Integrating Fuzzy Agent-Based Modeling and Multi-Criteria Decision-Making for Analyzing Construction Crew Performance

Nebiyu Siraj Kedir, S.M.ASCE, [1] Mohammad Raoufi, A.M.ASCE, [2] and Aminah Robinson Fayek, M.ASCE[3]

[1]PhD Student, Hole School of Construction Engineering, Department of Civil and Environmental Engineering, University of Alberta, 1-051 Markin/CNRL Natural Resources Engineering Facility, 9105 116 Street NW, Edmonton, Alberta, T6G 2W2, Canada; nebiyu@ualberta.ca

[2]Postdoctoral Fellow, Hole School of Construction Engineering, Department of Civil and Environmental Engineering, University of Alberta, 7-385 Donadeo Innovation Centre for Engineering, 9211 116 Street NW, Edmonton, Alberta, T6G 1H9, Canada; mraoufi@ualberta.ca

[3]Professor, Tier 1 Canada Research Chair in Fuzzy Hybrid Decision Support Systems for Construction, NSERC Industrial Research Chair in Strategic Construction Modeling and Delivery, Ledcor Professor in Construction Engineering, Hole School of Construction Engineering, Department of Civil and Environmental Engineering, University of Alberta, 7-287 Donadeo Innovation Centre for Engineering, 9211 116 Street NW, Edmonton, Alberta, T6G 1H9, Canada; aminah.robinson@ualberta.ca

ABSTRACT

Construction practitioners face considerable challenges when selecting economically feasible policies for maximizing crew motivation and performance. This paper proposes a methodology for integrating fuzzy agent-based modeling (FABM) with multi-criteria decision-making (MCDM) to develop a decision support system, which takes into account the complex relationships and social interactions between crews and crew members. This decision support system both accounts for the dynamic construction environment and captures the subjective and the objective factors that influence crew motivation and performance. The proposed methodology and decision support system are illustrated with a case study, which demonstrates that integration of FABM with MCDM serves to address subjective uncertainty when analyzing different policies related to crew motivation and performance. These findings can in turn help construction practitioners adopt economically feasible strategies to improve the motivation and performance of their crews, thus increasing their competitiveness in the market.

INTRODUCTION

Computer-aided simulation offers advantages in representing processes, interactions, and complex systems, which would have otherwise been impossible to capture. Agent-based modeling (ABM) is a technique that simulates interactions among a number of 'agents' (e.g., crew members, supervisors, departments) and their environment within a system.

Decision-making is a critical part of any construction-related process, such as budgeting, risk, bidding, productivity and performance, etc. The nature of many construction problems entails subjective uncertainties that cannot be addressed by ABM alone, nor by other available simulation techniques (Raoufi and Fayek 2018). In this regard, one of the major challenges lies in developing an approach that is able to support an MCDM model and that can integrate models to allow for interactive exchange of information, while accounting for complexities related to social behaviors (e.g., the effect of crew motivation on performance). On the basis of Zadeh's fuzzy set theory, Enrique Herrera-Viedma (2015) discussed fuzzy logic in MCDM, highlighting the significance of applying fuzzy logic concepts to help decision makers in situations that usually involve uncertain, imprecise, indefinite, and subjective data, which are onerous to represent and manage. FABM integrates fuzzy logic concepts with agent-based models and advances the application of ABM to address construction-related problems that are highly uncertain and subjective in nature.

In the literature, however, FABM has not yet been implemented as a decision support tool to help construction practitioners make critical decisions. MCDM models have yet to be integrated in FABM models to help advance FABM's application as a decision support system. The objective of this paper is to expand the current scope of FABM approaches through the integration of a decision support system. The challenge posed by such an integration lies in processing the FABM simulation results, which can differ depending on which combination of inputs is selected. The challenge becomes even more pronounced when studying the effects of variable input parameters. This research explores several scenarios involving iterative simulation of inputs using FABM and analyzes the results of each scenario to select the best solution for improving the performance levels of construction crews. The best solution would be an economically feasible scenario (in terms of cost) that takes into account the ramifications of a selected scenario on predefined criteria (e.g., schedule or safety). This paper begins by presenting a literature review of ABM and decision-making in construction. Studies related to the motivation and performance of crews are also briefly discussed. Next, a methodology to integrate FABM and MCDM into a fuzzy agent-based decision making (FABDM) model is proposed, and a case study is used to illustrate the model. Finally, conclusions and recommendations for future research are presented.

