Hybrid Fuzzy System Dynamics–Fuzzy Agent-Based Modeling of Construction Labor Productivity

by

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Abstract

Construction labour productivity (CLP) is a key performance indicator for determining the success of construction undertakings, and notably affects the profitability of construction companies. To this effect, the construction industry and researchers have pursued better ways of addressing the CLP problem. The CLP problem is a very complex problem that includes one or a combination of processes of: identifying factors that can influence CLP, modeling construction processes to effectively predict CLP, and proposing mitigation measures for improvement of CLP. Despite ongoing efforts, properly addressing the CLP problem remains a challenge in both research and the construction industry, because the related processes entail simultaneously capturing: 1) complexity arising from the subjective nature of some variables affecting CLP, owing to the use of linguistic terms such as *low temperature*, or *poor safety practices*; 2) complexity arising from the dynamic nature of variables; 3) complexity arising from the emerging nature of some variables affecting CLP, such as crew motivation; 4) complexity arising from the causal relationships between factors affecting CLP – hereafter called *situational/contextual variables* – which are context dependent and vary across different situations in which tasks are performed; and 5) the inputs of multiple heterogenous experts involved in addressing the CLP problem (i.e., construction practitioners), whose inputs vary owing to their backgrounds, experience, and varying areas of expertise. This research provides a comprehensive state-of-the-art literature review and content analysis on the topic of system dynamics (SD) as a viable tool to capture the dynamic nature of system variables and their complex causal relationships for CLP modeling. Moreover, this research provides a fuzzy analytic hierarchy process–fuzzy decision making trial and evaluation laboratory (FAHP-FDEMATEL) method to capture causal relationships between crew motivation and

situational/contextual variables affecting CLP. This research also provides a fuzzy system dynamics–fuzzy agent-based modeling (FSD-FABM) method to model CLP. The FAHP-FDEMATEL, and FSD-FABM methodologies proposed in this study are demonstrated and validated using a real industrial construction project in Alberta, Canada. This research also provides modeling frameworks that employ FSD-FABM with multi-criteria decision making (MCDM) and reinforcement learning (RL), which can be used to formulate CLP improvement strategies. These proposed frameworks on decision-making have also been validated using a case study on real construction projects.

The main contributions of this research are: 1) providing a state-of-the-art on SD research; 2) providing a systematic and structured model for determining causal relationship mapping between factors affecting CLP via the proposed FAHP-FDEMATEL method; 3) proposing a novel hybrid FSD-FABM for capturing and assessing complexities arising from non-linear behaviors and dynamic causal interactions between multiple factors in modeling and predicting CLP; and 4) proposing novel FSD-FABM-MCDM and 5) proposing a RL–FSD-FABM decision making frameworks that can be used to propose productivity improvement strategies. The results of this study indicate that the FAHP-FDEMATEL model was capable of providing a systematic and structured method to map the causal relationship mapping between factors affecting CLP, while considering expert weights. Moreover, the proposed FSD-FABM in this study was capable of predicting CLP while considering the causal relationships between crews' motivation and situational/contextual factors. In this regard, the proposed models (i.e., FAHP-FDEMATEL and FSD-FABM) and frameworks (i.e., RL-FSD-FABM and FSD-FABM-MCDM) can be used to provide solutions to the CLP problem.

Preface

This thesis is an original work by Nebiyu Siraj Kedir. The research project, based on which this thesis is written, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Research on Construction Productivity," Project ID: Pro00068631, approved on July 29, 2020. The research project, based on which this thesis is written also received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Study on motivation and performance of crafts in construction projects," Project ID: Pro00063112, approved on November 15, 2019. This research was funded by the Natural Sciences and Engineering Research Council of Canada Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. Aminah Robinson Fayek.

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Engineering: Kedir, N., Siraj, N.B., and Fayek, A. R. (2022), "Application of System Dynamics in Construction Engineering and Management: Content Analysis and Systematic Review." *Advances in Civil Engineering*, 49 manuscript pages, submitted Oct. 2022. Chapter 3 of this thesis has been submitted for publication in *Canadian Journal of Civil Engineering*: Kedir, N., and Fayek, A. R. (2022), "Integrated FAHP-FDEMATEL for Determining Causal Relationships in Construction Crew Productivity Modeling." *Canadian Journal of Civil Engineering*, 39 manuscript pages, submitted Oct. 2022. Parts of Chapter 4 and Chapter 5 of this thesis have been submitted for publication in *Automation in Construction*: Kedir, N. S., and Fayek, A. R. (2022)."Integrated Fuzzy System Dynamics–Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction." *Automation in Construction*, 61 manuscript pages, submitted Oct. 2022. Parts of Chapter 6 have been published in *Journal of Management in Engineering*: Kedir, N. S., Raoufi, M., and Fayek, A. R. (2020). "Fuzzy agent-based multicriteria decision-making model for analyzing construction crew performance." *Journal of Management in Engineering*, 36(5), 04020053. Parts of Chapter 6 have also been published in *Automation in Construction*: Kedir, N. S., Somi, S., Fayek, A. R., and Nguyen, P. H. (2022). "Hybridization of reinforcement learning and agent-based modeling to optimize construction planning and scheduling." *Automation in Construction*, 142, 104498. I was responsible for the data collection and analysis as well as the manuscript composition. Dr. A. Robinson Fayek was the supervisor of the research, and was involved with the formation of the research concept, technical review and the composition of each of the six manuscripts.

Dedication

To my parents, Wagaye Teklu and Siraj Kedir.

You shaped me into the person I am today.

To the love of my life, Mina Ahmed Jemal.

You have always been there for me. You - I can’t do without.

To my daughters Sabrina Nebiyu Siraj, and Ikhlas Nebiyu Siraj.

Alhamdullilah, your love I have no words for.

To my siblings Addisu Siraj, Zebib Siraj, Hawa Siraj, and Jitu Siraj

Your encouragements helped me get to this stage.

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List of Abbreviations

ABM	Agent Based Modeling
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANNs	Artificial Neural Networks
CEM	Construction Engineering and Management
CII	Construction Industry Institute
CLP	Construction Labor Productivity
FABM	Fuzzy Agent Based Modeling
FCM	Fuzzy C-Means
FIS	Fuzzy Inference System
FSD	Fuzzy System Dynamics
FDEMATEL	Fuzzy Decision Making Trial and Evaluation Laboratory
KPI	Key Performance Indicator
MAPE	Mean Absolute Percentage Error
NFS	Neuro-Fuzzy Systems
RL	Reinforcement Learning
RMSE	Root mean square error
SD	System Dynamics
SEM	Structural Equation Model

Chapter 1 Introduction[1]

1.1 Background

The construction industry is a multi-billion-dollar sector that contributes to a considerable amount of the gross domestic product of Canada. Productivity is an important facet in the construction industry, as it usually determines whether endeavors related to construction engineering and management (CEM) are successful. Construction productivity is one of the most researched topics in the literature because of its influence on the success of construction projects (CII 2013). Productivity as a key performance indicator (KPI) is a crucial element in estimating the duration and cost of construction operations (Hwang and Liu 2010). Studies related to construction productivity have mainly consisted of developing a reliable metric for measuring construction productivity, identifying factors that affect productivity, prediction of the productivity measure, identifying issues that can contribute to improvement or loss of productivity, and devising of strategies for improvement of the productivity. These topics combine to make up a significant

[1] Parts of this chapter have been published in *Journal of Management in Engineering*: Kedir, N. S., Raoufi, M., and Fayek, A. R. (2020). "Fuzzy agent-based multicriteria decision-making model for analyzing construction crew performance." *Journal of Management in Engineering*, 36(5), 04020053; Parts of this chapter have also been submitted for publication in *Automation in Construction*: Kedir, N. S., and Fayek, A. R. (2022)." Hybrid Fuzzy System Dynamics and Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction." *Automation in Construction*, 61 manuscript pages, submitted Oct. 2022. Parts of this chapter have also been submitted for publication in *Advances in Civil Engineering*: Kedir, N., Siraj, N.B., and Fayek, A. R. (2022), "Application of System Dynamics in Construction Engineering and Management: Content Analysis and Systematic Review." *Advances in Civil Engineering*, 49 manuscript pages, submitted Oct. 2022.

portion of the productivity research in the last 15 years (Dixit et al. 2019) and are usually considered as "the productivity problem."

In the literature, several definitions of productivity are presented. In its simplest form, *productivity* can be defined as the amount of goods and services produced by a productive factor within a unit of time, measured by a productivity index. This index can take any pre-defined form and simply be expressed as the ratio of input to output (or vice-versa). In this regard, productivity is most commonly measured using the ratio of measured output (completed work) to measured input such as labour, material, and equipment (Tsehayae and Fayek 2016; Zhao and Dungan 2019; Johari and Jha 2020). This ratio can be applied to capture productivity at the crew, activity, and/or project levels, where higher values are desired. There are also higher levels of productivity study, whereby factors that affect the measured productivity at the organizational-, provincial-, national, and global- level are assessed (CII 2013; Kedir et al. 2022). Labour is the primary input resource that is used to produce outputs in labour-intensive activities. Construction labour productivity (CLP) can be defined as the ratio of completed work or output, to work effort, often measured in labour hours (CII 2013; Zhao and Dungan 2019). In this regard, measuring CLP at the activity level is crucial to determining project performance, which in turn affects the profit margins of construction companies.

The problem of modeling CLP – that is, predicting, managing, and consequently improving it –is faced by construction organizations, which include contractors, owners, consultants, labour groups, and government owners. This is mainly due to the nature of CLP: its behaviour as a measurement susceptible to influences from different contributing variables. These variables are dynamic, have different natures (i.e., subjective versus objective variables), and representing them can be complex. For example, for a productivity model that takes into account several inputs, the change in productivity level during initial, middle, and final stages of construction renders the productivity model time-dependent, making the problem dynamic in nature. The challenge of quantifying variables that are usually linguistic in nature (weather, crew motivation, crew skills, etc.) can also further complicate the modeling process. Furthermore, the productivity problem entails predicting and improving the CLP measure, as having the best possible CLP is paramount for the success of any construction project undertaking. While studies on conventional methods of improving CLP, such as ensuring job security, controlling absenteeism, financial incentives, facilitating communication and increasing togetherness between members, have been present, innovative approaches that aim to improve productivity by focusing on different levels of detail (i.e., activity, crew, and project levels) needs to be studied using approaches that are able to measure and capture the construction process, which is often dynamic, subjective, and uncertain in nature.

1.2 Problem Statement

In productivity modeling, there is a challenge to incorporate a combination of inputs of factors affecting productivity, to develop a CLP model at different levels of detail. The problem of proposing a comprehensive model of CLP entails simultaneously capturing: i) the complexity arising from the subjective nature of some variables affecting CLP, owing to the use of linguistic terms such as *low* temperature, *poor* safety practices; ii) the complexity arising from the dynamic nature of variables, whose values are continuously changing throughout the project duration; iii) the complexity arising from the emerging behavior of some variables affecting CLP, such as crew motivation; iv) the complexity arising from the causal interrelationships between factors affecting CLP, which are context dependent, and vary across different situations in which tasks are performed. Such modeling challenge needs to be approached using hybridization of several individual modeling techniques, that are capable of addressing each set of problems. Modeling the nature of interdependencies among factors affecting CLP necessitates that some aspects of the model be captured as a global system using modeling techniques such as SD, and that other aspects of the model captured as a local system using modeling techniques such as ABM, which allow a global behavior to emerge from individual interactions. Moreover, the subjective nature of some variables affecting CLP also necessitates that some aspects of the model be captured using fuzzy set theory.

SD is appropriate for modeling problems that are "broad in details, holistic in perspective, continuous in behaviour, and also featuring qualitative or quantitative data" (Alzraiee et al. 2015). SD is widely used to solve problems with a high degree of complexity and dynamism to help policy makers and decision makers analyze different strategies, formulate policies, and improve the process of decision making (Siraj and Fayek 2019). Hence, SD has been a preferred approach in model construction systems, as it can be used to implement and understand the dynamics of complex processes that are not understood by other means (Abotaleb and El-adaway 2018). With the increased use of computer simulation approaches, the role of SD in capturing complex construction systems is becoming ever more pronounced, both as a standalone modeling approach and as part of hybrid models. In this regard, researchers need a more focused insight into SD's capabilities for capturing different construction systems, which can be accomplished through a comprehensive study of the SD literature as in this state-of-the art study of SD application within different CEM research areas. Current works related to an SD literature review and content analysis in CEM are not exhaustive in terms of the number of papers covered per journals or range of years assessed, and they lack a focused analysis that proposes potential avenues for SD hybridization. Furthermore, the literature lacks a state-of-the-art study on SD that can guide researchers by analyzing the SD research performed in recent years. Hence, the ***first gap*** that is addressed in this dissertation is the lack of state-of-the-art on SD research, which provides guidelines for effective SD modeling, and ways for implementing SD hybridization to solve various problems in CEM.

There are several approaches in the literature for capturing the existing complex causal relationships for dynamic modeling of productivity. Some of the most commonly used methods include literature reviews, modelers' assumptions, and verifying of model assumptions using focus groups, questionnaire surveys, and/or semi-structured interviews. Literature review methods are limited because relationships between model variables can only be obtained through literature if there is existing knowledge about those relationships. Moreover, methods such as focus groups, questionnaires, and surveys entail aggregating the inputs of several experts that take part in the assessment process. These experts are usually heterogenous, meaning they have varying level of expertise, which makes aggregation of information that is needed for the productivity modeling process complex. The ***second gap*** that will be addressed in this thesis is the lack of a systematic and structured methodology to establish causal relationships in the dynamic CLP modeling process, which involves 1) aggregating the inputs of heterogenous experts, 2) assessing the importance of, and causalities between the factors affecting CLP and 2) constructing causal loop diagrams (CLDs) which illustrate the dynamic relationships.

To model and predict construction productivity as a performance measure, it is important to properly capture the construction environment in which activities are performed. Such a construction environment is unpredictable, context dependent, and complex, whereby several parameters influence the productivity measure either directly or indirectly (Tsehaye and Fayek 2016). This is because construction projects are performed in a dynamic environment that results from numerous interactions between contextual/situational factors related to task, resources, management, project characteristics, and work setting conditions (Raoufi and Fayek 2018). SD can capture interrelationships between variables to model complex and dynamic construction systems (Siraj and Fayek 2021). However, SD is unable to capture uncertainties arising from subjective or imprecise information in construction systems (Gerami Seresht and Fayek 2020). Moreover, SD is not equipped to deal with model parameters that locally model interactions and analyze results to capture emerging phenomena. ABM is capable of dealing with problems that need to be modeled locally, such as the effect of crew interactions on crew motivation. ABM is able to predict the overall behaviour of systems by modeling the behaviour of system agents, thereby enabling the capture of complex construction systems, even when there is little information about the overall system behaviour (North and Macal 2007; Raoufi and Fayek 2018). However, both SD and ABM lack the ability to capture subjective uncertainty between variables and system relationships (Kedir et al. 2020), which necessitates the use of fuzzy-hybridized forms of these modeling approaches, or FSD and FABM. Furthermore, the CLP problem entails modeling subjective variables that affect the productivity measure, such as weather, crew skill, quality of supervision, and crew behavioural skills such as co-operation and teamwork (Raoufi and Fayek 2018; Fayek 2020). These variables interact with other input variables of emerging behaviours such as crew motivation, job satisfaction, and congestion. In this regard, using a single modeling technique fails to properly represent the inputs and processes of construction projects for a more accurate prediction of CLP. Combining different modeling approaches enables the modeler to produce a more powerful hybrid model that is capable of a more comprehensive abstraction by capturing the effects of multiple system variables such as subjectivity, dynamism, emerging behaviours. Therefore, the ***third gap*** that is addressed in this research is the lack of a methodology in the literature, to capture different features of the construction environment, which include subjective variables, dynamic causal relationships, and complex emerging behaviours, for modeling of CLP.

The other aspect of the productivity problem is a decision-making problem, which involves devising strategies to improve the productivity measure. In this regard, decision making is a critical aspect of construction-related processes. It usually requires that several criteria be analyzed before a decision is made, usually in an environment of differing stakeholder priorities, insufficient information, and disagreement among experts. Such endeavor requires that decisions be made using techniques that can handle the multi-criteria and uncertain nature of the construction environment. For example, policies must be economical, schedule oriented, and compliant with safety requirements. In this regard, the ***fourth gap*** that is addressed in this research is the need for a decision-making framework that captures the dynamic construction environment, and proposes productivity improvement strategies subject to multiple criteria.

Another feature of the decision-making problem is the optimization aspect of finding solutions. In devising productivity improvement strategies, the optimal solution is often selected from a set of finite solutions. However, the optimization problem is everchanging, because the environment, which includes the number of activities and the type and number of allocated resources, changes during execution of the project. A review of the literature emphasizes the need for an effective decision-making tool that can be easily used by stakeholders in accordance with their preferences for improving project performance (i.e., CLP) with respect to constraints such as time, cost, and quality. Hence, the ***fifth gap*** that is addressed in this research is the lack of knowledge in the construction literature regarding decision-making frameworks with the ability to learn, adapt with the dynamically changing construction environments, and propose an optimal set of solutions for construction productivity problems. This chapter utilizes the complementary aspects of ABM and RL to propose a framework capable of performing dynamic optimization during the decision making process. Agents in RL algorithms learn more efficient solutions even as the environment changes. ABM is capable of handling very complex real-world systems often containing large amounts of autonomous, goal-driven, and adapting agents (Chan et al. 2010). By incorporating FSD-FABM in an RL process, necessary features that support environment modeling, such as system parameters, system behaviours, and rules, are provided in order to enable an efficient representation of the dynamic construction environment and provide the RL platform with the necessary features to support environment modeling.

1.3 Research Objectives

The hypothesis of this research is as follows:

> Crew motivation and situational/contextual factors in a construction environment affect the crew productivity; and this complex and dynamic interrelationship can be effectively modeled using a hybrid FSD-FABM approach, to predict CLP and facilitate strategic decision making for productivity improvement.

The main objective of this research is to propose a model that is able to predict CLP while accounting for dynamic causal relationships and complex adaptive systems within the construction environment. The detailed objectives of this research are grouped under the following five main categories.

1. To address the lack of a comprehensive systematic review and content analysis in the application of SD in CEM research, and to assess the potential for SD hybridization with other modeling approaches, thereby addressing the ***first gap***.
2. To provide a systematic and structured methodology to define causal relationships between the most significant factors that affect CLP . This thereby addresses the ***second gap***. This objective includes:

a. To identify a set of criteria to perform expert assessment for assigning importance weights of heterogenous experts in the area of productivity research, to enable a proper aggregation of expert inputs during modeling.

b. To determine causal relationship mapping between crew motivation, and situational/contextual factors affecting CLP.

3. To propose a model that is able to capture subjective variables, dynamic relationships, and complex adaptive systems for a more comprehensive modeling of the construction environment; thereby addressing the ***third gap***.
4. To propose a decision support system that can allow construction practitioners to evaluate economically feasible solutions for improving CLP; which is able to take into account criteria such as time, cost, and safety for selecting the best alternatives from possible list of solutions.; thereby addressing the ***fourth gap***.
5. To propose an optimization-based decision support system that has the ability to learn, and adapt with the dynamically changing construction environments to propose an optimal set of solutions for improving CLP; thereby addressing the ***fifth gap***.

1.4 Expected Contributions

The expected contributions of this research are categorized under academic and industrial contributions to best elaborate the relevance to academic researchers and construction industry practitioners, respectively.

1.4.1 Academic contributions

The expected academic contributions of this research are as follows:

1. Providing a state-of-the-art on SD research, by presenting a detailed content analysis and comprehensive review of SD literature and assessing the potential for SD hybridization with other modeling and simulation approaches in order to identify modeling issues related to the use of SD in CEM and productivity modeling.
2. Proposing a novel FAHP-FDEMATEL method in order to provide a systematic and structured methodology to define causal relationships between the most significant factors that affect productivity and analyze their interrelated impacts.
3. Proposing a novel hybrid FSD-FABM that is able to capture subjective variables, dynamic relationships, and complex adaptive systems for a more comprehensive modeling of the construction environment.
4. Proposing a novel FSD-FABM-MCDM methodology that will help improve decision-making processes in construction by expanding the scope of MCDM through integration with FSD-FABM.

5. Proposing a novel RL-FSD-FABM framework that can be used in optimization-based decision making, by integrating the computational efficiency of RL with modeling capabilities of FSD-FABM.

1.4.2 Industry contributions

The expected industry contributions of this research are as follows:

1. To provide construction practitioners with the state-of-the-art in SD research, and provide useful perspective by presenting practical applications of SD in the construction industry, which serves as a useful reference in facilitating the effective implementation of SD modeling in construction projects.
2. Providing a hybrid FSD-FABM approach that can help construction practitioners identify reasons for CLP loss, and track the causal relationships between factors affecting CLP, to facilitate a more proactive planning.
3. Providing a predictive FSD-FABM that can help construction practitioners during the estimation process in the planning stage, by providing valuable insight of crew output (i.e., CLP).
4. Providing construction practitioners with a framework to make informed decisions and adopt economically feasible strategies for improving the CLP of their crews.

1.5 Research Methodology

The objectives of this research are achieved in five stages, as shown in Figure 1.1 The details of the methodology are elaborated in subsequent sections.

1.5.1 First Stage

The research commenced by conducting a comprehensive literature review on productivity in general, with a specific focus on crew productivity in construction. Several definitions of productivity were assessed, and different levels of productivity measurements were studied. Moreover, methods of productivity measurement and productivity modeling approaches were investigated. After conducting the literature review, the main theoretical framework and the rationale for the study were established. Past studies focusing on productivity and the different modeling techniques used to capture construction systems were examined to identify the research gaps, as outlined in Section 1.2. Accordingly, the productivity problem was proposed, which mainly has two major components: 1) predicting crew productivity and 2) devising effective strategies to improve productivity.

1.5.2 Second Stage

In the second stage, a comprehensive review of SD research was conducted to examine the applicability of SD as an effective modeling technique for capturing dynamic and complex construction systems. With the increased use of computer simulation approaches, the role of SD in capturing complex CEM systems is becoming ever more pronounced, both as a standalone modeling approach and as part of hybrid models. A systematic review and content analysis of 213 articles obtained from 21 high ranking peer-reviewed journals was performed in order to analyze the application of SD in CEM and derive directions for future research. The modeling issues

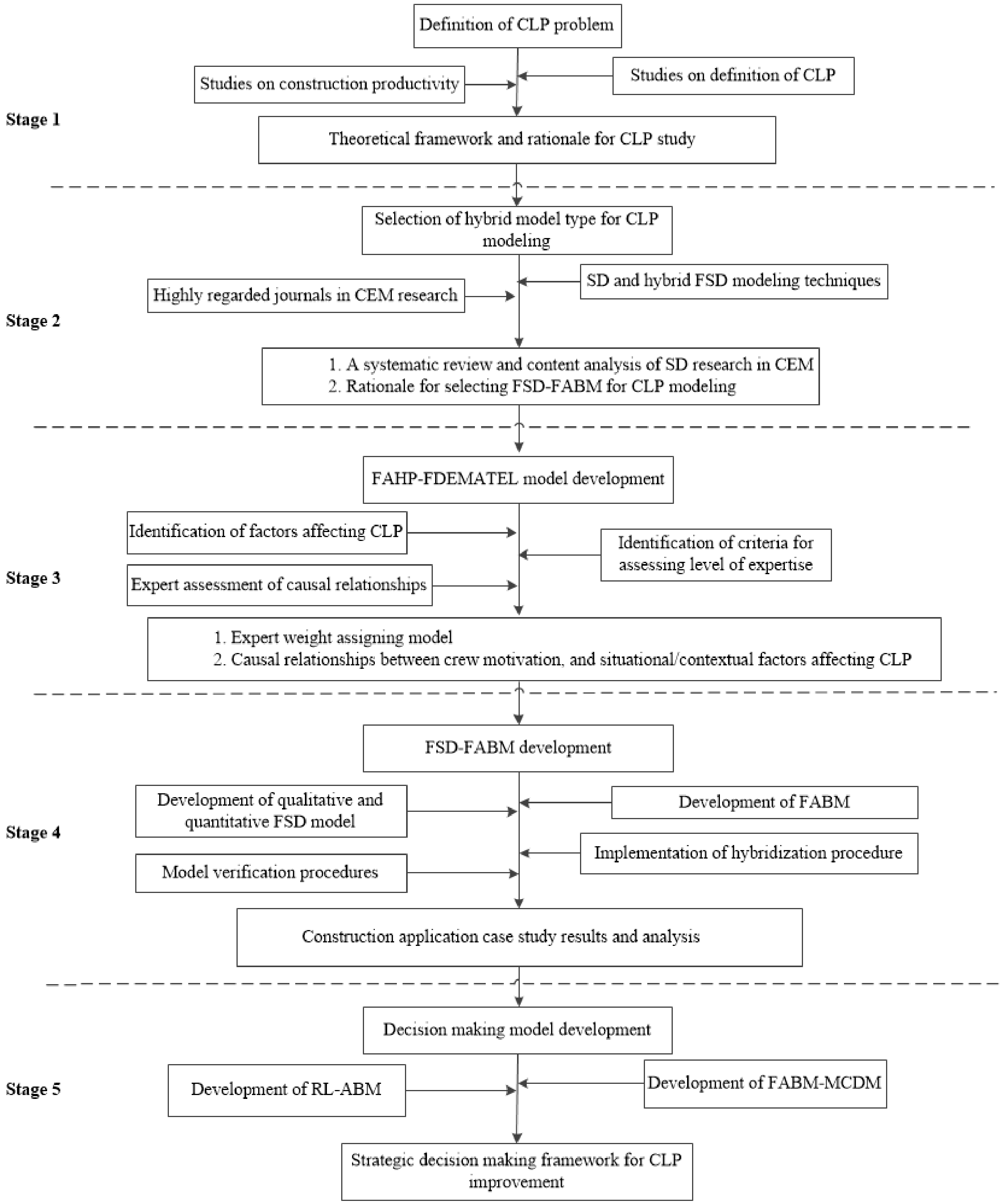

Figure 1.1 Research methodology stages.

associated with SD and the need to hybridize it with other modeling approaches were identified, and the potential of hybridization of fuzzy logic and ABM with SD was established in order to identify the best modeling approach for the predictive component of the productivity problem.

1.5.3 Third Stage

In the third stage of this research, a comprehensive investigation of the causal relationships between factors affecting crew motivation and situational/contextual factors for dynamic modeling of CLP was performed. This stemmed from the need to capture complex causal relationships in construction systems for dynamic modeling of CLP, which involves the process of eliciting the inputs of heterogenous experts. These heterogenous experts come from different backgrounds and have varying level of expertise. FAHP was used to weigh the inputs of the heterogenous experts by considering multiple criteria that are specific to the area of construction productivity. Consequently, a systematic and structured method for assessing the causal relationships between factors affecting CLP, while considering the inputs of heterogenous experts in the process, was developed using an integrated FAHP-FDEMATEL method. This FAHP-FDEMATEL method is novel in the area of productivity research. In this stage, a systematic method to gather group knowledge from individuals with different level of expertise, to capture causal relationships between factors, and to visualize these complex cause-and-effect interrelationships for productivity research is proposed using the weighted FDEMATEL approach.

1.5.4 Fourth Stage

In the fourth stage of this research, a novel FSD-FABM was developed in four phases, namely: 1) development of qualitative modeling of FSD to identify model boundary and level of aggregation, 2) development of quantitative modeling of FSD to quantify the effect of factors affecting productivity, 3) development of the FABM to model the effect of motivation, and 4) development of the information exchange interface to hybridize FSD and FABM. In the first phase, the qualitative modeling of FSD deals with identifying model boundary and level of aggregation. Once the nature of all the variables to be used in the FSD component is identified, the variables are categorized further into subjective and objective variables. Subjective variables are those variables which are best defined using fuzzy numbers and membership functions. Objective variables such as crew size, production rate, and crew composition have quantitative metrics and can therefore be expressed with numeric expressions using crisp numbers or probability distributions. Next, the causal relationships between the factors are formulated to determine the dynamics between CLP and the situational/contextual variables. In the second phase, the quantitative modeling stage defines hard variables and soft variables (Gerami Seresht and Fayek 2018). Hard variables are variables whose values can be computed through either one of deterministic or probabilistic approaches. For example, crew size is measured as number of crew members in the crew, minus the number of absentees. Soft variables are best defined by fuzzy sets, which are represented using linguistic terms to signify a given concept (e.g., "very low" motivation, or "high" crew morale). Next, the causal relationships and the stock and flow variables are determined quantitatively. For those variables whose relationships can be described using mathematical equations, the relationships are obtained using existing mathematical equations or statistical methods such as regression analysis, depending on data availability. For those relationships that are difficult to define using mathematical equations, fuzzy set theory is applied. In the third phase, the FABM is developed using four steps, namely defining 1) the FABM environment and processes, 2) agent attributes and behaviours, 3) interactions between agents, and 4) agent behavioural rules. In the first step of FABM, the main environment of the FABM is identified, the agents taking part in the

ABM are identified by answering the basic question of “what are the agents?” and the overall model architecture is proposed. Next, for each agents and agent group defined in the previous step, the corresponding attributes are defined. This can be achieved using either one of the three approaches, namely using 1) deterministic variables, 2) probabilistic variables, or 3) subjective variables. After the attributes and behaviours of each agent are defined, the next step is to define how different agents interact. In this chapter, the interaction of the crew agent is defined, which exhibits behavioural changes resulting from observing the behaviours of other crews. In the fourth phase, information exchange is defined, and interface variable is selected to hybridize FSD with FABM. In this chapter, crew motivation is the output of FABM, which is used in the FSD model. The hybridized FSD-FABM of CLP is then validated using a case study. Data collected on an industrial project was utilized to formulate a predictive CLP model of construction crews performing activities. The FSD-FABM is then verified using different forms of verification tests.

1.5.5 Fifth Stage

In the fifth stage, the strategic decision-making aspect of the productivity problem is addressed by proposing two decision-making models. The first is a novel FSD-FABM-MCDM, which addresses the need for decision support tools for use in construction, where problems exist in a dynamic environment with subjective uncertainties. This was achieved by integrating the capacity of FSD-FABM to address dynamic and subjective problems, with MCDM’s capacity to address multiple and sometimes conflicting expert opinions. The model can be adapted to several construction problems to help decision makers prioritize and select from several strategies intended to improve CLP, and other KPIs. The second model is a novel RL-FSD-FABM, which addresses the need to incorporate multiple system variables and multiple constraints during the decision making process in order to improve the CLP measure. A framework to produce an optimal set of solutions by simulating complex construction environments using FSD-FABM and optimizing dynamic parameters using RL is proposed.

1.6 Thesis Organization

Chapter 1 presents a brief background of the research, the problem statement that was established in the form of the *productivity problem*, and the objectives of this research. The expected academic and industrial contributions and the research methodology are also provided in this chapter. The rest of this dissertation is organized as follows.

Chapter 2 presents a brief background on construction modeling techniques used in productivity research, and focuses on the role of FSD and its applications in construction research. In addition, the state-of-the-art in SD modeling was presented by performing a systematic review and content analysis of 213 articles, obtained from 21 high-ranking peer-reviewed journals, to analyze the application of SD in CEM and derive directions for future research. The foundation for use of hybridized FSD-FABM in modeling productivity is also discussed in this chapter.

Chapter 3 presents a novel FAHP-FDEMATEL model to provide a systematic and structured method for determining causal relationship mapping between factors affecting productivity. This weighted FDEMATEL model is able address part of the productivity problem by proposing a systematic and structured methodology that integrates fuzzy system theory with the modeling approaches AHP, and DEMATEL, for use in dynamic modeling of productivity.

Chapter 4 presents the overall methodology and detailed steps for developing the hybrid FSD-FABM. This chapter discusses three major components of the modeling process, namely, the FSD, FABM, and the hybridized FSD-FABM components.

Chapter 5 presents the verification of the FSD-FABM using case study. This chapter also describes the how data collected was utilized in the model. Other verification techniques that were applied on the FSD-FABM, such as structural verification and behavioral verification, are also discussed in this chapter.

Chapter 6 presents two novel modeling methods for strategic decision making, namely, the FSD-FABM-MCDM, and the RL-FSD-FABM. The application of each decision-making model and the need to propose strategic decision-making solutions using each of the modeling techniques is also presented in this chapter.

Chapter 7 presents the conclusions, contributions, and limitations of this research, and also proposes recommendations for future research on construction productivity.

Chapter 2 Application of System Dynamics in Construction Engineering and Management: Content Analysis and Systematic Literature Review[2]

2.1 Introduction

In construction engineering and management (CEM) research, simulation enables practitioners to understand underlying behaviours of construction systems by developing and experimenting with their computer-based representations (AbouRizk et al. 2011). Traditional approaches to solving construction problems—examples include typical networking techniques such as critical path method (CPM), program evaluation and review technique (PERT), time–cost trade-off analysis, and resource leveling and allocation—fail to capture the intricate interdependencies between construction systems. In contrast, simulation has overarching benefits in CEM research, because experimentation with varying scenarios enables managers to obtain reliable results and optimize processes for efficiency (AbouRizk et al. 2011). The three major paradigms in construction simulation modelling are discrete event simulation (DES), agent-based modelling (ABM), and system dynamics (SD).

DES is a modelling technique used to capture systems, such as construction processes, that occur in discrete units of time (Raoufi et al. 2018). DES allows users to interact with the model and observe the model's changes as the simulation clock advances. ABM comprises discrete entities called agents, which have their own behaviours, characteristics, and rules of interaction. ABM is

[2] This chapter has been submitted for publication in *Advances in Civil Engineering*: Kedir, N., Siraj, N.B., and Fayek, A. R. (2022), Application of System Dynamics in Construction Engineering and Management: Content Analysis and Systematic Review." *Advances in Civil Engineering*, 49 manuscript pages, submitted Oct. 2022.

a bottom–up simulation technique that uses individual agents' defined behavioural characteristics to produce global behaviour resulting from non-linear agent interactions (Raoufi and Fayek 2018). The SD modelling approach focuses on capturing the dynamic nature of systems that usually exhibit varying properties in relation to time and through multiple feedback processes, interactions, and dependencies (Nasirzadeh et al. 2008). SD is a top–down modelling approach that initially abstracts the system at a higher (macro) level to identify variables that affect the state of the system. In terms of level of abstraction, DES is modelled with low to medium abstraction, where more details are necessary to represent the system than the other two modelling approaches. ABM can incorporate different levels of detail, ranging from low abstraction with more details to high abstraction with fewer details. SD is usually modelled at higher abstraction and analyses the system at the macro level.

CEM involves "the development and application of techniques that improve organizations' abilities to plan, structure, forecast, control, and evaluate projects in order to deliver results that meet or exceed performance objectives such as time, cost, productivity, quality and safety" (Fayek and Lourenzutti 2018). Construction projects exhibit complexity stemming from interdependencies between system components, such as human, environmental, technical, and organizational factors that affect construction processes (Nasirzadeh et al. 2008). These interdependencies also involve non-linear relationships with multiple feedback processes that are able to change through time, which makes the overall problem of CEM system abstraction highly dynamic (Sterman 2002) SD is appropriate for modelling problems that are "broad in details, holistic in perspective, continuous in behaviour, and also featuring qualitative or quantitative data" (Alzraiee et al. 2015). SD is widely used to solve problems with a high degree of complexity and dynamism to help policy- and decision-makers analyse different strategies, formulate policies, and improve the process of decision making (Siraj and Fayek 2019). Hence, SD has been a preferred approach in CEM, as it can be used to implement and understand the dynamics of complex processes that are not understood by other means (Abotaleb and El-adaway 2018).

