Framework for Simulating Crew Motivation Impact on Productivity – A Hybrid Modeling Approach

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ABSTRACT

Previous studies have identified motivation as one of the most important factors affecting the efficiency of labor utilization in construction processes. However, there is a lack of research on simulating the impact of motivation on labor productivity to track and devise productivity improvement strategies. Fuzzy system dynamics (FSD) has been used to model labor productivity because it captures subjective uncertainties and the dynamism of construction systems. However, FSD fails to capture complexity arising from individual components (e.g., crew members) that lead to emerging behaviors in crew motivation modeling. The main contributions of this paper are: (1) proposing a framework for combining FSD and fuzzy agent-based modeling, leading to a more comprehensive method for studying the impact of crew motivation on productivity; and (2) facilitating identification of more effective productivity improvement strategies by allowing construction stakeholders to track the dynamic relationships between motivation and labor productivity.

INTRODUCTION

Productivity is a key indicator for project success in the construction industry. The term *productivity* denotes a relationship between project output and associated inputs (e.g., goods and services) (Yi and Chan 2014). Labor is the primary resource in construction, so measuring labor productivity is crucial to determining project performance. Labor productivity can be defined as the ratio of completed work (output) to work effort, often measured in labor hours (Zhao and Dungan 2019).

Studies of productivity prediction have focused on capturing construction processes by simulating the outcome of certain combinations of inputs. While some modeling approaches address the challenge of capturing the dynamism that exists in construction processes at different levels (i.e., activity, project, or higher), using a single modeling technique fails to properly represent the inputs and processes of construction projects. Furthermore, the productivity problem entails modeling subjective variables that affect the productivity measure (e.g., crew behavioral skills such as cooperation and teamwork). These variables interact with other input variables of emerging behaviors (e.g., crew motivation, job satisfaction, congestion). Therefore, a need exists to enhance modeling techniques that address key challenges in construction (e.g., ensuring higher crew motivation or productivity). Combining modeling approaches can produce a more powerful hybrid model capable of capturing the effects of multiple system variables. To capture construction processes and predict labor productivity, a hybrid model also exploits the best features of the individual modeling techniques.

This paper proposes a framework combining the strengths of fuzzy system dynamics (FSD) and fuzzy agent-based modeling (FABM) techniques, which enables a more comprehensive modeling approach for construction labor productivity by capturing subjectivity and dynamism in system variables and assessing their relationships. The framework can therefore give construction practitioners a better understanding of the dynamic interaction between labor productivity and variables of emerging nature (e.g., crew motivation, job satisfaction, congestion).

This paper comprises three sections: a literature review section discussing construction labor productivity definitions, related studies, and modeling techniques for capturing productivity; a methodology section detailing the proposed FSD-FABM framework; and finally, conclusions and future studies.

LITERATURE REVIEW

Construction Labor Productivity Modeling Approaches. Several definitions of productivity exist in the literature. Zhao and Dungan (2019) used the ratio of output (measure of completed work) to input (work effort) in their analysis for lost labor productivity. This definition aligns with other labor productivity studies (Johari and Jha 2020; Yi and Chan 2014). Productivity can also be defined at different levels of abstraction, as a ratio of output to the incurred cost of input (Ghodrati et al. 2018). In this regard, productivity can be captured at the micro level by considering factors at the crew, activity, and/or project levels. One can also consider macro-level factors (i.e., organizational-, provincial-, national-, and global-level factors) that may have a direct or indirect influence on overall productivity (CII 2006).

