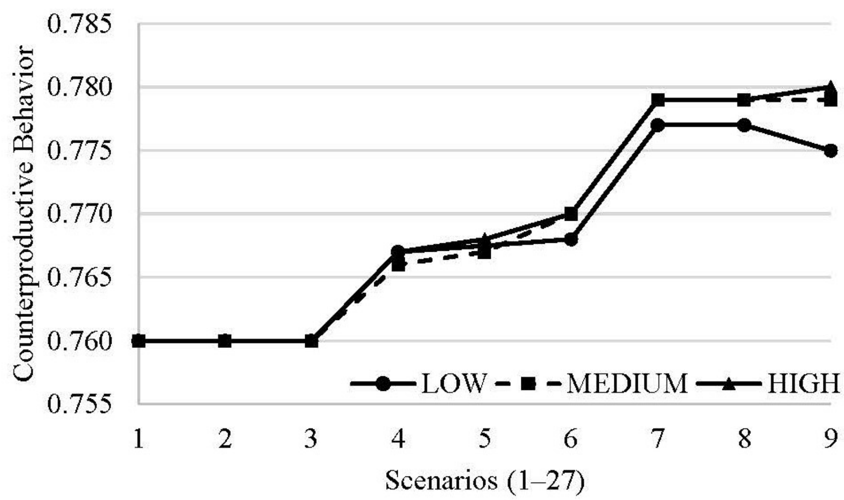

Fig. 5c. Counterproductive behavior based on contact rate.

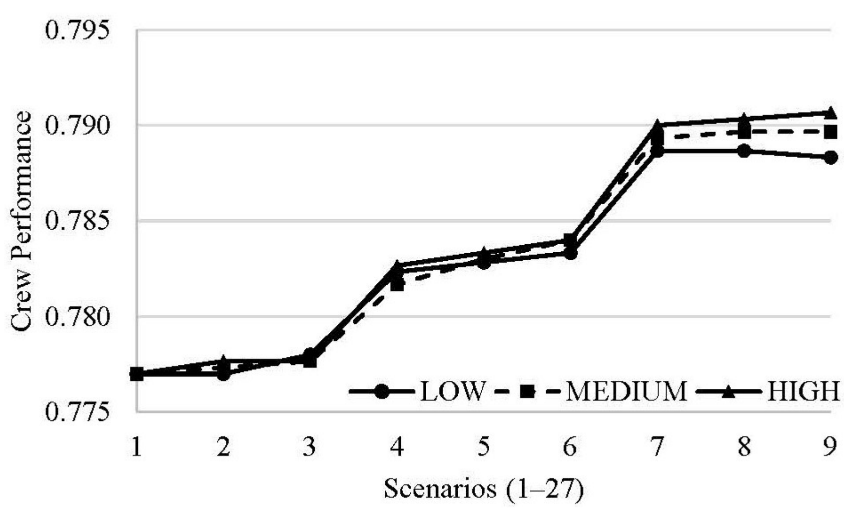

Fig. 5d. Crew performance based on contact rate.

The results show that a high contact rate can produce higher task performance, but the effect of a high contact rate is constant throughout the rest of the policies, except HLL. Contextual performance outputs did not show a significant variation based on contact rate, but they seemed to be more affected by the initial high-motivation states of crews. This is consistent with the performance index used to measure contextual performance that includes “helping,” “cooperating,” “motivating,” “compliance,” and “initiative” (Raoufi and Fayek 2018 a, b), and it is dependent on crews becoming and staying motivated.

Variations Based on Initial Percentage of Highly Motivated Crews

The results for this category show variations in performance measures (i.e., task performance, contextual performance, counterproductive behavior, and crew performance) based on the initial percentage of highly motivated crews. As shown in Fig. 6, there is a general trend of increasing crew performance as the initial percentage of high motivation level increases. There is no direct relationship between the influence of the other inputs and the crew performance output when the motivation state is kept constant. When the initial motivation level is kept constant, variations in the values of other parameters did not have a significant influence on crew performance. This lack of influence is even more visible in the values of task performance, contextual performance, and counterproductive behavior. Another significant finding is the level of influence the parameter initial high-motivation states of crews has on crew performance. In policies 1–9, for example, for low contact rate and low zealot percentage, increasing the initial high-motivation states of crews from low to medium visibly improves the crew performance measure. This change is even more visible for higher values of contact rate and zealot percentage. The effects of input parameter variations on task performance, contextual performance, counterproductive behavior, and crew performance are shown in Figs. 7a–7d, respectively. In these figures, the scenarios are grouped according to motivation state (i.e., low, medium, and high) while the values of contact rate and zealot percentage are varied.