With the increased use of computer simulation approaches, the role of SD in capturing complex CEM systems is becoming ever more pronounced, both as a standalone modelling approach and as part of hybrid models. In this regard, researchers need a more focused insight into SD's capabilities for capturing different CEM systems, which can be accomplished through a comprehensive study of the SD literature, as in this state-of-the-art study of SD application within different CEM research areas. Previous studies related to an SD literature review and content analysis in CEM are not exhaustive in terms of the number of papers covered per journal or range of years assessed, having only performed reviews of abstracts and studied citation records. They also classified areas of SD research within a limited set of published SD literature and lacked focused analysis that proposes potential avenues for SD hybridization. Furthermore, the literature lacks a state-of-the-art study on SD that can guide researchers by analysing the SD research performed in recent years. This paper provides a content analysis and critical review of existing literature related to the application of SD in CEM.

The objectives of this chapter are to: 1) provide a comprehensive review of SD journal articles and content analysis to profile the selected articles based on researchers' affiliations, case study projects, and geography; 2) identify CEM research areas and assess past studies and current trends in relation to the role of SD in these research areas ; 3) assess the potential for SD hybridization with traditional methods, and other modelling and simulation approaches; and 4) identify modelling issues related to the use of SD in CEM.

2.2 Background

Productivity is one of the most crucial metrics that is used to assess overall crew performance in construction (Nasirzadeh and Nojedehi 2013). Construction crew productivity has been effectively defined as the ratio of measured output – completed work, to measured input – work effort, by several studies (Zhao and Dungan 2019; Johari and Jha 2020; Yi and Chan 2014). This ratio can be applied to capture productivity at the crew, activity, and/or project levels. There are also higher levels of productivity study, whereby factors that affect the measured productivity at the organizational-, provincial-, national, and global- level are assessed (Kedir et al. 2022a; CII 2006).

Previous studies have attempted to address the productivity problem in part, or as a whole (Nasirzadeh et al. 2020; Rahman et al. 2019; Hasan et al. 2018; Kisi et al. 2017). Focusing on the studies that put modelling of crew productivity as a center piece, the implemented models in those studies can be summarized as: statistical methods (Ghodrati et al. 2018; Gurmu and Ongkowijoyo 2020; Hiyassat et al. 2016), artificial neural network (Gutiérrez-Ruiz et al. 2020; Golnaraghi et al. 2019; Ma et al. 2016), discrete event simulation (Plamenco et al. 2021; Abbasi et al. 2020; Larsson et al. 2016), agent based modeling (Wu et al. 2022; Dabirian et al. 2021; Jabri and Zayed 2017; Shehwaro et al. 2016), and system dynamics (Al-Kofahi et al. 2020; Javed and Pan 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019). These approaches have been used individually or in the context of hybrid models. Fuzzy logic concepts have also been incorporated into these approaches, some of which include: (Gerami Seresht and Fayek 2018; Nojedehi and Nasirzadeh 2017; Mirahadi and Zated 2016). In this regard, the modeling dimension in the productivity research has mostly emphasized on the need to consider crew productivity as a dynamic problem owing to the dynamic nature of construction projects. Moreover, dynamic modeling approaches are preferred owing to the need to track project changes that happen over time (Gerami Seresht and Fayek 2018), and need to capture the causal relationships formed from interactions among these factors (Kim et al. 2020).

The concept of SD was first introduced by Jay Forester in the mid-1950s to model complex systems (Sterman 2000). Since its inception, SD has been widely applied in different fields including agriculture, economics, health care, defense, education, and engineering. Sterman (2000) stated that in SD modelling, the initial step is problem articulation (boundary selection), which involves identifying key variables and their behaviours. This is followed by formulating the dynamic hypothesis, which involves identifying model boundaries, subsystems, causal loop diagrams (CLDs), delays, and stock and flow maps. The simulation is then formulated and used to test different model scenarios to eventually design and evaluate policies. Figure 2.1 depicts the major components of an SD model. In SD modelling, CLDs help to elicit mental models of experts, represent causal relationships, and depict important feedback loops within the system. The polarities (either positive "+" or negative "–") denote the causal influences among system variables. A positive link implies that variables change in the same direction, while a negative link indicates that variables change in opposite directions (Boateng et al. 2012). Stocks are represented by accumulation or depletion, which result from differences between inflows and outflows at any point in time. Flows are the rates at which a stock varies over a given amount of time (Sterman 2000). Delays are described by the lag between inputs and outputs and are used to model elapsed time between cause and effect, which is indicated by a double line perpendicular to the causal link in SD (Boateng et al. 2012).

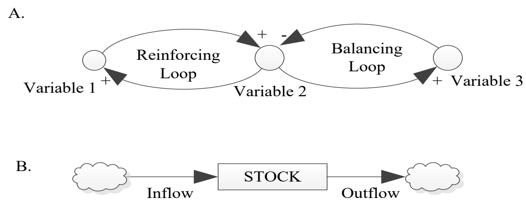

Figure 2.1 Components of system dynamics: A. Causal loop diagram; B. Stock and flow diagram.

Previous SD reviews focused mostly on SD's application to a specific CEM area, namely strategic management (Cosenz and Noto 2016), supply chain management (Rebs et al. 2019), or transportation (Shepherd 2014). Some studied the application of SD on limited aspects of project management (Lyneis and Ford 2007). Others studied critical review of SD research to a broader extent outside the scope of CEM (Kunc et al. 2018). Moreover, previous studies lacked a more focused and purposeful investigation of SD's application in major CEM research areas. This paper provides a state-of-the-art content analysis and systematic literature review that covers a wide scope of CEM fields and provides researchers with a more focused insight on SD developments and trends in CEM research.

2.3 Methodology

After reviewing several studies that performed content analysis and literature review related to CEM (i.e., Abotaleb and El-adaway 2018; Jang et al. 2019; Kifokeris and Xenidis 2017; Liu et al. 2019; Lyneis and Ford 2007)), this chapter utilized a multi-phase methodology, as shown in Figure 2.1 and elaborated in the following subsections.

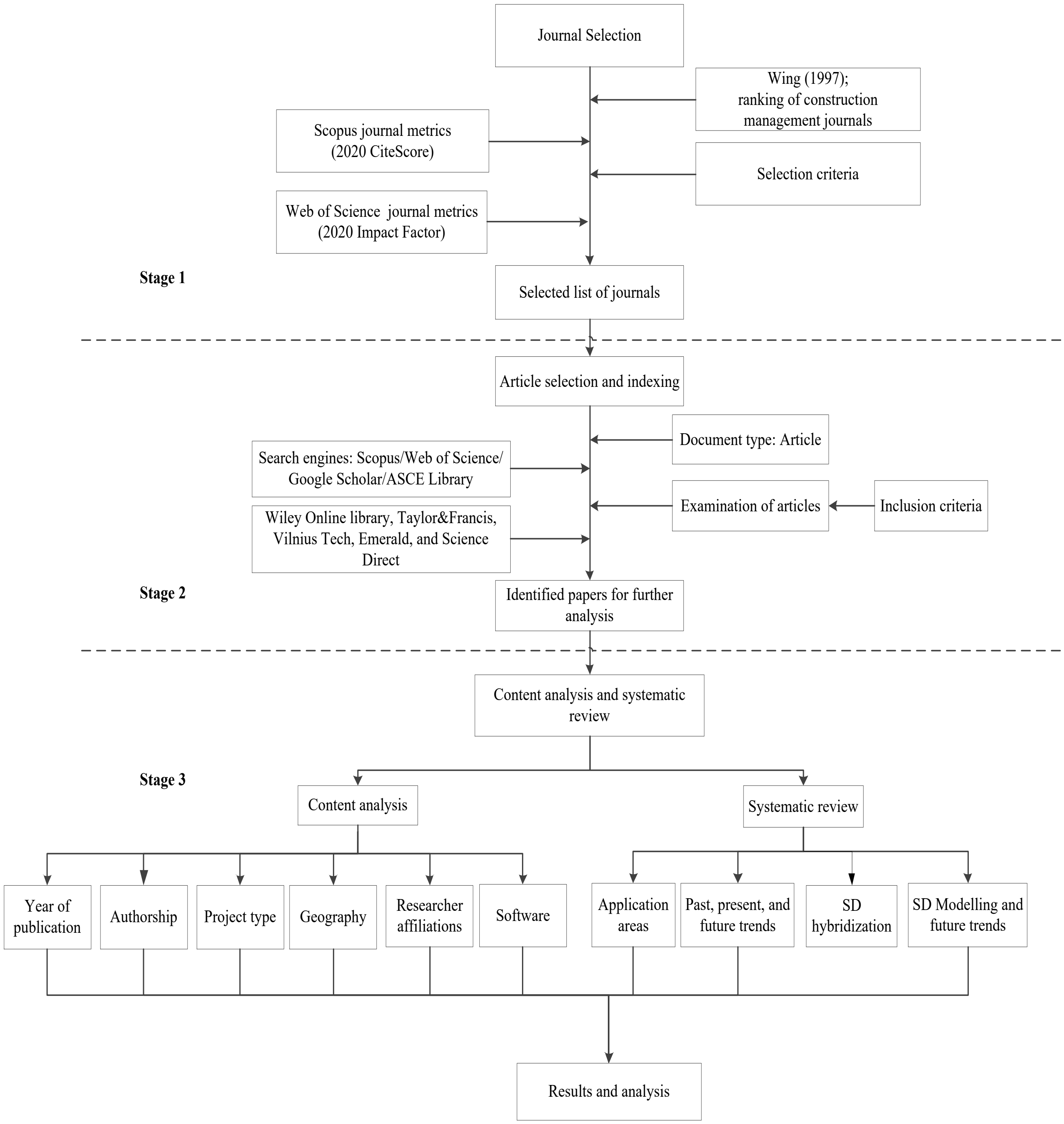

Figure 2.2 Research methodology for this chapter.

2.3.1 Stage 1: Journal selection

In the first stage, peer-reviewed journals with important impact and prominence in the field of CEM and which hosted published research works in the area of SD between 1995 and 2021 were selected. During the selection process, previous studies on journal rankings in CEM (e.g., Wing 1997) were referenced. Journals that had a CiteScore of ≥2.0 in the 2020 Scopus ranking and journals that had a journal impact factor of ≥2.0 in the 2020 Institute for Scientific Information's (ISI) Web of Science journal citation report were considered. Only peer-reviewed journals in the area related to SD were selected. Books, book chapters, book reviews, conference papers, editorials, forums and discussions, letters to the editor, indexes, introductions, forewords, seminar reports, briefing sheets, and comments were excluded. The following 21 journals were thus selected: *Accident Analysis and Prevention* (*AAP*), *Automation in Construction* (*AC*), *Building and Environment* (*B&E*), *Canadian Journal of Civil Engineering* (*CJCE*), *Computer-Aided Journal of Civil and Infrastructure Engineering* (*CAJCIE*), *Construction Innovation* (*CI*), *Construction Management and Economics* (*CME*), *Engineering Construction and Architectural Management* (*ECAM*), *European Journal of Operational Research* (*EJOR*), *International Journal of Civil Engineering* (*IJCE*), *International Journal of Construction Management* (*IJCM*), *International Journal of Project Management* (*IJPM*), *Journal of Civil Engineering and Management* (*JCiEM*), *Journal of Computing in Civil Engineering* (*JCCE*), *Journal of Construction Engineering and Management* (*JCEM*), *Journal of Infrastructure Systems* (*JIS*), *Journal of Management in Engineering* (*JME*), *Journal of the Operational Research Society* (*JORS*), *Korean Society of Civil Engineers-Journal of Civil Engineering* (*KSCE-JCE*), *Resources, Conservation and Recycling* (*RCR*), and *System Dynamics Review* (*SDR*).

2.3.2 Stage 2: Article selection and indexing

In the second stage, relevant articles from the selected journals were selected and indexed. Article searches were performed using the major available databases, namely the Web of Science, Scopus, Google Scholar, and the American Society of Civil Engineers (ASCE) library. Further article search was performed in the Wiley Online Library, Taylor & Francis, Vilnius Tech, Emerald, and Science Direct databases. For a more inclusive but focused search, the keyword *system dynamics* was searched in entire articles across each journal. This was done for two reasons First, introducing other keywords that have been alternatively used in SD articles would produce search results that are not within the context of SD. For example, the keyword *dynamic modelling* resulted in several articles not related to SD (e.g., ABM, fuzzy cognitive mapping, robotics). Second, executing a topic/abstract/keyword (T/A/K) search would limit those articles that proposed an SD model but do not use the specific words in any one T/A/K search result.

The online search was performed to include articles from the advent of SD as a tool by Forrester in 1956 (Forrester 1968). However, the search did not produce enough relevant articles related to CEM prior to 1995, because relevant articles that may have been published within that period were not archived in the database. For example, Scopus coverage of CEM-related articles started in 1995. Therefore, article selection was restricted to include articles published in the English language, in the year range between 1995 and 2021 (inclusive), and in-press articles not yet published in 2021. After performing the initial search in the major databases (e.g., Web of Science, Scopus, Google Scholar), further searches were performed in the database of each journal to find any missing articles and ensure completeness. As a result, 1,488 articles were downloaded and then indexed in Microsoft Excel. These results were further examined by reviewing the abstract, methodology, and summary sections of the texts to filter out articles that did not meet the predetermined inclusion criteria, which were 1) the article should specifically address the issue of utilizing SD for modelling, and 2) the article should discuss a topic in the area of CEM. The abstract, introduction, and methodology sections of each paper were then examined against these criteria. A total of 213 articles met the inclusion criteria and were selected for further analysis.

2.3.3 Stage 3: Content analysis and critical review

After journal selection and article identification, further analysis of the selected articles was performed by studying articles that carried out a similar analysis in other related areas (Chan et al. 2010; Olawumi and Chan 2018; Siraj and Fayek 2019; Vaidya and Kumar 2006). This content analysis included profiling the articles based on: 1) journal, year of publication, and number of authors per article, 2) university affiliation and geography of the authors, 3) project types that were considered in the articles, 4) research areas addressed in the articles, and 5) software used to model the SD problem in an article.

2.4 Results and Discussion

2.4.1 Descriptive and content analysis

2.4.1.1 Profile of selected articles based on journal types and year of publication

The 213 articles selected for further analysis were profiled based on the contributing journals and year of publication. The percentage contribution of each journal to the total number of articles is shown in Figure 2.3. More than 50% of the articles were published in seven journals: *JCEM* (16%), *JME* (10%), *ECAM* (8%), *IJPM* (7%), *CME* (6%), and *IJCM* (6%). Figure 2.4 shows the yearly contribution of each journal, tallied per a five-year period. Out of all articles, 60% (128 articles) were published after 2010. Close to 40% (82 articles) of the total articles were published after

2015, of which 53% of these publications were registered in four journals: *JME* (18%), *ECAM* (16%), *JCEM* (10%), and *JIS* (9%).

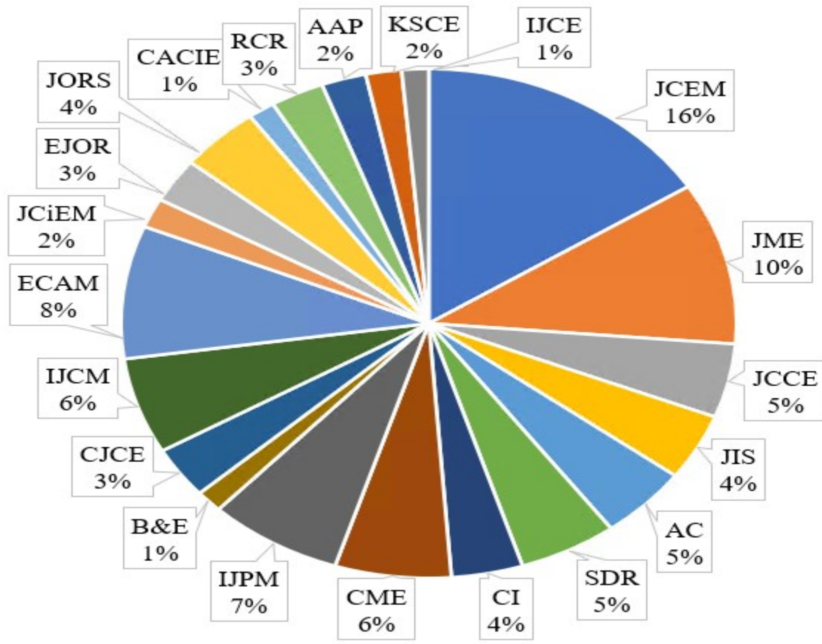

Figure 2.3 Percentage of total selected articles published in each journal.

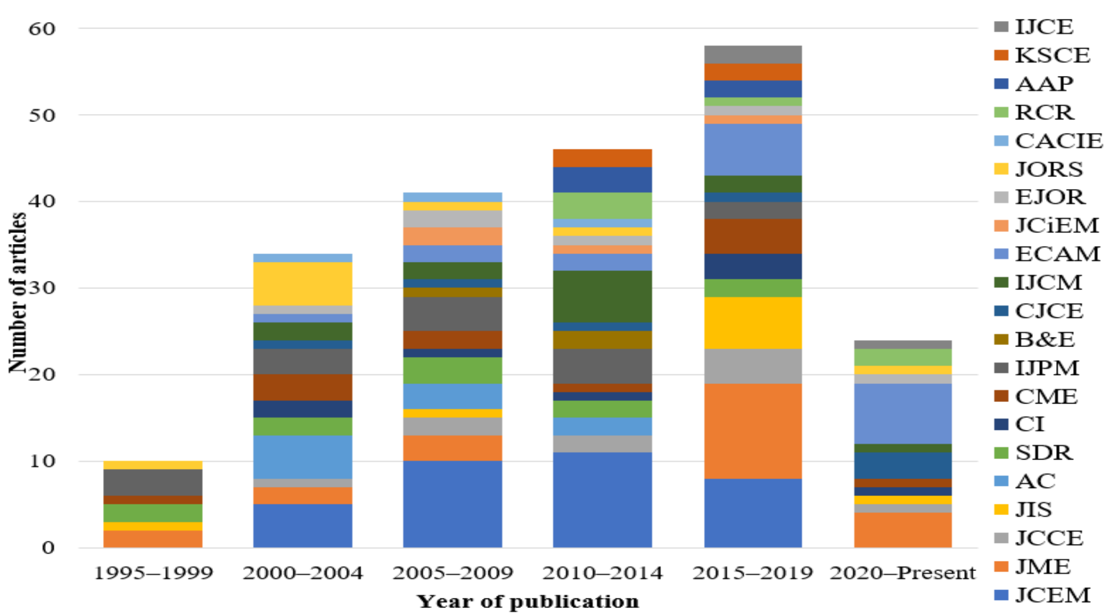

Figure 2.4 Number of selected articles by journal and year of publication.

2.4.1.2 Profile of projects in the selected articles

In this chapter, the types of projects presented in the selected articles were profiled in accordance with the type of construction work involved. This approach is adopted from previous studies that performed similar project type classification (Siraj and Fayek 2019). Table 2.1 presents the profile of projects in the selected articles. Of the 213 articles, 182 could be categorized under one of the following project types: *Infrastructure projects*, *General type*, *Building projects*, *Power and energy projects*, and *Heavy industrial projects*. A project was characterized as *General type* when no specific project type was given (e.g., design processes, development of qualitative SD models).

Table 2.1. Profile of project types in the selected articles.

Project type	No. of articles	Percentage	Rank
Infrastructure projects (e.g., highways, mass transit systems, tunnels, bridges, drainage systems, sewage treatment plants)	74	34.74	1
General type	57	26.76	2
Building projects (e.g., residential, office, commercial, mixed development, hospitals)	39	18.31	3
Power and energy projects (hydroelectric plants, solar energy, wind power, nuclear)	7	3.29	5
Heavy industrial projects (e.g., chemical, refineries, oil sands installation)	5	2.35	6
Uncategorized	31	14.55	4
Total	**213**	**100.00**	

The analysis indicates that SD research is heavily linked with infrastructure projects. This stems from the significance of infrastructure projects in a county's growth, as these projects play a key role in spearheading the economic development of several economic sectors(Hong et al. 2010; Yu et al. 2018). Infrastructure projects also cover a wide range of construcruction works that are usually complex and encompass a diverse nature of project requirements (Chong et al. 2016).

2.4.1.3 Profile of application areas in the selected articles

In this chapter, previous works by Lyneis and Ford (2007), Abotaleb and El-adaway (2018), and Liu et al. (2019) were used as a reference to examine most common application areas studied by researchers. Moreover, major construction management knowledge areas identified by the Project Management Institute (PMI 2013) were also used as input. The most frequently occurring keywords and phrases were analyzed to assist in identifying the focus of pertinent past, current, and future research. Consequently, the major construction application areas identified in this chapter are: *Decision making and policy analysis*; *Performance*; *Rework and change*; *Scheduling*; *Risk and contingency*; *Resource management*; *Productivity*; *Cost planning, estimation, and control*; *Bidding and procurement*; *Health and safety*; and *Claim and contract administration.* Based on these CEM research areas, 188 of the articles were categorized under one of these 11 categories.

It is important to note that intersections exist between the aforementioned application areas (e.g., effect of schedule delay on project cost), and some researchers have addressed more than one construction application area in a given article. In such cases, the research area given the most focus by the researchers was selected.

2.4.1.4 Profile of software used in the selected articles

Analysis of the reviewed literature indicates that seven software packages have been used to implement SD: AnyLogic®, Dynamo™, DynaRisk, iThink®, Powersim, Systems Thinking, Experimental Learning Laboratory with Animation (STELLA), and Vensim. Profiling was performed for 106 articles that either demonstrated or discussed the use of specific software in their models, as shown in Figure 2.5. Selection of software depends on several factors, such as availability and capability. For instance, Dynamo™ is no longer distributed commercially, so fewer and fewer papers are implementing it. Vensim is a relatively earlier software with discrete event functionality and simulation capabilities for the Markov chain and Monte Carlo methods. AnyLogic® is a newer software that is able to support a combination of SD, DES, and ABM, is able to perform hybrid modelling, and offers graphical user interface (GUI) for users to execute several types of stand-alone or hybrid simulation. Both STELLA and iThink® offer a GUI to simplify user experience and are mainly SD and DES modelling software with limited ABM capabilities.

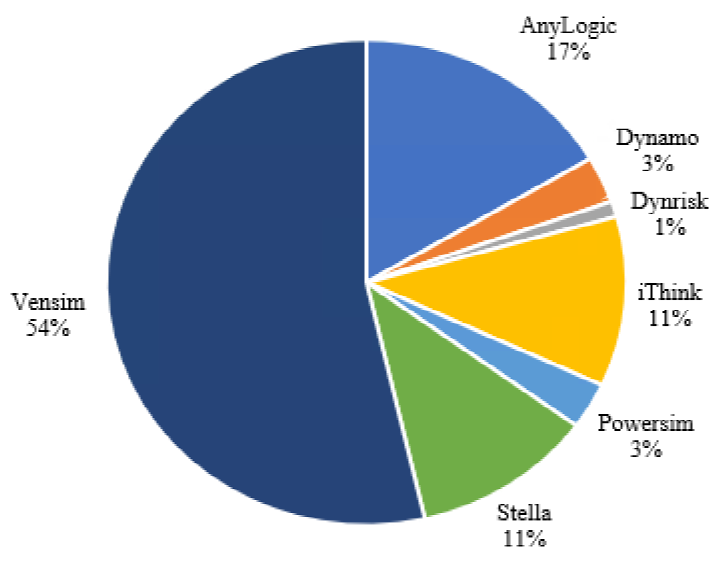

Figure 2.5 Software used in the selected articles.

2.4.2 Systematic Review

This section presents a systematic review of SD research in the main CEM application areas. The application areas were selected by: utilizing previous knowledge from the works of Lyneis and Ford (2007), Abotaleb and El-adaway (2018), and Liu et al. (2019); referring to the major construction management knowledge areas identified in PMI (PMI 2013); and analyzing the most frequently occurring keywords and phrases present in the selected articles. Next, the gaps in the current research are analyzed to propose potential areas for future research. In this chapter, only the relevant research areas are discussed.

2.4.2.1 Decision making and policy analysis

Beyond capturing the construction system to study causal relationships between system elements and feedback mechanisms, SD can be effectively applied to analyzing scenarios to devise policies and support decision making. In this regard, researchers and stakeholders have leaned towards the application side of SD and implementation of this modelling approach to devise solutions to different problems. In the literature, researchers have utilized SD to facilitate a systems-level approach to higher-level decision-making problems. The majority of early research focused on industry-level studies and infrastructure projects, including dynamic simulation of different maintenance policies for highway projects (e.g., Chasey et al. 1997; de la Garza et al. 1998; Fallah-Fini et al. 2010). Studies related to decision making and policy analysis have since focused on sustainability. Yao et al. (2011) proposed a SD model for evaluating the sustainability of highway infrastructure projects and exploring policy scenarios to improve poor sustainability performance areas. Xu and Coors (2011) proposed an integrated approach for assessing sustainability of urban residential development, in which SD was used to quantitatively investigate and help decision-makers identify the developmental tendency of sustainability indicators. Zhang et al. (2014) proposed an SD model for assessing sustainability of construction projects.

Within decision making and policy analysis research, the issue of sustainable infrastructure management has been a recurring theme. Related articles focused on studying the dynamics of maintenance and rehabilitation of highway projects for policy analysis and decision making (Andrijcic and Haimes 2017; Guevara et al. 2020; Zhang et al. 2018), environmental and economic impacts of infrastructure-highway projects (Ruiz and Guevara 2021). and financing of infrastructure projects (Hou and Wang 2021; Sihombing and Adventus Simanjuntak 2020). Furthermore, sustainability studies also used SD to explore the dynamics of causal relationships and strategies, and to realize sustainability improvement programs (Hessami et al. 2020; Ruiz and Guevara 2021; Thomas et al. 2016).

Future research may potentially capture more of the complexities and dynamic relationships between factors while analysing their impact on strategies. Further research on incorporating feedback delay into SD models would allow researchers to account for the delay resulting from strategy selection and strategy implementation in decision making. Moreover, producing better SD models that consider the effect of different policies on subsystems, detailed at different levels of aggregation within the model to support project and organizational-level decisions, should also be investigated. Potential to mitigate problems related to policy optimization and scenario analysis exists, which can enable decision makers to produce better solutions. Furthermore, more studies need to be performed to study the capabilities of hybrid models to capture human and social behaviours and analyse the social impacts of policies in decisions modelling.

2.4.2.2 Performance

Defining performance is an extensive research topic. Performance can be assessed using multiple metrics for gauging construction processes, practices, and outcomes and analysing their measurements based on previous or defined acceptable standards. Hence, performance can be defined differently based on the objective of a study (Raoufi and Fayek 2020). For this chapter, articles that primarily addressed performance as a topic and/or discussed multiple metrics (which are aggregated to indicate performance) were selected to be analysed under this research area category. Earlier studies on the applicability of SD for modelling performance focused on strategic management to enhance performance in construction organizations. Relevant research was conducted at the project and organizational levels, with more research on the latter.

At the project level, Peña-Mora et al. (2008) used SD for strategic management of an earthmoving project. Park et al. (2009) proposed qualitative SD model to explore and test design-build (DB) alternatives for enhancing DB performance. Ford and Bhargav (2006) studied the application of flexible strategies for project management quality improvement. Ogunlana et al. (2003) used SD to explore and enhance overall performance in an organization. Tang and Ogunlana (2003) similarly employed SD to study and improve an organization's performance behaviour using SD to suggest organizational performance improvement strategies.

Recent studies have focused more on forecasting performance of construction projects as part of monitoring and control of projects to achieve their objectives. With the concept of strategic management as a recurring theme, these studies worked towards mitigating the effects of dynamic parameters that affect project performance. Leon et al. (2018) used SD to simulate dynamic complexities between system variables and forecast project performance. They simulated intervention scenarios to improve project performance indicators, such as considering the interrelated structure and interaction of performance indices including cost, schedule, quality, profitability, safety, environment, team satisfaction, and client satisfaction. Nasir and Hadikusumo (2019) used SD for performance assessment by modelling the owner–contractor relationships in construction projects. Ecem Yildiz et al. (2020) used SD to develop a strategy map to manage performance in construction by assessing the impact of different strategies on aggregated performance measures. Kim et al. (2020) used an SD modelling approach to assess construction project behaviour, by studying the dynamic interrelationship between the causes and effects of skilled labour shortage on construction project performance indices. Wu et al. (2019) used SD to gain better understanding of labourers' behavioural diversities and the associated impacts on project performance. Vahabi et al. (2020) proposed a dynamic simulation model to evaluate the impact of project briefing clarity on the impact of project performance. Soewin and Chinda (2020) developed a dynamics model of construction performance indices to examine and improve these measures in the long term. Luo et al. (2021) investigated the impact of leadership dynamics on project performance by using SD to simulate the variation of leadership on the evolution of project performance. Tang et al. (2021) used SD to carry out dynamic performance measurement and simulation of a public–private partnership project to construct a unified project performance measurement indicator system.

In future, more studies should be conducted to capture dynamic relationships between key performance indicators (KPIs). This can be regarded as a two-part challenge: first, to be able to include more KPI parameters within the SD model, which can better assist in representing the construction environment; and second, properly capturing the dynamic relationships between these parameters to determine overall performance. Furthermore, factors affecting performance that have not investigated in detail, such as out-of-sequence work (Abotaleb and El-adaway 2018), should be duly studied.

2.4.2.3 Productivity

Several researchers have used SD to study productivity problems. Earlier studies utilized SD to capture construction systems and observe the impact of one or multiple factors on productivity. Chapman (1998) studied how changing key personnel impacted design productivity. Prasertrungruang and Hadikusumo (2009) studied how downtime resulting from equipment failure impacted productivity. SD has since been applied to shape management strategies aiming to increase productivity. Alvanchi et al. (2012) used SD modelling tool to investigate the effects of different working-hour arrangements on productivity.

Recent studies focused on simulating the construction process in order to observe in-depth interrelationships between different factors and the productivity measure. Nasirzadeh and Nojedehi (2013) used SD to model the complex relationships between different factors affecting labour productivity. Researchers have hybridized SD with other modelling approaches to propose predictive models of productivity, which can also be used to improve the productivity measure. Gerami Seresht and Fayek (2018) developed a fuzzy SD (FSD) predictive model for productivity of equipment-intensive activities using fuzzy logic principles to capture subjective variables within the SD model. Khanzadi et al. (2019) used a hybrid SD-ABM approach to predict and improve the labour productivity measure.

Review of the literature on productivity indicates that no unified definition of productivity exists. Hence, SD models solving productivity problems are specific to problem context and the definition of productivity used in the model. In addition to capturing the impact of factors that contribute to the productivity loss, the objective of productivity improvement at the project or organizational level entails also studying the dynamic effect of factors that positively affect productivity. In this regard, future research needs to propose informed solutions based on studies of the dynamic impact of best practices and their contribution to the overall improvement of productivity measures. Furthermore, opportunity exists to further investigate how some dynamic factors affect productivity using the increasingly popular approach of integrating SD with other modelling techniques. Some research potential includes further investigation into the impact of workplace congestion and worker motivation on productivity at the project and organizational levels using hybrid modelling methods such as SD-ABM.

2.4.3 Past and Present Trends of SD Application Based on Research Application Areas

To analyze research trends, the selected articles were categorized based on the previously defined research application areas and were grouped as articles published in five-year intervals between 1995 and 2019. Publications from 2020 to 2021 were also included in the analysis, and the relatively fewer number of publications for this two-year period was taken into consideration. As illustrated in Table 2.2 and Figure 2.6, a significant increase in SD application occurred between 2012 and 2021. Figure 2.6 shows trends in SD-based CEM research areas. Each year range in the figure shows the article count for five-year intervals for 1995 to 2019 and a two-year interval for 2020 to 2021.The top five CEM research areas where SD was used as part of the modelling process were: *Decision making and policy analysis* (27%), *Performance* (16%), *Rework and change* (11%), *Scheduling* (8%), and *Productivity* (7%).The application of SD for the purpose of *Decision making and policy analysis* is the most discussed topic in the literature. The area of *Decision making and policy analysis* also has the most intersection with other research areas, because providing solutions to a problem related to another research area can be phrased as a decision-making problem (e.g., improving performance, reducing rework, improving project schedule). The research area with the second most focus is *Performance*. This stems from the various ways to define performance, which can encompass the discussion of one or multiple construction metrics (i.e., performance indicators), mostly at the project or organizational levels. *Rework and change* ranked third, with decreasing interest shown since 2015.

Analysis of trends in the literature indicates clusters of research areas that researchers have shown interest in and those with a decreasing trend in publications. Despite the fewer number of articles, *Scheduling* and *Health and safety* have garnered more interest relative to previous periods in their respective areas. For *Scheduling*, researchers have capitalized on SD's potential for modelling delays to address delay-related scheduling problems. *Performance* is another area of CEM research that has seen increasing publications since 1999. Conversely, *Cost planning, estimation, and control* and *Bidding and procurement* have received much less interest since about 2009.

Table 2.2 Publications under the identified research areas.

No.	CEM research area	1995–1999	2000–2004	2005–2009	2010–2014	2015–2019	2020–2021	Total
1	Decision making & policy analysis	3	1	3	15	17	11	**50**
2	Performance	1	6	4	4	9	5	**29**
3	Rework & change	2	3	5	5	4	2	**21**
4	Scheduling	1	6	1	1	5	1	**15**
5	Resource management	1	1	4	4	2	2	**15**
6	Productivity	1	1	1	3	5	2	**13**
7	Health and safety	1	0	0	3	6	2	**12**
8	Risk & contingency	0	1	2	4	3	2	**12**
9	Claim and contract administration	0	2	3	1	2	0	**8**
10	Cost planning, estimation, & control	1	2	2	0	0	2	**7**
11	Bidding & procurement	1	1	4	0	0	0	**6**
	5-year total	**12**	**24**	**29**	**40**	**53**	**29**	**188**

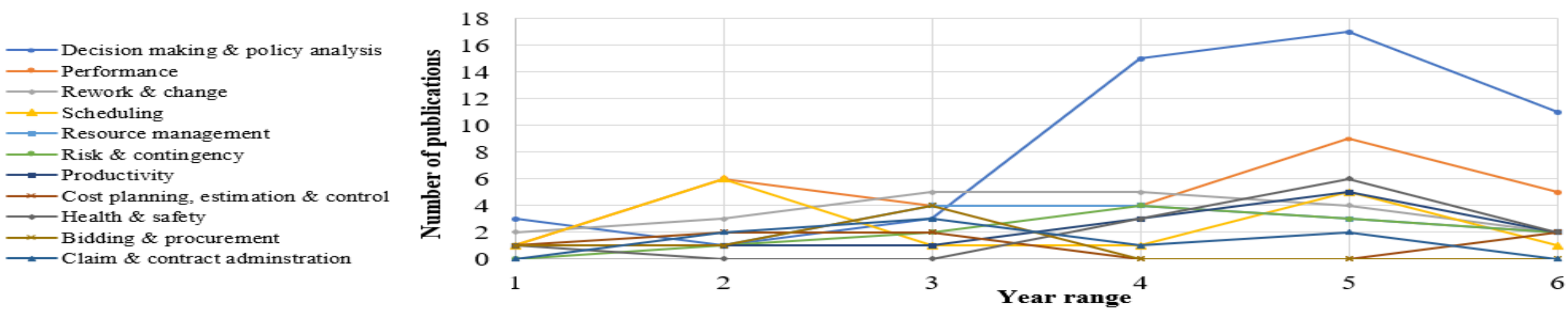

Figure 2.6 Trends of SD based CEM research areas.

