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APPLICATION OF FUZZY LOGIC INTEGRATED WITH SYSTEM DYNAMICS IN CONSTRUCTION MODELING

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Abstract: Construction projects are complex systems and their behaviors are extremely dynamic throughout their life cycles. This complexity and dynamism makes them perfect candidates for system dynamics modeling for management purposes. However, ill-known variables, a lack of historical data, uncertainties, subjectivity, and the use of linguistic terms in defining construction variables all complicate the application of system dynamics in construction. Fuzzy logic is an artificial intelligence technique that has the ability to model vague, incomplete, linguistically-expressed, and subjective data in a precise way. Since the quality of system dynamics modeling relies significantly on the accuracy of the data, integrating system dynamics with fuzzy logic makes for a powerful construction project simulation tool. Integrated fuzzy system dynamics models can effectively capture the dynamic characteristics of construction projects and simulate them more precisely by using fuzzy logic to capture subjective and linguistically-expressed information. In this paper, we illustrate how fuzzy logic and system dynamics can be integrated for use in construction project simulation. Moreover, we present a review of potential applications of integrated fuzzy system dynamics models in construction. Finally, we compare the performance of system dynamics with integrated fuzzy system dynamics for a construction-related problem adopted from the literature, and discuss how integrating fuzzy logic can enhance system dynamics capabilities for construction modeling.

1 INTRODUCTION

Construction projects always involve uncertainties and complexity, which makes construction management a critical task in the industry. During the last century, several managerial tools and approaches have been developed in construction or adopted to this area from other industries to help managers plan and control their projects effectively. Simulation models—one such managerial tool—help managers to observe the conditions and performance of their projects prior to the execution phase. Simulation models are powerful planning tools that can help managers to identify the key factors affecting their projects in order to proactively manage problems before they arise. Among simulation models, the system dynamics (SD) approach, developed by Forrester (1961) for the analysis of complex industrial systems, has unique characteristics that make it well-suited to construction planning purposes. SD models can effectively capture the dynamism of the systems where the state of the system can continuously change. This characteristic of SD models suits construction modeling, since construction projects are always changing under the effects of various factors. Moreover, SD models describe interrelationships between the elements of the systems with cause and effect loops (Ford 1995), which also makes these models an ideal choice for the construction context, where there are often numerous interactions between elements in a project.

Previous research by Lyneis and Ford (2007) shows SD models have been successfully applied in project management. Sterman (1992) asserts that project management is one of the most poorly performing areas of management and SD modeling can help the managers of large scale engineering projects. There are several applications of SD models in construction project management by researchers as well. Mowdesley and Al-Jibouri (2009) developed a SD model for construction productivity at the project level, Park (2005) used SD models for resource management, and Lee et al. (2006) used SD modeling for dynamic planning in construction. However, despite the extensive use of SD models in construction project management, SD models are limited in their ability to capture qualitative and linguistic variables in simulation (Levary 1990). In order to address this deficiency, Levary (1990) introduced the use of fuzzy logic in SD modeling.

Fuzzy logic, developed by Zadeh (1965), gives the human cognitive process mathematical precision. Fuzzy logic is a tool for modeling subjective and imprecise variables or variables that are expressed in linguistic terms. Fuzzy logic is a powerful modeling technique well suited to construction, since construction projects are unique in terms of their characteristics, and lack of historical data is one of the biggest challenges that researchers and practitioners face when modeling construction problems. Fuzzy logic has been implemented to solve construction-related problems successfully many times before (see Chan et al. 2009 for a review).

In this paper, we illustrate how fuzzy logic and SD can be integrated for use in construction project simulation. Moreover, we present a review of potential applications of integrated fuzzy SD models in construction. Finally, we compare the performance of SD with integrated fuzzy SD for a construction-related problem adopted from the literature, and discuss how integrating fuzzy logic can enhance SD capabilities for construction modeling. For the remainder of this paper, system dynamics (SD) integrated with fuzzy logic will be referred to as fuzzy system dynamics (FSD).

This paper is organized as follows; first a brief literature review of FSD is presented, followed by applications of SD and FSD models in construction. Secondly, different methods of integrating SD and fuzzy logic are discussed. Then, a comparison is made between SD and FSD models in a construction-related problem, followed by a discussion of how the integration of SD with fuzzy logic can enhance the capabilities of SD in construction modeling. Finally, future extension to the current research is discussed.