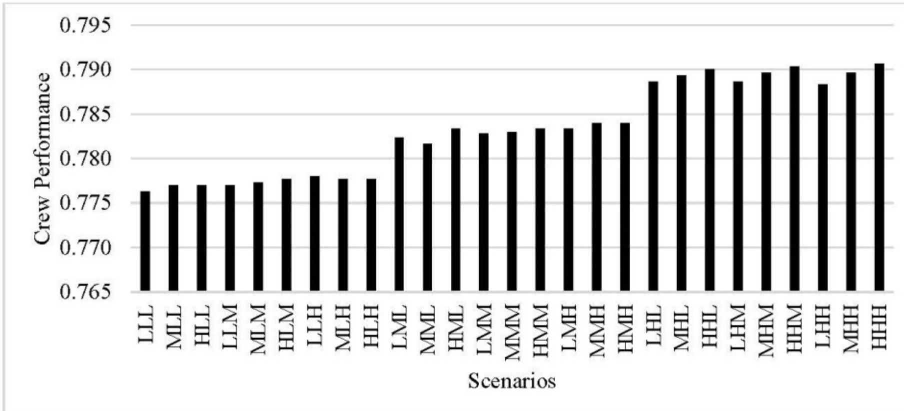

Fig. 6. Crew performance results based on initial high-motivation states of crews.

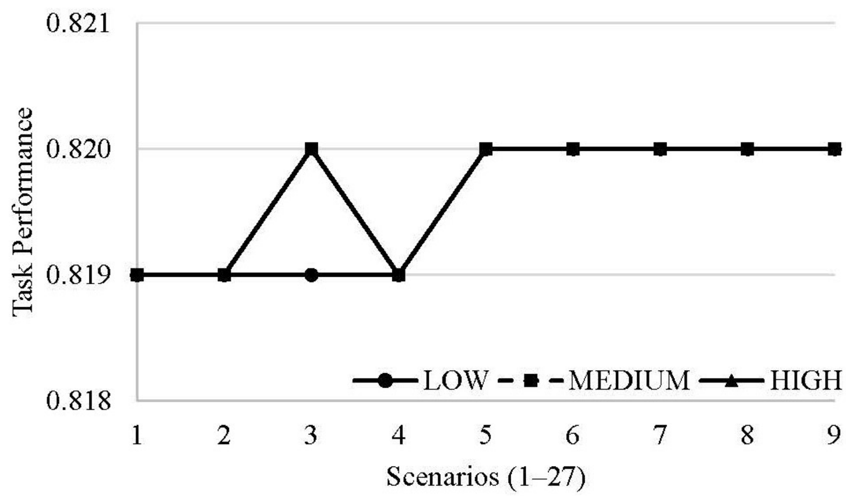

Fig. 7a. Task performance based on initial percentage of highly motivated crews.

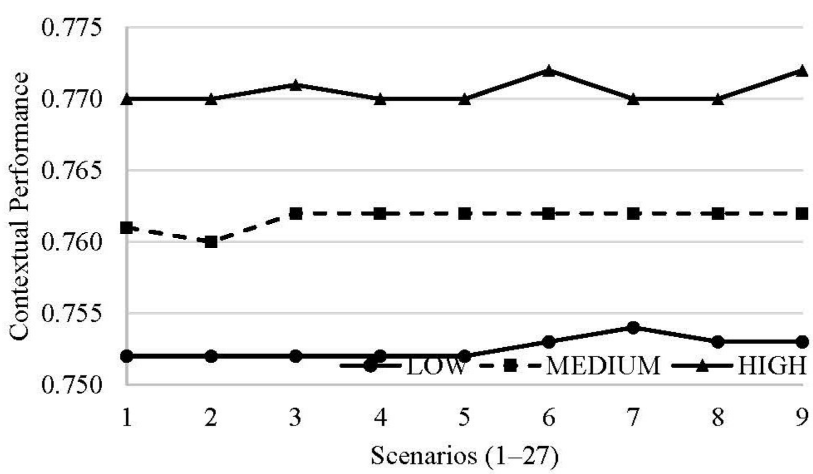

Fig. 7b. Contextual performance based on initial percentage of highly motivated crews.