2.4.4 Integration of SD Modelling with Other Methods

This section presents the review of the selected articles, which indicates the use of SD modelling with other methods (i.e., traditional methods, and other modelling approaches) to model CEM problems. Integration of SD with fuzzy logic is also discussed to elaborate the implementation of fuzzy logic principles in SD modelling to capture different problems in CEM.

2.4.4.1 Integration of SD with Other Modelling and Simulation Techniques

Hybridization of SD with other modelling techniques has become an increasingly preferred practice by researchers, as it enables modelers to use the potential benefits offered by the model components. In this regard, researchers have used SD to complement different simulation and modelling techniques, such as DES, and ABM.

In the context of construction research, hybridization of SD with DES was an early form of hybrid modelling approach and goes back to the early 2000s (Alvanchi et al. 2011). Although DES is suitable to analyzing the stochastic nature of construction parameters at the tactical level, DES is not capable of modelling construction systems at the holistic level and also falls short in capturing dynamic feedback processes between system variables (Alzraiee et al. 2015). Hybrid SD-DES combines the sequential modelling benefits of DES with the dynamic modelling capabilities of SD. Xu et al. (2018) used a hybrid SD-DES model in which DES captured construction activities' micro-level variables, such as resource allocation and predecessor–successor relationships, and SD represented the construction environment as a macro-level phenomenon and captured feedback relationships between different model subsystems (i.e., construction process, resource, project scope, schedule target, project performance subsystems). Alzraiee et al. (2015) used SD-DES modelling for dynamic planning in which operational-level parameters (i.e., duration, activity sequence) were modelled using DES, and the dynamics arising from interactions between the model's variables were modelled using SD. Similarly, other researchers have used DES to capture sequential processes and other operational model parts at the micro level and SD to capture feedback relationships and other dynamic aspects of the model at the macro level. Some areas of this research include productivity (Alvanchi et al. 2011), performance (Moradi et al. 2015; Peña-Mora et al. 2008), cost estimation, planning, and control (Peña-Mora et al. 2008), claim and contract administration (Menassa and Peña-Mora 2010), and resource management (Alvanchi et al. 2011).

Hybridization of SD with ABM in CEM research is a relatively new topic, following the increasing popularity of ABM within the research community. ABM is not best suited to modelling policies, investigating which processes dominate in aggregated systems, and investigating aggregated system-level dynamics (Martin and Sclüter 2015). Nasirzadeh et al. (2018) highlighted the main limitations of SD, which include difficulty in modelling heterogeneous environments, as SD works mainly on aggregate variables, and difficulty in modelling systems that evolve through time, as the system's structure is fixed in SD. Thus, hybrid SD-ABM uses SD to capture higher-level dynamics, complex feedback relationships, and continuous factors and ABM to model micro-level variables, complexities, and emerging behaviours arising from agent interactions as well as the spatial nature of agent behaviours (Al Hattab and Hamzeh, 2018). Some examples include the hybrid SD-ABM by Khanzadi et el. (2019), in which SD was used to simulate continuous factors affecting labour productivity and their dynamic feedback relationships and ABM was used to model congestion, which results from interactions between different agents. Nasirzadeh et al. (2018) used hybrid SD-ABM to model construction workers' safety behaviour, where SD was used to capture multiple governing feedback relationships of several continuous variables and ABM was used to capture the complexity that emerges from agent interactions.

2.4.4.2 Integration of SD modelling with fuzzy logic

The fuzzy logic approach, introduced in 1965 by Zadeh (1965), is an extension of classical Boolean logic to handle real-world parameters by enabling mathematical translation of linguistic variables. Fuzzy logic theory is applicable in modelling CEM problems whose variables exhibit subjectivity or vagueness and require reasoning with ambiguous, incomplete, and/or imprecise data (Zadeh 1965).

Researchers have integrated fuzzy logic with SD to produce FSD models. Fayek (2020) discussed the importance of incorporating fuzzy logic to model CEM problems and summarized the aspects of CEM problems that are best suited for fuzzy logic modelling and fuzzy hybrid techniques. Some of these aspects include: when there is a reliance on experts for decision making based on subjective information and experience; when variables are imprecise or unstructured and there is a need to capture the complex relationship between these variables; and when the need arises to facilitate experts' decision making using linguistic terms instead of strict numerical terms. In this regard, FSD models are able to capture real-world systems with non-probabilistic (i.e., systems with subjective variables or linguistically expressed information) and probabilistic uncertainties (Levary 1990).

In the CEM literature, fuzzy logic has been used in FSD modelling for two purposes. First, in the qualitative stage of SD modelling, FSD is used to define model variables whose nature cannot be expressed using crisp values or probabilistic terms and to qualitatively define causal relationships between these variables (Gerami Seresht and Fayek 2020), which include factors such as crew motivation, haul road condition, adequacy of maintenance program, and familiarity with new techniques. Fuzzy logic can be used with other methods to identify variables and capture causal relationships within the FSD model. Siraj and Fayek (2021) and Rostamnezhad et al. (2020) used expert inputs in their FSD models, and they used fuzzy decision-making trial and evaluation laboratory (FDEMATEL) to capture uncertainty and vagueness arising from human judgements. Palikhe et al. (2019) used fuzzy analytical hierarchical process to identify critical factors and underlying relationships for their FSD model. Second, fuzzy logic is also used in the quantitative stage to quantify fuzzy system variables and quantitatively define causal relationships between variables. In this regard, FSD has been implemented to quantify claims (Nasirzadeh et al. 2018), model productivity (Gerami Seresht and Fayek 2018; Marzouk and Hamdy 2013; Nojedehi and Nasirzadeh 2017), and model quality management Nasirzadeh et al. 2013). FSD models have been most common in the area of risk and contingency (Khanzadi et al. 2012; Nasirzadeh et al. 2014; Nasirzadeh et al. 2008; Siraj and Fayek 2021), which may be due to fuzzy logic's ability to capture subjective uncertainties and the imprecise nature of risks.

2.4.5 Modelling Aspects of SD

In this section, the major steps in SD modelling, that is, qualitative and quantitative modelling, are studied in terms of underlying application issues in CEM research to identify potential areas for advancements and/or improvements.

2.4.5.1 Issues in qualitative and quantitative modelling

The initial SD modelling step of defining the model boundary and level of aggregation is crucial to system understanding. Systematically structuring the problem to be modelled can lead to a better boundary definition and can be done using model boundary charts (Boateng et al. 2012) or cognitive maps. Siraj and Fayek (2021) identified model boundaries and aggregation level for risk analysis using a model boundary chart to define the model scope and define the model subsystem at the work package level. Defining model boundaries and system abstraction can also be done at higher levels. Mostafavi et al. (2014) studied interdependencies between policy metrics at project, regional, and national levels for policy analysis of infrastructure systems. However, a review of the selected articles in CEM literature indicates that most studies have not discussed their process for defining model boundaries, including defining endogenous and exogenous variables and aggregation level.

Following the system understanding and problem articulation phase, the SD modelling process can be summarized as consisting of qualitative and quantitative stages. This chapter found that in the qualitative modelling stage, most researchers identified system variables and established the qualitative relationships between them using one or a combination of existing knowledge, literature review, and expert inputs. However, extracting knowledge from experts (e.g., using interviews) alone is insufficient and should be supplemented with other forms of data (Sterman 2000). Some system variables can also be "soft" (not measurable), making it impossible to always use numerical data (Sterman 2002). Moreover, the quantitative stage deals with formulating the model by building quantitative relationships between model elements and variables (Gerami Seresht and Fayek 2018). This is achieved by using numerical values or probability distribution functions for defining system variables and using table functions or mathematical equations to define causal relationships between system variables (Sterman 2000).

Construction systems whose causal relationships involve subjective variables do not have numerical metrics and are linguistically expressed. This chapter found that utilizing approaches such as probabilistic and analytical methods to capture these systems can be problematic owing to lack of sufficient historical data and that the use of fuzzy logic concepts has been widely utilized in these contexts (Nasirzadeh et al. 2008; Nojedehi and Nasirzadeh 2017; Siraj and Fayek 2019). An important aspect of fuzzy logic application is fuzzy arithmetic, which replaces classical arithmetic to perform algebraic operations involving fuzzy variables. Hence, the type of fuzzy arithmetic method selected significantly impacts the accuracy of the results; implementation of fuzzy arithmetic in the mathematical equations of FSD models can result in overestimation of uncertainty, reducing users' ability to accurately predict system output (Gerami Seresht and Fayek 2018). Of the two methods for carrying out fuzzy arithmetic operations, the a-cut method and the extension principle, analysis of the published articles in CEM literature shows a lack of research in the implementation of the extension principle in fuzzy arithmetic operations.

There is a lack of a systematic method for qualitatively capturing system variables, developing stock-and-flow and causal relationships, and performing quantitative modelling. In the presence of data, relationships between system variables can be captured using artificial intelligence-based approaches (Pan and Zhang 2021), such as machine learning, such as artificial neural networks (ANN) and fuzzy logic, to learn system rules from historical data. When data exhibits subjectivity, fuzzy logic–based methods such as neuro-fuzzy inference systems (NFIS) (Gerami Seresht and Fayek 2020) and data-driven fuzzy rule base systems (Siraj and Fayek 2021) can be used to facilitate SD model development. However, the potential of these methods to capture system complexity in SD modelling is not yet fully explored. Very few articles explored the use of other methods to elicit relationships between system variables in the absence of data. Procedures in methods such as FDEMATEL can be improved by incorporating weights to account for experts' profiles and their disparity in capabilities. The FDEMATEL methods proposed by some researchers (Rostamnezhad et al. 2020; Siraj and Fayek 2021) and the structural equation modelling (SEM) proposed by others (Luo et al. 2021; Zhang et al. 2020) involve lengthy and more complicated algorithms and may necessitate computer tools or software for a wider audience.

2.4.5.2 Delays in SD

Some researchers have incorporated time-delayed response systems in their models. Alvanchi et al. (2012) used a feedback delay element in their FSD model to signify the delayed effect of increased working hours to signify the adverse effect of set overtime on the productivity ratio, which occurs a week later. Prasertrungruang and Hadikusumo (2009) used delay elements in their SD model to capture the time-delayed occurrence of severe equipment breakdown when quality maintenance and new equipment is provided. Delays are critical sources of dynamics in almost all systems (Sterman 2000), and their impacts become more pronounced in dynamic models that capture complex construction systems for the purpose of decision making. However, a review of the selected articles in CEM literature found that the use of delays in the SD models is underutilized, as few studies have incorporated delay concepts in their models.

2.4.5.3 Validation

This chapter found that a wide range of validation methods were used in several SD models. These methods can be categorized as structural and behavioural validation tests (Sterman 2000), performed to assess whether qualitative and quantitative models have contradicted the structure of or closely captured the real system. These tests are performed with the understanding that it is impossible to prove that a model is right (Sterman 2002) and that efforts are made towards building trust in the method followed during modelling (Guevara et al. 2020). In this regard, most studies have used different variations of the structural validation test including boundary adequacy, rationality of qualitative relationships or parameters, dimensional consistency, and extreme conditions. Ruiz and Guevara (2021) used dimensional consistency, integration error, and anomaly tests. Nojedehi and Nasirzadeh (2017) and Hou and Wang (2021) used structure assessment tests, boundary adequacy, dimensional consistency, and extreme conditions. Luo et al. (2021) used structural validity and dimensional consistency tests. Very few researchers performed behavioural validation tests, which can be attributed to the absence of historical data. Articles that used behaviour reproduction to assess the model's capacity to reproduce historical data include Xu et al. (2018), Qayoom and Hadikusumo (2019), Li et al. (2021), Luo et al. (2021), and Ruiz and Guevara (2021).

2.4.6 Future Trends in SD modelling

Analysis of the selected articles on application of SD for CEM research indicates that SD modelling has transformed into different forms of hybrid SD. Such hybridization has been performed to either improve modelling capabilities featuring SD itself (i.e., improving the qualitative and quantitative modelling stages) or capture more of the problem context in CEM research; that is, to better capture CEM problems not effectively captured by SD modelling alone.

In this regard, there is potential to further explore the application of the fuzzy logic approach in SD qualitative and quantitative modelling stages in order to improve fuzzy arithmetic implementation in FSD modelling and increase the accuracy of FSD models. This can be performed by incorporating different types of fuzzy numbers (i.e., triangular, trapezoidal, Gaussian) and experimenting with several t-norms (Yager t-norms, Hamacher t-norms, Schweizer-Sklar t-norms) (Siraj and Fayek 2021). Moreover, FSD application in CEM is still limited owing to its low accuracy in capturing non-linear and highly dimensional relationships among system variables (Gerami Seresht and Fayek 2020). Hence, there is potential to explore integration of FSD models with data-driven approaches such as neuro-fuzzy systems (Gerami Seresht and Fayek 2020), which are able to better define relationships between such system variables.

Moreover, there is potential for future research to complement the modelling capabilities of SD by integrating it with other modelling approaches, which would enable development of more holistic hybrid models capable of capturing more complexities of given CEM systems. Further studies could focus on hybridizing fuzzy, SD, and ABM paradigms. This can enable modellers to quantify different types of uncertainties (i.e., probabilistic, subjective), understand the system's governing dynamic relationships and feedback interactions, and capture complexities arising from the spatial nature of agents and the dynamic interactions between agents that give rise to emergent behaviours.

Despite the capabilities they add to modelling, hybridization approaches can add to model complexity, which will also directly impact the model validation phase. Hybrid simulation challenges owing to lack of modelling framework and absence of communication architecture between individual modelling paradigms (Alvanchi et al. 2011) can also contribute to lagging interest of many researchers to implement different types of hybrid modelling approaches within different CEM research areas. In this regard, more work should be done to produce hybrid modelling frameworks (Swinerd and McNaught 2012) that clearly delineate the exchange of information between different modelling approaches.

SD application in CEM has mostly been confined to research purposes, owing to some underlying challenges in SD implementation. Although models are a very important part of communicating results and conclusions (Featherston and Doolan 2012), more work can be done in communicating the modelling process to end users, because much of the learning comes from such processes.

Building large models that are difficult to communicate and too complex to critically evaluate has also been a source of criticism of SD models (Forrester 2007). Construction practitioners will not implement SD in their projects when they are unaware of the value of SD, which can stem from lack of knowledge about the concept, seldom use of SD in their organizations, or the misconception that SD is impractical (Rumeser and Emsley 2016).

2.5 Chapter Summary

In this paper, systematic review and content analysis of 213 articles obtained from 21 high-ranking peer-reviewed journals was performed to analyse the application of SD in CEM and derive directions for future research. The novelty of this chapter lies in its approach of covering articles spanning more than 25 years to get a comprehensive picture of SD research in CEM. The findings of this chapter indicate that the use of SD in the area of CEM research steadily increased from 1995 to 2021. This chapter used analytical and objective approaches to study research trends, contributions of authors and their affiliations, and provide a profile of CEM projects with SD applications. The main contributions of this chapter are 1) addressing the lack of a comprehensive systematic review and content analysis in the application of SD in CEM and 2) providing researchers and construction practitioners with the state-of-the-art in SD research and application within the construction industry. Furthermore, this chapter provides researchers and practitioners a focused resource on SD research because it incorporates different approaches to structuring the systematic review by defining major areas of CEM research areas and analysing the trends of SD research within those research areas. For researchers interested in the use of SD modelling in CEM, this chapter thus provides a comprehensive review to identify modelling issues related to the use of SD in CEM and assesses the potential for SD hybridization with other modelling paradigms.

This chapter profiled the available SD literature in the 21 ranked journals, and found that the top three contributors to this field were *JCEM*, *JME* and *ECAM*. Analysis of top contributing authors and their affiliations was also presented. The top contributing countries to SD research were found to be the United States, United Kingdom, and China. Analysis of the profile of projects for SD application shows that infrastructure projects were used most in SD model applications, which indicates the significance attributed to such types of projects by different countries. The analysis also found that a significant number of articles only provided either qualitative SD models or SD models without application on real projects. Although SD has had relative success in terms of its application to project management compared with other CEM research areas, SD's practical application in construction management was found to be relatively less and confined to individual projects, which confirms conclusions by Lyneis and Ford (2007). This highlights the significant challenge to use SD modelling for CEM problems, stemming from either lack of historical data or reluctance from construction stakeholders to apply SD methods. In this regard, there is a need to produce more SD models that can be generalized, particularly at the organizational level.

This chapter identified eleven major research areas within CEM and assessed the role of SD in abstracting and modelling problems in each. SD was mainly used in the research areas of *Decision making and policy analysis*, *Performance*, and *Rework and change* between 1995 and 2021. *Scheduling* and *Health and safety* acquired relatively more interest among researchers between 2017 and 2021, with the number of publications in these fields increasing relative to previous years. This chapter also identified some major potential areas of future research in different CEM application areas, which can be used to guide researchers to further SD's application within these eleven research areas.

A critical review of the literature also identified the possible areas of improvement regarding SD hybridization with traditional methods and other modelling approaches. Analysis of the literature indicates that more work needs to be done in integrating SD with more traditional tools, which can help facilitate a better understanding of SD among construction practitioners and increase SD's applicability and presence across a vast spectrum of projects. There is also potential for further research in SD hybridization with other methods, especially in the areas of 1) SD-ABM modelling to capture the spatial natures of construction environments and emerging nature arising from individual interactions, and 2) SD-BIM to facilitate a more collaborative decision-making process in dynamic construction environments. Moreover, there is a potential to improve the qualitative and quantitative modelling processes in SD using modelling approaches such as machine learning, ANN, NFIS, FDEMATEL, and SEM. This chapter also identified the added complexity that may result from hybrid SD modelling owing to system abstraction, aggregation, and model validation.

This chapter details a comprehensive study on SD applications in CEM. A systematic literature review and content analysis that was performed is used to utilize the strength of SD as a modeling approach. This study was used to select the approach to hybridize of the SD modeling methodology with fuzzy logic (i.e., FSD). The next chapter discusses FAHP-FDEMATEL modeling approach, which will be used to establish a systematic and structured methodology for causal relationship mapping, which complements the FSD modeling methodology used in this research.

Chapter 3 Hybridization of Fuzzy Analytic Hierarchy Process and Fuzzy Decision-Making Trial and Evaluation Laboratory to Determine Causal Relationships in Construction Crew Productivity Modeling[3]

3.1 Introduction

Construction productivity has been a major area of study owing to its significance in determining the success of a construction undertaking. Construction productivity problems can include various aspects, such as assessment of factors that affect productivity, prediction of crew productivity, and identification of improvement strategies for crew productivity. Previous studies have attempted to identify factors that affect crew productivity and develop modeling approaches to monitor and establish productivity improvement strategies. Construction projects are performed in a dynamic environment that is a result of various interactions between situational/contextual factors related to tasks and resources such as labor and materials, management, project characteristics, and work-setting conditions (Raoufi and Fayek 2018). Situational or external factors, such as economic, social, and technological, have certain impacts to crew productivity and performance while contextual factors, such as age, gender, culture, and personal interests, are also included in the crew productivity research domain (Raoufi and Fayek 2018). As one of the primary project performance indicators, crew productivity can be described as a function of the efficiency of utilization of resources (i.e., labor), which is affected by crew motivation. In this regard, it is

[3] This chapter has been submitted for publication in submitted for publication in *Canadian Journal of Civil Engineering*: Kedir, N., and Fayek, A. R. (2020), " Integrated FAHP-FDEMATEL for Determining Causal Relationships in Construction Crew Productivity Modeling.", *Canadian Journal of Civil Engineering*, 39 manuscript pages, submitted Oct. 2022.

imperative to properly assess crew productivity by identifying the relevant factors, such as crew motivation as well as situational/contextual factors, that affect productivity of different crews in construction projects; and by properly capturing existing complex causal relationships between these factors which form the dynamic environment.

There have been a variety of approaches in the current construction literature for capturing the complex causal relationships for dynamic modeling of productivity. Some of the most commonly used methods include literature reviews, modelers' assumptions, and verifying of model assumptions using focus groups, questionnaire surveys and/or semi-structured interviews (Gerami Seresht and Fayek 2018; Khanzadi et al. 2019; Nasirzadeh and Nojedehi 2013). Literature review methods are limited because relationships between model variables can only be obtained through literature if there is existing knowledge about those relationships. Moreover, methods such as focus-groups, survey questionnaires, and interviews entail aggregating the inputs of several experts that take part during the assessment process (Cyr 2016; Paradis et al. 2016). These experts are usually heterogenous, with varying level of expertise thus making crew productivity modeling process complex.

Despite the presence of several productivity-related studies in the literature, there is a need to consider importance weight of experts in aggregating the opinion of heterogenous experts that take part in productivity-related decision making. Moreover, there is a lack of systematic and structured methodology to establish causal relationships in the dynamic productivity modeling process, which involves: assessing the importance of, and causalities between the situational/contextual factors, and constructing the causal loop diagrams which are functions of the dynamic relationships between system variables. The FDEMATEL method applies fuzzy set theory to capture subjective uncertainties in the DEMATEL approach; which enables the method to capture complex causal relationships that affect the overall system of productivity, while also enabling the modeler to assess the influence of each variable using IRM and other metrics (Han and Wang 2018). Even though the use of FDEMATEL to identify causal relationships is present in other areas of construction research, there is a gap in the literature in the use of FDEMATEL to identify causal relationships, and map influence between system elements to complement the dynamic modeling of crew productivity.

This chapter has three objectives: 1) to identify a set of criteria to perform expert assessment for assigning importance weights of heterogenous experts in the area of productivity research; 2) to propose a systematic and structured methodology to define causal relationships between the most significant factors that affect crew productivity, and analyze their interrelated impacts in the form of influence relation maps (IRM) using fuzzy AHP - fuzzy DEMATEL method; and 3) to map the causal relationships between crew motivation, situational/contextual factors and crew productivity from the outputs of the FDEMATEL method, which can be used to perform qualitative system dynamics (SD) modeling of crew productivity.

This chapter is organized as follows. First, the literature review is presented in the next section, which discusses current dynamic modelling approaches, and existing methods used to identify and assess causal relationships. Next, the methodology section is presented, which discusses in detail the proposed model, and how to integrate the different modelling paradigms in fuzzy AHP, and weighted fuzzy DEMATEL. The proposed integrated approach is then implemented on a real construction project to demonstrate the methodology. Finally, results are presented, and conclusions and recommendations for future works are discussed.

3.2 Literature Review

This section provides a background on establishing causal relationships between factors affecting crew productivity. In addition, the proposed methods Fuzzy AHP and Fuzzy DEMATEL are also described.

3.2.1 Establishing Causal Relationships between Factors Affecting Crew Productivity

Crew productivity is usually a factor of several variables that are rarely independent of each other and involve some degrees of interrelationship (Nasirzadeh and Nojedehi 2013). Several approaches could be considered to analyze these relationships. Interpretive structural method (ISM) has an elaborate visual representation, and enables the factors to be grouped into dependent, independent, autonomous, and linkage clusters. However, ISM cannot consider the interactions between those factors belonging in different categories (Tavakolan and Etemadinia 2017) (e.g., crew-level factors versus project-level factors). Analytic network process (ANP) is relatively simpler to understand and can capture relationships between different categories. However, establishing the relationships between the factors is a lengthy process resulting in computational complexity (Li et al. 2019; Valipour 2015). Fuzzy cognitive mapping (FCM) can model complex relationships that involve causalities and feedbacks (Case and Stylios 2016). However, FCM is unable to capture dynamism arising from time-based change of relationships (Mpelogianni et al. 2018; Lazzerini and Mkrtchyan 2011) between system elements (i.e., factors affecting productivity).

SD is a modeling approach that is used to capture dynamic behavior of systems where changes in the system correspond to variables that make up the system (Shokouh-Abdi et al. 2011). SD is appropriate to model problems that feature qualitative or quantitative data, and problems that are “broad in details, holistic in perspective, continuous in behavior” (Alzraiee et al. 2015). Hence, SD focuses on capturing the dynamic nature of systems that exhibit varying properties, using multiple feedback processes, interactions, and dependencies (Nasirzadeh et al. 2008). Elements that make up the SD modeling are causal loop diagrams (CLDs) which are formed by connecting variables with causal links, stocks which represent accumulation phenomenon, flows (rates) which measure the change of stocks over a given duration, and delays to capture the dynamic behaviour of complex systems over time (Sterman 2000). SD modeling can be considered as consisting of two stages, namely, qualitative modeling and quantitative modeling (Ecem Yildiz et al. 2020; Sterman 2000).

Qualitative modeling of productivity is the most important phase of the dynamic modeling process. It entails constructing a conceptual model that defines stocks and flows and maps the causal relationships and influence between system elements (Siraj and Fayek 2021). Establishing of causal loop diagrams and feedback relationships is critical to the SD modeling concepts as it allows for avoiding the event-oriented, open-loop worldview that leads to an “event-oriented and reactionary” approach to problem solving (Sterman 2000). The main advantage of the SD method is that it allows for assessing the relationships between system elements in such a way that drivers of the system can be identified. The steps in SD involve mapping the causal relationships in terms of feedback loops, for use in dynamic simulation process. These feedback loops can either be positive, such as reinforcing and amplifying changes, or negative, such as balancing and self correcting to seek equilibrium (Boateng et al. 2012).

Qualitative approaches have been used to identify causal relationships and construct causal loop diagrams as part of the SD modeling process in different areas of construction (Siraj and Fayek

2021). The majority of studies in the area of construction, and specifically in the area of crew productivity obtained causal loop diagrams using expert inputs utilized through one or a combined approach of literature reviews, modelers' assumptions, and experts' verification through focus groups, questionnaire surveys, or semi-structured interviews (Al-Kofahi et al. 2020; Leon et al. 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019; Moradi et al. 2017). In this regard, a systematic method to gather group knowledge from individuals with different level of expertise, to capture causal relationships between factors, and to visualize these complex cause-and-effect interrelationships is lacking in productivity research. Therefore, a structured and systematic approach which utilizes FAHP and FDEMATEL; for use in dynamic productivity modeling is proposed to address the aforementioned limitations.

3.2.2 Fuzzy DEMATEL

The DEMATEL method was created by the Geneva Research Center of Battelle Memorial Institute (Fontela and Gabus 1976), to find integrated solutions for the fragmented and antagonistic phenomena of world societies. The DEMATEL method captures the complex causal relationships amongst factors that affect a system, and also enables the assessment of the strength of influences using directed graphs, and metrics that capture the contextual relationships between several elements of the system (Han and Wang 2018; Chien et al. 2014). Fuzzy DEMATEL method applies linguistic variables and incorporates fuzzy logic concepts into the DEMATEL approach. The use of fuzzy logic is significant owing to the need to process the human way of thinking (Samani and Shahbodaghlou 2012) which is evident while processing the inputs of multiple experts that give subjective responses. Fuzzy logic enables processing of imprecise data and ambiguous human judgement (Seker and Zavadskas 2017; Shokouh-Abdi et al. 2011).

There are many studies that implement FDEMATEL for different problems (Sangaiah et al. 2017; Yeh and Huang, 2014; Lin 2013). In the area of construction, FDEMATEL method has mostly been applied to find interrelationships between system elements and identify causal mappings in the area of risk identification and assessment (Li and Xu 2021; Hatefi and Tamošaitienė 2019; Seker and Zavadskas 2017). In addition to risk, other areas also include sustainability (Li et al. 2022; Rostamnezhad et al. 2020; Mavi and Standing 2018; Jeong and Gomez 2018), safety (Chai et al. 2022; Shakerian et al. 2020; Vosoughi et al. 2019), and planning (Jeong and Ramírez-Gomez 2018; Jeong et al. 2016). Despite the presence of a comprehensive literature in the application of FDEMATEL in other areas of construction, the use of FDEMATEL to identify causal relationships, and map influence between system elements to complement the dynamic modeling of crew productivity is lacking.

The input analysis in FDEMATEL entails analyzing the inputs of different experts, who can vary in technical or managerial points of view, experience, knowledge, and expertise level (Tavakolan and Etemadinia 2017). Hence, incorporating a methodology to capture inputs of heterogenous experts with varying expertise level can enable the fuzzy DEMATEL approach to become especially applicable and effective method to visualize the structure of interdependent and complicated relationships between system elements using matrices and/or digraphs. Consequently, the results of this weighted FDEMATEL output can be used to perform a systematic qualitative system dynamic modeling that can identify the causal relationships and feedback loops between situational/contextual factors and crew motivation affecting crew productivity.

3.3 Methodology

The methodology in this chapter can be summarized in two stages, as shown in Figure 3.1. In stage 1, the expert weight assigning model first identifies the set of criteria to be used for expert assessment. FAHP is then applied to weigh the importance of the criteria. The importance weights of the criteria will then be used to perform expert weight assignment. In stage 2, crew motivation, and situational/contextual factors affecting crew productivity are identified and prioritized. FDEMATEL is then applied on the prioritized factors to construct IRM, establish causal relationships and feedback loops, for use in dynamic productivity modeling. The following section discusses the proposed two stages of the model in further detail.

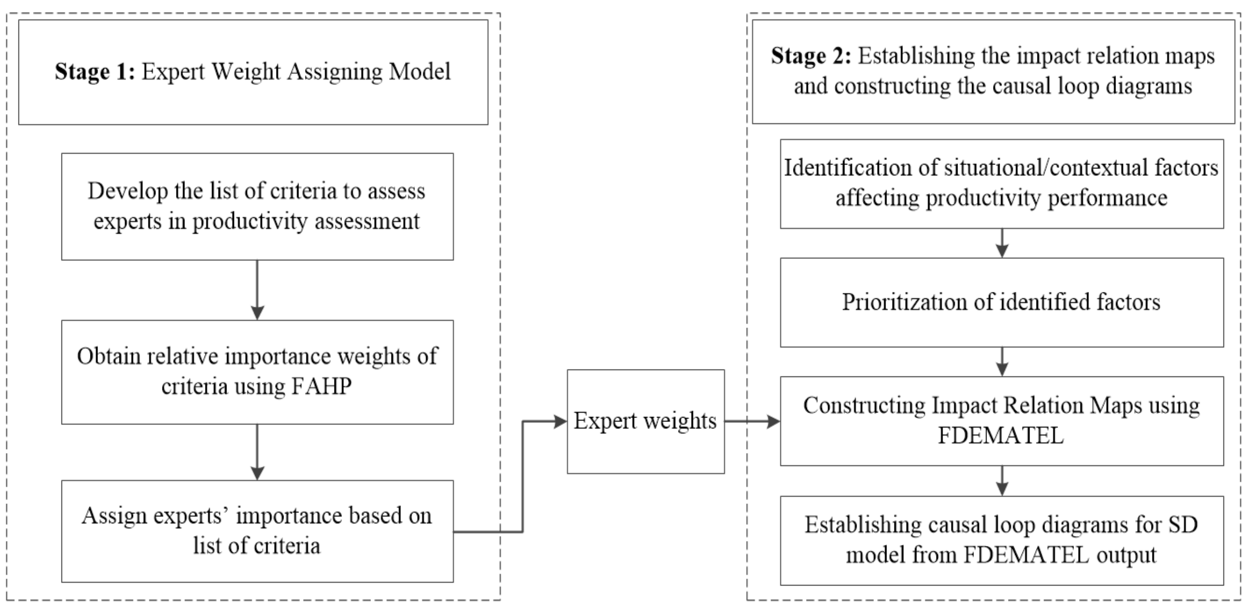

Figure 3.1 Stages in the FAHP-FDEMATEL model.

3.3.1 Expertise Level Assessment Using Fuzzy AHP

In the fuzzy AHP process, the problem hierarchy is first constructed using the set of criteria and sub-criteria to assess the level of expertise. The steps in the fuzzy AHP are shown in ***Figure 3.2***, and discussed further in detail.

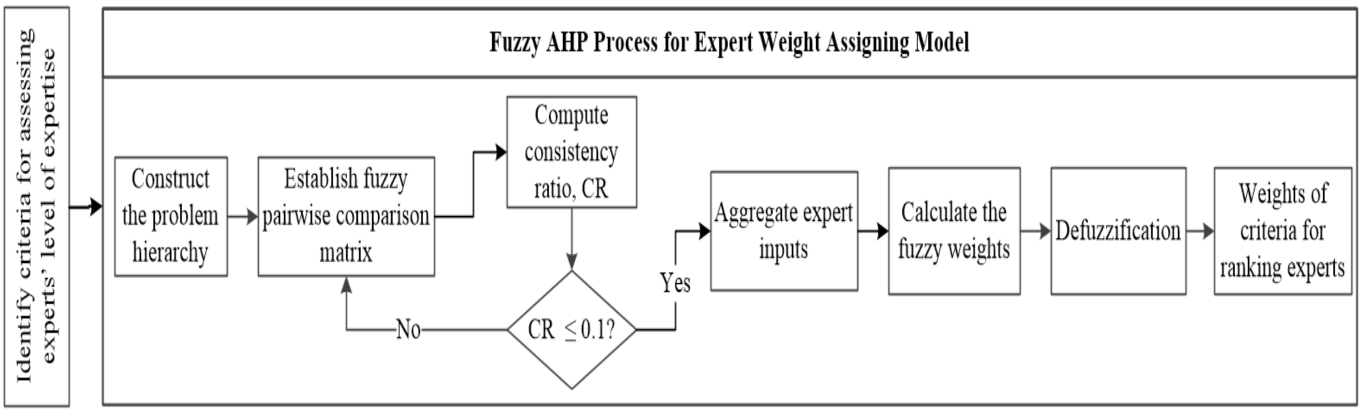

Figure 3.2 Fuzzy AHP process for Expert Weight Assigning Model.

3.3.1.1 Developing list of criteria and constructing the problem hierarchy

In this process, criteria to assess the level of expertise, and their corresponding qualification attributes used as sub-criteria in this chapter are identified along with their scales of measure. The list of criteria and sub-criteria were first collected from studies in other areas of construction management in the literature (Monzer et al. 2019; Siraj and Fayek 2021; Farrington-Darby and Wilson 2006) and modified to enable expert assessment in productivity domain. The list of identified qualification attributes is shown in Table 3.1, and is organized into 7 criteria and 24 sub-criteria attributes. For example, the "productivity-related project management practices" is comprised of four sub-criteria, namely: average hours of work in productivity related work per week, level of management training related to productivity, experience in conferences related to productivity management, and functional skills related to productivity management.

The list of developed qualification attributes is measured using qualitative or qualitative scales, as shown in Table 3.1. For those qualification attributes which cannot be measured using numerical scales, a predetermined the Likert scale of 1–5 is adopted from Monzer et al. (2019), which enables objective quantification of the qualitative sub-criteria for a more accurate decision making. For example, the *personal attributes and skills* criterion is composed of five sub-criteria, namely, *Level of communication skills, Level of teamwork skills, Level of leadership skills, Level of analytical skills,* and *Level of ethics.* Each of these sub-criterion is measured using a predetermined rating (a Likert scale of 1–5).

Table 3.1 Scale of measure and range of data input for sub-criteria.