2 LITERATURE REVIEW

2.1 Fuzzy System Dynamics

Levary (1990) introduced the idea of integrating SD with fuzzy logic in order to enhance the capability of SD models for simulation of real-life systems. Common approaches of SD modeling use crisp numbers to define the variables, and the relationships between the variables are defined by either mathematical or table functions. However, there are subjective variables in real-life systems which are better expressed in linguistic terms than crisp numeric values (e.g., good weather). Therefore, as Levary (1990) discussed, integrating SD and fuzzy logic solves a major problem associated with quantitative variables modeling. Integration of these two methods has two requirements: (1) defining subjective variables by fuzzy membership functions and (2) defining the interrelationships between the fuzzy variables either by using fuzzy arithmetic in mathematical equations or fuzzy rule-based systems.

Ghazanfari et al. (2003) presented a review of the literature of different approaches for integrating fuzzy logic and SD modeling. Polat and Bozdag (2001), Nasirzadeh et al. (2008), and Khanzadi et al. (2012) provide some examples of applications of FSD models in different disciplines. Tessem and Davidsen

(1994) developed a simple FSD model with three fuzzy variables for population estimation using fuzzy arithmetic in mathematical equations. They pointed out that the use of fuzzy arithmetic in their system caused fast growth of the support of the fuzzy output (i.e., population) and the output of the system contained too much uncertainty. Sabounchi et al. (2011) developed a FSD model for product diffusion based on customer-based propagation of product (i.e., word of mouth) using two fuzzy variables in a SD molecule. They replaced the equation that contained fuzzy variables with a fuzzy rule-based system to avoid the growth of the support of fuzzy outputs. In the FSD model proposed by Sabounchi et al. (2011), in each time step the output of the fuzzy rule-based system is defuzzified and used as a crisp input in other equations.

2.2 System Dynamics in Construction

Lyneis and Ford (2007) conducted an extensive review of applications of SD models in all disciplines of project management (software development projects, manufacturing, etc.). There have also been some recent applications of SD models for project management specifically in construction. Mowdesley and Al-Jibouri (2009) developed a SD model for simulation of construction productivity at the project level. Mowdesley and Al-Jibouri (2009) refer to the large number of the factors that affect productivity in construction projects and the complex relationships between the variables and conclude that SD models are good candidates for modeling productivity. Nasirzadeh and Nojedehi (2013) developed a SD model for the simulation of labour productivity in construction projects. Their model was composed of four sub-models, each with different levels of the factors affecting labour productivity. Nasirzadeh and Nojedehi (2013) assert that the factors that affect labour productivity are rarely independent from each other and that therefore, SD models are the best options for the simulation of labour productivity. Park (2005) referred to the dynamism of construction projects and proposed a SD model for resource management. The dynamic simulation of construction projects Park (2005) proposed minimizes the idle time of resources and decreases project costs. Despite the widespread use of SD models in construction contexts, some recent studies (e.g., Khanzadi et al. 2012) refer to some deficits of this modeling tool for construction modeling. Khanzadi et al. (2012) assert that because of the subjectivity of some variables in construction, integrating SD models with fuzzy logic can improve this modeling tool for the construction domain.

2.3 Fuzzy System Dynamics in Construction

Most applications of FSD models have been developed in business and the social sciences until recently. The FSD model for construction risk assessment proposed by Nasirzadeh et al. (2008) is one of the first applications of FSD models in construction. Nasirzadeh et al. (2008) adapted the SD model for risk management developed by Ford and Sterman (1998) for production projects to suit the construction context. They proposed the use of fuzzy numbers to represent the risks' magnitudes and possibilities due to subjectivity and lack of historical data for probabilistic representation of construction risks. Fuzzy arithmetic, based on alpha-cuts (α-cuts) and interval analysis, was used to calculate the risk consequences. In the application presented by Nasirzadeh et al. (2008) there are only five major risks affecting the project, and the model has not been tested for more risk factors.

Khanzadi et al. (2012) proposed a FSD model to estimate the concession period of BOT projects. In their model, the concession period is estimated based on the magnitude of the project's risks. The relationships between the fuzzy variables are defined using fuzzy rule-based systems and the results are defuzzified for further calculations. Nasirzadeh et al. (2013) developed a FSD model for quality management in construction projects. In their model, the variables affecting the quality management process are estimated as fuzzy numbers and entered as fuzzy inputs to a FSD model which uses mathematical equations and fuzzy arithmetic. Nasirzadeh et al. (2013) use fuzzy arithmetic based on α-cuts and interval calculations; however, they do not discuss their system's problem of growing support in fuzzy results as previously pointed out by Tessem and Davidsen (1994).