LITERATURE REVIEW

In recent years, there has been a growing amount of research exploring the integration of ABM with other approaches. Ben-Alon and Sacks (2017) proposed a combination of ABM and building information modeling (BIM) to better study production systems in construction. Cheng et al. (2018) integrated ABM and BIM to simulate accidents and improve evacuation planning. Xiao et al. (2018) used ABM to study the impact of water demand management on the behavior of different municipal and industrial users. Raoufi and Fayek (2018) developed a fuzzy agent-based model of construction crew motivation and performance, capable of handling subjective uncertainties.

Literature on decision-making has covered modeling approaches that can be used for a wide range of construction problems. ABM has been directly used for decision-making when the decision-making elements have been explicitly modeled. For example, in research by Bernhardt et al. (2007), when ABM was used in decision-making processes for infrastructure management, decisions were made with four aspects in mind: the agents within the system, their values and characteristics, the learning capacity of some (or all) agents, and their interactions with one another and the environment. ABM can also be used with other decision-making models to achieve better performance. Eid and El-Adaway (2018) presented a holistic, sustainable disaster recovery approach using a decision-making framework, which employs agent-based modeling. In addition, Marzouk and Mohamed (2018) integrated simulation results from ABM into an MCDM model to evaluate the evacuation performance of buildings under different scenarios, including minor design changes, in case of a fire emergency.

Decision-making models have allowed for integration of a decision-making tool with a range of techniques (e.g., fuzzy analytic hierarchy processes (FAHPs), genetic algorithms, ABM-MCDM, etc.). However, a modeling approach that can account for dynamic and complex social interactions within model elements (e.g., ABM) and that can incorporate subjective uncertainties explained in a fuzzy environment (e.g., fuzzy-agent based modeling) into an MCDM model is yet to be developed for use in the construction industry. Even with the vast application of ABM models in decision-making problems, there is a gap in the literature in terms of integrating FABM with

MCDM. Moreover, there is a need to be able to assess subjective uncertainties related to the social aspects of a construction problem and to analyze multiple scenarios for decision-making through predefined criteria and constraints. To address this gap, this paper covers the development of a methodology for integrating FABM and MCDM and illustrates the methodology using analysis of a real case scenario in the context of improving construction crew motivation and performance.

In addition to earlier theories of motivation that focused on 'expectancy theory' (e.g., Maloney, 1986), researchers such as Maloney and McFillen (1987) investigated motivational factors and the impact of motivation on construction crews as a compound effect of individual and work crew performance. Other researchers have tried to address (increasing) motivation in the construction setting by focusing on identifying motivational parameters for individuals (e.g., managers) (Shoura and Singh 1999) or by addressing groups of construction workers and looking for ways to increase their motivation (Cox et al. 2006). Raoufi and Fayek (2018) provided a comprehensive framework for identifying factors affecting construction crew motivation and performance that can address both individual and crew behavior.

MODEL DEVELOPMENT

This section presents a model to integrate FABM with MCDM, as elaborated in Figure 1. The FABDM model has two major components, which are highlighted in Figure 1. The first component (FABM) integrates fuzzy logic (in MATLAB) and ABM (in AnyLogic). The FABM simulates a combination of inputs to provide results of mean crew performance. Sensitivity analysis is then performed to systematically select and simulate only those main inputs that have a significant correlation with the output. The second component (MCDM) model receives the results of a parametric variation study that follows the FABM simulation model and uses the defined criteria and alternatives to provide MCDM model results (e.g., revealing the most feasible scenario among several scenarios). The two components are connected by the parametric variation study, which is performed by varying the inputs of the FABM simulation model within a predefined range.