Criteria Name	Sub-criteria Name	Scale of measure	Range of Data Input
1. Experience	1.1 Total years of experience	Integer	0-35
	1.2 Relevant experience	Integer	0-20
2. Knowledge	2.1 Academic knowledge	Integer	0-15
	2.2 Education level	1-5 rating	1-5
	2.3 On the job training	Integer	0-10
3. Professional performance	3.1 Current occupation in the company	1-5 rating	1-5
	3.2 Years in current occupation	Integer	0-35

Criteria Name	Sub-criteria Name	Scale of measure	Range of Data Input
4. Productivity-related project and construction management practices	4.1 Average hours of work in productivity-related work per week	Integer	0-20
	4.2 Level of management training related to productivity	Integer	0-5
	4.3 Experience in conferences related to productivity management	Integer	0–5
	4.4 Functional skills related to productivity management	1–5 rating	1–5
5. Project specifics	5.1 Project size limit	Integer	1mil –2 bil
	5.2 Commitment to time deadlines	Integer	0–100
	5.3 Commitment to cost budget	Integer	0–100
	5.4 Safety adherence	Integer	0–5
	5.5 Geographic diversity experience	Integer	0–20
6. Reputation	6.1 Social acclimation	1–5 rating	1–5
	6.2 Willingness to participate in survey	1–5 rating	1–5
	6.3 Professional reputation	1–5 rating	1–5
7. Personal Attributes and Skills	7.1 Level of communication skills	1–5 rating	1–5
	7.2 Level of teamwork skills	1–5 rating	1–5
	7.3 Level of leadership skills	1–5 rating	1–5
	7.4 Level of analytical skills	1–5 rating	1–5
	7.5 Level of ethics	1–5 rating	1–5

The list of criteria is then evaluated by experts with extensive knowledge of the construction industry and productivity research, using surveys (Appendix A). The experts are also prompted to suggest additional criteria that was not found in the list. The survey is prepared based on the final list of criteria and sub-criteria, and is used to elicit responses from the experts. For the list of *n*-criteria, each having their respective set of sub-criteria, the expert ranking is performed based on the hierarchy shown in Figure 3.3.

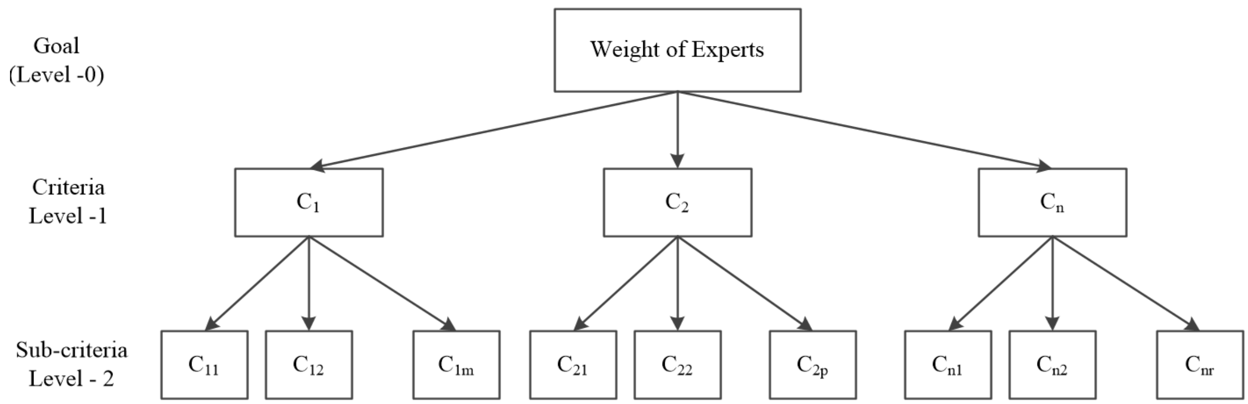

Figure 3.3 Hierarchical structure for expert importance weight assignment

where the n*,* p *and* r *in sub-criteria (level-2), are the number of sub-criteria for criteria 1, criteria 2, and criteria* n*, respectively*

3.3.1.2 Establish the fuzzy pairwise matrix

The next step in the FAHP process is to establish the fuzzy pairwise comparison matrix for performing expert weight assessments. To achieve this, the relative importance of each criterion for performing expert weight assessment was obtained using a predetermined scale. Because FAHP is an extension of the AHP method that uses crisp inputs while assessing the relative importance of criteria; the pairwise comparison matrix in FAHP is written in the form of fuzzy numbers instead of crisp inputs to represent the linguistic terms used during information synthesis.

Each particular linguistic term is associated with its own fuzzy set. A series of such fuzzy sets combine to form a fuzzy scale to describe the levels of the linguistic terms, linking the verbal and numerical expressions.

In this regard, the most common fuzzy scales in the literature are the 9-level and the 5-level fuzzy scales (Liu et al. 2020). In this chapter, the 5-level fuzzy scale from Zimmer et al. (2017) is adopted and modified because of its relative simplicity. This five-scale approach, namely: *equally important*, *weakly important*, *fairly strong important*, *very strongly important*, and *absolutely important*, is adopted and discussed in more detail in later sections. Use of the type of fuzzy sets to represent the fuzzy scale also depends on several factors. In this chapter, the tree-diagram approach for selecting fuzzy sets proposed by Liu et al. (2020) was used to select triangular fuzzy numbers. The fuzzy scale used for comparison is shown in Table 3.2. The sample pairwise comparison matrix for the criteria and sub-criteria level is shown in Table 3.3 and Table 3.4 respectively.

Table 3.2 Fuzzy scale used for pairwise comparison (Adopted from Zimmer et al. 2017).

Fuzzy Scale	Fuzzy Number	Triangular fuzzy number	Reciprocal of triangular fuzzy number
Equally important (EI)	$\widetilde{1.0}$	(1, 1, 1)	(1, 1, 1)
Weakly important (WI)	$\widetilde{1.5}$	(1/2, 3/2 , 5/2)	(2/5, 2/3, 2)
Fairly strong important (FSI)	$\widetilde{2.5}$	(3/2, 5/2 , 7/2)	(2/7, 2/5 , 2/3)
Very strongly important (VSI)	$\widetilde{3.5}$	(5/2, 7/2 , 9/2)	(2/9, 2/7 , 2/5)
Absolutely important (AMI)	$\widetilde{4.5}$	(7/2, 9/2 , 11/2)	(2/11, 2/9 , 2/7)

Table 3.3 Pairwise comparison matrix for criteria (level-1).

Criteria	**Experience**	**Knowledge**	**.**	**.**	**Professional performance**	**Personal attributes and Skills**
Experience	EI		.	.		
Knowledge		EI	.	.		
Professional performance			EI	.		
.				EI		
.					EI	
Personal Attributes and Skills						EI

Table 3.4 Pairwise comparison matrix for sub-criteria (level-2).

Sub-criteria ID	**Sub-criteria**	**1.1 Total years of experience**	**1.2 Relevant years of experience**	**.**	**.**	**7.4 Level of analytical skills**	**7.5 Level of ethics**
1.1	Total years of experience	EI		.	.		
1.2	Relevant years of experience		EI	.	.		
.	.			. EI	.		
.	.			.	.		

Sub-criteria ID	Sub-criteria	1.1 Total years of experience	1.2 Relevant years of experience	. .	7.4 Level of analytical skills	7.5 Level of ethics
7.4	Level of analytical skills			. .	EI	
7.5	Level of ethics			. .		EI

Designating F to be the pairwise matrix of an expert m, comprised of triangular fuzzy numbers that assess the relative importance of criterion i (c_i) over criterion j (c_j); the fuzzy pairwise comparison matrix F_m is shown in Equation (3.1).

$$\mathrm{F_m} = \begin{bmatrix} (1,1,1) & \tilde{c}_{12}^{(m)} & \cdots & \tilde{c}_{1n}^{(m)} \\ \tilde{c}_{21}^{(m)} & (1,1,1) & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{c}_{n1}^{(m)} & \tilde{c}_{n2}^{(m)} & \cdots & (1,1,1) \end{bmatrix} \tag{3.1}$$

where: $\tilde{c}_{ij}^{(m)} = 1 / \tilde{c}_{ji}^{(m)}$

3.3.1.3 Compute and check for consistency ratio

Each of the experts' judgements (F_m) is then checked for consistency by using the equation of Saaty's consistency ratio (Liu et al. 2020; Saaty 2008) as shown in Equation (3.2) and Equation (3.3) This is performed by using the principle of crisp consistency, whereby the fuzzy numbers in the TRM are first defuzzified before computing the consistency ratio.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{3.2}$$

where:

CI = consistency index

$\lambda_{\max}$ = the largest eigenvalue of the comparison matrix

n = dimension of the square matrix

$$CR = \frac{CI}{RI(n)} \tag{3.3}$$

where:

n = dimension of the square matrix

CR = consistency ratio

RI = random index, obtained from the random index table of different matrix sizes (Zadeh 1965).

A CR value of not greater than 0.1 is acceptable for a consistent matrix (Saaty 2008). If the matrix does not comply with such requirement, the expert is prompted to repeat the pairwise comparisons until such criteria. The expert inputs are then aggregated to construct the representative matrix that combines the inputs of all involved experts. The following steps (i.e., aggregation of expert inputs; obtaining fuzzy weights; obtaining the non-fuzzy values) to obtain the ranking of expert assessments were adopted from Monzer et al. (2019).

3.3.1.4 Obtain weights of criteria for ranking experts

The final step in the FAHP is to utilize the outputs of the matrix (i.e., relative importance weights between criteria), and assign relative importance weights to experts. To achieve this, the result of the assessment in the sub-criteria (Table 3.4) are normalized in the range of [0-1], and used to evaluate each expert that is involved in the decision-making process (i.e., experts involved in the assessment of the causal relationship between the factors, which is used in the FDEMATEL process). In this regard, the weights obtained for criteria and sub-criteria levels are applied to score each expert's expertise level, using Equation (3.4).

$$S_i = \sum_{j=1}^{n} \sum_{k=1}^{nC_j} w_{C_j} \; w_{S_{jk}} \; I_{S_{jk}}(i), \qquad i = 1\ldots,E \qquad (3.4)$$

where, $I_{S_{jk}}(i)$ is the normalized evaluation of expert j in a total of E experts, based on sub-criterion k, and criterion C_j

w_{C_j} is the weight of criterion C_j, and $w_{S_{jk}}$ is the weight of sub-criterion S_{jk}

n is the total number of criteria C_j and nC_j is the total number of sub-criteria k

The scores in Equation (3.4) are then normalized using Equation (3.5) below, and will be used as weights by multiplying each expert's assessment with the importance weight (IW) of each expert.

$$IW_i = \frac{S_i}{\sum_{m=1}^{E} S_m}, \quad i = 1\ldots,E \qquad (3.5)$$

Consequently, a survey is prepared in order to formulate the application of the FAHP discussed above, and also to provide inputs for the FDEMATEL process. In this survey (Appendix B), the criteria and sub-criteria identified in the FAHP are formulated in a question format in part -one of the survey, to perform profiling of the experts that take part in the survey. The output of part-one of the survey is used to determine the importance weight of experts.

3.3.2 FDEMATEL Process

The FDEMATEL process focuses on categorizing the identified factors into cause-and-effect groups, establishing the causal relationships, and influence relation maps, and constructing the causal relationship diagrams. The FDEMATEL process is shown in below, and elaborated in the subsequent sections.

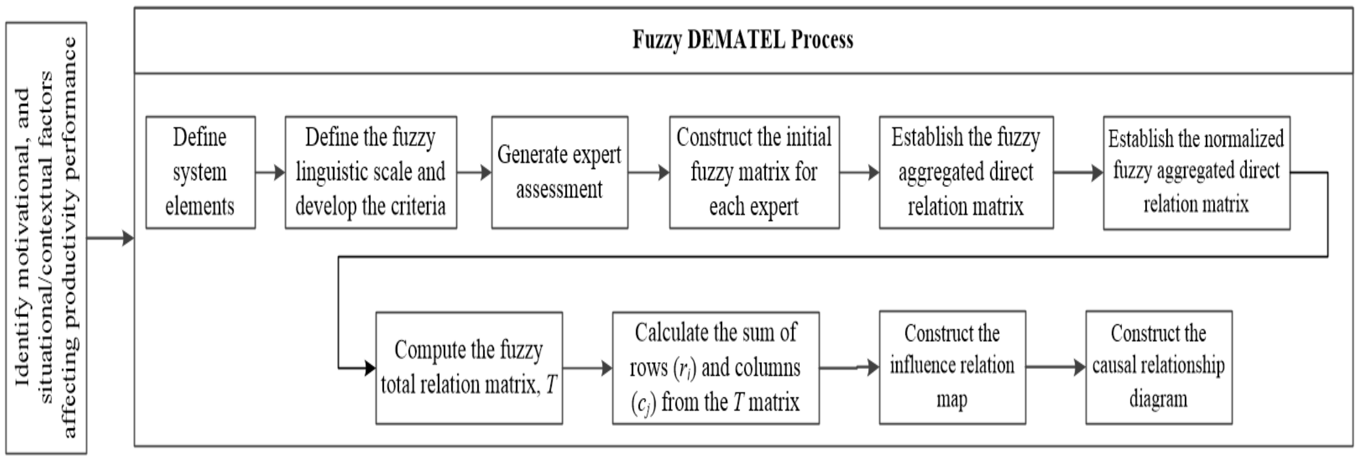

Figure 3.4 Steps in the FDEMATEL process.

3.3.2.1 Factor identification

Factors that affect crew motivation and productivity are identified and collected from past literature (Tsehaye and Fayek 2014; Gerami Seresht and Fayek 2018; Raoufi and Fayek 2018). The identified factors are grouped into situational/contextual factors at the crew level and situational/contextual factors as well as at the project level. At the crew level, these factors were sub-categorized into task-related factors, labor-related factors and foreman-related factors. The factors at the project level were sub-categorized into task-related factors, management-related factors, work-setting conditions, resources, and safety. Categorization of the list of factors was adapted from Raoufi and Fayek (2018). Identification of the most critical factors affecting crew productivity are then established using expert inputs. Interview surveys are designed to elicit knowledge from the experts (i.e., project management staff, and project tradespeople staff). In this regard, experts will rank the influence of the factors on crew productivity, based on two scores: i.e., agreement score (to what extent does expert agree that the factor is present in their project), and impact score (to what extent does the factor impacts productivity). In this chapter, Likert scale is used to obtain the measurement scale for the agreement and impact scores as it is one of the most fundamental and frequently applied tools in research (Joshi et al. 2015). Hence the 7-point Likert scale is chosen, as suggested by (Taherdoost 2019; CII 2006). In effect, the agreement score was measured using the seven-point scale: *Strongly Disagree*, *Disagree*, *Slightly Disagree*, *Neither Agree nor Disagree*, *Slightly Agree*, *Agree*, and *Strongly Agree*; and the impact score was measured using the seven-point scale: *Strongly Negative*, *Negative*, *Slightly Negative*, *No Impact*, *Slightly Positive*, *Positive*, *Strongly Positive*. After expert inputs on these factors are collected, statistical analysis is performed to select the factors with the maximum positive or negative impact on crew productivity (Gerami Seresht and Fayek 2019). In this regard, Pearson correlation analysis is preferred as it is the most common technique for correlation analysis (Pandey 2020), which is an indication of relationship between independent variables (i.e., motivational, and situational/contextual factors) and dependent variables – crew productivity. It is important to note that Pearson's correlation analysis does not establish causation between the factors (Gogtay and Thatte 2017). Once a strong relationship between factors is established, these factors are then used in the subsequent steps to define system elements in the FDEMATEL process.

3.3.2.2 Define system elements, the fuzzy linguistic scale and generate expert assessments

The next step in the FDEMATEL process is to define system elements which will influence the behavior of the system (Rostamnezhad et al. 2020). These system elements consist of the identified list of top-factors that affect crew productivity. In this step, a survey is prepared to provide inputs for the FDEMATEL process (Appendix B). This survey uses fuzzy linguistic scales (Mavi and Standing 2018; Seker and Zavadskas 2017), to generate expert assessments on the causal relationship between the factors using expert inputs, as shown in Table 3.5. This survey also establishes the type of causal relationships (i.e., positive or negative polarity between the links). A positive link implies a similar change of direction between the factors (e.g., increase/decrease in crew size can lead to increase/decrease in congestion); whereas a negative link implies an opposite change of direction between the factors (e.g., higher rework volume impacts work progress negatively).

Table 3.5 Fuzzy scale used to assess the degree of causal influence.

Linguistic terms	**Triangular fuzzy number**
No influence	(0.00 0.00 0.00)
Very low influence (VL)	(0.00 0.00 0.25)
Low influence (L)	(0.00 0.25 0.50)
Medium influence (M)	(0.25 0.50 0.75)
High influence (H)	(0.50 0.75 1.00)
Very high influence (VH)	(0.75 1.00 1.00)

3.3.2.3 Construct the initial fuzzy matrix and compute the total relation matrix

The generated expert assessments are used to obtain the initial fuzzy matrix for each expert. In this regard, each expert will provide their assessment of the causal relationships between the factors in the form of a fuzzy matrix $\tilde{X}^{E}$, shown in Equation (3.6).

$$\tilde{X}^E = \left[\tilde{x}_{ij}^{(e)}\right]_{nxn} = \begin{bmatrix} 0 & \tilde{x}_{12}^{(e)} & \cdots & x_{1n}^{(e)} \\ \tilde{x}_{21}^{(e)} & 0 & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1}^{(e)} & \tilde{x}_{n2}^{(e)} & \cdots & 0 \end{bmatrix} \tag{3.6}$$

i,j = 1,2,...n, and *e =1,2,...E*

where: n = total number of elements in the system and, E = total number of experts assessing the causal relationships

Next, the set of initial fuzzy matrix $\tilde{X}^E$, obtained from a set of experts E, are aggregated to form the aggregated direct relation matrix $\widetilde{D}$. Each of the elements in the aggregated matrix is obtained by multiplying the weights of the experts (w) obtained from the FAHP process, with the elements in the direct matrices of respondents, as shown in Equation (3.7) and Equation (3.8) (Seker and Zavadskas 2017).

$$\widetilde{D} = \sum_{e=1}^{E} w_e \otimes \widetilde{x}_{ij}\ , where\ \tilde{x}_{ij} = (x_{ij}^l, x_{ij}^m, x_{ij}^u), \text{ and } i\ , j = 1,2...n \tag{3.7}$$

Hence,

$$\widetilde{D} = [\ \tilde{d}_{ij}]_{nxn}, where\ \tilde{d}_{ij} = (d_{ij}^l, d_{ij}^m, d_{ij}^u) \tag{3.8}$$

This direct relation matrix is used to obtain the normalized fuzzy aggregated direct relation matrix N, as shown in Equation (3.9) and Equation (3.10):

$$\widetilde{N} = \widetilde{D} * \lambda \tag{3.9}$$

where:

$$\lambda = \frac{1}{\max\limits_{1 \le i \le n} \left(\sum\limits_{j=1}^{n} d_{ij} \right)}, i, j = 1,2,...n \tag{3.10}$$

The fuzzy total relation matrix *T* represents the total degree of causal influence of factor *i* on factor *j*, which is obtained using Equation (3.11), Equation (3.12), and Equation (3.13) (Rostamnezhad et al. 2018).

$$T = D(I - D)^{-1} \tag{3.11}$$

where:

$$\tilde{T} = D + D^2 + D^3 + \cdots + = \sum_{i=1}^{\infty} D^i \tag{3.12}$$

I is represented by an *n* x *n* identity matrix.

Hence,

$$\tilde{T} = \left[\, \tilde{t}_{ij} \right]_{nxn}, where\ \tilde{t}_{ij} = \left(t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{u}\right), and\ i, j = 1,2, \ldots n \tag{3.13}$$

3.3.2.4 Calculate the sum of rows and columns and construct influence relation maps

Next, the sum of rows (r_i) and columns (c_j) is computed as shown in Equation (3.14) and Equation (3.15); and ($R_i + C_j$) and ($R_i - C_j$), using Equation (3.16) and Equation (3.17). These sums are used in the construction of the IRM. In the IRM, the defuzzified values of horizontal axis ($R_i + C_j$) are named “prominence” (Zhou et al. 2014) and signify the degree of relationship of each factor with the rest of the other factors. With higher values of ($R_i + C_j$) indicating higher causal relations with the other factors. The defuzzified values of the vertical axis ($R_i - C_j$) is referred to as “relation”

(Zhou et al. 2014). Positive values of the relation measure indicates that the factor is in the cause group, and negative value indicates that the factor is in the effect group.

$$r_i = \sum_{1 \le j \le n}^{n} t_{ij} \quad \forall i \tag{3.14}$$

$$c_j = \sum_{1 \le i \le n}^{n} t_{ij} \quad \forall j \tag{3.15}$$

$$(R+C)_i = r_i + c_j \quad i, j = 1, 2, \ldots \mathrm{n} \tag{3.16}$$

$$(R-C)_i = r_i - c_j \quad i, j = 1, 2, \ldots \mathrm{n} \tag{3.17}$$

3.3.2.5 Construct the causal loop diagrams

In the final process, causal loop diagrams which present the causal relationships between crew motivation and situational/contextual in affecting crew productivity are established to use in dynamic modeling of productivity. To achieve this, the total relation matrix T, obtained in Equation (3.13) will be defuzzified using the center-of-area method to achieve the T^{def} matrix. This defuzzified matrix represents the degree of causal influence between the factors affecting crew productivity. In this regard, T_{ij} represents the degree of causal influence of factor i on factor j. The direction of the arrows for drawing the CLD is drawn in such a way that factors in each row affect the factors of the columns of the matrix. From this matrix, the values of T_{ij} that signify a stronger relationship between factors i and j are selected using a threshold value. A threshold value is important to filter out negligible effects between factors, which can otherwise make the resulting model too complex to comprehend (Si et al. 2018). The threshold value can be obtained using expert inputs (Li and Tzeng 2009), brainstorming (Azadeh et al. 2015), based on a given percentile (Si et al., 2018), the average of the elements in the matrix (Sumrit and Anuntavoranich 2013), or other approaches. Consequently, values of T_{ij} which comply with the threshold requirement are selected to plot the relationship mappings that form the causal loop diagrams.

3.4 Case study

The proposed fuzzy hybrid method is demonstrated using data collected from a real-world industrial construction project in Alberta, Canada. The case study utilizes the findings on factors affecting crew motivation and performance (Raoufi and Fayek 2018), in the context of the aforementioned project. Accordingly, this section is discussed to elaborate the data formulated as case-study in two-stages, to reflect the proposed modeling approach in the methodology section.

In the first stage, a survey was prepared to perform expertise level assessment and assign importance weight to experts. The pairwise matrix used in the survey is shown in Appendix A. In this survey, experts with extensive knowledge in construction, and related productivity research were utilized to validate and weigh the criteria identified for expert ranking, as described in the methodology section. The experts had an average of over 15 years of experience in the construction industry, and participated in productivity research. The responses of these experts were obtained in the form of a pairwise comparison matrix as input for the FAHP process. Once the list of criteria was identified and validated using expert inputs, the relative importance weights of each criteria for assessing level of expertise were obtained by applying FAHP method. The weights were computed from the pairwise comparison data obtained using the format shown in Table 3.3 and Table 3.4. This obtained data is converted into a fuzzy pairwise comparison matrix using the fuzzy scale in Table 3.2, and formulated as Fm, as shown in Equation (3.1). These results were then checked for consistency using Equation (3.2) and Equation (3.3). The result of relative importance weights for each criteria and sub-criteria is presented in Table 3.6.

Table 3.6 Calculated weights of criteria and sub-criteria.

No.	Criteria Name	Weight	Sub-criteria Name	Weight
1	Experience	0.16	1.1. Total years of experience	0.60
			1.2. Relevant experience	0.40
2	Knowledge	0.16	2.1. Academic knowledge	0.21
			2.2. Education level	0.30
			2.3. On the job training	0.49
3	Professional performance	0.15	3.1. Current occupation in the company	0.40
			3.2. Years in current occupation	0.60
4	Productivity-related project management practices	0.31	4.1. Average hours of work in productivity-related work per week	0.35
			4.2. Level of management training related to productivity	0.30
			4.3. Experience in conferences related to prod. mgmnt	0.15
			4.4. Functional skills related to productivity management	0.20
5	Project Specifics	0.06	5.1. Project size limit	0.26
			5.2. Commitment to time deadlines	0.23
			5.3. Commitment to cost budget	0.23
			5.4. Safety adherence	0.16
			5.5. Geographic diversity experience	0.12
6	Reputation	0.03	6.1. Social acclimation	0.34
			6.2. Willingness to participate in survey	0.33
			6.3. Professional reputation	0.33

No.	Criteria Name	Weight	Sub-criteria Name	Weight
7	Personal Attributes and Skills	0.13	7.1. Level of communication skills	0.24
			7.2. Level of teamwork skills	0.24
			7.3. Level of leadership skills	0.27
			7.4. Level of analytical skills	0.14
			7.5. Level of ethics	0.11

The final result related to *Stage-1* deals with using the previously obtained relative importance of the criteria and sub-criteria (Table 3.6) to assign experts' weights. This is achieved by utilizing part-one of the survey shown in Appendix B, which captures the profile of experts that take part in the subsequent decision-making processes discussed in *Stage-2* of the methodology section. Using the survey as input, Equation (3.4) and Equation (3.5) are applied to obtain normalized expert weights. In this regard, the result of the expert weight assessment, performed on the six experts (E_1, E_2, E_3, E_4, E_5, E_6) is computed as (0.13, 0.17, 0.21, 0.16, 0.19, 0.14).

In the second stage, factors affecting crew motivation and performance were prioritized using data collection on a real construction project (Raoufi and Fayek 2018). The field data (Raoufi and Fayek 2018) is collected over a period of 3 months from an industrial project located in Alberta, Canada. In this regard, data on situational/contextual factors, crew motivation, and several crew performance measures were collected using different data collection methods (i.e., interview surveys, project documents such as safety logs, and external databases such as weather data). For this case-study, data on interview surveys with crew members, supervisors and project managers was utilized to rank the factors impacting crew motivation and performance; whereby respondents were prompted to assess the extent to which a factor exists in the project, and also evaluate its corresponding degree of importance. Moreover, data collected on situational, contextual, and crew motivational factors was analyzed to identify the most important factors that affect crew productivity. From the total of 129 situational/contextual factors identified at the crew level (Raoufi and Fayek 2018) that affect crew performance, Pearson correlation analysis was performed (as described in the methodology) to identify factors that had a relationship with crew productivity. Pearson's correlation coefficient value of greater than 0.5 are chosen (Raoufi and Fayek 2018), to select the factors with strong relationship with crew productivity.

Next, the identified list of motivational, and situational/contextual factors affecting crew productivity were utilized to define system elements. To achieve this, a two-part survey was designed (Appendix B), whereby questions to profile the expertise level of the respondents formed part-one, and questions to capture the relationships between the identified system variables using a pairwise-matrix formed part two of the survey. In the FDEMATEL process, the defined system elements are used to construct the IRM, and categorize factors into cause-and-effect groups. To achieve this, results from part-two of the survey (Appendix B) are utilized. In this portion of the survey, experts' assessments of the causal relationships between each system element (i.e., situational/contextual, and motivational factors), are derived in the form of a pairwise matrix. There are a total of 38 system elements that form the pairwise-comparison matrix. A similar matrix to identify the polarity of the relationships between these elements also forms part-two of the FDEMATEL survey; in other words, polarity between two elements is positive if an increase/decrease in system element *i* causes an increase/decrease in element *j*, respectively, and negative vice versa.

After obtaining survey data from part-two of the FDEMATEL survey, Table 3.5 was used to convert the responses of the experts from a linguistic scale to a triangular fuzzy number. Generating the expert assessments in a matrix form was performed using Equation (3.6). The responses of each expert, which are now in a triangular fuzzy number format, were multiplied by their corresponding expert weights, obtained from the FAHP model of Stage-1. Consequently, the normalized fuzzy aggregated direct relation matrix was obtained using Equation (3.7) - Equation (3.10). Next, the total relation matrix T, which is the relative influence between the system elements, was computed using Equation (3.11), Equation (3.12), and Equation (3.13). The overall fuzzy total relation matrix is a 38x38 matrix with 114 rows and 114 columns, which is cumbersome to show in the results section. Hence, Table 3.7 is presented, which depicts part of the fuzzy total relational matrix $\tilde{T}$.

Table 3.7 Fuzzy Total Relation Matrix.

T		**T1**			**T2**			**…**	**T37**			**T38**		
		T_l	T_m	T_u	T_l	T_m	T_u		T_l	T_m	T_u	T_l	T_m	T_u
	ID	**1.1**			**1.2**			**…**	**7.1**			**7.2**		
T1	**1.1**	0.0	0.00	0.00	0.01	0.02	0.03	. . .	0.01	0.02	0.03	0.00	0.00	0.00
T2	**1.2**	0.0	0.01	0.02	0.00	0.00	0.00	. . .	0.00	0.01	0.02	0.00	0.00	0.00
T3	**1.3**	0.0	0.00	0.01	0.02	0.03	0.04	. . .	0.00	0.00	0.01	0.00	0.00	0.00
.	**.**	.	.	.	.	.	.	. . .	.	.	.	.	.	.
T37	**7.1**	0.0	0.0	0.00	0.00	0.00	0.00	. . .	0.00	0.00	0.00	0.01	0.02	0.03
T38	**7.2**	0.0	0.0	0.00	0.00	0.00	0.00	. . .	0.03	0.04	0.04	0.00	0.00	0.01

The matrices and diagrams are a representation of the contextual relationship between the factors in the system, whereby the numeric value measures the strength of influence (Bavafa et al. 2018). The total relation matrix $\tilde{T}$ shown in Table 3.7 is defuzzified using the center-of-area method to obtain the corresponding defuzzified matrix T_{def}. Table 3.8 depicts part of the defuzzified total relation matrix T_{def}.

Table 3.8 Defuzzified total relation matrix.

	ID	**T1**	**T2**	**T3**				**T37**	**T38**
T1	**1.1**	0.0	0.021	0.031	.	.	.	0.0	0.021
T2	**1.2**	0.01	0.000	0.039	.	.	.	0.0	0.010
T3	**1.3**	0.003	0.031	0.000	.	.	.	0.0	0.003
.	**.**	.	.	.	.	.	.	.	.
T37	**7.1**	0.0	0.0	0.0	.	.	.	0.0	0.021
T38	**7.2**	0.0	0.0	0.0	.	.	.	0.039	0.000

The values of the $\tilde{T}$ matrix are used to obtain the sum of rows (R) and the sum of columns (C), using Equation (3.14) and Equation (3.15). The values of $(\tilde{R} + \tilde{C})$ and $(\tilde{R} - \tilde{C})$ were also calculated using Equation (3.16) and Equation (3.17), and were defuzzified using center of area method to obtain the *prominence* and *relation* values respectively. The *prominence* is a measure of the role of each factor on the overall system in terms of its causality. Hence higher prominence values indicate higher causal relations with the other factors. The *relation* values in the vertical axis allow for assessment of the factors by categorizing them into cause-and-effect groups. The *relation* values are used to categorize the factors into cause-and-effect group, whereby factors with positive *relation* values are categorized into cause group, and vice versa. In order to facilitate the interpretation of the matrices and diagrams that are the results of the FDEMATEL process, the prominence and relation values that are in the top 75th percentile are summarized in Table 3.9 and Table 3.10, respectively. The values of prominence ($R + C$) and relation ($R - C$) are simultaneously analyzed by mapping these values to formulate the IRM, as shown in Figure 3.5.

Table 3.9 Factors with higher degrees of prominence.

Factor Name	$R_i + C_j$
Ability to perform	1.297
Reliability	1.133
Work progress	1.128
Visibility of outcome	1.120
Project scheduling	1.042
Project time management	1.023
Performance monitoring	1.021
Safety management	0.979
Project safety management	0.969
Rework	0.958
Safety facilitation and implementation	0.943
Crew experience	0.940

Factor Name	$R_i + C_j$
Goal-setting (crew level)	0.924
Foreman experience	0.914

Table 3.10 Summary of relation values.

Cause group		Effect group	
Factor	$R_i - C_j$	**Factor**	$R_i - C_j$
Crew motivation	0.60	Work progress	-0.56
Crew experience	0.49	Project time management	-0.45
Foreman experience	0.48	Ability to perform	-0.39
Foreman knowledge	0.43	Material handling	-0.33
Task repetition	0.42	Project scheduling	-0.32
Crew composition	0.34	Hazards identification & mitigation	-0.27
Rework	0.23	Cleanness	-0.21
Safety trainings	0.17	Safety management	-0.21
Visibility of outcome	0.15	Fairness	-0.18
Access points	0.15	In-site transportation	-0.18

Cause group		Effect group	
Factor	**R_i - C_j**	**Factor**	**R_i - C_j**
Task identity	0.12	Safety facilitation and implementation	-0.17
Project environmental management	0.09	Performance monitoring	-0.16
Temperature	0.09	Goal-setting	-0.15
Change in weather conditions	0.09	Reliability	-0.13

Finally, outputs of the FDEMATEL process are used to identify causal interrelationships, and construct CLD for dynamic productivity modeling. The defuzzified values of the T matrix shown in Table 3.8 were used to map the causal influence relationships between the factors. While constructing the CLD, it is imperative to consider the extent to which causal relationships between variables are considered. In a matrix of 38 variables, there are potentially 1,444 relationships which can be considered. Considering these relationships can become too complex, and unfeasible to implement. Therefore, from causal relationships that exist between two variables, a threshold value of 75 percentile of the defuzzified total-relation matrix (T) was set by selecting values greater than or equal to 0.021.

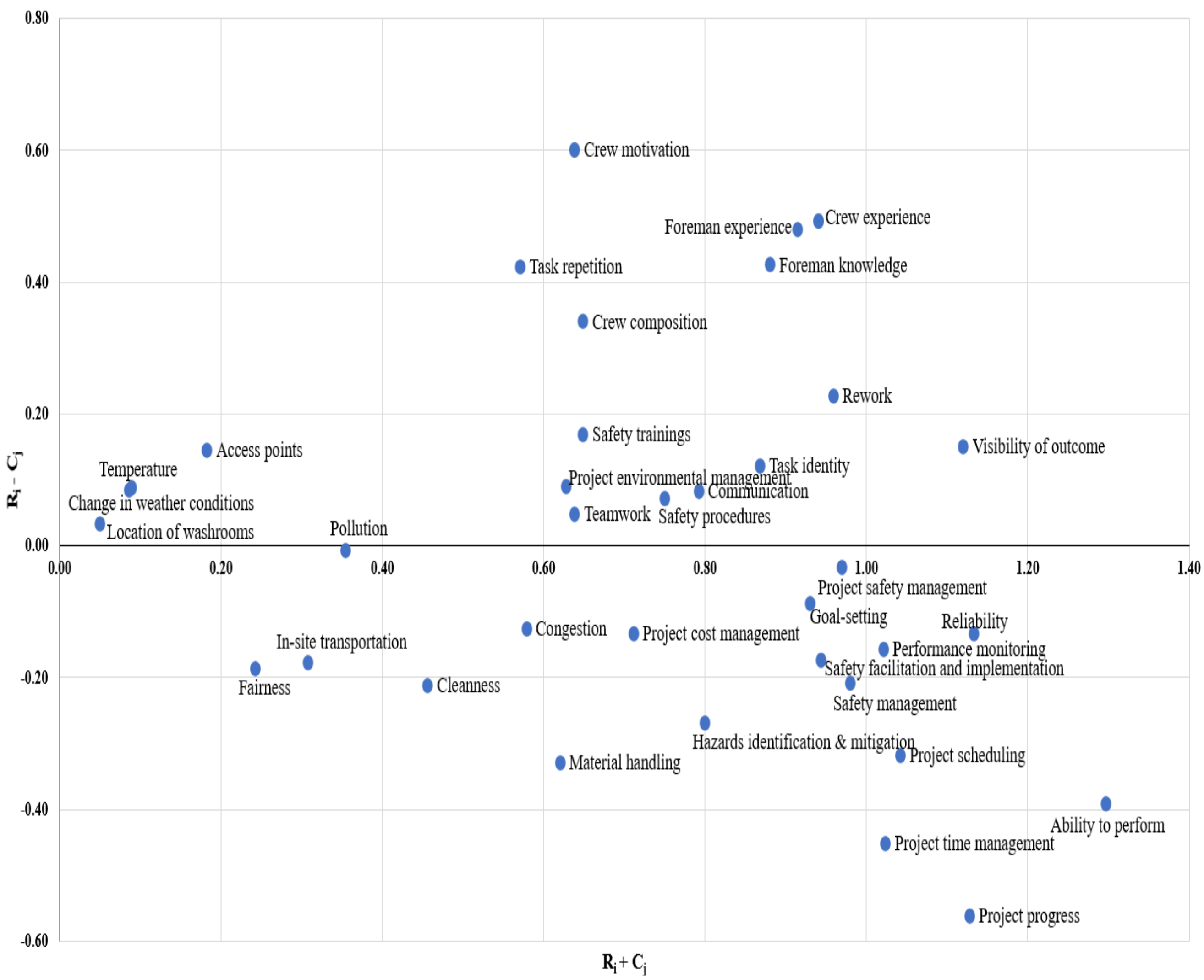

Figure 3.5 Influence relation map.