3 METHODS OF INTEGRATION OF FUZZY LOGIC WITH SYSTEM DYNAMICS

As previously discussed in Section 2.1, integration of the SD modeling approach with fuzzy logic enhances the performance of SD for modeling real-life systems. Fuzzy logic can contribute SD modeling by defining linguistic and subjective variables and relationships for simulation of real-life systems. Moreover, fuzzy logic can model uncertain variables when sufficient historical data are not available for probabilistic distribution fitting. Integration of fuzzy logic with SD should be implemented in two steps: fuzzy variable definition and fuzzy relationship definition. The process of integrating the two methods is explained below:

1. Variable definition: The subjective variables that need to be defined with fuzzy membership functions should be selected first. Then, membership functions for defining the variables should be developed. Membership functions can be defined with one of several different approaches proposed by the literature, using expert judgment or historical data. Fuzzy *c*-means (FCM) clustering, for use when historical data is available, is one example (Bezdek 1981; Pedrycz and Reformat 2006).

2. Relationships definition: Once the subjective variables of the system have been defined with fuzzy membership functions, the relationships between these variables must be modeled using fuzzy logic techniques. For defining the relationships between the system fuzzy variables, there two alternatives:

   - Fuzzy arithmetic and mathematical equations: In this method, as in SD models, the relationships between the system’s variables are defined by mathematical equations. However, here the classical arithmetic is substituted with fuzzy arithmetic where some variables of the equations are fuzzy numbers. This method provides a quick approach for developing FSD models, as it is mostly based on pre-developed SD models but with the slight modification that some of the crisp variables are changed to fuzzy variables. However, the main deficiency of this method is the fast growth of the support of the fuzzy results of the system (Tessem and Davidsen 1994).

   - Fuzzy rule-based systems: In this method, the relationships between the fuzzy variables of the systems are defined by fuzzy rule-based systems. Fuzzy rule-based systems can be defined using a few different approaches. FCM clustering (Bezdek 1981) is an alternative for defining fuzzy rule-based systems where historical data is available. Khanzadi et al. (2102) used expert judgments for developing a fuzzy rule-based system in their FSD model where historical data was unavailable. Usually, the outputs of a fuzzy rule-based system have irregularly shaped membership functions. Therefore, the results must be either defuzzified or approximated by a regular membership function for further calculations. Defuzzification is the process of converting the fuzzy memberships to a single crisp value. The most common defuzzification method is the center of area (CoA) method.

The flowchart presented in Figure 1 summarizes the steps for developing a FSD model as discussed in this section.