The study of productivity in construction is not new. Several works have tried to address different problems in construction. These can be grouped as studies focused on: identifying factors that affect productivity using different methods (Gerami Seresht and Fayek 2020; Liao et al. 2011); benchmarking and analysis of productivity trends (Zhang et al. 2017); or productivity prediction and improvement. Despite the vast literature, current approaches to productivity prediction and modelling are mostly static in nature (Gerami Seresht and Fayek 2018). These include artificial neural network models (Heravi and Eslamdoost 2015), statistical models (Gurmu and Ongkowijoyo 2020), and models based on fuzzy inference systems (Tsehayae 2016) or discrete event simulation (Khanh and Kim 2020). However, the nature of the construction productivity problem is highly dynamic, as model components change with time and continuously interact (Gerami Seresht and Fayek 2020). Thus, other modelling approaches, as discussed in this paper, have been proposed to account for different aspects of dynamism in construction.

When studying labor productivity from the holistic perspective of factor identification, predictive model development, and improvement strategy formulation, the modelling approaches used should have the capability to capture the different dynamisms exhibited by the problem. Such models would allow stakeholders to assess productivity trends during construction, study interactions between model elements that influence the productivity measure, and make informed decisions while suggesting productivity improvement strategies. Thus, it is challenging to capture the interdependencies between micro- and macro-level factors while also capturing the unique nature of construction systems across different projects. For example, crew motivation, a factor significantly overlooked in construction research (Raoufi and Fayek 2020), has an impact across multiple micro (crew, activity, and project) and macro (organizational) levels. Furthermore, the nature of the work, worker privacy, and difficulties in collecting data also make labor productivity estimation difficult (Kisi et al. 2018). The data needed for productivity estimation also depend on the level of detail researchers need to capture while considering factors related to productivity modeling. Thus, advanced modeling approaches are needed that are capable of representing the dynamism that arises from interactions between micro- or macro-level factors.

Agent Based Modeling (ABM). The literature points to more focus on ABM application in recent years. These include works in scheduling and planning (Jabri and Zayed 2017), decision making (Eid and El-Adaway 2018), and safety (Palaniappan et al. 2007). Raoufi and Fayek (2018) studied the effect of motivation on construction crew performance and later incorporated Monte Carlo simulation to account for random uncertainties (Raoufi and Fayek 2020). Kedir et al. (2020) integrated multi-criteria decision making and FABM to propose construction performance improvement strategies.

Although ABM is able to capture interactions leading to emerging behaviors, using modeling approaches such as system dynamics (SD) to capture other facets of the dynamism of construction significantly enhances the advantages of using ABM to model construction problems. For models that need to be abstracted at a higher scale (e.g., productivity modeling at different levels) and models usually described with cause-and-effect relationships, using SD greatly simplifies the modeling challenge.

System Dynamics (SD). SD is a top-down approach involving dynamism through interactions with multiple feedback processes and dependencies, usually exhibiting varying properties in relation to time (Nasirzadeh et al. 2008). SD is therefore appropriate for construction problems, because it can address the complexity that arises with abstracting construction systems.

Several researchers have used SD to model construction systems and processes (Siraj and Fayek 2020; Gerami Seresht and Fayek 2018; Rashedi and Hegazy 2015). However, these modeling techniques cannot capture problems related to dynamism arising from interactions that lead to emerging behaviors (e.g., crew motivation, congestion, job satisfaction). SD's object-oriented approach means model components will always be bound by a set of rules, which can sometimes be difficult to delineate in problems related to social behaviors.

ABM is suited to modelling dynamic systems that contain active objects (e.g., individuals) of differing natures whose behavior gives rise to the overall behavior of the system (Raoufi and

Fayek 2018). SD is suited for dynamic systems that include interdependent components and multiple feedback processes (Siraj and Fayek 2020). By combining the advantages of these techniques, a more comprehensive set of problems in construction systems may be addressed. However, the individual or combined techniques of SD and ABM cannot address the subjective uncertainties associated with system variables or the vague interdependencies between variables (Nasirzadeh et al. 2008). Thus, modeling techniques are needed that combine the strength of these individual methods while also capturing vague interdependencies and the subjectivity arising from linguistic approximation and measurement imprecision.