Hence, only the stronger relationships are considered to map causal relationships between variables. As described in the methodology section, the direction of the arrows for drawing the CLD is obtained from the T-matrix, whereby factors in each row affect the factors of the columns of the matrix. In this regard, the CLD was progressively constructed hierarchically by first considering contextual/situational factors at the crew-level as shown in Figure 3.6. The contextual/situational factors at the foreman-level, and project-level were subsequently introduced into the crew-level variables as shown in Figure 3.7 and Figure 3.8 respectively, to demonstrate the proposed methodology.

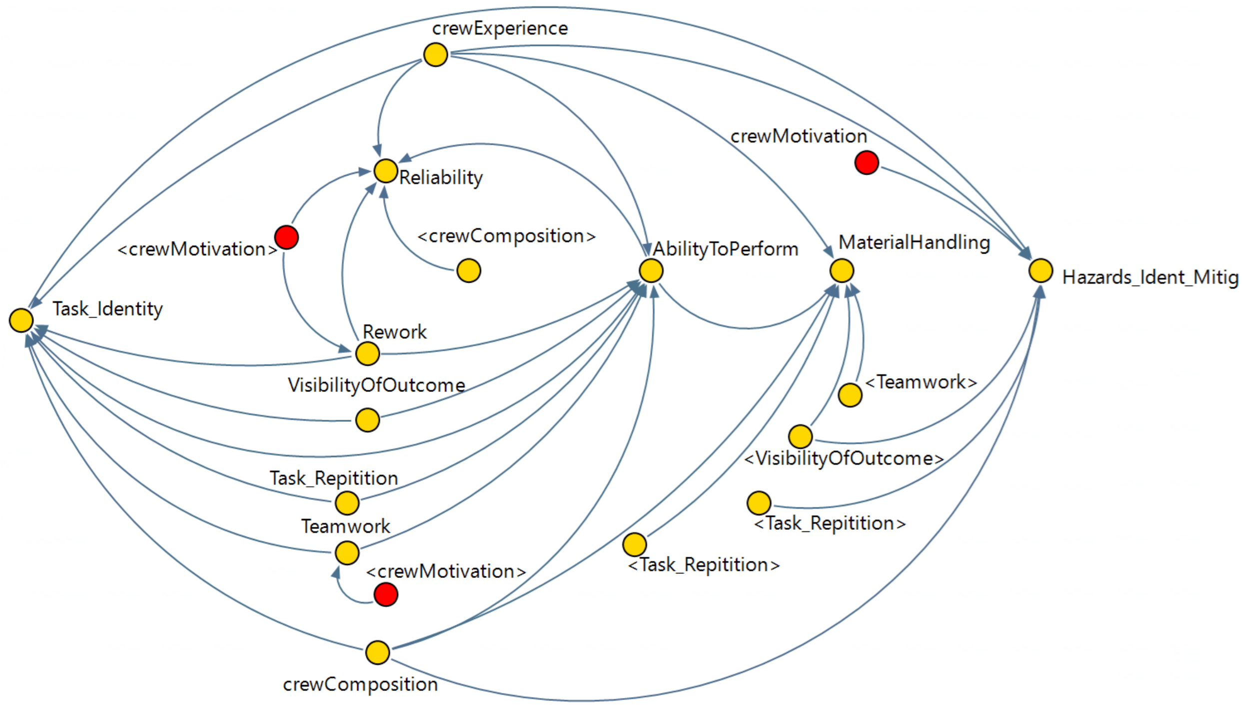

Figure 3.6 Sample CLD between factors affecting productivity at crew level.

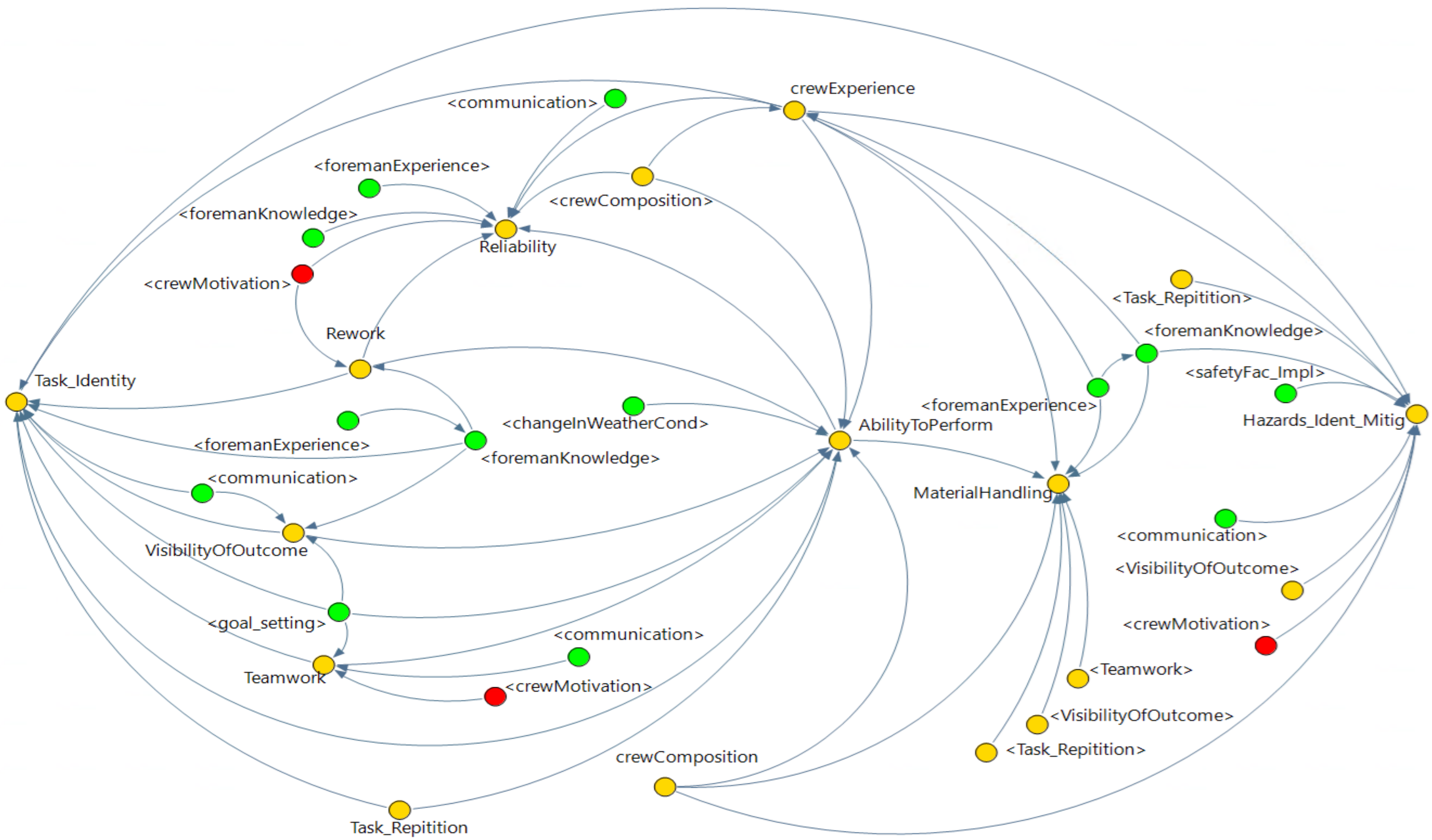

Figure 3.7 CLD between factors affecting productivity at crew level (Including foreman related factors).

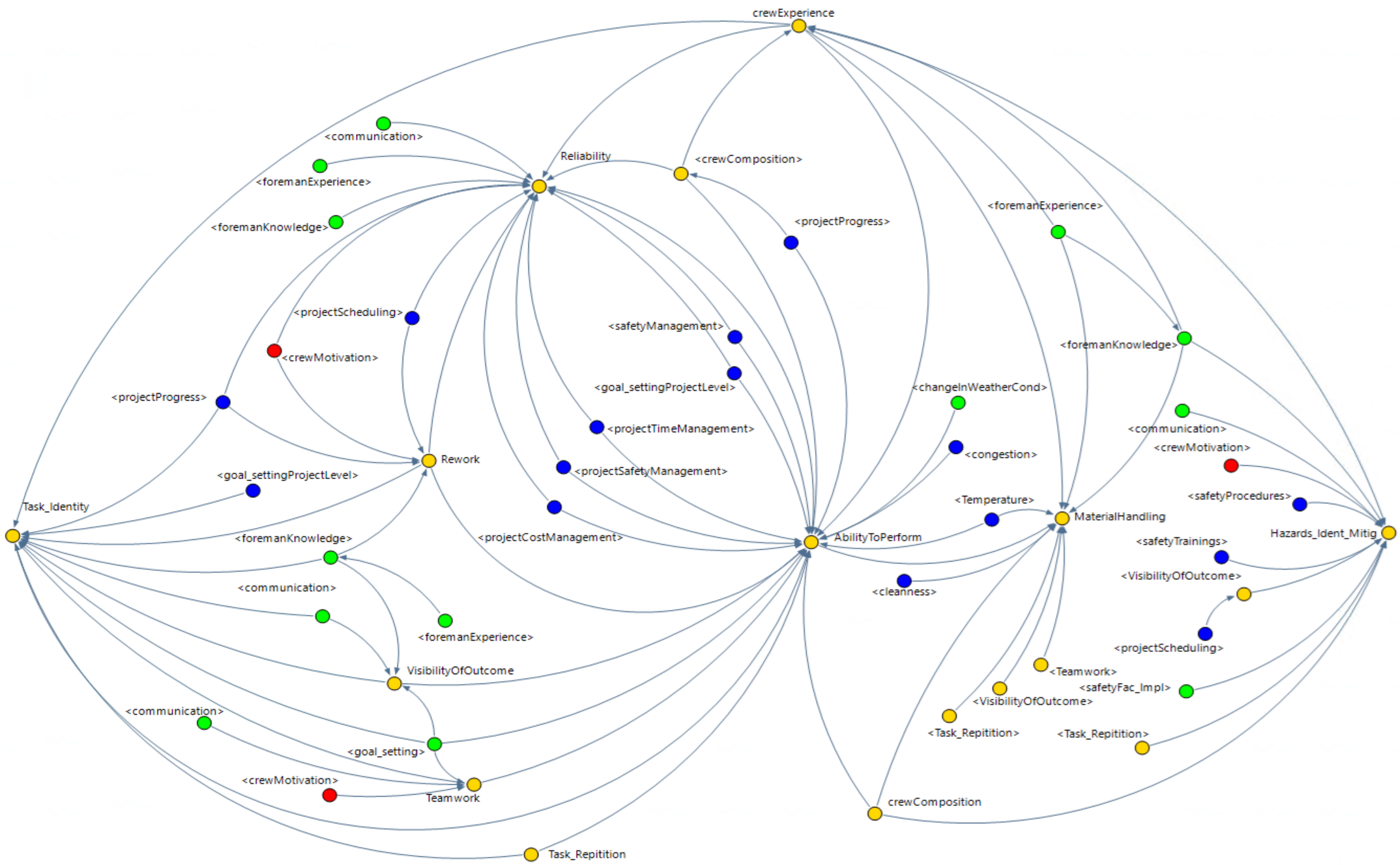

Figure 3. 8 CLD between factors affecting productivity at crew-level (Including foreman- and project-level factors)

3.5 Results

In this chapter, the proposed methodology is demonstrated using a case study, and the findings were discussed in two parts. In the first part, results related to *Stage-1* of the methodology are discussed, where 1) findings related to the developed list of criteria for expert weight assignment, and 2) findings on the relative importance weights of each criteria using the FAHP approach, are presented. In the second part, results related to *Stage-2* of the methodology are discussed, where 1) findings on the categorization of motivational, and situational/contextual factors into cause-and-effect groups, 2) construction of the IRM using the FDEMATEL approach, and 3) findings on the established CLD for dynamic modeling of crew productivity are presented.

First, in the expert weight assigning model (Stage-1), this chapter identifies a list of criteria to perform expert weight assignment. Related findings indicate that, *productivity-related project and construction management practices* was identified amongst the list of criteria which can be considered unique for assessing decision makers' inputs in the area of productivity; with sub-criteria of: *average hours of work in productivity-related work per week*, *level of management training related to productivity*, *experience in conferences related to productivity management, and functional skills related to productivity management.* Moreover, the criteria with the highest relative importance in relation to assignment of expert importance weights is *productivity related project management practices*, with a weight of 0.31. This indicates the need to give relatively more consideration for experts' involvement in productivity-related activities during the decision-making process. The results also show that both experience and knowledge are ranked second with an overall weight of 0.16, while *reputation* was ranked as the criteria with the lowest importance for expert assessment.

Second, the output of the FDEMATEL process is used to identify cause and effect groups within the factors affecting crew productivity, and draw influence relation maps between the factors. This is achieved by first computing the $\tilde{T}$matrix. These values of the $\tilde{T}$ matrix are used to obtain values of $(\tilde{R} + \tilde{C})$ and $(\tilde{R} - \tilde{C})$, which were defuzzified to obtain the *prominence* and *relation* values respectively. As shown in Table 3.9, factors with higher *prominence* values that indicate higher causal relations with the other factors are presented. In this regard, *ability to perform, reliability, work progress, visibility of outcome,* and *project scheduling* make-up the top-five factors with highest prominence, representing the most relationship with the other factors. Hence, the top factors have a higher strength of interrelationship with the other factors and strongly influence the other factors in terms of their causal relationship. Conversely, *location of washrooms*, *change in weather conditions*, *temperature*, *access points*, and *fairness* were found to be the factors with the minimum prominence values indicating their relatively low influence over the other factors in terms of causal relationship.

Moreover, Table 3.10 shows the relation values, where the factors are categorized into cause- and effect- groups based on positive and negative values of the relation measure. In this regard, *crew motivation, crew experience, foreman experience, foreman knowledge, task repetition, crew composition,* and *rework* were found to be among the top factors in the cause- group. These factors are shown to impose more impact on the system (R values) than they receive (C values), which enables them to have higher causal influence on the other factors and the overall behavior of the system. Therefore, improving these factors can result in the improvement of crew productivity measurement. Conversely, work progress, project time management, ability to perform, material handling, and project scheduling were found to be among the top factors that have high degree of being strongly influenced by the other factors.

The values of *prominence* and *relation* values are also used to plot the IRM. IRM is a very effective approach to analyze the cause- and effect- groups in terms of their overall influence on the system's behavior. In this regard, factors that have registered the highest prominence values and were also categorized as ranking highest under cause- group are focused on first, for discussion purposes related to improving the overall behavior of the system. Hence, *crew experience, foreman experience, foreman knowledge, crew motivation, crew composition, visibility of outcome,* and *rework* were found to be amongst the factors with higher combined prominence and relation values relative to the other factors affecting crew productivity. In terms of managerial decision making to improve the overall behavior of the system and better crew productivity, these results show that focusing on working to improve the factors with a higher measure of both prominence and relation values is imperative. Moreover, factors that have registered the highest prominence values and were also categorized as ranking highest under the effect- group were found to be *work progress, project time management, ability to perform, project scheduling, safety management, performance monitoring, reliability,* and *safety facilitation and implementation*. The results show that these factors are affected most by the other factors, and also have more interaction with the other factors in terms of their causal relationship. In effect, improving the factors that have most interactions while also having the highest causal- impact on the other situational/contextual factors can have a significantly positive impact in improving those group of factors with categorized as ranking highest under the effect group-, thereby improving the overall behaviour of the system and crew productivity.

Furthermore, the FDEMATEL output is used to obtain the causal relationship diagrams and feedback loops, which is crucial in the qualitative modeling process of SD modeling.

3.6 Chapter Summary

Improving construction crew productivity is a complex process due to a combination of various problems, such as identification of factors that can be used as predictors of productivity, identification of the issues that can contribute to improvement of productivity, and proposing mitigation measures for improvement of the crew productivity. These processes mostly involve the inputs of heterogenous experts, who usually come from different backgrounds, experience, and varying areas of expertise. Furthermore, capturing the inherent causal interrelationships between factors that can contribute to productivity improvement, and between factors that are used as predictors for crew productivity is crucial to formulating a comprehensive solution for the productivity problem. In this regard, this chapter aims to address the productivity problem by proposing a systematic and structured methodology that integrates fuzzy set theory with the modelling approaches AHP, and DEMATEL, to use in dynamic modeling of crew productivity.

This chapter identified a list of criteria to perform expert weight assignment in the context of productivity study. The FAHP proposed also enables expert weight assessment to account for heterogenous experts involved in productivity studies. Moreover, this chapter proposes FDEMATEL method to identify cause and effect groups within the factors affecting crew productivity, to capture the influence relationships between the factors, which can be used in strategic decision making on productivity improvement. Results of the FDEMATEL output were also used to obtain the causal relationship diagrams and feedback loops.

The contribution of this chapter is threefold. First, the study proposes a method to aggregate inputs of heterogenous experts in the area of productivity study. Second, this chapter proposes a FDEMATEL methodology to identify cause- and effect- groups from the factors affecting crew productivity using a case study on a real construction project in Alberta, Canada. The identified cause- and effect- groups can serve as crucial inputs for strategic decision making in productivity improvement. Third, this chapter makes use of FAHP and FDEMATEL, to propose a systematic and structured methodology to identify and define causal interrelationships between the factors, including situational/contextual factors, motivation, that affect crew productivity, and also to identify the feedback loops and formulate IRM. The outputs of FAHP-FDEMATEL form a crucial input for a more representative modelling of dynamic construction productivity.

This chapter details the methodology to perform weighted FDEMATEL modeling. This chapter presents 1) identification of criteria and sub criteria to perform expert ranking, 2) performing weight assessment using the FAHP methodology, and 3) establishing of causal relationship mapping and identification of cause-and-effect groups of factors affecting CLP. The next chapter discusses the methodology to utilize the outputs of the FAHP-FDEMATEL model to perform FSD-FABM model to predict CLP.

Chapter 4 Hybrid Fuzzy System Dynamics and Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction[4]

4.1 Introduction

Construction productivity is one of the most researched topics because of its influence on the success of construction projects (CII 2013). Productivity as a key performance indicator (KPI) is a crucial element in estimating duration and cost of construction operations (Hwang and Liu 2010). Studies related to construction productivity have mainly consisted of developing a reliable metric for measuring construction productivity, identifying factors that affect productivity, predicting a productivity measure, identifying issues that can contribute to productivity improvement or loss, and devising strategies for productivity performance improvement (Dixit et al. 2019). These topics together comprise a significant portion of productivity research in the last 15 years and are usually considered "the productivity problem."

Construction productivity can be assessed using several metrics that can vary based on whether the measurement is made at the activity, project, or a higher level (Ayele and Fayek 2019). Examples of productivity metrics include unit rate (ratio of labor cost to output units) and productivity factor (ratio of scheduled work to actual work hours). The most common metric used amongst researchers is labor productivity, which the ratio of measured output (completed work) to measured input (work effort) (Johari and Jha 2020; Tsehayae and Fayek 2016; Yi and Chan

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[4] Parts of this chapter has been submitted for publication in *Automation in Construction*: Kedir, N. S., and Fayek, A. R. (2022)." Integrated Fuzzy System Dynamics–Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction " *Automation in Construction*, 61 manuscript pages, submitted Oct. 2022.

2014; Zhao and Dungan 2019). At higher levels of productivity study, factors that affect measured productivity are assessed at the organizational, provincial, national, or global level (CII 2013; Kedir et al. 2022). Thus, measuring activity-level labor productivity is crucial to determining project performance, which in turn affects construction companies' profit margins.

Several approaches in the literature have been developed to predict productivity including: regression analysis, machine learning methods, and simulation approaches. These methods have inherent limitations. Regression analysis methods are simple to implement but lack data-capturing ability and lose accuracy with increasing number of inputs (Heravi and Eslamdoost 2015). Machine learning methods, such as artificial neural network (ANN), expert systems, and fuzzy systems, rely on the quality and amount of data to produce accurate models, which are difficult to obtain in most construction settings (Yi and Chan 2014). ANN also lacks the ability to explain the quality of the input-output mapping process (Mirahadi and Zayed 2016), which results in models that are not transparent and difficult for construction practitioners to understand, thereby limiting their applications to new project contexts (Tsehayae and Fayek 2016). Traditional expert systems formulate understanding of the system based on simple *IF-THEN* rules inferred from expert inputs (Sackey and Kim 2018) and cannot capture the subjectivity associated with human thinking and linguistic terms (Qiu et al. 2018). Fuzzy systems have consistently been used to capture subjective uncertainties arising from the use of linguistic terms and model input-output relationships. However, fuzzy systems alone lack the ability to learn from data and optimize their model parameters, so cannot capture the dynamic conditions usually associated with construction environments (Fayek 2020). Simulation approaches such as discrete event simulation (DES) are mostly effective in modeling tasks with repetitions and finding durations of activities, utilization of resources, and delays (Raoufi et al. 2016). However, DES cannot to capture dynamic relationships between model elements. Effectively, these methods all lack ability to capture complexity and dynamism that arise from the continuous change in values of system variables owing to their time-varying nature and causal interactions.

The construction environment is unpredictable, context dependent, and complex, where factors such as crew experience, crew motivation, foreman knowledge, and congestion influence the productivity measure either directly or indirectly (Tsehayae and Fayek 2016). Construction projects are performed in a dynamic environment that results from numerous interactions between contextual/situational factors related to task, resources, management, project characteristics, and work-setting conditions (Raoufi and Fayek 2018). Therefore, to model and predict construction productivity, dynamism and uncertainty of the construction environment must be properly captured.

The problem of proposing a comprehensive model of construction labor productivity (CLP) entails simultaneously capturing: 1) complexity arising from the subjective nature of variables affecting CLP, owing to the use of linguistic terms such as *low temperature* or *poor safety practices*, 2) complexity arising from the dynamic nature of variables, whose values are continuously changing throughout project duration, 3) complexity arising from the emerging behavior of some variables affecting CLP, such as crew motivation, and 4) complexity arising from the causal interrelationships between factors affecting CLP, which are context dependent and vary across different situations in which tasks are performed. Therefore, a gap in the literature exists regarding methods that can capture dynamic causal relationships between factors affecting CLP and the emergent nature of some variables, while addressing subjective uncertainty in modeling and predictive processes. Combining different modeling approaches such as FSD and FABM enables modelers to produce a more powerful hybrid model capable of a more comprehensive abstraction, by capturing the effects of multiple system variables such as subjectivity, dynamism, and emergent behaviors.

The objective of this chapter is to propose a hybrid FSD-FABM model that can capture causalities between crew motivation and situational/contextual factors that impact CLP while addressing subjective uncertainties in the predictive modeling process. This chapter also aims to investigate predictive accuracies of multiple modeling approaches with FSD-FABM. This chapter is organized as follows: first, the topic of productivity is introduced; a brief literature review on productivity in construction is then presented, as are simulation approaches used to model productivity. Next, the FSD-FABM methodology is presented.

4.2 Literature Review

4.2.1 Simulation Methods for Construction Productivity

4.2.1.1 System Dynamics Modeling

SD was first introduced by Jay Forester in the mid-1950s for the purpose of modeling complex systems (Sterman 2000). Early studies on SD-based productivity investigated the impact of one or multiple factors on productivity. These included studies on the impact on productivity of: changing key personnel (Chapman 1998); downtime resulting from equipment failure (Prasertrungruang and Hadikusumo 2009) and varying arrangements of personnel working-hours (Alvanchi et al. 2012). More recent SD studies have better utilized SD's potential to model dynamic systems, observe critical interrelationships between several system elements, and capture their impacts on productivity. Nasirzadeh and Nojedehi (2013) developed SD model for construction labor productivity, which was appropriate for capturing interrelationships between the factors affecting productivity measure. Li and Taylor (2014) developed SD to model, and evaluate the effect of reworks in construction projects. Nojedehi and Nasirzadeh (2017) proposed a FSD model for modelling and improving productivity. Gerami Seresht and Fayek (2018) Proposed a fuzzy system dynamics model for multi factor productivity of construction activities; that accounted for labor, equipment and material.

When SD models are hybridized with fuzzy logic approaches, the proposed models are able to capture the subjective nature of model variables, thereby providing a more comprehensive representation of the construction environment. Although hybrid fuzzy SD models offer more comprehensive solutions in modeling subjective variables that also exhibit dynamism, fuzzy SD models cannot efficiently capture those variables having a spatial nature (e.g., congestion). Fuzzy SD models also cannot properly represent heterogeneity of different agents and their interactions (Khanzadi et al. 2019) or emerging behavior of model variables such as crew motivation (Kedir et al. 2020). Therefore, hybrid SD models must incorporate methods capable of capturing heterogeneity and emerging nature of system variables, to be able to propose a more comprehensive predictive model of construction productivity.

4.2.1.2 Agent Based Modeling

ABM consists of agents that interact with each other and their environment, with the primary goal of predicting possible emerging system behavior (Khodabandelu and Park 2021). Agents are entities that are discrete, have their own unique set of behavioural rules, and are classified by type (e.g., crews, crew members), whereby each type has distinguishing features (e.g., crew member years of experience, crew size) (Raoufi and Fayek 2018). Jabri and Zayed (2017) used ABM to simulate, and thus, improve the accuracy and planning of earthmoving operations. Cao et al. (2015) used ABM to develop a scheduling framework to improve occupant satisfaction and energy efficiency in residential buildings. Ben-Alon and Sacks (2017) proposed a hybrid model of ABM and BIM to better study production systems in construction that can capture the motivation and behaviour of individual crews and workers, as well as their interaction within a physical and process environment. This signifies ABM's potential when used with other modelling approaches. While fuzzy hybrid ABM approaches can capture construction systems containing subjective parameters, heterogeneity, and active individual objects defined by behavioural rules, FABM is not best suited to investigate processes dominating in aggregated systems nor aggregated system-level dynamics (Martin and Schlüter 2015). For models that need to be abstracted at a higher scale to study feedbacks with cause-and-effect relationships, SD methods are better suited to capture complexities associated with these systems. Thus, hybridizing FSD and FABM is imperative, because it enables modelers to combine the strength of individual method, while capturing vague interdependencies and the subjectivity arising from linguistic approximation and measurement imprecision.

4.2.1.3 Fuzzy Logic in Construction

Zadeh (1965) first introduced fuzzy set theory. This concept transformed the perception of modelling uncertainties, as fuzzy sets extended the notion of classical sets and Boolean logic. Hence, fuzzy logic is able to handle natural language and approximate reasoning, by mathematically translating linguistic variables into numeric form and allowing users to make definite conclusions from ambiguous information and incomplete data (Zadeh, 1965). Fuzzy sets are represented using membership functions (MBFs). In fuzzy hybrid models, appropriately representing linguistic variables and fuzzy rules, employing the right fuzzy arithmetic method, and selecting the most suitable defuzzification methods are essential (Fayek and Lourenzutti 2018).

4.2.1.4 Integrating FSD and FABM in Modeling Productivity

In viewing productivity modeling as a complex system whose inputs continuously interact with themselves and the environment, an efficient abstraction necessitates an integrated simulation approach that takes advantage of multiple simulation methods. Thus, a hybrid SD-ABM based approach uses SD to consider productivity as a dynamic system with complex feedback relationships whose behaviour is captured over time, and uses ABM at the micro level to capture the individual systems whose individual components interact with each other and the environment per a given set of rules.

Research interest in hybrid SD-ABM approaches is increasing in different construction areas. Nasirzadeh et al. (2018) proposed a framework for modeling construction workers' safety behavior using a hybrid SD-ABM modeling approach. Wu et al. (2019) proposed SD-ABM to gain better understanding of laborers' behavioural diversities to improve project management. Hwang et al. (2021) proposed an agent-embedded SD model to analyze worker policies and investigate construction workers' social absenteeism. In the area of productivity, a few studies on hybrid SD-ABM exist. Khanzadi et al. (2019) used a hybrid SD-ABM approach to predict and improve the labor productivity measure, where SD was utilized to simulate dynamic feedback relationships between factors affecting labor productivity, and ABM was used to model congestion.

The three major methods of hybridizing SD and ABM in the literature (Swinerd and McNaught 2012) are integrated, interfaced, and sequential hybrid designs. In integrated modeling, connection between SD and ABM is performed through a feedback mechanism that allows for information interchange. In interfaced modeling, ABM and SD models run individually, and the final output has the outputs of the ABM and SD model components. In sequential modeling, either SD or ABM runs first, and the resulting information is sent into the subsequent step. These three approaches are suitable based on the modeler's objectives, as the approaches have advantages and disadvantages. Hence, selection criteria depend on problem characteristics and model requirements (e.g., data availability, following a policy, spatiality, learning members, complex interactions) (Nasirzadeh et al. 2018). Integrating fuzzy logic approaches with both ABM and SD to produce FSD-FABM will enable individual modeling techniques to model subjective uncertainties associated with construction systems, namely the vague interdependencies between variables (Nasirzadeh et al. 2018).

4.3 Research Methodology for Hybridizing FSD and FABM

The proposed hybrid FSD-FABM methodology comprises four components: 1) factor identification and system variable selection, 2) FSD, 3) FABM, and 4) FSD-FABM. The factor identification stage identifies the variables necessary to define the system. The FSD component captures causal relationships between factors affecting CLP. FABM captures the emerging nature of the *Crew motivation* variable and establishes the model environment by forming the agents for crews and project work packages. Fuzzy logic is embedded within the hybrid FSD-FABM component to capture subjective uncertainties. The FSD-FABM methodology is shown in Figure 4.1 and discussed below.

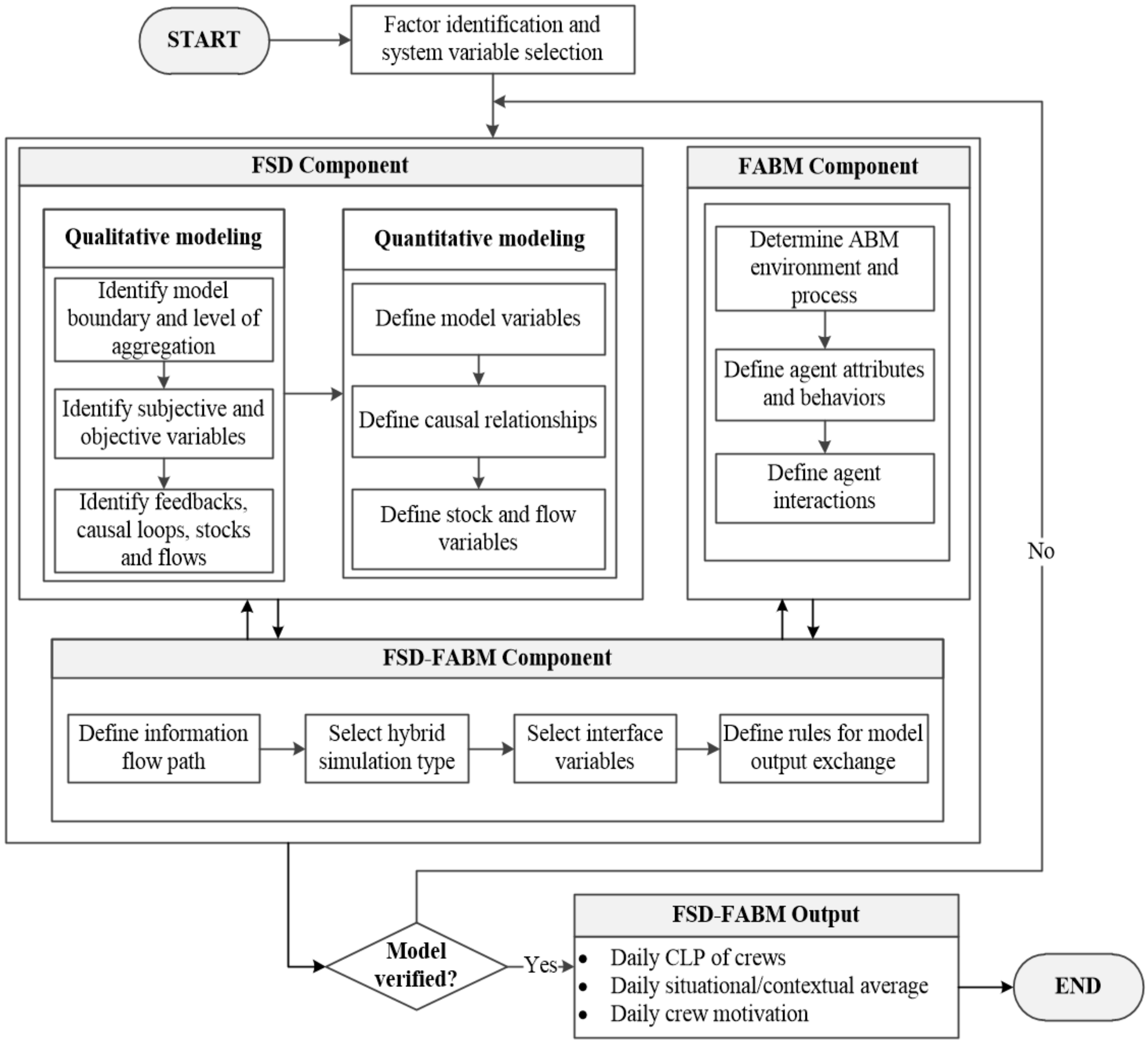

Figure 4.1 FSD-FABM methodology.

4.3.1 Factor Identification and System Variable Selection

In the process of factor identification and system variable selection, the first step is to identify factors that affect productivity. Factors that affect crew motivation and productivity are identified and collected from past literature (Raoufi and Fayek 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019; Nasirzadeh and Nojedehi 2013; Tsehaye and Fayek 2014). After identifying the list of factors within the literature, these identified factors are categorized into different hierarchies of situational/contextual factors. These hierarchies include labor and crew-related, materials and consumables, equipment and tools, task related factors, location related factors, supervisor related factors, engineering and instructions, safety, project management practices, project nature and project conditions. In this regard, 111 factors were identified and categorized under these hierarchies (Appendix C). A sample of these factors is shown in Table 4.1.

Table 4.1 Situational/contextual factors affecting productivity.