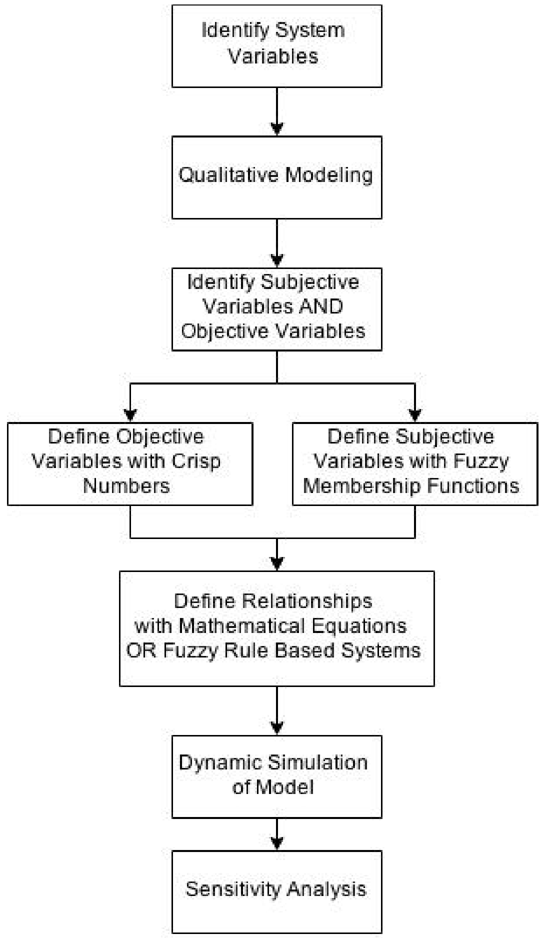

Figure 1: FSD development flowchart

4 APPLICATION OF FSD MODELS IN CONSTRUCTION

4.1 FSD Model for Crew-Related Factors Influencing Construction Productivity

In this section, we develop a construction-related SD model to illustrate how fuzzy logic can contribute to SD modeling for construction applications. In this model the effect of crew and labour characteristics on construction labour productivity at the crew level. Tsehayae and Fayek (2014) conducted extensive research on identification of the key parameters that influence construction labour productivity in different levels. They categorize the factors influencing construction labour productivity into 18 groups based on their sources. For the model developed in this study uses only one of these categories: crew and labour characteristics. Next, the factors that change on a daily basis and affect labour productivity at the crew level are extracted for modeling and are modified to some extent to fit the SD modeling approach. For developing the model, we studied three concrete construction projects and collected a total of 32 data points for the selected factors for analysis purposes.

For qualitative model development, each factor is analyzed to find which factors affect it (i.e., feature selection is performed). For this purpose, the correlation-based feature selection (CFS) method is used for its simplicity. Hall (1999) introduces CFS as a simple filter algorithm which ranks the features through a heuristic evaluation function. The CFS algorithm uses historical data and identifies the features that have the greatest effect on each variable. Table 1 shows the variables of the system and the attributes selected for each factor that are used for developing causal loops. Then, based on the results of CFS, the causal loops for each variable of the system can be identified. Finally, the qualitative model is developed as presented in Figure 2.

Table 1: Qualitative model variables and their selected attributes for causal loops

Variable	Selected Features
Discontinuity in crew makeup	Crew size
Crew composition	Crew size
Crew size	-
Co-operation among craftspeople	Crew composition, fairness of work assignment
Fairness of work assignment	-
Motivation valence	Fairness of work assignment
Motivation expectancy	Fairness of work assignment, labour productivity
Motivation instrumentality	Fairness of work assignment, labour productivity
Labour productivity	Crew composition, crew size, co-operation among craftspeople, fairness of work assignment, motivation valence, motivation expectancy, motivation instrumentality
Production rate	Labour productivity, crew size, working hours
Working hours	-