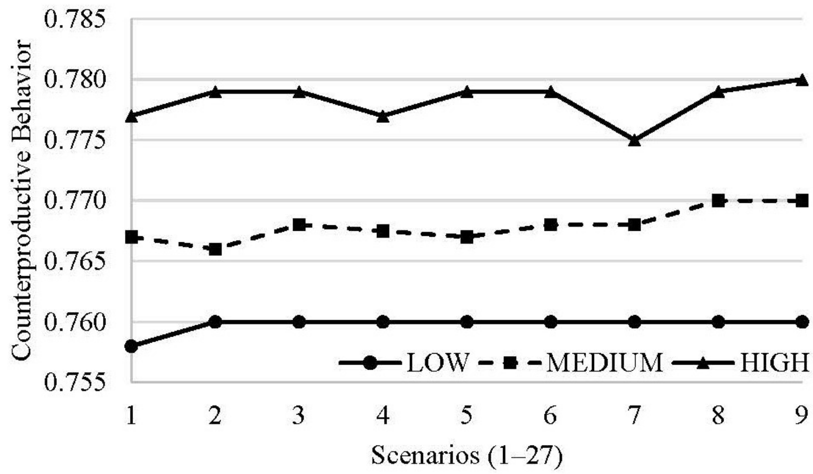

Fig. 7c. Counterproductive behavior based on initial percentage of highly motivated crews.

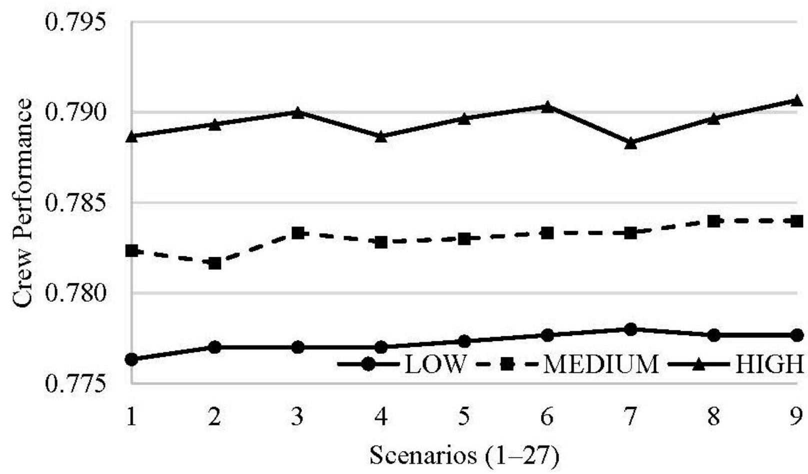

Fig. 7d. Crew performance based on initial percentage of highly motivated crews.

The results for task performance, contextual performance, and counterproductive behavior show that an increase in the initial motivation of crews produces an increase in the performance measures, especially for scenarios with a high motivation level, as shown in Figs. 7a, 7b, and 7c. Policy selection may therefore depend on which output measures are targeted for improvement and which policy provides the desired result using the least amount of resources.

Variations Based on Zealot Percentage

The results for this category show variations in performance measures (i.e., task performance, contextual performance, counterproductive behavior, and crew performance) based on zealot percentage. As shown in Fig. 8, variations in crew performance occurred mainly because of variations in the initial high-motivation states of crews. Zealot percentage can be understood as a parameter that enables better performance when it is combined with other parameters, such as contact rate. The effects of input parameter variations on task performance, contextual performance, counterproductive behavior, and crew performance are shown in Figs. 9a–9d, respectively. In these figures, the scenarios are grouped according to zealot percentage (i.e., low, medium, and high) while the values of contact rate and initial high-motivation state are varied.