Factor group	Factor name	Factor used as measurement
Labour and crew-related	Crew is experienced and has the necessary technical skills to perform the tasks.	Crew experience
	Crew has a well-balanced composition (Journeymen and Apprentices).	Crew composition
	Efforts are taken to minimize crew turnover (people are not leaving the project regularly)	Crew turnover rate
	Craftspeople trust the skills and judgment of their supervisors.	Craftsperson trust in foreman
Materials and consumables	Material is always delivered on time.	Availability of task materials
Equipment and tools	Work tools and equipment are readily available.	Availability of work equipment (crane, forklift)

After these factors are identified, interview surveys are prepared to obtain experts' responses. The surveys are prepared for supervisors and forepersons. These experts will rank each of the factors based on the factors' influence on productivity, using two scores: agreement score and impact score. The agreement score represents the extent to which the expert agrees that the factor is present in their project while the impact score represents the extent to which the factor affects productivity. In this chapter, the five-point scale: *Strongly Disagree*, *Disagree*, N*either Agree nor Disagree*, *Agree*, and *Strongly Agree* is used to rate the agreement levels of experts. The impact score was measured using the five-point scale: *Strongly Negative*, *Negative*, *No Impact*, *Positive*, and *Strongly Positive*.

The responses of these experts are then collected to perform statistical analysis to select the factors with the maximum positive or negative impact on crew productivity. As the most common technique for correlation analysis (Pandey 2020; Bobko 2001; Gerami Seresht and Fayek 2019); Pearson correlation analysis was explored. Pearson correlation analysis indicates relationship between independent variables (i.e., motivational, and situational/contextual factors) and dependent variables – crew productivity. Pearson's correlation analysis does not establish causation between the factors (Gogtay and Thatte 2017). The data was first checked to satisfy the assumptions test, necessary to perform the correlation analysis. The assumptions test carried out include randomness, continuity, independence of observations, existence of paired sample for X and Y variables, and absence of outliers. Expert selection was randomized to comply with the randomness test, and the data are measured on a continuous scale to comply with the continuity test. For example, crew experience was measured in years, temperature is measured in degrees. Moreover, there is no relationship between the experts who were selected in the data collection process to make sure there is independence of observations. The data also contains paired samples of dependent and independent variables, and the selected data was checked not to include outliers. Once a strong relationship between factors is identified, the selected factors are then used as system variables in the subsequent modeling stages of FSD and FABM.

4.3.2 FSD Component

The FSD component captures the causal relationships between situational/contextual factors, and crew motivation. The dynamic variables that make-up the construction environment in the form of situational/contextual factors are represented in the FSD component by capturing their causal interrelationship. There are two major steps in the FSD component, namely, qualitative, and quantitative modeling.

4.3.2.1 Identify Model boundary and level of aggregation

In the first step, the qualitative modeling of FSD deals with identifying model boundary and level of aggregation. The model boundary defines the modeling scope. The factors affecting productivity obtained from the previous step of factor identification and system variable selection step, are grouped into the 9 categories, namely: *labour and crew-related factors, materials and consumables, equipment and tools, task-related factors, location-related factors, engineering and instructions, safety, project management practices, and project nature and project conditions.* These factors are used as system variables, and based on the definition of the model boundary, they are divided into endogenous, and exogenous variables (Appendix D). Endogenous variables such as crew size, crew composition, project scheduling, are influenced by the other variables in the system, whereas exogenous variables such as temperature, nature of project owner, humidity, are not influenced by other variables. The desired modeling scope, level of complexity, and available information can be used to distinguish between endogenous and exogenous variables.

After the model boundary is defined, the level of aggregation for the model is identified. The level of aggregation defines how system variables are grouped into sub-systems to achieve a realistic abstraction. The aggregation level of the FSD component is shown in Figure 4.2.

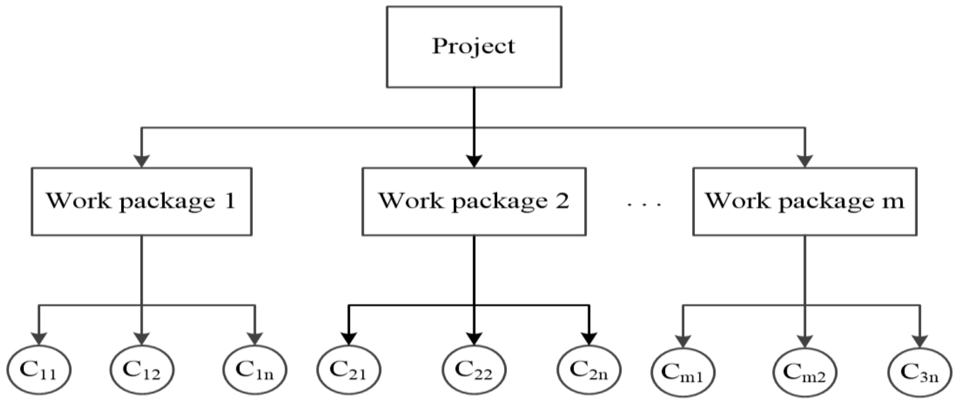

Figure 4.2 Aggregation level of FSD model

where: C_{ij} is the productivity of crew *j* that are working on work package *i*.

It is important to note that the crew allocation to the work packages in the project is a planning problem and is not addressed in this chapter. In the level of aggregation shown in Figure 4.2, crew 1 may be allocated to work only on work package 1, or a combination of the *m* work packages in the project (i=1, m). In this regard, the FSD component models the dynamics of the situational/contextual factors affecting productivity of the crews, that are performing a given set of work packages.

4.3.2.2 Identify subjective and objective variables

Once the nature of all the variables to be used in the FSD component is identified, the variables are categorized further into *subjective* and *objective* variables (as shown in Appendix D). Subjective variables are those variables which are best defined using fuzzy numbers and membership functions. Variables that show subjective uncertainties arising from imprecision or linguistic expression of information (Zadeh 1978), are best described using the principle of fuzzy sets. These variables do not have numeric attributes, and are linguistic in nature, such as *high* temperature, *low* crew motivation, *low* crew morale. Objective variables such as crew size, production rate, crew composition, have quantitative metrics and can be expressed with numeric expressions.

4.3.2.3 Identify feedbacks, causal loops, stocks and flows

Next, the causal relationships between these factors are formulated to determine the dynamics between crew productivity, and the situational/contextual variables. The causal relationships between the variables can be obtained using literature reviews, questionnaire surveys, or semi-structured interviews, modelers' assumptions, and experts' verification through focus groups (Leon et al. 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019; Moradi et al. 2015). In this chapter, causal loop diagrams and feedback loops were obtained using fuzzy analytical hierarchy process–fuzzy decision making trial and evaluation laboratory (FAHP-FDEMATEL) method. The FAHP-FDEMATEL method addresses the lack of systematic and structured methodology of obtaining causal relationships between system variables in the context of productivity modeling. The proposed methodology utilizes expert knowledge using surveys to identify causal relationships using the FDEMATEL method. In the FDEMATEL method, experts' assessments on the causal relationships between factors affecting productivity was obtained in the form of a fuzzy matrix $\tilde{X}^E$., as shown in Equation (4.1).

$$\tilde{X}^E = \left[\tilde{x}_{ij}^{(e)}\right]_{nxn} = \begin{bmatrix} 0 & \tilde{x}_{12}^{(e)} & \cdots & x_{1n}^{(e)} \\ \tilde{x}_{21}^{(e)} & 0 & \cdots & \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1}^{(e)} & \tilde{x}_{n2}^{(e)} & \cdots & 0 \end{bmatrix} \tag{4.1}$$

$i,j = 1,2,...n,$ and $e = 1,2,...E$

where:

n=total number of elements in the system and,

E= total number of experts assessing the causal relationships

Next, the set of initial fuzzy matrix $\tilde{X}^E$, obtained from a set of experts E, are aggregated to form the aggregated direct relation matrix $\widetilde{D}$, as shown in Equation (4.2).

$$\widetilde{D} = \left[\,\tilde{d}_{ij}\right]_{nxn}, where\ \tilde{d}_{ij} = (d_{ij}^{l}, d_{ij}^{m}, d_{ij}^{u}) \qquad (4.2)$$

This direct relation matrix is used to obtain the normalized fuzzy aggregated direct relation matrix N, as shown in Equation (4.3) and Equation (4.4) below

$$\widetilde{N} = \widetilde{D} * \lambda \qquad (4.3)$$

where:

$$\lambda = \frac{1}{\max\limits_{1 \le i \le n}\left(\sum\limits_{j=1}^{n} d_{ij}\right)}, i, j = 1,2,...n \qquad (4.4)$$

The fuzzy total relation matrix T represents the total degree of causal influence of factor i on factor j, which is obtained using Equation (4.5), and Equation (4.6) (Rostamnezhad et al., 2018).

$$T = D(I - D)^{-1} \qquad (4.5)$$

where I is represented by an n x n identity matrix.

Hence,

$$\tilde{T} = \left[\,\tilde{t}_{ij}\right]_{nxn}, where\ \tilde{t}_{ij} = \left(t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{u}\right), and\ i, j = 1,2, \dots n \qquad (4.6)$$

In the final process, causal loop diagrams, and causal relationships between crew motivation, and situational/contextual in affecting productivity are established for use in dynamic modeling of productivity. To achieve this, the total relation matrix *T*, obtained in Equation (4.6) will be defuzzified using the center-of-area method to achieve the T^{def} matrix. This defuzzified matrix represents the degree of causal influence between the factors affecting productivity. In this regard, T_{ij} represents the degree of causal influence of factor *i* on factor *j*. The direction of the arrows for drawing the CLD is drawn in such a way that factors in each row affect the factors of the columns of the matrix.

In addition to the FDEMATEL approach, pre-existing causal relationships that were already established and well-verified in previous models (Ford and Lyneis 2020; Nasirzadeh et al. 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019) were also used. Moreover, the stocks, and flows of the dynamic model are also identified in the qualitative modeling stage. The stocks represent the accumulation, or depletion resulting from the differences between inflows and outflows, while flows represent the rate at which stocks change over time (Sterman 2000). In this chapter, three stock variables are identified, namely: *work to do*, *work completed*, and *direct labor cost*. The flow variables include the *daily work rate,* and the *labor cost rate.* In effect, interdependencies between model variables 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.

4.3.2.4 Define model variables

In this stage, the model variables are defined quantitatively by assigning measurements based on the type of variable under consideration. In this regard, there are two types of model variables, namely: objective and subjective variables (Gerami Seresht and Fayek 2018). Membership functions, which assume values between 0 and 1 are used to characterize the linguistic terms that are used to describe the subjective variables.

4.3.2.5 Define causal relationships, stocks and flows

Next, the causal relationships, and the stock and flow variables are determined quantitatively. In this step, there are two types of relationships between system variables, namely: 1) hard relationships, which are relationships that can be defined by mathematical equations, and 2) soft relationships, which are relationships that are difficult to capture using mathematical equations. The hard relationships are defined by using existing mathematical equations, or by using statistical methods such as regression analysis. For example, crew size is measured as number of crew members in the crew, minus the number of absentees; and production rate is measured in amount produced per unit of time. Equation (4.7) to Equation (4.16) show some of the hard relationships which are defined by mathematical equations.

$$\text{Crew size } [\boldsymbol{number}] = \text{Planned crew size } [\boldsymbol{number}] \text{ - Absenteeism } [\boldsymbol{number}] \tag{4.7}$$

$$\text{Daily Work Time } \left[\frac{\boldsymbol{hr}}{\boldsymbol{day}}\right] = \text{Planned Work Hour } \left[\frac{hr}{day}\right] + \text{Overtime } \left[\frac{hr}{day}\right] \tag{4.8}$$

$$\text{Labor Direct Cost Rate}\left[\frac{\$}{day}\right]\text{=Daily Work Time}\left[\frac{person\ hr}{day}\right]\text{*Workforce Unit Cost}\left[\frac{\$}{person\ hr}\right] \tag{4.9}$$

$$\text{Productivity } \left[\frac{units}{person\ hr.}\right] = \text{Production Rate } \left[\frac{units}{day}\right] \div \text{Daily Work Time } \left[\frac{person\ hr}{day}\right] \tag{4.10}$$

$$\text{Productivity Loss}\left[\frac{units}{person\ hr.}\right]\text{=BenchmarkProductivity}\left[\frac{units}{person\ hr.}\right]\text{-Productivity}\left[\frac{units}{person\ hr.}\right] \tag{4.11}$$

$$\text{Remaining Work } [units] = \text{Work to Do - Work Completed } [units] \tag{4.12}$$

$$\text{Labor Cost Rate } \left[\frac{\$}{day}\right] = \text{Labor Direct Cost Rate } \left[\frac{\$}{day}\right] + \text{ Labor Indirect Cost Rate } \left[\frac{\$}{day}\right] \tag{4.13}$$

$$\text{Daily Work Rate } \left[\frac{units}{day}\right] = \text{Production Rate } \left[\frac{units}{day}\right] \tag{4.14}$$

$$\text{Work Completed [units]} = \int Daily\ Work\ Rate\ \left[\frac{units}{day}\right].dt\ [day] \tag{4.15}$$

$$\text{Total labor Direct Cost (\$)} = \int Labor\ Direct\ Cost\ Rate\ \left[\frac{\$}{day}\right].dt\ [day] \tag{4.16}$$

For the mathematical equations that consist of fuzzy variables, fuzzy arithmetic methods (extension principle or alpha-cut) can be applied. The second type of relationships includes soft relationships, which is performed by connecting the SD with the fuzzy logic component. If there is available data, neuro-fuzzy systems or data-driven fuzzy rule base systems are proposed.

4.3.3 FABM Component

The FABM component constitutes of three major steps, namely: 1) defining the FABM environment and processes, 2) defining agent attributes and behaviors, 3) define interactions between agents, and agent behavioral rules. Each of these steps are elaborated in more detail as follows.

4.3.3.1 Define FABM environment and Processes

In this step, the main environment of the FABM is identified, the agents taking part in the FABM are identified by answering the basic question of “what are the agents?” and the overall model architecture is proposed. In the FABM component, the primary output of the model is crew motivation. In this regard, the main environment is the top-level agent where all the model parameters, and immediate lower-level agents are created. The main environment is also where the necessary java functions which enable connection with the fuzzy component are placed. In the

ABM, there are three types of agents: namely, the project agent, the crew agent, and the work package agent. Figure 4.3 shows the FABM environment and processes.

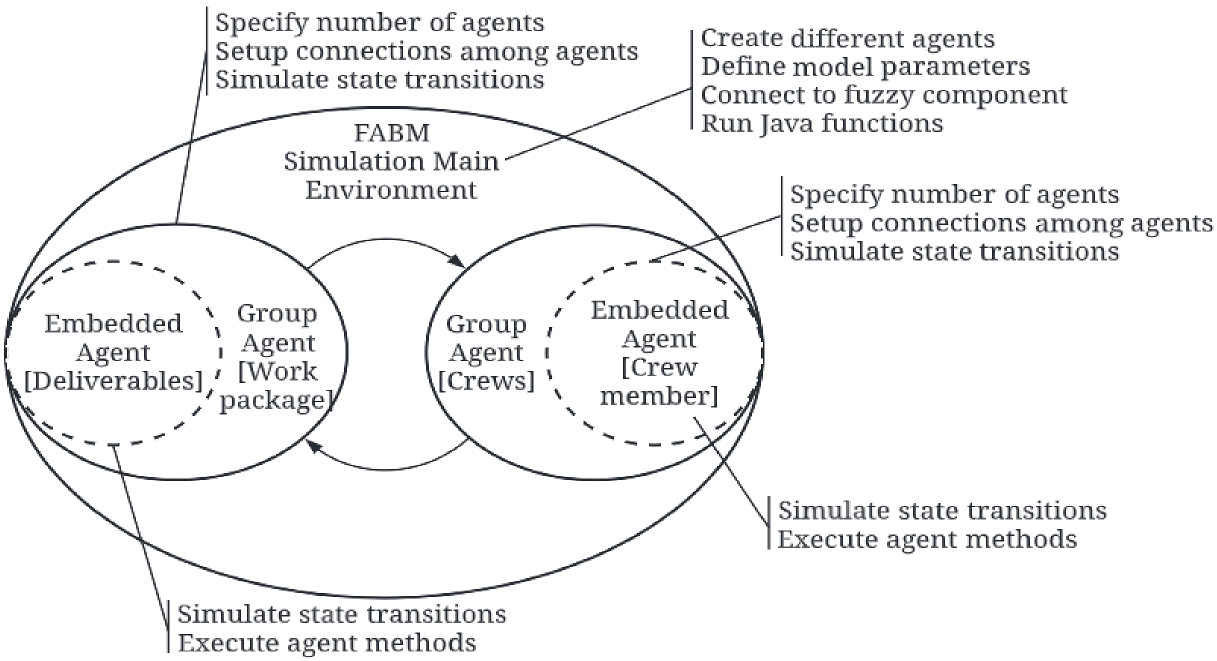

Figure 4.3 FABM environment and processes.

As shown in Figure 4.3, the simulation main environment of the FABM component includes the group agent of crews that can contain embedded agents of crew members, and the group agent of Workpackage that can contain the embedded agent of deliverables. During the initial step of creating agents, the number of agents, and the connections between these agents are specified. The connections between the group agents of *crews* and *Workpackage* signify that the crews perform tasks designated in the *Workpackage* environment. After these connections are established, state transitions are then specified in the state charts. All agents are created in the simulation main environment.

4.3.3.2 Define Agent Attributes and Behaviors

In this step, the basic structure of agents is formulated. For each of the agents and agent groups defined in the previous step, the corresponding attributes is defined. This can be achieved using either one of deterministic, probabilistic or subjective approaches. The first approach is using deterministic variables for those variables with defined values such as crews' year of experience, number of crews. The second approach is using probabilistic variables for the variables that exhibit probabilistic nature such as the susceptibility of crews to change their motivation (Raoufi and Fayek 2018). The third approach is using subjective variables for those variables that exhibit subjective uncertainties such as *teamwork*, *foreman knowledge*, and *crew knowledge*.

To model subjective variables, a fuzzy set theory approach is used to capture those variables in the FABM environment, where membership functions were used to quantify the degree of belongingness of the variable to its respective fuzzy set. Depending on the availability of data, neuro-fuzzy systems or data-driven fuzzy rule base systems are used. When there is no data available, expert based fuzzy rule base systems are proposed to formulate relationships between the variables. Implementation of the fuzzy set theory to model the subjective variables is discussed in detail in the *fuzzy logic component.* The basic structure of agent, which establishes the agent attributes and behaviors is described in Figure 4.4.

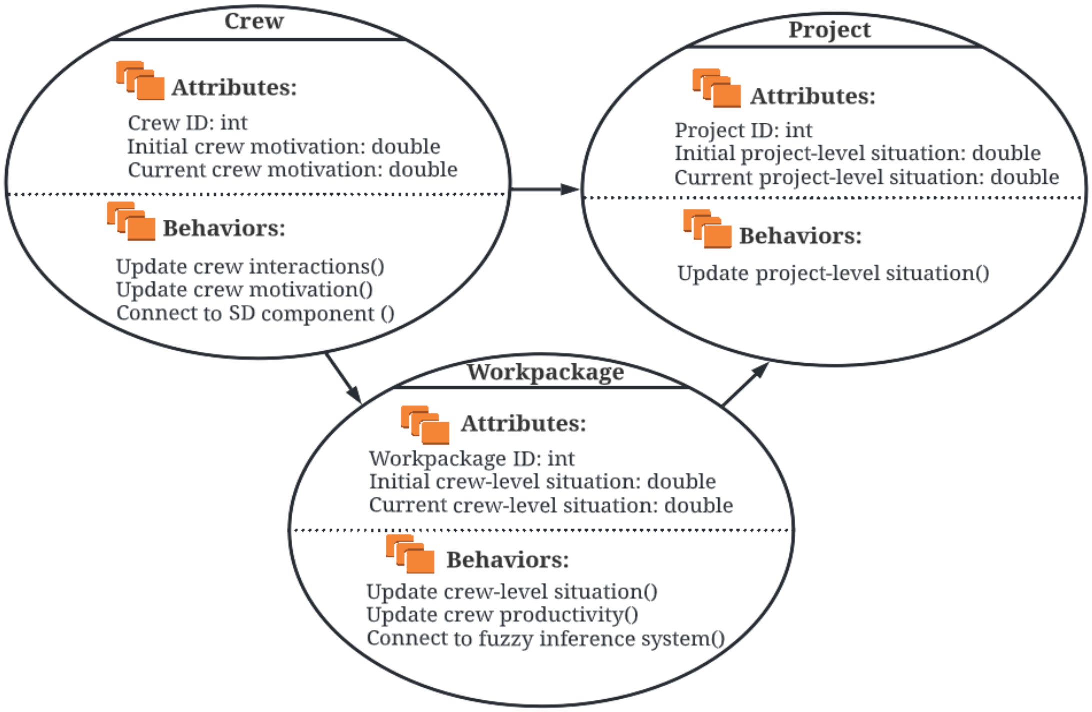

Figure 4.4 Agent attributes and behaviors.

As shown in Figure 4.4, the basic structure of agents is divided into agent attributes, and agent behaviors for the three different types of crews, project, and Workpackage agents. The attributes of all the three agent types deal with initializing parameters, and variables that will be used to hold information. For example, the crew ID, and initial crew motivation are initialized at the start of the simulation, while the current crew motivation is the value that is computed at every time step. These attributes are set for each agent. Secondly, the agent behaviors are represented by what the agent performs. For example, the crew agent updates interactions of each crew to calculate the crew motivation at each timestep, and also connects to the FSD component so that the values of crew motivation can be used in the FSD component of the model.

4.3.3.3 Define Agent Interactions and Agent Behavioral Rules

After the attributes and behaviors of each agent are defined, the next step is to define how different agents interact. ABM is able to capture the dynamism resulting from the dynamic interactions between agents by first establishing rules for agent interactions. For example, crews working in a congested area have greater reduced outputs than crews that are working in less congested areas (Watkins et al. 2009). The reduction of outputs, as a function of congestion is then established using mathematical equations. There are several mathematical equations that quantify predefined interaction rules in the literature (Dabirian et al. 2021; Al Hattab and Hamzeh 2018; Azar and Ansari 2017). Depending on the type of agent, the mathematical equations that define interaction rules can be different. In this chapter, the crew agent exhibits behavioral changes resulting from observing the behaviors of other crews. The formula used to calculate the interaction between crew agents, to simulate the attribute of agent A is adopted from Raoufi and Fayek (2018), as shown in Equation (4.17).

$$.CM_i^t = (1 - Z \times CR \times S) \times CM_i^{t-1} + (Z \times CR \times S) \times \frac{\sum_{j=1}^{N} CM_j^{t-1}}{N} \tag{4.17}$$

where t = current time step, t–1 = previous simulation time step; i and j are indices of the agent type; Z = agent type that observes the attribute of other agents to change its own attribute; CR = contact rate, S = susceptibility (the probability that an interaction between the agents leads to a change in the attribute of the agent); CM = crew motivation, N = number of crew agents that interact with A_i.

4.3.4 Fuzzy Logic Component

The method proposed in the fuzzy logic component is intended to expand the scope of SD and ABM approaches by introducing fuzzy logic into each of the approaches. In this regard, the fuzzy logic component is an integral aspect of both the ABM and the SD models. By integrating the ABM and SD model with the fuzzy logic component, FABM, and FSD can be established, which is crucial to capture subjective uncertainties within the model. This integration is shown in in Figure 4.5.

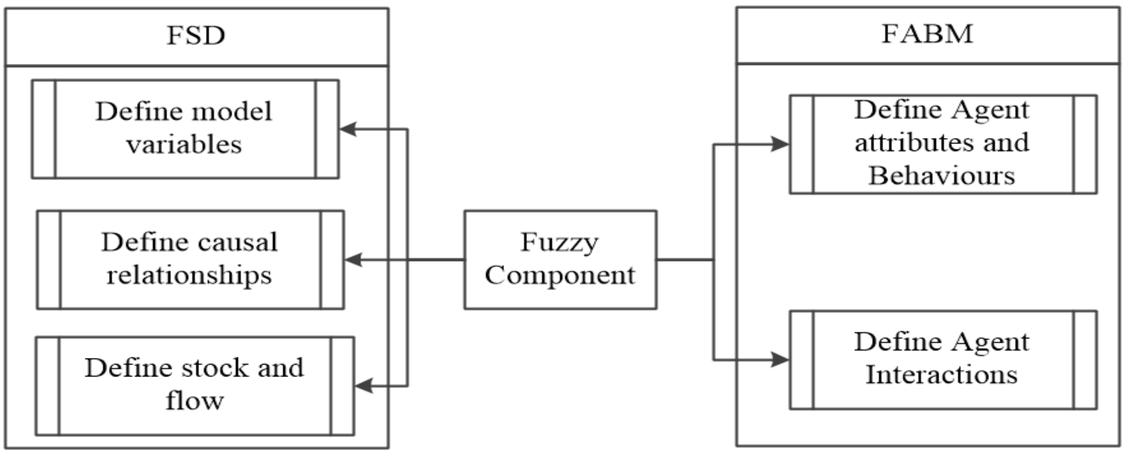

Figure 4.5 Integration of Fuzzy Logic Component with SD and ABM.

As shown in Figure 4.5, the fuzzy logic component is utilized for 1) SD in the steps of quantitative model variable definition, causal relationship definition, and stock and flow definition, and for 2) ABM in the steps of agent attribute and behavior definition, and agent interaction definition. Using processes in the fuzzy logic component, the SD and ABM approaches are transformed into FSD and FABM components. The interaction of the fuzzy logic component, with the SD and ABM is performed by applying either one of the two processes explained in the fuzzy logic component. The processes performed in the fuzzy logic component can be summarized in two parts, namely: obtaining fuzzy rules and membership functions, and the fuzzy inference system (FIS), as shown in Figure 4.6.

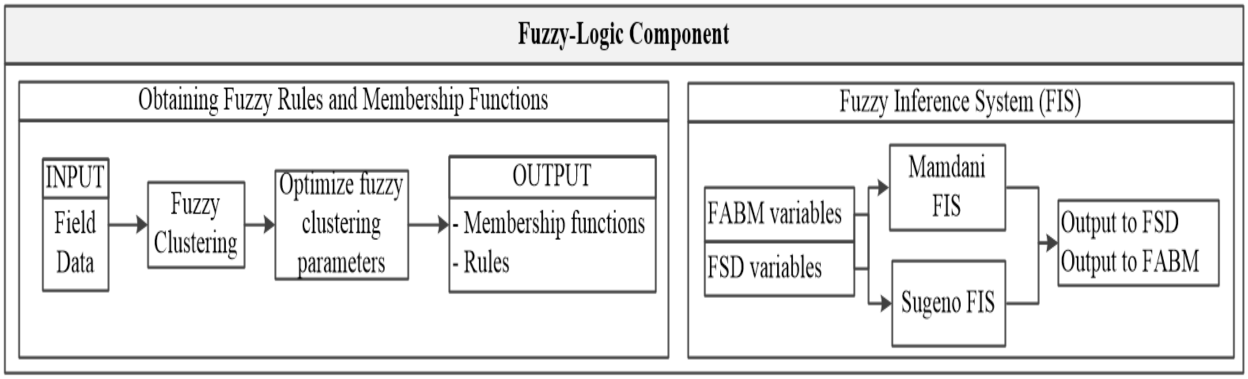

Figure 4.6 Fuzzy logic component.

Figure 4.6 shows the two main processes that take place in the fuzzy logic component. The first process deals with describing the subjective variables, such as crew knowledge, and crew experience using membership functions. The second process deals with formulating relationships between the subjective variables using FIS by using the variables in the FABM and FSD environment.

4.3.4.1 Obtaining Fuzzy Rules and Membership Functions

In the first part, fuzzy rules and membership functions are obtained using inputs from field data on situational/contextual factors, such as expert rankings of *safety procedures*, *safety facilitation and implementations*, the quality of *hazard identification and mitigation processes*. These fuzzy sets are defined by their membership functions, which map the degree of belongingness of an element to a set and how the element fits the concept expressed by the linguistic term (Fayek 2020). There are several types of membership functions, such as, triangular, trapezoidal, and gaussian. In this chapter, the Gaussian membership functions (MBFs) have been used to capture variables with uncertainties due to the impression, subjectivity, or linguistic expression of information (i.e., non-probabilistic uncertainties). This is because Gaussian MBFs are continuous and smooth, have non-zero values at all points, are suitable for optimization because they have only two parameters (i.e., the modal value and standard deviation), and are interpretable (Tsehayae and Fayek 2016; Pedrycz and Gomide 2007). The Gaussian membership function is defined in Equation (4.18) as shown below:

$$M(x, \sigma, \mu) = e^{-\left[\frac{(x-\mu)^2}{2\sigma^2}\right]} \qquad (4.18)$$

where x = the value of the variable in the universe of discourse; M=the membership function for a linguistic term, μ=the modal value, and σ = standard deviation.

The fuzzy rules can be developed using expert inputs, or data-driven approaches. Expert driven approaches include vertical, horizontal, pairwise comparison, inference, intuition, and exemplification methods (Raoufi and Fayek 2018). Data-driven methods such as clustering methods, utilize existing data to identify groups of data, and assigns a degree of belongingness (between 0 and 1) of each data to each of the groups within the dataset. In this chapter, fuzzy rules are formulated using fuzzy c-means clustering (FCM) technique as it is the most popular and established method for data analysis and construction of models (Nayak et al. 2015; Suganya and Shanthi 2012). For a given data of *N* instances, with n input variables and one output variable *y*, the dimensional vector *p* will have (N+1) dimensions. The k^{th} data instance x_{ki}, where *I* represents the i^{th} input variable for the k^{th} data instance, is denoted by Equation (4.19) as shown below:

$$p_k = \{x_{k1}, x_{k2}, x_{k3}, \dots, x_{kn}, y_{k1}\} \qquad (4.19)$$

The result of the FCM algorithm produces a partition matrix U, by minimizing an objective function. This partition matrix *U* is formulated as shown in Equation (4.20) and Equation (4.21) as shown:

$$U = [u_{st}], \quad s = 1, 2, 3 \dots c, \ and\ t = 1, 2, 3 \ \dots N \qquad (4.20)$$

$$U_{st} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|p_t - v_t\|}{\|p_t - v_j\|}\right)^{\frac{2}{m-1}}}, \quad s = 1,2,3 \dots c, \quad and \quad t = 1,2,3 \ \dots N \tag{4.21}$$

where p_t = data instance *t*; v_t= t^{th} prototype; and *m* = fuzzification coefficient.

Moreover, for each cluster center, the optimization algorithm for the FCM returns cluster centers (prototypes) *V*, as shown in Equation (4.22) and Equation (4.23).

$$V = [v_{ij}], \quad i = 1,2,3 \dots c, and \ j = 1,2,3 \ \dots N \tag{4.22}$$

$$v_{st} = \frac{\sum_{k=1}^{N} u_{ik}^{m} p_{kt}}{\sum_{k=1}^{N} u_{ik}^{m}} \ i = 1,2,3 \dots c, and \ j = 1,2,3 \ \dots N \tag{4.23}$$

The total number of prototypes *c* determine the number of rules. In this chapter, fuzzy rules are utilized in both the FSD component and FABM component.

The next step is optimization of the FCM parameters to minimize information loss in encoding and decoding of data, by ensuring that the optimal number of fuzzification coefficient and number of clusters have been selected. The number of clusters impact the detail of the granular representation of data, while m values influence the shape of the membership functions (Pedrycz and de Oliveira 2008). The following steps detail the decoding process, whereby minimization of the decoding error, is calculated.

For the U_{st} and v_{st} calculated in Equation (4.21) and Equation (4.23), per each iteration:

Carryout the degranulation procedure of the training data from the calculated partition matrix and prototypes of each number of cluster and "m" values, as shown in Equation (4.24).

$$\hat{x} = \frac{\sum_{i=1}^{c} u_i^m(x) v_i}{\sum_{i=1}^{c} u_i^m(x)} \tag{4.24}$$

Compute the average reconstruction error for each number of clusters and "m" values considered and compute the optimum "m" value for which the reconstruction error is at its lowest, written as Equation (4.25).

$$V = \frac{1}{N}\sum_{i=0}^{n}\left\|x_k - v_j\right\|^2 \qquad (4.25)$$

where V = reconstruction error.

The FCM algorithm in Equation (4.21) and Equation (4.23), along with the steps in Equation (4.24) and Equation (4.25) are performed iteratively for training and testing dataset, until the performance evaluation criterion of the minimum reconstruction error is met (Pedrycz and de Oliveira 2008).

4.3.4.2 Fuzzy Inference System

The prediction process of FIS involves the following steps (Tehayae and Fayek 2016): fuzzifying input variables, input aggregation, fuzzy input-output implication, rule aggregation and output decoding. In the second part of the fuzzy logic component, Mamdani FIS and adaptive neuro-fuzzy inference system (ANFIS) are applied to capture the soft relationships in model, to process computations within the predictive blocks.

As shown in Figure 4.6, the variables in the FSD and FABM components are used to implement FIS in the fuzzy logic component. By using the variables in the FSD and FABM environment, inference systems are applied to form relationships between these variables. For example, when the soft relationships in the FSD components are formed using FIS, the input to the FIS are the dynamic variables in the FSD component. These inputs are processed in the FIS, to give an output used in the FSD component.

4.3.5 FSD-FABM Component

The FSD-FABM component combines FSD and FABM using the three applicable hybrid SD-ABM design classes: interfaced class, sequential class, and integrated class (Swinerd and McNaught 2012). In this chapter, both the SD and ABM are integrated with the fuzzy component to produce FSD and FABM respectively. Hence, the proposed hybridization approach in this chapter is discussed in terms hybridizing FSD and FABM components by extending the existing principles of integrating SD and ABM approaches in (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. Figure 4.7 shows the method for selecting the hybrid simulation method (Nasirzadeh et al. 2018). 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. However, if there is a bidirectional exchange of information between SD and ABM, the integrated class of stocked agents or agents with internal structure is selected, based on the hierarchy level of the SD and ABM.

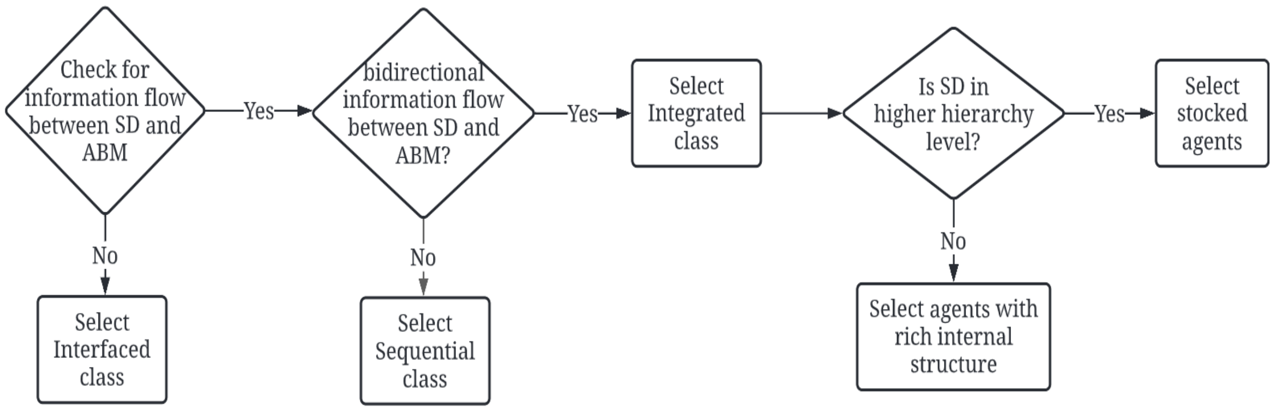

Figure 4. 7 Selection procedure for selecting the hybrid FSD-FABM type.