Hybrid Fuzzy System Dynamics–Fuzzy Agent Based-Modeling (FSD-FABM). Fuzzy logic (Zadeh 1965) is able to handle natural language and approximate reasoning to help users make conclusions from subjective data and incomplete information. In the construction sector, there exists a wide spectrum of fuzzy hybrid-modeling approaches with varying applications (Raoufi et al. 2016). In viewing productivity as a complex system whose inputs continuously interact both with themselves and the environment, an efficient abstraction requires a simulation approach using SD, which considers productivity as a system whose behaviour is captured over time, and ABM, whose individual components interact with each other and the environment according to a given set of rules.

Swinerd and McNaught (2012) summarized the existing literature to propose three basic types of approaches in hybrid SD-ABM simulation, namely integrated, interfaced, and sequential hybrid designs. In integrated modeling, SD and ABM are connected through a feedback mechanism, allowing for a continuous interchange of information. In interfaced modeling, SD and ABM run individually, and the final output has components from both techniques. In sequential modeling, either SD or ABM runs first, and the information is fed into the subsequent step. All three approaches have advantages and disadvantages; so, selection criteria clearly depend on problem characteristics and model requirements (e.g., data availability, following a policy, spatiality, learning members, complex interactions) (Nasirzadeh et al. 2018). For example, a sequential modeling approach using SD and ABM may be more computationally appealing than integrated modeling, as the two techniques can be treated separately. However, a sequential modeling approach might not provide a holistic solution, because it cannot facilitate a continuous exchange of information between SD and ABM components. With the advantages gained from processing variables with subjective uncertainties, hybrid SD-ABM modeling capitalizes on the advantages of the individual modeling techniques.

METHODOLOGY

This section proposes a framework for productivity modeling by combining FSD and FABM. To provide input data for the modeling phase, the factor identification process is performed. In this process, several factors that affect productivity in a construction project are identified through literature review and content analysis. The listed factors are then verified and ranked using expert inputs. Next, surveys and interviews are used to identify the most important factors affecting labor productivity. Feature selection and dimensionality reduction are performed on the data collected from the surveys and interviews. The end result of this factor identification step is a list of the most important factors that impact construction labor productivity, categorized under predetermined hierarchies (i.e., crew, activity, and project levels).

This framework consists of the qualitative modeling phase and the quantitative modeling phase, and focuses on the steps that follow the factor identification stage. In the qualitative modeling phase, the results from the factor identification process are used to identify variable types (i.e., FSD and FABM variables) and identify qualitative relationships between variables at different levels of aggregation. In the quantitative modeling phase, input variable relationships and model behaviors are defined quantitatively to perform FSD-FABM hybridization.

Qualitative Modeling. The qualitative modeling phase focuses on input data obtained from the factor identification process, as shown in Figure 1. The set of factors resulting from the factor identification step are categorized into FSD and FABM variables. This facilitates a more effective modeling approach by identifying which sets of variables are best fit within the two modeling paradigms, FSD or FABM. This is done by answering the two key questions: "What are the agents in the FABM?" and "What are the system variables in FSD?" In this step, variables better represented by cause-and-effect relationships and feedback processes are part of the FSD model (i.e., variables related to project duration, project cost, productivity measure, rework). On the other hand, construction workers and the crews they are part of are identified as individual entities in the FABM environment.

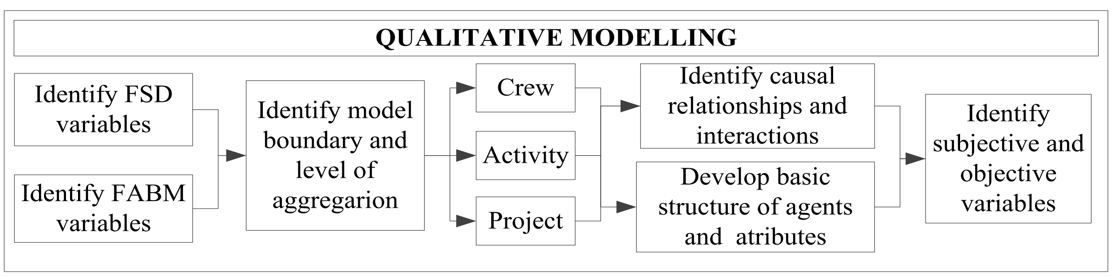

Figure 1. Qualitative modeling phase.