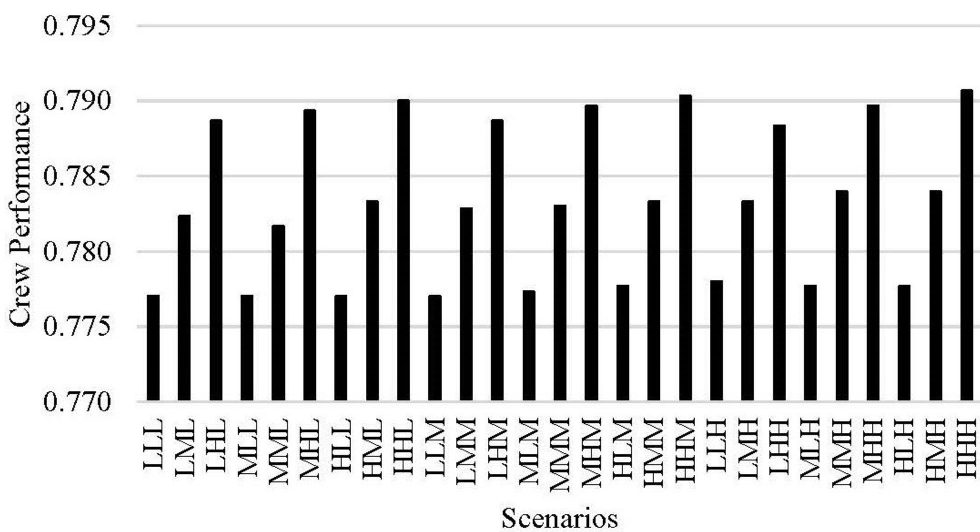

Fig. 8. Crew performance results based on zealot percentage.

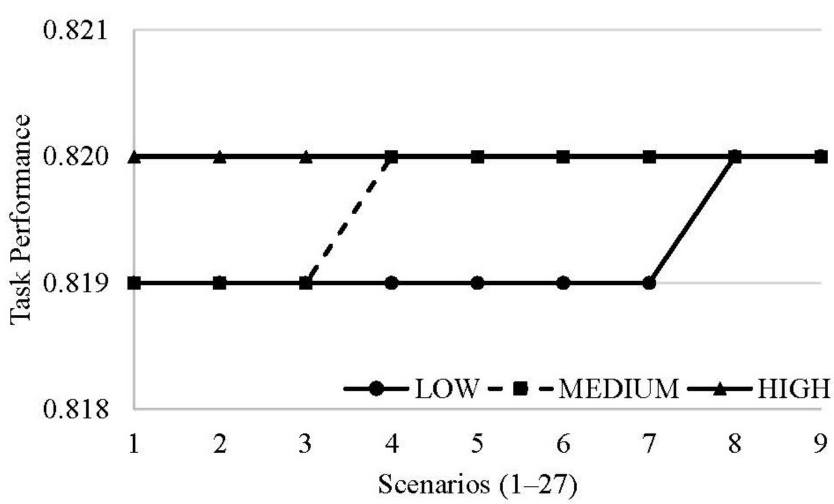

Fig. 9a. Task performance based on zealot percentage.

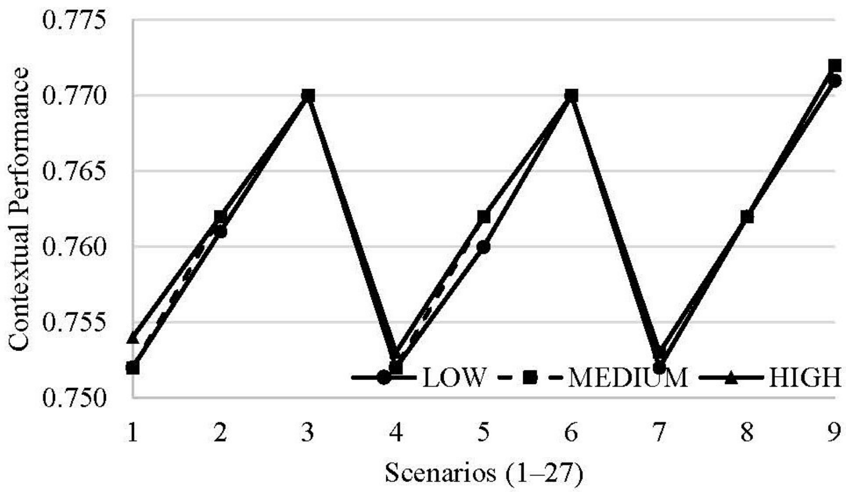

Fig. 9b. Contextual performance based on zealot percentage.