In this chapter, crew motivation is the output of the FABM component which will be used in the FSD component. Hence, the *connect to SD* behavior of the crew agent is activated at every time-step to send the values of daily crew motivation by performing the *update crew motivation* process. Moreover, the daily average situational/contextual variables will be computed in the FSD component and be sent to the Workpackage agent. In the FSD-FABM, the inputs from FSD to FABM are the daily average values of situational/contextual variables, while the inputs from FABM to FSD are daily values of crew motivation. Moreover, the FABM is at the lower hierarchy-level, and FSD is at a higher hierarchy-level.

Figure 4.8 illustrates the processes taking place in the proposed FSD-FABM approach, and the different types of models that are proposed as part of the FSD-FABM. The expected outcomes of the FSD-FABM are the simulation of the construction system, whereby the causal relationships between the identified situational/contextual factors and crew motivation are captured in the model to produce the daily average values of situational/contextual variables, crew motivation, and the CLP of crews that are performing tasks in the work packages of the construction project.

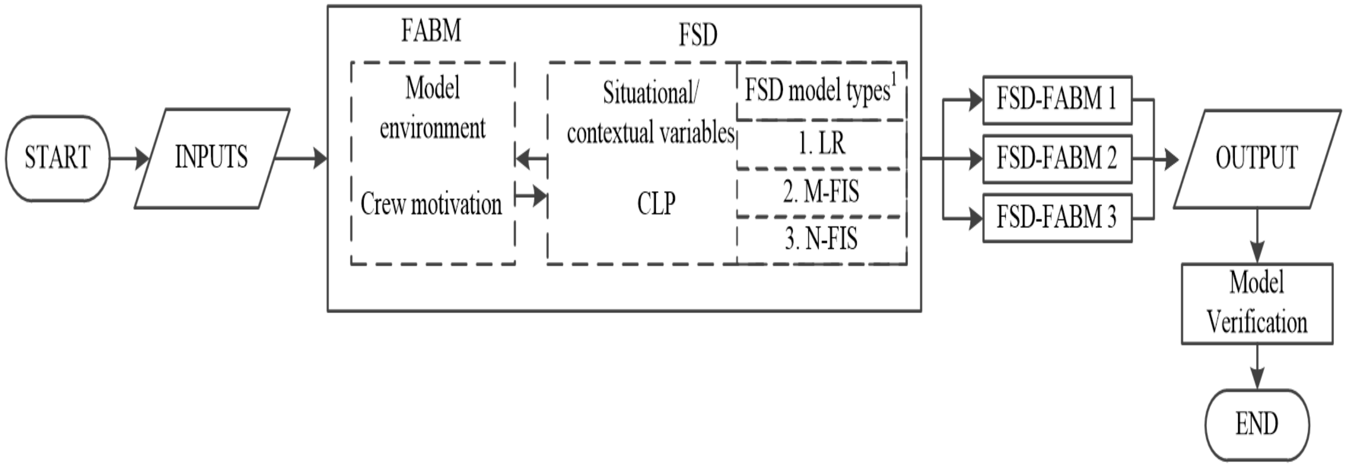

Figure 4.8 Simplified Illustration of the FSD-FABM process.

[1]The FSD model types are based on the techniques used to capture soft relationships in the FSD model, which correspond to the type of resulting FSD-FABM

4.4 Chapter Summary

Construction activities are performed in a dynamic environment, whereby different factors such as crew motivation, and situational/contextual factors are interacting during the project duration. Therefore, modeling of these construction activities to predict a pre-determined performance measure such as productivity entails that these factors (i.e., system variables) are captured using appropriate modeling techniques.

The FSD-FABM proposed in this chapter predicts the CLP of multiple work packages that make up a construction project. The proposed model is also able to predict the motivation of the crews working on the different work packages on the project, and the impact of crews' motivation states on their productivity. Moreover, the proposed model simulates the dynamic interrelationships between situational/contextual variables to assess the impact of situational/contextual average on daily productivity of crews.

In this chapter, the overall methodology for performing the hybrid FSD-FABM has been detailed. The steps which need to be performed to 1) perform the FSD modeling, 2) FABM, and 3) hybridization of the two modeling approaches have been discussed at length. The next chapter demonstrates the proposed FSD-FABM methodology using a case study.

Chapter 5 Construction Application and Model Verification: Case Study[5]

5.1 Introduction

In order to demonstrate the methodology, a case study based on a real industrial construction project in Alberta, Canada is proposed. The case study utilizes the data collected for the study of crew motivation and performance (Raoufi and Fayek 2018). The data collection protocol (Raoufi 2018) details the procedure followed to collect the necessary data on crew motivation, situational/contextual factors and crew performance measurements. Participants in the field data collection consisted of crew members, foremen, and the management staff. For data collection related to crew motivational factors, the data collector collected data on randomly selected crews, where crew members perform self-evaluation on their individual-level motivational factors and crew-level motivational factors were obtained from the supervisor evaluation. A similar approach was followed for the data collection on situational/contextual factors (Raoufi 2018). For the crew performance metrics, project documents such as score cards, time sheets, schedule updates, and cost estimates were used. In this regard, data collected on crew productivity, and motivational and situational/contextual factors of seven crews were utilized in this case study. The seven crews included six excavation/backfilling (EB) crews and one sandblasting/coating (SC). The model proposed in this chapter examines the dynamic relationship between crew motivation, and situational/contextual factors, in affecting in affecting CLP of the project. The dynamic

[5] Parts of this chapter has been submitted for publication in *Automation in Construction*: Kedir, N. S., and Fayek, A. R. (2022)." Integrated Fuzzy System Dynamics–Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction." *Automation in Construction*, 61 manuscript pages, submitted Oct. 2022.

relationship between crew motivation and situational/contextual variables are modeled to give the output CLP of the crews involved in execution of the work packages. In this model, the crew-level situation in which crews are performing their tasks is modeled in the Workpackage agent, and the project-level situation is an aggregation of the situational factors of all the crews working on the project, in addition to project-level situational factors. The steps of the methodology are discussed accordingly in the subsequent sections.

5.2 Factor Identification and System Variable Selection:

The process of identifying system variables and aggregating those system variables into different hierarchies is elaborated in the methodology section. For the purpose of demonstrating the case study, this chapter utilizes the data collected on factors affecting crew motivation and performance (Raoufi and Fayek 2018), whereby interview surveys were implemented to identify critical factors influencing construction crew motivation and performance. For factors affecting crew motivation, the four main motivational factors that were adapted from the literature outside of the construction domain, were identified (Raoufi and Fayek 2018). These factors include efficacy (Hannah et al. 2016), commitment/engagement (Cesário and Chambel 2017), identification (Lin et al. 2017), and cohesion (Chiniara and Bentein 2018). In the construction context, these four measures are defined are as follows (Raoufi and Fayek 2018): *efficacy* = judgement of an ability to perform a specific task; *commitment and engagement* = emotional attachment to, and involvement in the organization; *identification* = the emotional attachment that members hold to their membership in a group; *cohesion* = the extent to which members want to "stick together" in the group. Individual and crew level measures of factors affecting crew motivation were collected using interviews of project personnel, which included crew members, field supervisors, foremen, and project managers. For the situational/contextual factors, and crew productivity measures, the previously stated methods were extended to include data on actual documents such as such as time sheets, score cards, safety logs, change order logs, inspection test plans, and cost estimates. From the total of 129 situational/contextual factors identified at the crew and project level (Raoufi and Fayek 2018) that affect crew performance, a statistical analysis was performed to identify the most critical factors. In this regard, Pearson correlation analysis was performed to identify factors that had a relationship with crew productivity. Pearson's correlation coefficient value of greater than 0.5 are chosen (Raoufi and Fayek 2018), to select the factors with strong relationship with crew productivity. In effect, 38 situational/contextual factors were identified as system variables, in addition to the crew motivation variable (Appendix D). A sample of the situational/contextual factors is shown in Table 5.1.

Table 5.1 Sample of the situational/contextual factors selected in the FSD-FABM.

System variable	Description and Scale of Measure	Type
Visibility of outcome	Rating - To what extent does performing the tasks provide crew members with visibility of the outcomes of the work.	Subjective
Rework	The measure of the total reworked volume in relation to the total volume of work.	Objective
Crew composition	The ratio of journeyman to apprentice	Objective
Crew experience	Number (average years of experience in current position)	Objective
Ability to perform	Rating - Ability of the crew to perform tasks	Subjective
Material handling	Rating - Ability of the crew to move, protect, and/or store materials throughout the construction process.	Subjective

5.3 FSD Component

The FSD component is discussed simultaneously with the fuzzy logic component for clarity. In the FSD component, the two major steps (i.e., qualitative and quantitative modeling) involve interactions with the fuzzy logic component, as shown in the previous step in Figure 4.5.

5.3.1 Qualitative Modeling - Model boundary and level of aggregation

Identifying the model boundary entails dividing the system variables into endogenous and exogenous variables, as described in the methodology section. It is important to have fewer exogenous variables in the model (Sterman 2000). A list of endogenous and exogenous variables is shown in Appendix D. The identified exogenous variables of the model include weather conditions, with sub-categories of temperature, humidity, precipitation, wind speed, and change in weather conditions.

After defining the model boundary, the variables are used to model the system based on the defined level of aggregation. In this chapter, there are seven crews each performing tasks according to the work packages they are assigned to. The crews have been numbered in such a way that corresponds to the work packages which range from one to seven. For example, crew-1 is assigned to work package 1.

5.3.2 Qualitative Modeling - Identify Subjective and Objective Variables

In this step, the system variables that were considered for use in the FSD modeling were further classified into subjective and objective variables, as described in the methodology. For the subjective variables, membership functions are developed to represent their numeric scales. Some of these variables include level of communication, crew motivation, task identity, noise, visibility of outcome, and reliability of crews to perform their tasks. The objective system variables are represented by numeric scales. Some of the objective system variables include foreman experience (number of years), crew composition (ratio of journeypersons to apprentice), rework (ratio of total reworked volume to total work volume), foreman experience (number of years).

5.3.3 Qualitative Modeling - Identify feedbacks, causal loops, stocks and flows

In order to identify feedback relationships between system variables, and formulate causal loop diagrams, expert knowledge is utilized by using surveys to identify causal relationships using the weighted FDEMATEL method as described in the methodology section. Using the weighted FDEMATEL method, causal loop diagrams which capture the causal relationships between situational/contextual factors, crew motivation and crew productivity, are established for dynamic modeling of productivity, as described in the methodology section.

5.3.4 Quantitative Modeling - Define model variables

In this step, the identified variables in the qualitative stage are defined quantitatively. As described in the methodology, the objective variables of the model have readily quantifiable scales, while the subjective variables are defined by fuzzy sets, using membership functions. In this chapter, the gaussian membership functions expressed in Chapter 4, Equation (4.18) are used to define the shape of membership functions, as detailed in the methodology section.

5.3.5 Quantitative Modeling - Define causal relationships, stocks, and flows

The causal relationships and feedback loops which were identified in the qualitative modeling stage are defined quantitatively in this stage. For the hard relationships which can be captured using mathematical equations, the mathematical equations are proposed. For the soft relationships with no predefined mathematical equations: 1) a statistical approach to determine the mathematical equations describing the relationships, and 2) a data-driven FRBS using the FCM clustering approach are investigated to formulate the soft relationships. The error measure of each of the two approaches was used as a selection criterion, where the approach with the lower RMSE was selected. This was approach was performed for the seven work packages, as the measurements of situational/contextual variables vary in the work packages, and there is no standard approach to capture these relationships. Accordingly, the soft relationships in the FSD component of the model for work package 1 are shown in Table 5.2.

Table 5.2 Formulation of soft relationships between system variables.

Output Variable	System variables used as input
Ability to perform	crew knowledge, crew experience, foreman knowledge, foreman experience, teamwork
Absenteeism	crew motivation, fatigue
Crew knowledge	visibility of outcome, crew composition, crew size
Foreman knowledge	visibility of outcome
Goal setting	task repetition, reliability
Hazard identification and mitigation	safety facilitation and implementation, fatigue, foreman experience
Performance monitoring	project cost management, project time management
Project cost management	project scheduling
Work progress	ability to perform, crew motivation, hazard identification and mitigation, congestion, rework, performance monitoring, change in weather conditions, absenteeism
Project scheduling	work progress

Output Variable	System variables used as input
Project time management	project scheduling
Reliability	work progress
Safety facilitation and implementation	safety trainings, safety procedures
Task identity	visibility of outcome
Visibility of outcome	goal setting, communication

Table 5.2 shows the soft relationships for each work package. The fuzzy component in the FSD model optimizes the fuzzy clustering parameters, namely the fuzzification coefficient (m) and number of clusters (c) for use in formulating the Mamdani FIS and the N-FIS. Using the steps discussed in the methodology to compute the reconstruction errors for each predictive block, the FCM parameters have been optimized. The reconstruction error was performed by writing a Python code to execute the steps discussed in the methodology. The optimal number of clusters for the work progress predictive block has been demonstrated in Figure 5.1, whereby the python code was implemented to compute the optimal parameters for m ($m = 2$) and number of clusters ($c = 7$).

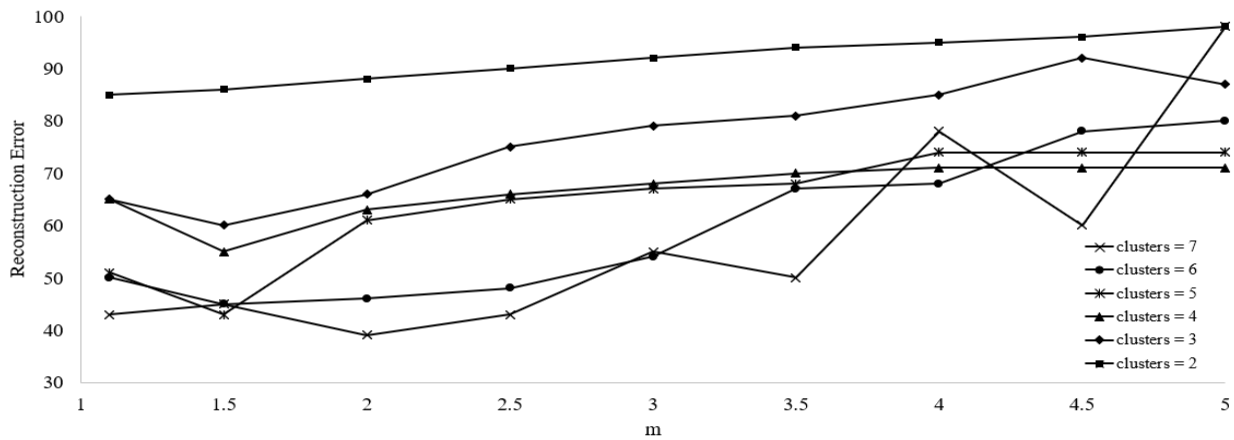

Figure 5.1 Optimization of FCM parameters using minimum reconstruction error.

The hard relationships between the system variables making-up the CLD, and the stock and flow diagrams are shown in Chapter 4 of Equation (4.7) to Equation (4.16).

5.4 FABM Component

The FABM component constitutes of four major steps, namely: 1) defining the FABM environment and processes, 2) defining agent attributes and behaviors, 3) define interactions between agents, and 4) define agent behavioral rules. Each of these steps are elaborated in more detail as follows.

5.4.1 Define the FABM environment and Processes

The simulation main environment for the FABM incorporates the project agent class, the crew agent class, and the Workpackage agent class. There is only one project considered in the case study, which constitutes of several work packages performed by seven crews (6 EB crews and 1 SC crew). Moreover, the FABM main environment is defined to incorporate all the processes carried out by agent classes, in addition to the simulation methods that are used to define agent interactions, collect statistics, and connect with MATLAB to execute the fuzzy inference system.

5.4.2 Define Agent Attributes and Behaviors

The agents, whose attributes are defined are the project agent, the crew agent and the Workpackage agent. To define the behaviors of agents, the fuzzy logic component is integrated with the ABM to use membership functions and apply fuzzy rules, as described in the methodology.

5.4.3 Project Agent Class

The project agent class is created to capture the all the active projects to be considered in the FSD-FABM methodology. The attributes of the project agent are the Project ID, and current project-level situation. Because there is only 1 project in the study, the project ID shows no variation in the modeling. However, the methodology is capable to model multiple projects. The process taking place in the project agent class is updating daily project situation. The daily project level situation attribute is calculated as the mean of the normalized situational/contextual variables of existing in each work package of the Workpackage environment. The developed project class is shown in Figure 5.2.

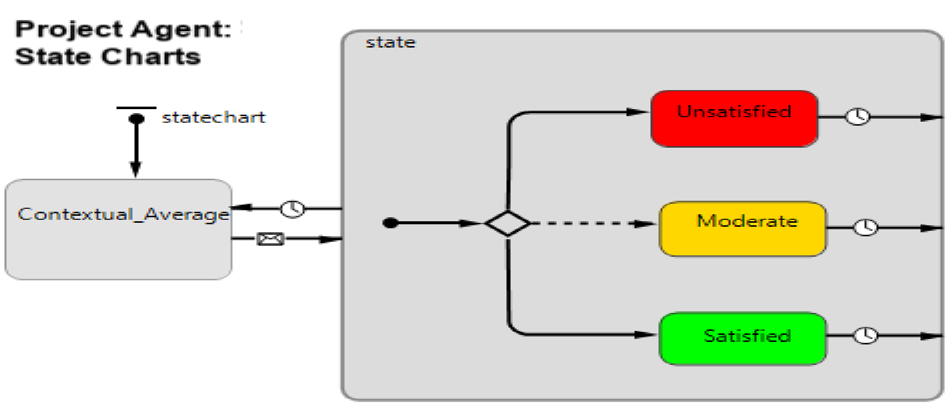

Figure 5.2 Project agent class.

In the project agent class, the daily contextual average is *sent* from the Workpackage agent for each of the work packages. These values are sent from the *contextual average* state chart to the *state* state chart so that the daily contextual average will be identified as unsatisfied, moderate, and satisfied. The timers in each state chart are set to facilitate calculations of the project contextual average at a time-step of one day.

5.4.4 Crew Agent Class

The crew agent class is created to simulate the construction crews that are active in the construction project. The attributes of the crew agent are crewID, initial crew motivation, current crew motivation, and current crew-level situation. The behaviors of the crew agent class are described using processes executed the agent class, namely: update crew motivation, and update crew-level situation. The developed crew agent class is shown in Figure 5.3. The seven construction crews (6EB, 1SC) are designated by their crewID's. The rules for the state charts, state transitions, and agent behaviors were adapted from Raoufi (2018). In the crew motivation state chart, the calculation of crew motivation for each of the agents is initiated in the *interaction* state chart. The *state* state-chart is the where the calculated daily motivation of the crews gets sent to any of the inner-state charts of *high*, *medium*, or *low* motivation.

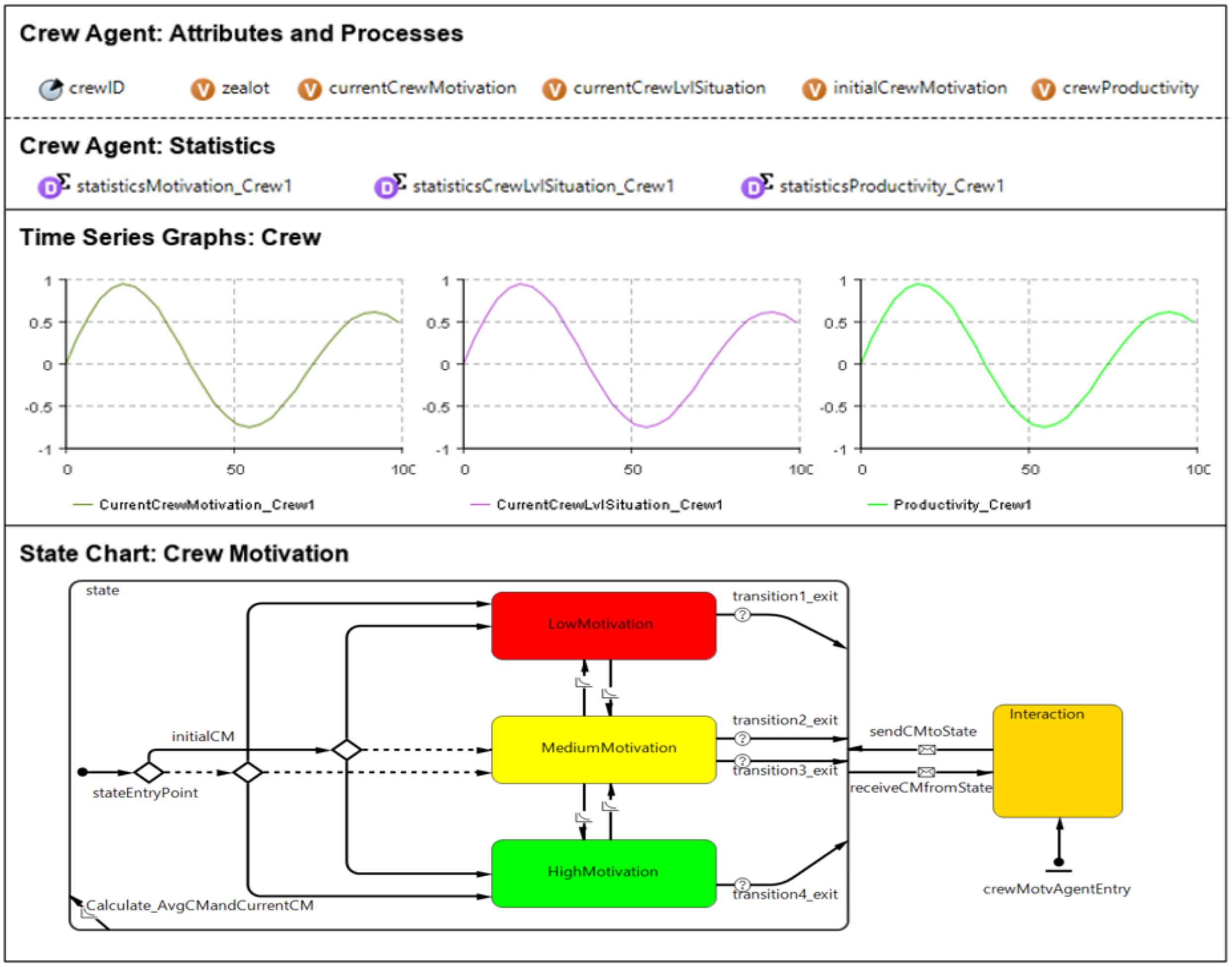

Figure 5.3 Crew agent class.

As shown in Figure 5.3, there are three components in the crew-agent class. The first component defines the crew agent attributes and process, which were described in the methodology section. The variables are used to store the corresponding values at each simulation time-step. The statistics store the data that is the output of every simulation time so that time-series graphs of each crew can be plotted. The crew motivation state chart performs calculations for the motivation of the crews at each simulation timestep in the *state* state chart. The crew motivation, and average motivation of other crews is computed in the 'calculate_AvgCMandCurrentCM' rate, which executes Equation (4.17) in Chapter 4, at each time step. The icons in between the state charts signify the rate of change of motivation from each motivation state, which varies for each of the crews in the project. Therefore, crew motivation gets calculated at each timestep, in the form of current crew motivation for each crew according to their motivation state of low, medium or high motivation. For each of the crews, crew motivation is computed from the data collected on the crew motivational factors, as the mean of the normalized measures of the motivational factors (Raoufi and Fayek 2018). Moreover, the crew-level situational/contextual variables for each crew are computed as the average of the situational/contextual factors that are existing in the work package environments each crew is working at. For this project, each crew is working in a separate work package. Therefore, the situational/contextual variables that make-up the environment of each work package (e.g., Workpackage=1) corresponds to the measure of the crew-level situation a crew (e.g., crewID=1).

5.4.5 Workpackgage Agent Class

The Workpackage agent class is created to capture situational/contextual factors that are continuously interacting in the construction environment. The population of the Workpackage agent is 7, indicating the seven work packages being undertaken in the project. For each of the work packages, the crew-level measurements of the situational/contextual factors are different. For example, variables such as crew size, absenteeism, crew experience will depend on the specific crew allocated for each of the work packages. Moreover, variables such as congestion, task repetition, task identity, level of rework will also interact to form the context for the construction environment of each work package. This dynamic process is captured by the FSD component of the model, which represents the dynamic interrelationships between the situational/contextual variables. The Workpackage agent class is shown in Figure 5.4.

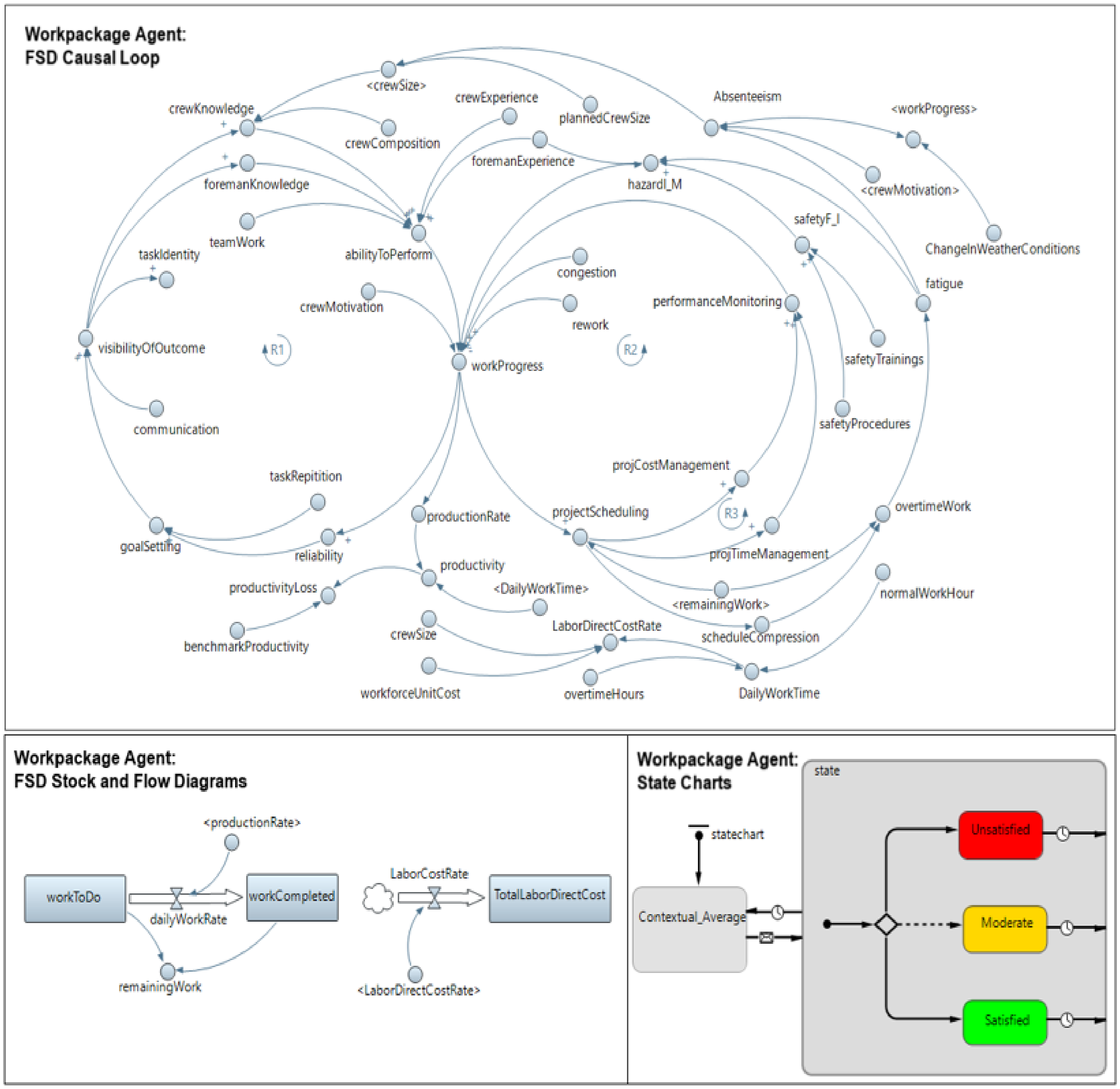

Figure 5.4 Workpackage agent class.

As shown in Figure 5.4, there are three main components in the workpackage agent class, namely: FSD causal loop, FSD stock and flow diagrams, and state charts. The FSD causal loop and the FSD stock and flow diagrams were constructed as the result of the quantitative stage of FSD modeling. The FSD model components were elaborated in the methodology section. The work package agent state charts are used to compute the daily situational/contextual average for each of the work packages in the project. In this regard, the *contextual average* state chart calculates the daily situational/contextual average of each of the work package, and sends it to the *state* state chart, where the status of the daily situational/contextual average gets transferred to unsatisfied, moderate or satisfied project level situation.

5.4.6 Define Agent Interactions

In this chapter, crew motivation is modeled as a dynamic variable resulting from interactions between individual agents (i.e., crews). The motivation level (CM) of a crew agent i, is computed as resulting from interactions between other crew agents in the environment, as shown in the Equation (4.17) of the methodology section of Chapter 4.

5.5 FSD-FABM Component

The FSD-FABM component performs the hybridization of FSD and FABM components. The steps performed in the FSD-FABM component are described as follows.

5.5.1 Define Information Flow Path

In this case study, there are two instances of exchange of information between FSD and FABM components. The first information flow path is the crew motivation information where the crew motivation values for each crew calculated in the FABM component are sent to the FSD component, to be used as system variable to predict crew productivity. The second information flow path is the crew level situation information, whereby daily averages of situational/contextual variables are computed in the FABM component, using the input of daily measures of situational/contextual variables form FSD component. The FABM component uses the information on daily averages to determine work package agent behavioral rules using state charts. The information flow occurs at every time step, with the use of functions to facilitate the onedirectional exchange of information from FABM to FSD, and vice versa. Modeling for such type of exchange of information is demonstrated using Figure 5.5 shown below.

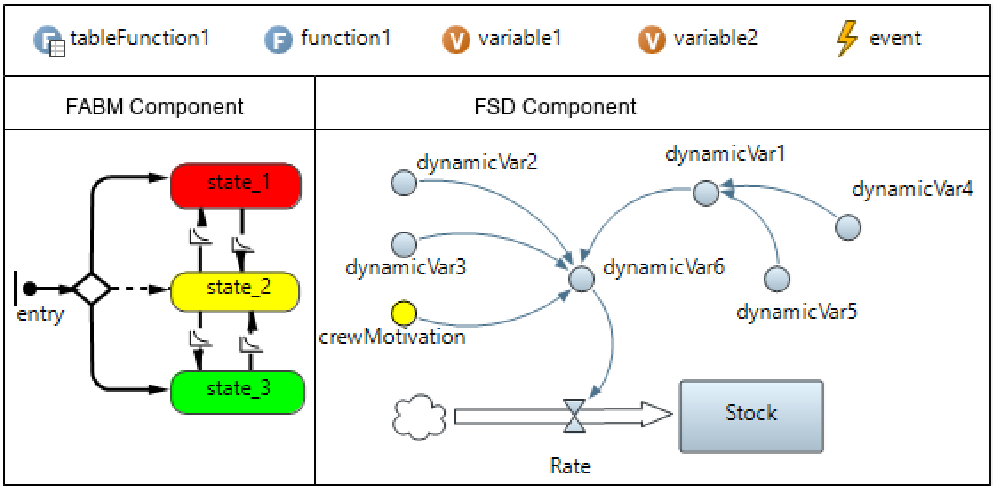

Figure 5.5 Information exchange between FSD and FABM components.

As shown in Figure 5.5, the information exchange between FABM and FSD components is facilitated using inputs and processes. Inputs to the dynamic variables are located in elements such as table functions, where the dynamic inputs throughout the simulation time are given. The relationships between the dynamic variables can be processed using functions. For example, the calculation for dynamicVar6 is performed using function1. The event is used to schedule action in the model, to let the model know at what time a specific action is performed, such as sending output values from the FABM state charts to the FSD component. Processes that are performed in the states are stored in variables such as Variable1 and Variable2, where necessary calculations are performed by locating the values in the required variables.

5.5.2 Select Hybrid Simulation, Interface Variables, and Define Rules for Model Output Exchange

The selection procedure in Figure 4.7 of Chapter 4, is utilized to select the hybrid simulation type. Because there is no bidirectional exchange of information, the sequential class is selected. The interface variables selected depend on what information to send to each of the hybrid model components. In the first information flow path (i.e., from FABM to FSD), *crew motivation* is sent to the FSD component at every time step. Therefore, crew motivation is selected as the interface variable. In the second information flow path (i.e., from FSD to FABM), the situational/contextual variables at every time step are used to compute the daily situational/contextual average, which will be used in the state charts of the FABM. Therefore, the daily situational/contextual average variable is the interface variable. Moreover, the level of hierarchy is established as described in Figure 4.2 of Chapter 4, where FABM component is at a lower hierarchy level than the FSD component. Consequently, the rules for model output exchange signify which dynamic variable, or process, in the FSD component has access to the FABM, and vice versa. In this chapter, the information exchange occurs daily (i.e., at every time step); the *crew motivation* dynamic variable created in the FSD component has access to the FABM output of crew motivation; and the FABM process of *crew level situation* has access to the FSD output of daily situational/contextual average.

5.6 Results and Discussion

In this chapter, a novel hybrid FSD-FABM is introduced. First, the initial input parameters of the model are first set by the user. The data collected on crew motivation (Raoufi and Fayek 2018) was utilized to formulate the initial parameters for the FABM component. These parameters are [number of crews, contact rate, zealot percentage, susceptibility, non-interactive motivation variability, initial motivation states of crews]. Accordingly, these inputs have been set to [7, 1, 0.2857, 0.09419, 0.01098, {0.2857 for low, 0.4286 for high}]. Furthermore, the initial dataset for FSD includes those exogenous variables that were considered in the model. Because these parameters are dynamic parameters whose values change over time, their values have been entered in a table format. The tables are prepared to include daily values of these input parameters, to be used by the FSD component during the simulation time. Some of these variables include crew experience, foreman experience, planned crew size, and safety trainings.

After the inputs are identified, the data is normalized by maximum, as shown in Equation (5.1).

$$Y_{i,norm} = \frac{Y_i}{\max(Y)} \quad (5.1)$$

where, $Y_{i,norm}$= the normalized value of system variable Y, and Y_{max} = maximum value of the system variable Y.

In addition to forming part of data pre-processing, normalization of data is also performed as part of data confidentiality requirements. After input parameters are entered, the next step is running the simulation and obtaining results on different system variables.

The first set of results that is presented hereafter is to compare the predictive capabilities of the three FSD-FABM models that implemented LR, M-FIS, and ANFIS to capture the soft relationships in the FSD part of their model. Table 5.3 shows the CLP results of crew-1, that performed activities in work package-1 during the 30 days of construction period. Error measures used to compare prediction accuracy are RMSE and MAPE, which were computed based on Equation (5.2), and Equation (5.3).

$$RMSE = \sqrt{\frac{\sum(Actual - Predicted)^2}{n}} \text{ x } 100 \quad (5.2)$$

$$MAPE = \frac{\sum_{i=1}^{n} Abs\left(\frac{Actual-Predicted}{Actual}\right)}{n} \text{ x } 100 \tag{5.3}$$

where n = number of instances, *Actual* = actual field data, and *Predicted* = output of the simulation.

Table 5.3 Actual versus predicted results for CLP of Work package 1.