Furthermore, variables that are part of complex adaptive systems exhibiting emerging behavior (i.e., crew motivation, job satisfaction); and variables representing spatial properties (i.e., congestion) are also part of the FABM. The qualitative modeling step is used to abstract the model's input and output parameters. After FSD and FABM variables are identified, model boundaries, such as endogenous and exogenous variables, are determined. For example, government policies, whose output can affect some system variables, are treated as exogenous variables.

Following variable categorization, the next step focuses on the FSD part of the model. In this step, causal relationships are identified, and stock and flow diagrams are constructed. Causal relationships can be identified in different ways for two types of variables: (1) variables whose relationships can be identified using predefined mathematical relationships (e.g., crew size as a function of absent workers) or using statistical analysis (e.g., regression analysis performed to identify variables' positive or negative relationship with the productivity measure); (2) variables whose relationships cannot be clearly defined using mathematical approaches and are instead mapped using existing understanding about real-world systems through literature review studies and expert knowledge (i.e., using analysis of interviews, questionnaire, and surveys). The interdependencies are mapped, then causal loop diagrams are developed by establishing causality through the use of arrows, assigning polarity to the arrows, indicating delays in the causal links, naming the loops, and linking the feedback loops with the model's stocks and flows. Similarly, the FABM part of the model is defined by developing basic structure of agents, agent attributes, and agent behaviors. This enables identification of governing interactions between agents using fuzzy rule base systems (FRBS), either through expert-based or data-driven techniques.

Quantitative Modeling. The quantitative modeling phase of the proposed framework has four platforms, as shown in Figure 2: fuzzy platform, SD, ABM, and FSD-FABM. Variables obtained from the qualitative modeling stage are used to quantitatively define relationships between factors affecting labor productivity and the labor productivity measure. Hence, causal relationships for the FSD environment and governing interactions among agents for the FABM environment are quantitatively defined. There are two types of variables under consideration: objective and subjective variables. Objective variables are further divided into deterministic and probabilistic variables. Deterministic variables are represented by crisp numbers, and the probabilistic variables are represented by probabilistic distributions.

The fuzzy platform deals with the input and output data related to fuzzy numbers and subjective variables. Variables related to measurement uncertainties are represented through fuzzy numbers. Subjective variables are best defined by fuzzy sets, which are represented using linguistic terms to signify a given concept (e.g., "very low" or "high"). Membership functions, which assume values between 0 and 1, are used to characterize the linguistic terms used to describe the subjective variables. Fuzzy rule base systems and fuzzy arithmetic are used to capture the relationships between multiple variables in the SD and/or ABM platform.

In the SD platform, causal relationships and stock and flow relationships are quantitatively defined. In the ABM platform, governing interactions between agents and agent attributes are quantitatively defined. For deterministic variables with defined mathematical relationships, mathematical equations are used. Furthermore, fuzzy arithmetic is utilized from the fuzzy platform to carry out algebraic operations. This is performed whenever a fuzzy variable is involved in a mathematical equation that is needed to determine an intermediate or final output, such as causal relationships from the SD platform and agent behavioral rules from the ABM platform. For variables whose relationships are explained using mathematical equations, fuzzy arithmetic is performed using either of the underlying concepts of alpha-cut method or extension principles. Field data or expert inputs can also be used to define relationships in the SD or ABM platform if the use of mathematical relationships is not possible.