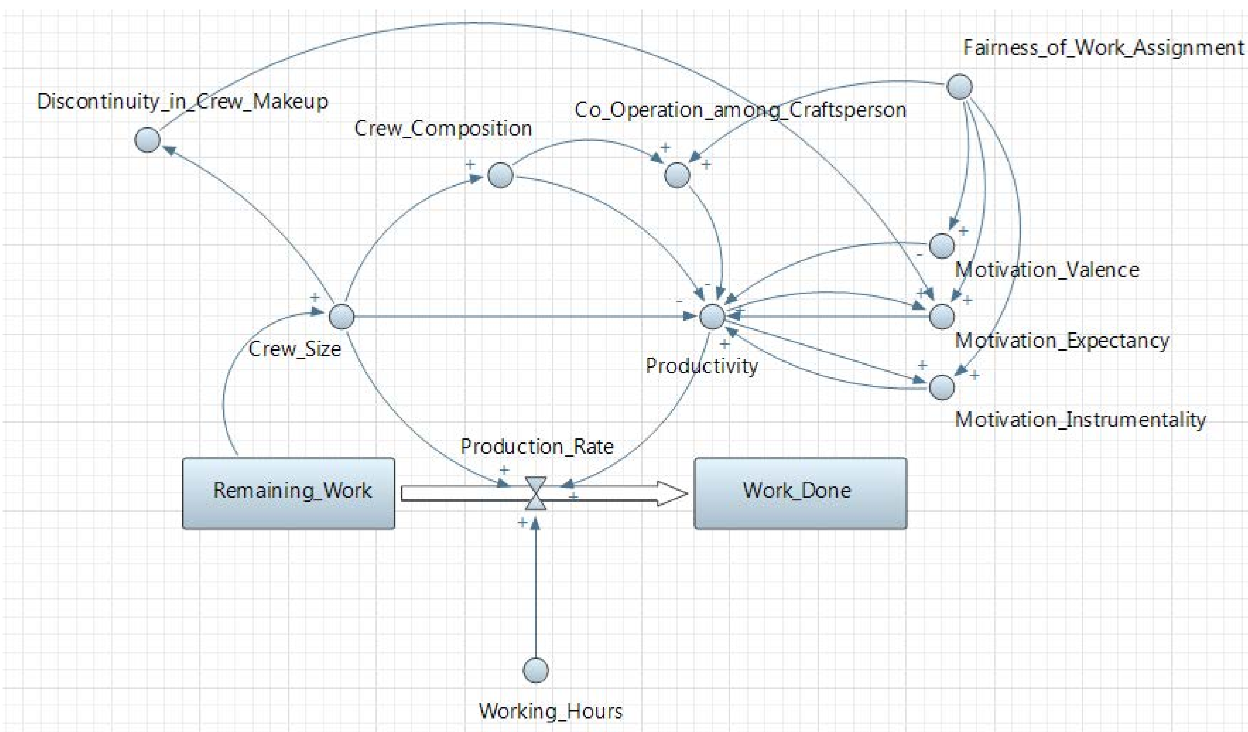

Figure 2: Qualitative FSD model for crew-related factors influencing construction labour productivity

Like the SD model, the FSD model is based on the qualitative model presented in Figure 2. However, the difference between the two approaches lies in their method of quantification (i.e. definition of the variables and their relationships). For quantification purposes, the SD model considers all the variables as crisp variables and the relationships are defined by mathematical equations using statistical extrapolation. To define the relationships between the variables in this model using statistical extrapolation, this model uses the linear regression method. Two of the model's equations are presented in Table 2: (1) labour productivity, the measurement of which is the main objective of the model, and (2) production rate, which is used to compare the results of the SD model with those of the FSD model. The equation for calculating the production rate is selected for further comparison with the FSD to show that FSD models can also accept crisp values in their equations. Based on the equations presented in Table 2, the accuracy of the two models in defining the relationships between their variables is discussed. Once the relationships between the system variables are defined by mathematical equations, quantification of the SD model is complete.

For quantification in the FSD model, first, the subjective variables (i.e., cooperation among craftspeople, fairness of work assignment, motivation valence, motivation expectancy, and motivation instrumentality) of the system are defined by fuzzy membership functions. Since labour productivity is a function of both these fuzzy variables and other crisp variables (i.e., crew composition and crew size), it is also defined by membership functions. As discussed in Section 3, the resulting membership function for labour productivity can be defuzzified to find the crisp value for labour productivity. FCM clustering is an approach for defining of the fuzzy membership functions when historical data are available. In this model triangular membership functions are selected while they are simple and widely used. Therefore, all variables of the system are defined by triangular membership functions using FCM clustering method. The membership functions which define labour productivity are presented in Figure 3 as an example. The next step for quantification of the FSD model is defining the relationships between the fuzzy variables as mentioned in Section 3. For defining the relationships between the fuzzy variables, fuzzy rule-based systems are selected. Where the historical data is available, FCM clustering is used for development of the fuzzy rule-based systems. The fuzzy rule-based system developed for estimating labour productivity is presented in Table 2.

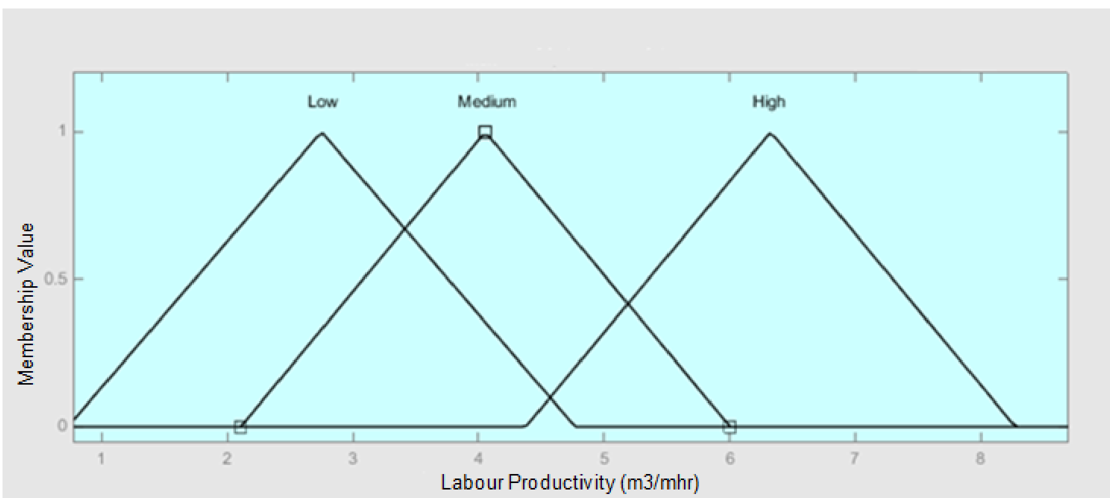

Figure 3: Labour productivity membership functions developed by FCM clustering

The results of the fuzzy rule-based system can be defuzzified and used in further calculations of the system. In the example shown in Figure 2 and Table 2, labour productivity is defuzzified using the center of area (CoA) method and used to calculate the production rate.