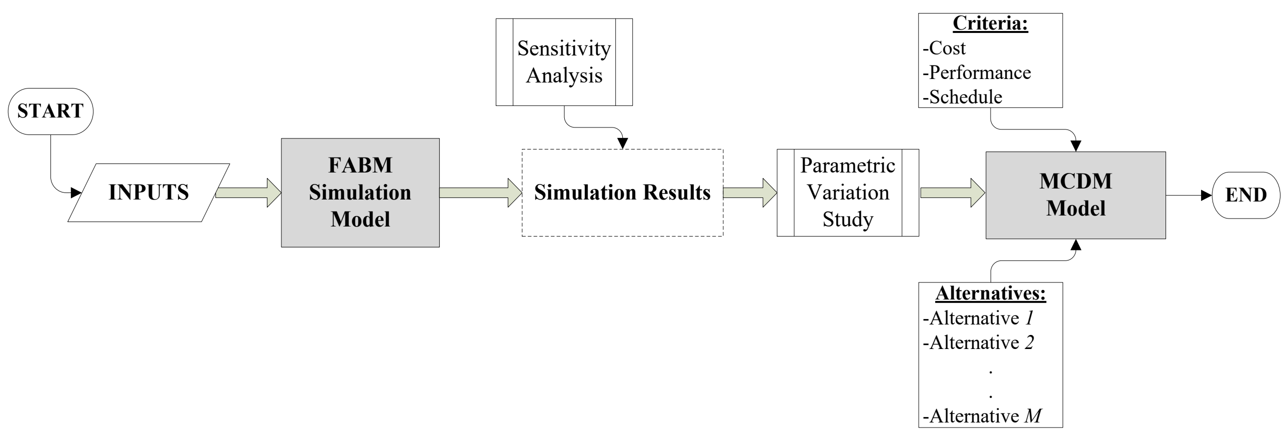


Figure 1. FABDM model.

Each range is used to simulate possible combinations of parameters in the FABM simulation model. An example of the results of the parametric study are several 'alternatives (Alt.)', each representing a set of inputs and an associated output value of cost, crew performance (Perf.), and schedule (Sch.). These outputs are considered the criteria.

This paper uses the FABM simulation model developed by Raoufi and Fayek (2018). The MCDM model is developed using the following steps. First, a criteria matrix is developed for each alternative based on the results of the parametric variation study. Equation 1 shows a criteria matrix for '*N*' number of criteria and '*M*' number of alternatives.

$$\textit{Criteria Matrix} = \begin{array}{cc} & \begin{array}{cccc} Alt.1 & Alt.2 & & Alt.M \end{array} \\ \begin{array}{r} Cost \\ Perf. \\ Sch. \\ \ldots \end{array} & \begin{bmatrix} C_{11} & C_{12} & . & C_{1M} \\ C_{21} & C_{22} & . & C_{2M} \\ . & . & . & . \\ C_{N1} & C_{N2} & . & C_{NM} \end{bmatrix} \end{array} \qquad (1)$$

Second, the criteria (in relation to their importance to the project) are scored by experts (e.g., construction practitioners), and a weight matrix is developed, as shown in Equation 2. Hence, for '*N*' number of criteria, there will be an *NxN* matrix of scores with scales ranging from 1 to 5, which are obtained by pairwise comparisons. The FAHP is used for defining the relative weights of each pair of criteria, as this procedure is easy to implement, and it allows for better consistency of results compared to direct weighting methods.

$$Weight\ Matrix = \begin{array}{cc} & \begin{array}{cccc} Cost & Perf. & Sch. & \ldots \end{array} \\ \begin{array}{r} Cost \\ Perf. \\ Sch. \\ \ldots \end{array} & \begin{bmatrix} 1 & W_{12} & . & W_{1N} \\ C_{21} & 1 & . & W_{2N} \\ . & . & 1 & . \\ W_{N1} & W_{N2} & . & W_{NN} \end{bmatrix} \end{array} \qquad (2)$$

Third, the resulting eigenvectors ($E_1, E_2 \ldots E_N$) are normalized for use as final weights for the corresponding values of '*Cost'*, '*Perf.*', '*Sch.*', and other criteria. This process is repeated for '*M*' number of alternatives. Hence, the alternative matrix is of the form shown in Equation 3.

$$\textit{Alternative Matrix} = \begin{array}{cc} & \begin{array}{cccc} Alt.1 & Alt.2 & & Alt.M \end{array} \\ \begin{array}{r} Cost \\ Perf. \\ Sch. \\ \ldots \end{array} & \begin{bmatrix} E_{11} & E_{12} & . & E_{1M} \\ E_{21} & E_{22} & . & E_{2M} \\ . & . & . & . \\ E_{N1} & E_{N2} & . & E_{NM} \end{bmatrix} \end{array} \qquad (3)$$

Finally, for each alternative, the aggregated score is computed based on the corresponding eigenvectors and criteria for each alternative, as shown in Equation 4. The output of the MCDM model will then be a ranking of all the alternatives proposed by construction practitioners.

$$Score\ (Alt_j) = \sum_{i=1}^{N} E_{ij} * C_{ij} \qquad j = 1, M \qquad (4)$$

CASE STUDY

In this case study, the fuzzy agent-based model of construction crew motivation and performance developed by Raoufi and Fayek (2018) has been integrated with MCDM to illustrate the proposed FABDM model. Crew motivation is defined based on four motivational concepts (i.e., efficacy, commitment/engagement, identification, and cohesion) and crew performance is determined by 55 key performance indicators (e.g., productivity) using the FABM framework [see Raoufi and Fayek (2018) for the list of motivational factors and crew performace metrics as well as the method of data collection and measurement]. The sensitivity analysis performed by Raoufi and Fayek (2018) produced five parameters (as shown in Table 1), which showed correlation with crew performance.