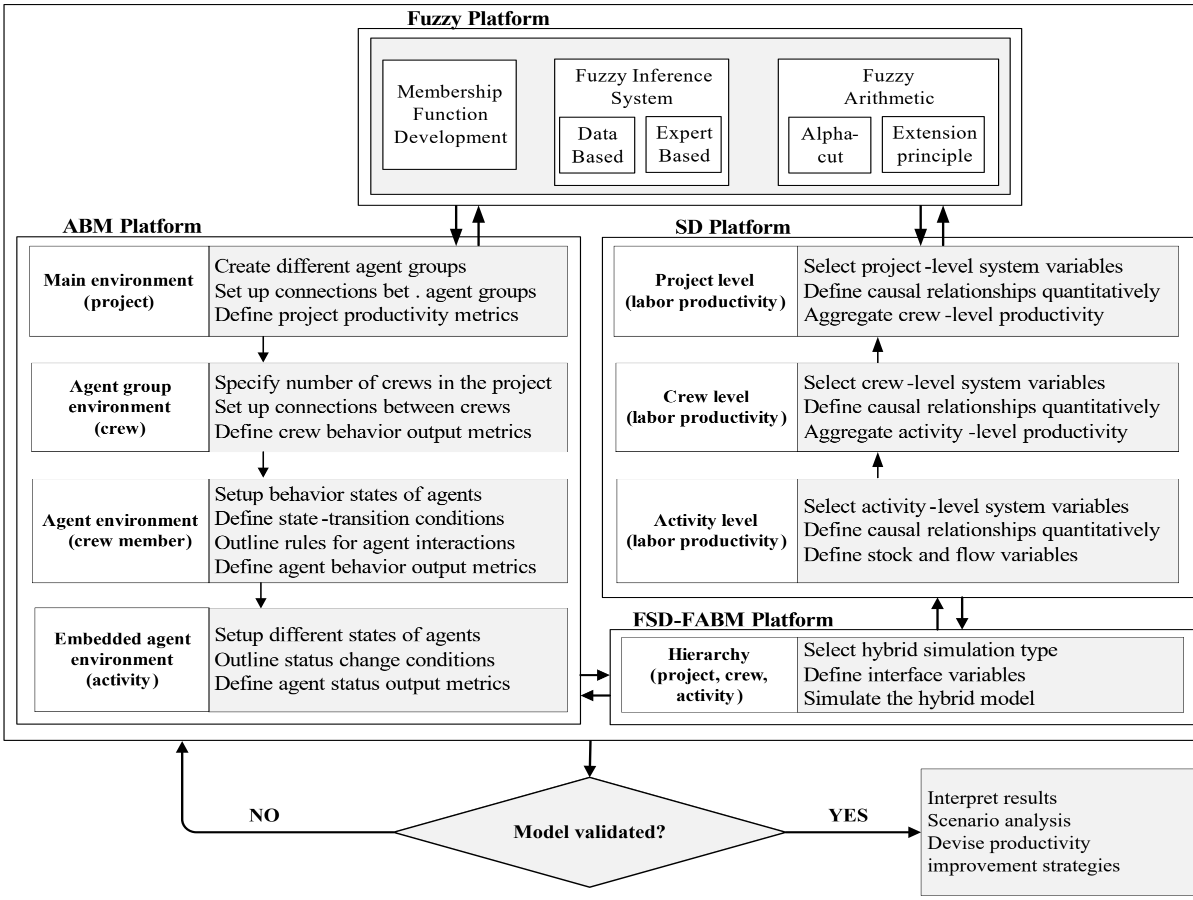

Figure 2. Model hybridization.

The FSD-FABM platform combines FSD and FABM using the three applicable hybrid SD-ABM design classes: interfaced class, sequential class, and integrated class (Swinerd and McNaught 2012). The first criterion to be checked in selecting the hybrid modeling type for this FSD-FABM platform is if an exchange of information occurs between FSD and FABM. If there is no interaction between the SD and ABM platforms, but individual results need to be combined, interfaced class modeling approach is used. If the information exchange is only one-way, that is from SD to ABM or vice versa, sequential class modeling type is used.