Once quantification is complete, the accuracy of the two models is tested for predicting labour productivity using the historical data. While the performance of the models strictly depends on how well the variables and their relationships have been defined, the model with the more precise estimate for the variables potentially performs better for simulation. Results of the analysis show that in this case, the FSD model with the fuzzy variables and fuzzy rule-based system predicts a labour productivity value with a root mean square error (RMSE) of 0.19. However, the SD model with the mathematical equation as presented in Table 2 predicts a labour productivity value with a RMSE of 0.24.

Table 2: Relationships between variables of the FSD and SD models

Model	Relationship	Unit	RMSE
SD	$\text{Productivity} = 0.30 - 0.15 \times \text{crew size} + 0.10 \times \text{crew composition} + 0.09 \times \text{cooperation among craftspeople} - 0.30 \times \text{fairness of work assignment} + 0.09 \times \text{motivation expectancy} + 0.09 \times \text{motivation instrumentality}$	$\left(\frac{\mathrm{m}^3}{mhr}\right)$	0.24
	$\text{Production rate} = \text{Working hours} \times \text{labour productivity} \times \text{crew size}$	$\left(\frac{\mathrm{m}^3}{day}\right)$	
FSD	1. If (crew size is *high*) and (crew composition is *low*) and (cooperation among craftspeople is *low*) and (fairness of work assignment is *low*) and (motivation expectancy is *low*) and (motivation instrumentality is *low*) then (labour productivity is *low*) 2. If (crew size is *average*) and (crew composition is *average*) and (cooperation among craftspeople is *average*) and (fairness of work assignment is *average*) and (motivation expectancy is *average*) and (motivation instrumentality is *average*) then (labour productivity is *average*) 3. If (crew size is *average*) and (crew composition is *high*) and (cooperation among craftspeople is *high*) and (fairness of work assignment is *high*) and (motivation expectancy is *high*) and (motivation instrumentality is *high*) then (labour productivity is *high*)	$\left(\frac{\mathrm{m}^3}{mhr}\right)$	0.19
	$\text{Production rate} = \text{Working hours} \times \text{labour productivity} \times \text{crew size}$	$\left(\frac{\mathrm{m}^3}{day}\right)$	

The results of analysis of the SD and FSD models shows that the integration of fuzzy logic with system dynamics can increase the accuracy of the resultant model when there are subjective variables in the system. In this study, historical data were available and used for the definition of the fuzzy variables' membership functions and the fuzzy rule-based system for the FSD model. In cases where historical data are unavailable, other methods of defining the fuzzy variables and fuzzy rule-based system—such as expert judgment and consensus methods—can be used.

5 CONCLUSION

Integration of the system dynamics (SD) modeling approach with fuzzy logic develops a powerful tool for construction modeling which captures the subjectivity and complexity of construction projects at once. In this study, integration of SD modeling with fuzzy logic is illustrated and some applications of these models in construction are presented. Moreover, an application of SD and fuzzy SD (FSD) approaches for modeling the effect of crew characteristics on construction labour productivity at the crew level is presented. The comparisons between the two models (i.e., the SD model and the FSD model) verified that the FSD model is more accurate in predicting construction labour productivity at the crew level based on the sample problem. However, this study only develops sub-models for the purpose of testing and comparing their performances in a construction context. To extend this research, a comprehensive model for simulating construction labour productivity can be developed. Moreover, in this study, a fuzzy rule-based system is used to define the relationship between the system variables, which results in a better performance than when linear regression is used for this purpose. The relationships between the system variables are usually defined by extrapolation methods. However, the mathematical equations that are used in SD models can also be substituted with artificial intelligence tools (e.g., neural networks). Investigating which options for defining the system variable relationships in SD models might serve as the best substitutes for statistical extrapolation is another area of extension to this study.

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