Table 1. Input parameters.

No.	Input	Range
1	Contact rate (no. per day per crew)	[0.5–3.0]
2	Susceptibility (probability that an interaction leads to a change in motivation)	[0.05–2.0]
3	Rate of non-interactive motivation variability (perf/day/crew)	[0–0.2]
4	Initial percentage of low motivated crews	[0–1.0]
5	Initial percentage of high motivated crews	[0–1.0]

For this study, input parameters that contribute to the randomness of the model (e.g., susceptibility and non-interactive motivation variability) have been kept constant. Furthermore, the percentage of low-motivated crews is not considered in the analysis. The corresponding intervals for the chosen input parameters were selected by splitting the range into three symmetrical ranges: *low* (L), *medium* (M), and *high* (H). A total of 9 alternatives have been investigated using a combination of these categories, as shown in Table 2. For all these alternatives, only simulations to obtain the results of crew performance were carried out. The associated normalized cost in each alternative is not actual cost, and it has been assumed for the following analysis and discussions. The related schedule was not considered due to the lack of data in this case study.

RESULTS AND DISCUSSION

The parameter variation experiment produced several combinations of 'contact rate' and 'initial motivation of crews'. The most frequent defuzzified crew performance (normalized values) for each alternative, as provided by FABM, are shown in Table 2.

The results indicate two significant findings. The first is that the increase in the initial motivation of crews could lead to higher crew performance. This trend can be seen in Figure 2, where crew performance improved consistently with the increase in motivation irrespective of lower or higher contact rates (Alt. 1–3, Alt. 4–6, and Alt. 7–9). The second observation is related to the importance of contact rate in improving overall crew performance. When initial crew motivation was low (Alt. 1, 4, and 7), the increase in contact rate did not affect crew performance. This finding is important, as it suggests that decision makers can avoid the extra cost of increasing crew motivation if they do not intend to have meetings and discussions (i.e., increasing the contact rate).

Table 2. Input and output of each alternative.

Alternative (Alt.)	Input		Output	
	Contact rate	Initial motivation of crews	Crew performance (Perf.) [0–1]	Cost [0–1]
1	L	L	0.785	0.598
2	L	M	0.790	0.667
3	L	H	0.796	0.736
4	M	L	0.784	0.649
5	M	M	0.791	0.718
6	M	H	0.798	0.787
7	H	L	0.785	0.699
8	H	M	0.792	0.768
9	H	H	0.798	0.837

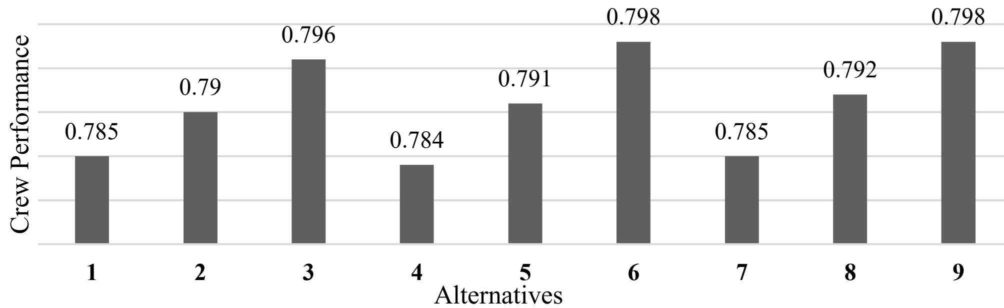
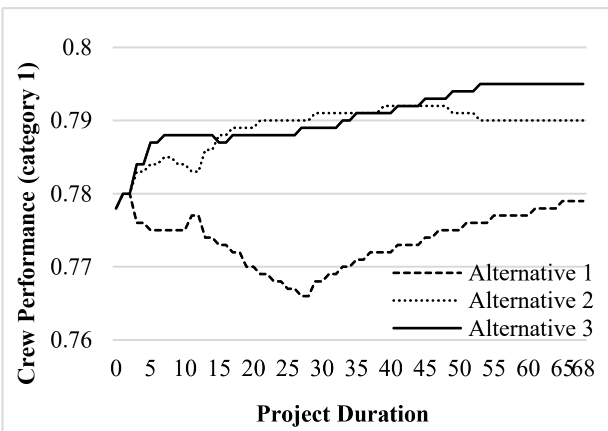
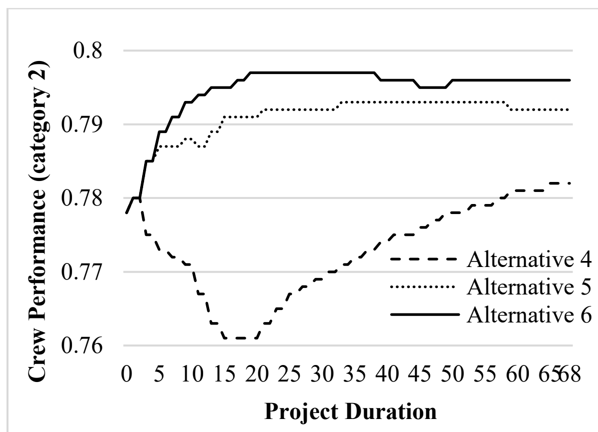