The proposed framework focuses on integrated class approach, because the nature of labor productivity modeling involves several interactions between variables in the FSD and FABM components. Consequently, interface variables are chosen that are used to exchange data between FSD and FABM. Figure 3 shows an example of an interface variable (crew motivation). Details for using FABM to model crew motivation can be found in Raoufi and Fayek (2018). The value of crew motivation is used as a dynamic variable in the SD platform to obtain labor productivity per time-step. This labor productivity value is in turn used in FABM to compute the motivation levels of the next time-step. Other variables can also be selected as interface variables.

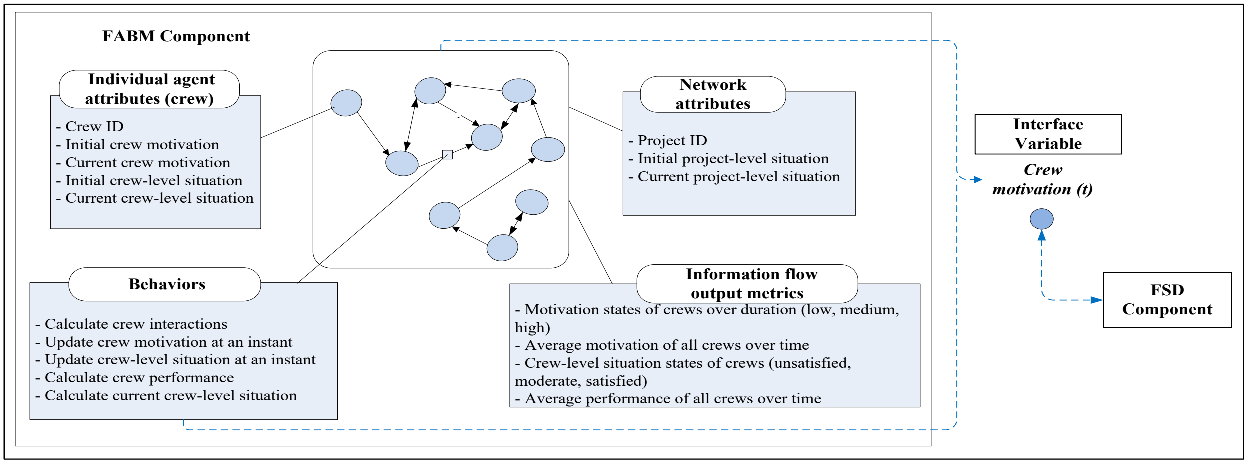

Figure 3. Crew motivation as interface variable.

Calculations for the level of crew motivation are shown in Eq. (1) below (Raoufi and Fayek 2018). This definition of crew motivation is used as part of the system model in the calculation of productivity.

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

where t and $t - 1$ are used to denote current and previous time steps, respectively, for crew indices i and j. CM refers to crew motivation, Z refers to the crew agent that changes crew motivation behavior based on the motivation change of other agents, S refers to the probability that an interaction between the agents leads to a change in motivation level, and N refers to the number of crew agents interacting with crew i.

Finally, the results of the integrated FSD-FABM approach are then validated to perform result interpretation. Productivity improvement strategies can also be devised to improve labor productivity measure by improving one or a combination of input variables.

CONCLUSIONS AND FUTURE WORK

In this paper, a novel framework combining FSD and FABM is proposed, to address a research gap. The proposed framework takes advantage of key features of both modeling techniques and presents a novel approach for processing input data and selecting the most important variables (i.e., factors affecting productivity) to be used at different hierarchies (activity, crew, and project levels). This hybrid FSD-FABM modeling approach is able to capture the dynamism of construction processes while exploiting FABM's ability to capture emerging behaviors (e.g., crew motivation levels), allowing stakeholders to better capture construction processes. In the future, the proposed framework will be used to model a real-life construction project. This case study will be used to validate and provide a walkthrough of the methodology. Furthermore, additional interface variables will be investigated (e.g., congestion, crew spatial movements) to create a more holistic approach for modeling construction labor productivity and devising improvement strategies.

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