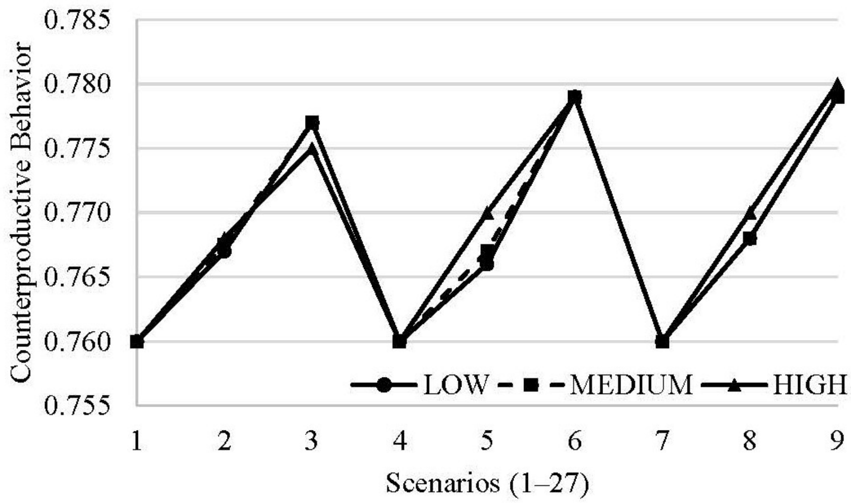

Fig. 9c. Counterproductive behavior based on zealot percentage.

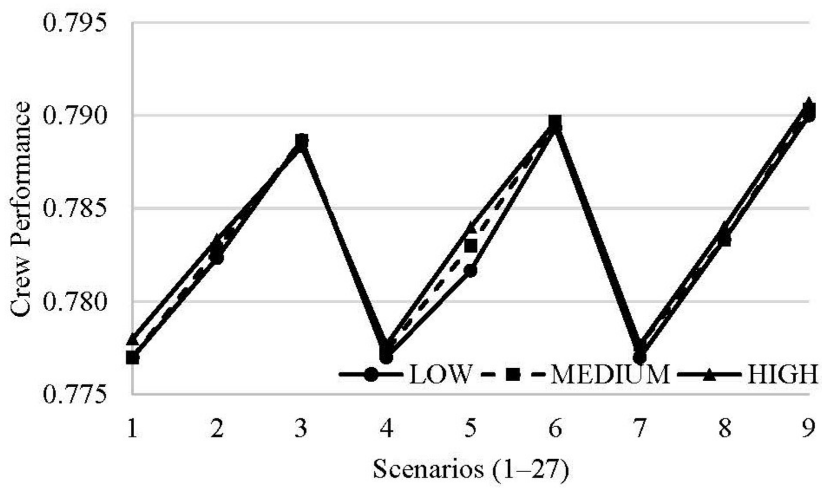

Fig. 9d. Crew performance based on zealot percentage.

An analysis of the effect of the initial high-motivation states of crews on contextual performance, counterproductive behavior, and overall crew performance shows there is a visible direct correlation between the initial motivation of crews and output measures, as shown in Figs. 9b, 9c, and 9d. Policy selection may therefore depend on which output measures are targeted for improvement and which policy provides the desired result using the least amount of resources.

Conclusion

In this paper, a methodology for the development of a fuzzy agent-based multi-criteria decision-making (FABM-MCDM) model is provided to address the need for decision support tools for use in construction, where problems exist in a dynamic environment with subjective uncertainties. The methodology is then elaborated using collected field data on construction crew motivation and performance. This paper demonstrates that the developed methodology is able to offer an applicable and representative approach to the overall process of decision-making in construction by integrating the capacity of FABM to address dynamic and subjective problems with MCDM's capacity to address multiple, sometimes conflicting expert opinions.

The contributions of this paper are twofold. First, it proposes a methodology to integrate FABM with MCDM in order to improve decision-making processes in construction. Second, it develops an FABM-MCDM model that helps construction practitioners adopt economically feasible strategies that improve the motivation and performance of construction crews. Furthermore, the methodology proposed in the study can be adapted to several construction problems to help decision makers prioritize and select from several strategies intended to improve different crew performance measures.

In the future, sensitivity analysis of the MCDM model should be performed to analyze which alternatives have the most influence on the decision-making process. When the AHP is used in decision-making, changes in an individual piece of data or a minor change in the weights of criteria should be studied, as these may have an influence on the ranking of inputs, and thereby on the strategies that are adopted at the company level. Furthermore, the applicability of the developed decision support model should be validated with data from other construction contexts (e.g., building construction) to ensure the model can be applied to the development of strategies for performance improvement in other sectors of the construction industry.

Data Availability Statement

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

Acknowledgments

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