Figure 2. Mean performance of crews for each alternative.

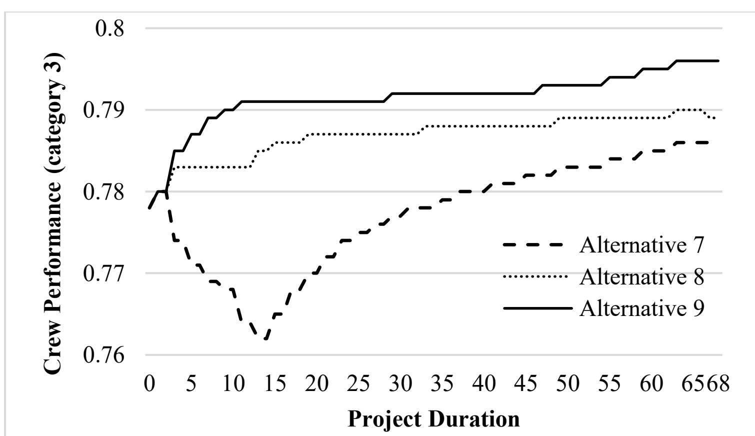
In order to better investigate the effect of contact rate on groups of alternatives, a set of simulations was carried out by categorizing the alternatives into three distinct groups. Each category includes the alternatives with the same contact rate (Category 1 = Alt 1–3; Category 2 = Alt 4–6; and Category 3 = Alt 7–9). The mean crew performance for each category was calculated from the start of the project over its 68-day duration and is shown below in Figures 3a to 3c.



a. Category 1



b. Category 2



c. Category 3

Figure 3. Crew performance over time for alternatives 1–9.

Irrespective of the contact rate, increasing crew motivation affects crew performance more during the earlier stages of the project. Thus, implementing a policy of increasing crew motivation in these stages can result in higher crew performance in later project stages. Similar experiments can be performed for other criteria. For example, the cost of implementing each alternative throughout the 68-day project duration can be assessed based on the costs incurred from providing incentives to increase crew motivation, the cost of meetings (including briefings by experts), and the benefits of improved crew performance. A sample of normalized cost values is provided in Table 2. Then, using Equations 1 through 3, a combination of several criteria (e.g., crew performance and cost) can be used to select the best alternative. The implications of this endeavor are that decision makers can investigate several policy alternatives for improving crew performance on a project, such as increasing the frequency of meetings held on site; increasing incentives, rewards, and recognitions; and facilitating positive interactions among crew members through safety meetings, daily meetings, or training.

CONCLUSIONS AND FUTURE WORK

Addressing factors that affect crew motivation and performance is paramount for success in the construction industry. In projects that involve labor, capturing complex relationships and social interactions between crews and crew members is critical in proposing a decision-making scheme that can improve crew performance with optimal cost. This paper has introduced an advancement in fuzzy agent-based modeling techniques to support decision-making and improve construction crew performance. The proposed methodology has been used to carry out a decision-making process, which is illustrated in a case study. Moreover, the results of the case study have shown that the proposed FABDM model can be implemented in construction research.

This paper makes two contributions. First, it proposes a methodology to integrate FABM and MCDM in order to improve decision-making processes in construction. Second, it uses the proposed methodology and develops an MCDM processor to analyze the implications of implementing different construction crew motivation and performance improvement policies. The FABM uses the motivation level that is calculated by accounting for both individual and crew level situations (which is lacking in previous studies). In addition, the integration of FABM with MCDM advances the literature by proposing a framework for decision-making that involves scenarios described by dynamic agent interaction. Future research will investigate additional inputs contributing to crew performance as well as more criteria to increase the applicability of the model within a broader context. In larger projects, and in more dynamic project situations, more factors (i.e., crew size, rate of project-level situation variability, zealot percentage, etc.) need to be investigated, as other factors may also contribute to overall crew performance. Finally, the implications of adopting crew performance improvement policies on project scheduling will also be investigated.

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