Time (day)	**Actual**	**Predicted**			**Abs (error)**		
		Linear regression	**Mamdani FIS**	**N-FIS**	**Linear regression**	**Mamdani FIS**	**N-FIS**
1	0.379	0.326	0.528	0.314	0.053	0.149	0.065
2	0.284	0.086	0.114	0.182	0.198	0.170	0.102
3	0.238	0.072	0.126	0.164	0.166	0.112	0.074
4	0.275	0.063	0.126	0.232	0.212	0.149	0.043
5	0.275	0.061	0.126	0.257	0.214	0.149	0.018
6	0.528	0.186	0.582	0.497	0.342	0.054	0.031
7	1.000	0.601	0.752	0.851	0.399	0.248	0.149
8	0.261	0.184	0.467	0.181	0.077	0.206	0.080
9	0.238	0.079	0.116	0.142	0.159	0.122	0.096
10	0.275	0.193	0.126	0.269	0.082	0.149	0.006
11	0.275	0.081	0.126	0.254	0.194	0.149	0.021
12	0.528	0.348	0.681	0.601	0.180	0.153	0.073
13	0.573	0.168	0.702	0.621	0.405	0.129	0.048
14	0.550	0.382	0.601	0.576	0.168	0.051	0.026
15	0.311	0.199	0.261	0.248	0.112	0.050	0.063
16	0.358	0.315	0.514	0.271	0.043	0.156	0.087

Time (day)	Actual	Predicted			Abs (error)		
		Linear regression	Mamdani FIS	N-FIS	Linear regression	Mamdani FIS	N-FIS
17	0.812	0.340	0.981	0.898	0.472	0.169	0.086
18	0.247	0.233	0.612	0.516	0.014	0.365	0.269
19	0.245	0.035	0.114	0.164	0.210	0.131	0.081
20	0.244	0.252	0.112	0.168	0.008	0.132	0.076
21	0.266	0.276	0.344	0.301	0.010	0.078	0.035
22	0.523	0.579	0.825	0.611	0.056	0.302	0.088
23	0.465	0.510	0.498	0.487	0.045	0.033	0.022
24	0.465	0.499	0.514	0.491	0.034	0.049	0.026
25	0.499	0.686	0.814	0.576	0.187	0.315	0.077
26	0.349	0.472	0.112	0.307	0.123	0.237	0.042
27	0.797	1.000	0.917	0.905	0.203	0.120	0.108
28	0.373	0.475	0.521	0.314	0.102	0.148	0.059
29	0.251	0.326	0.311	0.245	0.075	0.060	0.006
30	0.211	0.255	0.242	0.231	0.044	0.031	0.020
		RMSE			19.4%	16.7%	8.3%
		MAPE			38.44%	41.79%	19.07%

Consequently, the results of the three predictive models were plotted against the actual data, as shown in Figure 5.6.

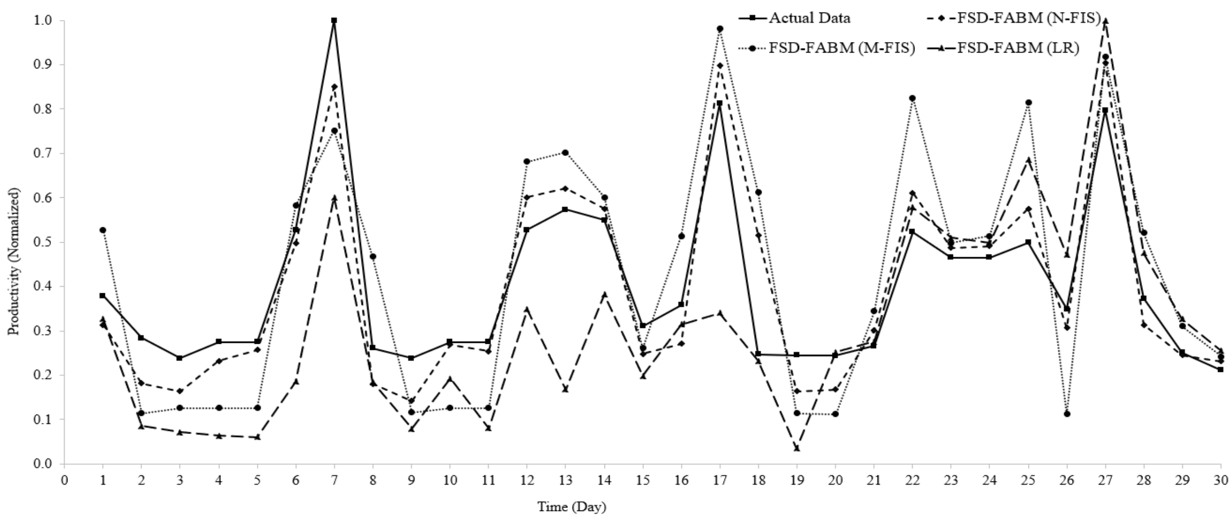

Figure 5.6 Actual versus predicted values of CLP of Crew-1.

In terms of prediction errors, the FSD-FABM that uses N-FIS to capture the soft relationships outperformed with a RMSE of 8.3%. The Mamdani FIS and the linear regression methods had RMSE of 16.7% and 19.4% respectively. However, the RMSE does not usually reflect the model's predictive performance relative to actual data. MAPE is a measure of the predicted values vs the actual values, and expresses errors as a percentage of actual data, which makes it ideal to judge the differences in capabilities of predictive models (Raoufi and Fayek 2018). In this regard, the MAPE showed that the three methods registered higher error measures, with the M-FIS and LR methods having the error measure of 41.79% and 38.44%, respectively. The N-FIS method had the minimum error and produced better results with a MAPE of 19.07%. Moreover, the FSD-FABM that uses N-FIS predicted the behavior of the system better than the other methods, by predicting the trends of increase and decrease of the predicted CLP value. Trends (an increase or decrease in the value between any two consecutive points), and extreme conditions test (the minimum, or maximum value of actual value vs predicted value) can be used to determine a model's capacity to predict the behavior of construction systems (Gerami Seresht and Fayek 2020).

In this regard, the FSD-FABM that uses N-FIS predicted 27 out of 30 of the trends in actual values (90%), while the M-FIS and LR methods predicted 80% and 66.67% respectively. In terms of extreme conditions test, the global and local minimum and maximum values of actual CLP data were compared with the corresponding predicted values. The results show that the FSD-FABM that uses N-FIS predicted correctly, the local minima and local maxima values, including the global minimum and global maximum values in all instances. The days in which the values were compared are days 3,7, 13, 15, 17, 22, 25, 26, 27, and 30. On the other hand, the Mamdani FIS did not accurately predict the local minimum for day 3; while the linear regression approach did not predict the local extreme values for day 3, 13, and 17 respectively. Hence, the FSD-FABM that uses N-FIS was shown to be more accurate for predicting the CLP of the crews' performing activities in the work packages.

The next result that is presented is the average values of the daily situational/contextual factors of the construction environment. The average of the situational/contextual variables was calculated by giving equal weight to each situational/contextual variable under consideration, to avoid bias. The result of daily situational/contextual average gives important information about the construction environment in the range of 0–1, where 0 = undesired value and 1= desired value. Because the situational/contextual variables are dynamic in nature, whose values change over time, a comparative investigation of the effect of situational/contextual factors on CLP was performed to compare the trends (i.e., increasing or decreasing) by using the three-day moving average of the daily normalized values, as shown in Figure 5.7 and Figure 5.8. Using the moving average calculation, a general trend can be observed in terms of studying the effect of situational/contextual values on CLP. For comparison purposes, the motivation of crew-1 is also presented in Figure 5.9.

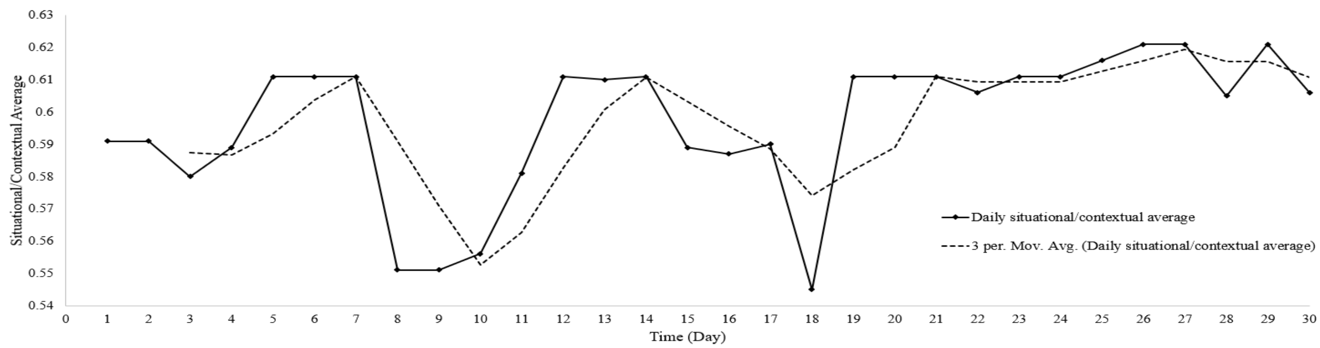

Figure 5.7 Daily situational/contextual values with 3-day moving average for work package 1.

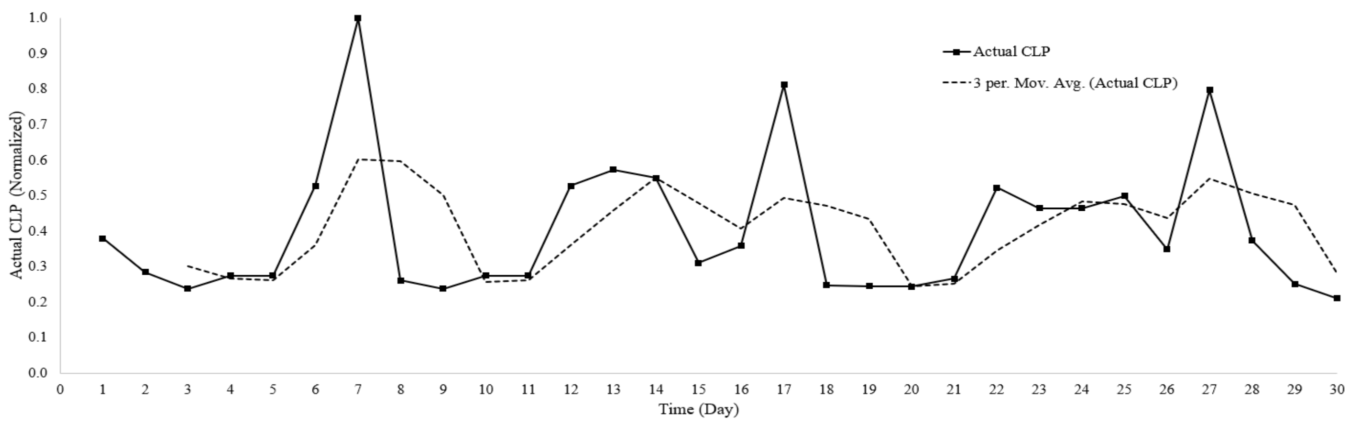

Figure 5.8 Daily actual CLP values with 3-day moving average for work package 1.

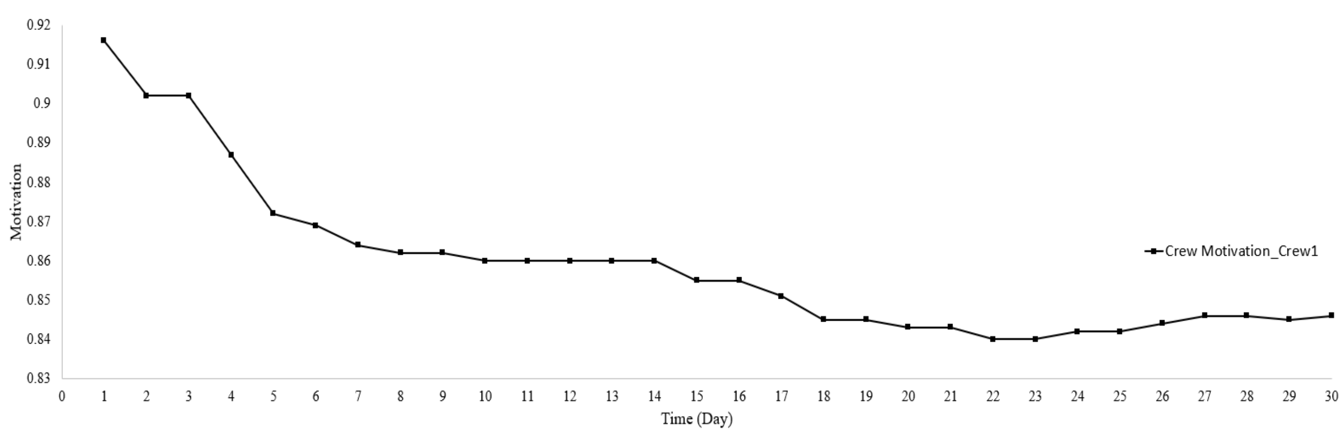

Figure 5.9 Crew motivation values for crew-1.

As can be seen from Figure 5.7 and Figure 5.8, the moving average of situational/contextual and CLP values show a similar increasing/decreasing trends. This shows that on the days when situational/contextual average registered higher values with increasing trend relative to previous days, the CLP was also showing a similar trend. For example, the normalized situational/contextual average registered the second highest measurement on day 4 - day 7. The corresponding CLP values showed an increasing trend between day 4 - day 7 with the maximum CLP value at day 7. The converse was also true on the days of day 7 - day 10, where the situational/contextual average was on a steeply decreasing trend. A similar decreasing trend in the CLP also occurred between day 7 - day 10. Such trend was consistent throughout the project duration. However, another observation can be made, where the situational/contextual average consistently increased and registered peak values, while the CLP values had low values. This occurred especially after day 19. This can be attributed to the consistently decreasing value of the crew's motivation. Even though the crew's motivation at the start of the project was high, the interaction between other crews that have low motivation, and the random rate in which crews change their motivation attributed to the lower motivation values of the crew after project start time. As can be seen in Figure 5.9, the minimum value of the crew-1's motivation was 0.84 during the 30-day period. This value was repeatedly observed after day 18, which could contribute to the decreasing CLP in those days where higher CLP was to be expected because of higher situational/contextual values.

The results for the two other work packages, which have differing type of work compared to work package 1, (i.e., backfilling and sandblasting) have been presented in Table 5.4.

Table 5.4 Results for work package 2 (Backfilling), and work package 6 (Sandblasting).

Time (day)	Workpackage 2			Workpackage 6		
	Actual	Predicted	Error	Actual	Predicted	Error
1	0.114	0.118	0.004	0.952	0.821	0.131
2	0.367	0.443	0.076	0.393	0.311	0.082
3	0.041	0.013	0.028	0.795	0.662	0.133
4	0.038	0.017	0.021	0.905	0.796	0.109
5	0.080	0.101	0.021	0.950	0.889	0.061
6	0.110	0.126	0.016	1.000	0.924	0.076
7	0.024	0.047	0.023	1.000	0.891	0.109
8	0.017	0.031	0.014	0.547	0.516	0.031
9	0.074	0.117	0.043	0.500	0.486	0.014
10	0.061	0.041	0.020	0.308	0.201	0.107
11	0.040	0.042	0.002	0.308	0.208	0.100
12	0.094	0.065	0.029	0.380	0.471	0.091
13	0.094	0.065	0.029	0.380	0.321	0.059
14	0.094	0.061	0.033	0.307	0.297	0.010
15	0.409	0.481	0.072	0.375	0.447	0.072
16	0.409	0.483	0.074	0.314	0.284	0.030
17	0.374	0.362	0.012	0.257	0.197	0.060
18	0.060	0.023	0.037	0.351	0.284	0.067
19	0.060	0.076	0.016	0.233	0.147	0.086
20	0.098	0.104	0.006	0.233	0.149	0.084

Time (day)	Workpackage 2			Workpackage 6		
	Actual	**Predicted**	**Error**	**Actual**	**Predicted**	**Error**
21	0.098	0.102	0.004	0.233	0.117	0.116
22	0.111	0.098	0.013	0.397	0.443	0.046
23	0.060	0.021	0.039	0.397	0.514	0.117
24	0.370	0.421	0.051	0.645	0.741	0.096
25	0.217	0.208	0.009	0.424	0.377	0.047
26	0.137	0.112	0.025	0.230	0.116	0.114
27	0.105	0.084	0.021	0.293	0.118	0.175
28	0.344	0.386	0.042	0.615	0.561	0.054
29	0.619	0.685	0.066	0.975	0.871	0.104
30	0.160	0.214	0.054	0.975	0.883	0.092
		RMSE	0.037		RMSE	0.090
		MAPE	0.297		MAPE	0.202

As can be seen in Table 5.4, the results of predicted CLP values for work package 2 and work package 6 registered RMSE values of 3.7% and 9%; and a MAPE values of 29.7% and 20.2% respectively. As the FSD-FABM that used N-FIS to capture the soft relationships in the FSD part of the hybrid model was demonstrated to produce better results, the FSD-FABM with the N-FIS model was used to demonstrate the results of CLP in the other work packages. In this regard, the proposed FSD-FABM was capable of predicting the CLP values of the different work packages.

5.7 Verification of the FSD-FABM

Model verification is a very crucial step to ensure the model is produced according to the fundamental concepts and enables understanding of the model's limitations (Al-Kofahi et al. 2020). In this chapter, four different methods (Sterman 2000) were used to verify the FSD-FABM, namely, boundary adequacy, structure verification, dimensional consistency, and sensitivity analysis. These tests are discussed briefly hereafter.

5.7.1 Boundary adequacy

The boundary adequacy test is performed to check if the essential concepts for addressing the problem (i.e., system variables selected) are endogenous to the model (Sterman 2000), and that changing the parameters of the model inputs produce variations in the model output. In this regard, the model complied with the boundary adequacy test as the model variables that were selected in the form of endogenous variables, such as CLP, crew composition, work performed, congestion, etc. were selected from the extensive literature that existed on this research area (Raoufi and Fayek 2018; Ford and Lyneis 2020; Nasirzadeh et al. 2018; Gerami Seresht and Fayek 2018; Khanzadi et al. 2019).

5.7.2 Structure Verification

Structure verification tests whether the model is congruous with the knowledge of the real system. In this regard, the cause-and-effect relationship of the model, which represents the construction system explains construction knowledge that is consistent with the real system. In this regard, the model complies with the structure verification test. An example is discussed where increased schedule compression leads to more overtime work, which can lead to fatigue. Crews' increased fatigue can then have an impact on their ability to adequately perform hazard identification mitigation on the construction site. Feedback relationships that make-up the first reinforcing CLD (R1) of the system consist of crews' ability to perform and their motivation (Figure 5.4). In this chapter, crews' ability to perform tasks was modeled as a function of crews' knowledge of the work, their experience, and the experience and knowledge of their direct supervisor, in addition the crews' teamwork. The crews' tendency to impact the system in terms of progress or work performed in the work packages, results from crews' ability to perform, and crews' motivation. This result aligns with previous studies (Raoufi and Fayek 2018) which stated that crews' ability to perform their tasks, and their motivation directly affects crews' performance, which can be indicated by KPIs such as CLP.

5.7.3 Dimensional Consistency

Dimensional consistency is checked for those relationships with defined mathematical equations (i.e., hard relationships). A sample of the dimensional consistency test is presented below as Equation (5.4) for demonstration purposes, to ensure that the unit measures in each side of the mathematical relationships are consistent.

$$\text{Productivity}\left[\frac{\boldsymbol{units}}{\boldsymbol{person\ hr}.}\right] = \text{Production Rate}\left[\frac{units}{day}\right] \div \text{Daily Work Time}\left[\frac{person\ hr}{day}\right] \qquad (5.4)$$

As shown in Equation (5.4), the relationship satisfies dimensional consistency, as the left and right sides of the equations equate to give a similar dimension (i.e., units/person hr.). This which is also demonstrated for all of the other mathematical relationships expressed in the methodology section. Hence, the model is shown to satisfy the dimensional consistency test.

5.7.4 Sensitivity Analysis

Sensitivity analysis is performed to identify those parameters that impact the output of the model. AnyLogic® is used to perform the simulation analysis for the FSD-FABM, whereby several parameters are varied to investigate their effect on the output of the model. In this regard, the parameter chosen to demonstrate the sensitivity analysis performed in this chapter is crew motivation. The causal effect of crew motivation on CLP can be visualized using a sensitivity analysis, as shown in Figure 5.10. Previous studies have shown that increasing the percentage of initially highly motivated crews in a project, results in higher motivation of crews (Raoufi and Fayek 2020), especially in instances that the contact rate between crews is higher (Kedir et al. 2020). After performing a parameter variation test, whereby the initial percentage of highly motivated crews was increased to show an increase in the observed crew motivation, a sensitivity analysis was performed. This sensitivity analysis investigates the effect of increasing initial percentage of highly motivated crews on CLP within the range of 0–1, which can also be interpreted as investigating the effect of increase in crew motivation on CLP.

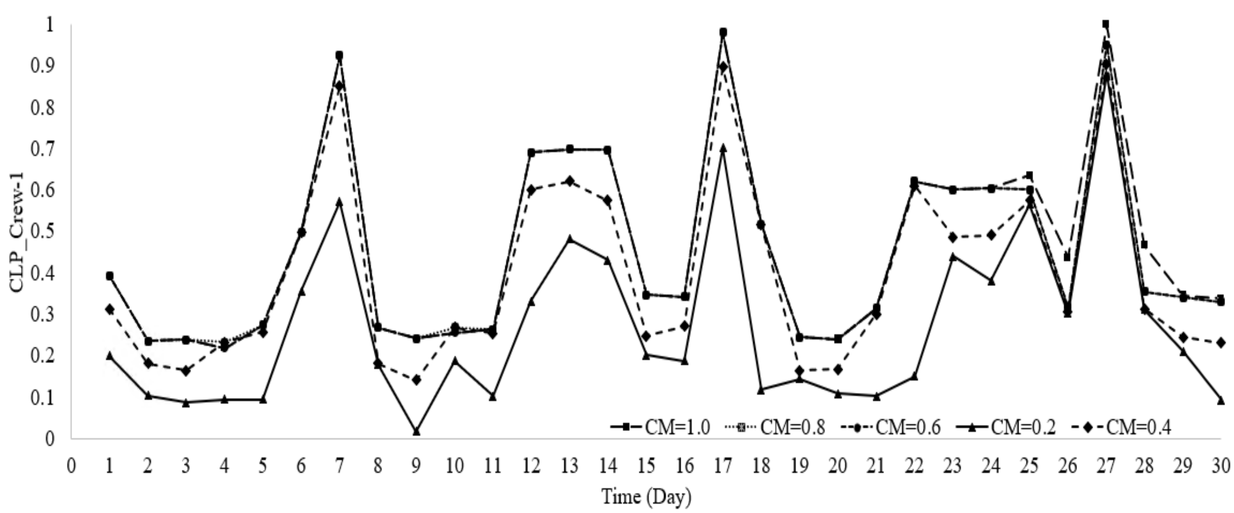

Figure 5.10 Sensitivity analysis for effect of motivation on CLP.

As can be seen in Figure 5.10, the general trend of increase in CLP can be observed when increasing the crew motivation. Moreover, results of CLP showed varied trends for varying initial percentage of highly motivated crews. When the initial percentage of highly motivated crews was 0.2, the predicted values of CLP was the lowest, indicating the negative effect of lower crew motivation on CLP. Moreover, the effect of increasing the percentage of highly motivated crews on CLP also diminished for values higher than 0.6. Effects of higher motivation such as CM = 0.8, and CM = 1.0 on CLP were extending the days were local maxima of CLP occurred (days 12–14, and days 22–25). This effect needs to be investigated further as to why a similar effect did not occur on days 7, 17, and 27, which could be because of a local minima values of situational/contextual average, which may have precluded a sustained CLP increase.

5.8 Chapter Summary

The FSD-FABM methodology has been applied using a case study on an industrial construction project. The results of this chapter showed that the FSD-FABM methodology proposed was capable of predicting crew motivation, daily contextual average values of the construction environment, and CLP of the crews. Moreover, the results showed that the hybrid FSD-FABM which utilized N-FIS in the FSD component of the model outperformed the other predictive models that used LR, and M-FIS in the FSD component of the model. This indicates the capabilities of the ANFIS approach in learning from data while also utilizing information from the membership functions in the FIS. Moreover, the results also indicated the impact of crew motivation in affecting CLP of crews that are performing their tasks in the work packages. Using the predictive model proposed in this chapter, it was possible to attribute the increase and decrease of CLP to variations in crew motivation and the daily situational/contextual average during different stages of the project.

The contribution of this chapter to the body of knowledge is to propose a hybrid FSD-FABM, which captures and assesses the impacts of multiple variables exhibiting dynamic causal interactions, emergent behavior, and non-linearity in modeling and predicting of CLP. In addition, the proposed FSD-FABM technique can capture subjective uncertainty in the predictive modeling processes. The FSD-FABM, which incorporated ANFIS was found to have higher predictive accuracy compared to other models, including linear regression and M-FIS. In comparison to previous models that captured productivity, the FSD-FABM proposed in this chapter is a novel approach to capture dynamic construction systems that exhibit multiple types of uncertainties, such as subjective uncertainties, and objective uncertainties, in addition to capturing complex adaptive systems that exhibit emergent behaviors. In comparison to previous models (Gerami Seresht and Fayek 2018; Nojedehi and Nasirzadeh 2017; Nasirzadeh and Nojedehi 2013; Al-Jibouri and Mawdesley 2009), that used crew motivation as an input parameter, the proposed FSD-FABM offers a better approach by modeling crew motivation as an emergent behavior that is dynamic throughout the project. Moreover, the proposed FSD-FABM uses FDEMATEL in the qualitative modeling stage of FSD, which allows for a systematic, and structured methodology for obtaining causal relationships in comparison to previous models. In this regard, this chapter is an advancement to previous research (Jeong et al. 2022 Al-Kofahi et al. 2022; Gerami Seresht and Fayek 2020; Gerami Seresht and Fayek 2018; Nojedehi and Nasirzadeh 2017). In comparison to previous FABM models that studied the effect of motivation on performance by analyzing the overall crew performance (i.e., task performance, contextual performance, and counterproductive behavior), and investigated the moderating effect of crew motivation on performance; the proposed FSD-FABM presents a better solution. The proposed model presents a single output of CLP rather than an aggregated performance measure, which is a preferred approach in cases where higher performance measure of one parameter (e.g., task performance) may mask lower performance measures of other categories. In addition to the increased performance in model accuracy; the FSD-FABM offers a more comprehensive method to understand the effect of specific variables on the overall system. In this regard, the proposed model advances previous research (Raoufi and Fayek 2018; Kedir et al. 2020; Raoufi and Fayek 2021) by assessing performance of dynamic construction systems using a specific KPI such as CLP and investigating the causal impact of crew motivation on CLP.

In this chapter, the FSD-FABM methodology presented in Chapter 4 of this thesis is demonstrated with a case study and verified. In order to apply the methodology to other projects, data collection on factors affecting CLP first needs to be performed. Next, the FAHP-FDEMATEL methodology demonstrated in Chapter 3 should be applied. Next the FSD-FABM should be applied where membership functions are modified to represent the new context of the project. After identifying the factors that affect CLP most, and using those factors as variables to predict CLP, the next step is to apply the FSD-FABM for strategic decision-making purposes.

Using the FSD-FABM in the decision-making process allows the formulation of a decision-making frameworks which has two components (i.e., the predictive component and the decision-making component). In this regard, the next chapter discusses how the FSD-FABM can be used in the decision-making process by proposing two decision-making frameworks. Accordingly, two decision-making frameworks that address the optimization aspect, and the selection aspect of decision-making are discussed in the next chapter.

Chapter 6 Framework for Strategic Decision Making to Improve Productivity[6]

6.1 Introduction

Construction crew performance is assessed using key performance indicators (KPI) that measure a given performance metric. In addition to the most common KPIs used in construction (i.e., time, cost, quality, safety), crew productivity can be regarded as one of the most important KPIs that has an impact on project performance. This is because productivity at the crew level (as a KPI metric) has an impact on project performance, and improvement in project performance can lead to improvement in organizational performance. The significance of these KPIs varies based on the project management policies and strategies (e.g., safety improvement, team satisfaction, client satisfaction).

Current decision-making approaches mostly comprise one of or a combination of the following: expert opinion and experience, mathematical and heuristic formulations, intelligent methods, evolutionary methods, and simulation techniques. Methods involving expert opinion and experience can exhibit potential uncertainty and might not significantly benefit objective problems that involve rigorous computation (Alemi-Ardakani et al. 2016). Mathematical methods, such as

[6] Parts of this chapter have been published in *Journal of Management in En*gineering: Kedir, N. S., Raoufi, M., and Fayek, A. R. (2020). "Fuzzy agent-based multicriteria decision-making model for analyzing construction crew performance." Journal of Management in Engineering, 36(5), 04020053. Parts of this chapter have also been published in *Automation in Construction*: Kedir, N. S., Somi, S., Fayek, A. R., and Nguyen, P. H. (2022). "Hybridization of reinforcement learning and agent-based modeling to optimize construction planning and scheduling," Automation in Construction, 142, 104498.

integer, linear, or dynamic programming, are computationally cumbersome, complex, and easily trapped in a local optimum (Hegazy 2001). Heuristic methods are a collection of proposed rules that do not use rigorous mathematical formulations (Siu et al. 2016) and offer a much simpler approach using rules-of-thumb and experience (Hegazy 2001). Some examples of heuristic and meta-heuristic approaches can be found in the work of Yahya and Saka (2014). Heuristic methods perform differently in different problem contexts and do not always guarantee optimum solutions, as no direct approach exists for selecting the best heuristic approach (Hegazy and Kassab 2003). In situations where insufficient data is available for modeling and computing processes, intelligent methods could be used to establish WBS and identify the proper sequence of activities. Evolutionary methods can become difficult to implement and make the computation process extremely intensive and expensive to perform (Slowik and Kwasnicka 2020). Some studies have also proposed hybrid simulation approaches that simulate construction problems using a simulation approach (such as DES, ABM) and an optimization method.

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. Fuzzy agent-based modeling (Raoufi and Fayek 2018) integrates fuzzy logic with agent-based models, and makes it possible to address construction-related problems that are highly dynamic and involve subjective uncertainties. After applying FABM, or other equivalent dynamic simulation approaches (i.e., FSD-FABM) to capture 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.

Another decision-making approach which falls under the category of optimization is Reinforcement learning (RL). RL is very effective for decision-making processes in construction problems. RL algorithms are able to solve optimization problems with higher constraints (Ratajczak-Ropel 2018) and perform efficiently with increasing complexity and number of activities (Soman and Molina-Solana 2022). The RL agent learns to implement better actions, including optimal sequencing of activities, through training achieved from exploiting local rewards and exploring random actions despite lower rewards. Hence, RL can help fill the aforementioned shortcomings of current decision-aid methods in construction planning by developing a local decision-making policy for each agent, based on communication channels, and by breaking down the problem into sub-problems, all of which contributes to computational efficiency. Using RL assists construction practitioners in facilitating generalizations through the learning process, because different problems can be broken down into similar sub-problems. Moreover, RL facilitates agent communications and enables agents to arrive at a set of decisions involving a set of joint actions. This results in a faster convergence to the optimum global policy. However, the dynamic nature of modeling in the construction environment, arising from the complexity caused by various interactions between system components (Raoufi and Fayek 2018) is not captured by RL. In a construction setting, however, having a model of the construction environment is crucial.

Simulation techniques have been used to capture the dynamic nature of the construction environment as well as uncertainties in the modeling process (Abdelmegid et al. 2020). ABM is capable of handling very complex real-world systems often containing large amounts of autonomous, goal-driven, and adapting agents (Chan et al. 2010). ABM uses a bottom-up approach where the system is described as interacting objects with their behaviors, which allow complex emergent behaviors to be captured. ABM enables tracking of agent interactions in their artificial environments to understand overall processes that lead to global patterns (Watkins et al. 2009). By incorporating FSD-FABM in an RL process, necessary features that support environment modelling, such as system parameters, causal relationships, system behaviors, and rules, are provided in order to enable an efficient representation of the dynamic construction environment and provide the RL platform with the necessary features to support environment modelling.

In this chapter, the need to develop better decision-making models in construction by helping decision makers prioritize and select from several strategies intended to improve productivity is addressed. This chapter presents a multi-criteria decision-making modeling framework that uses FSD and FABM (i.e., FSD-FABM-MCDM) to address both the dynamic nature of construction projects and subjective uncertainties involved in construction variables. The proposed framework is an extension of the FABM-MCDM model as part of this study in Kedir et al. (2020). Moreover, this chapter also presents an alternative to other methods currently found in the literature (i.e., RL-FSD-FABM): a simulation engine that provides a scientific method for finding an optimal set of solutions for crew productivity problems by simulating the environment using FSD-FABM, in an optimization platform which utilizes RL to take into account the objective function and pre-defined constraints. This proposed framework is an extension of the RL-ABM model as part of this study in Kedir et al. (2022b).

This chapter is organized as follows: first, the literature review section, which briefly discusses MCDM, simulation, and optimization approaches for strategic decision making is presented. Next, a framework of FABM-FSD-MCDM, and RL-FSD-MCDM is proposed to discuss the application of strategic decision making in improving crew productivity measurements

6.2 Literature Review

In this section, a brief review of decision making in construction is first presented, followed by a literature review on performance modeling and management strategies in construction, giving emphasis to crew productivity. Next, a literature review of ABM, its applications in construction, and its use and limitations in decision-making is presented, followed by a brief literature review on the use of RL for decision making.

6.2.1 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.

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.

6.2.2 Performance Management Strategies in Construction

Cost, time, quality, safety, and productivity are the traditional performance measures in construction (Kagioglou et al. 2001). Other dimensions of performance may include profitability, environment, team satisfaction, and client satisfaction, and are usually governed by the type of KPIs used to capture project objectives, preferences, policies, and strategies (Leon et al. 2018). When the effort to measure productivity is focused at the crew level, the effect of crew-level motivation on performance (i.e., productivity) should also be considered (Raoufi and Fayek 2018).

However, the impact of crew motivation on construction crew productivity has been largely overlooked in the literature.

From the studies that focused on improving productivity, Ghodrati et al. (2018) used statistical analysis to study the effectiveness of management strategies on improving labor productivity. They used a 7-point Likert scale to assess both labor productivity and the level of implementation of management practices. The Likert scale approach, however, is limited by its subjectivity. Additionally, the relationship between management strategies and labor productivity was determined using multiple regression analysis, which does not account for possible interrelationships between independent variables. Durdyev et al. (2018) used a structural equation model of the factors affecting construction labor productivity, which confirmed the significance of management team competency level and workforce quality in enhancing labor productivity.

Although past research in the construction domain on productivity modeling and management strategies has provided valuable results, there is still a need to account for the dynamic nature and subjective aspects of most construction processes. Simulation methods can model the dynamic nature of construction processes, and fuzzy logic can address subjective uncertainty. In the area of decision-making in construction, using modeling approaches that account for the dynamism and subjectivity of construction processes is important to assess the impact of applied managerial strategies on performance and recommend better practices for improving productivity.

6.2.3 Agent-Based Modeling for Decision Making

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 (2018) 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 (2018) 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 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 (2017) 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. 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.

6.2.4 Reinforcement Learning for Decision Making

RL settings can be classified as single-agent RL or multi-agent RL (MARL) depending on the number of autonomous agents that influence the system's state and reward (Zhang et al. 2020). RL can also be classified as model-based or model-free RL (Sutton and Barto 2018). In terms of its applications, RL has been used in various applications in the field of civil engineering owing to its capabilities that make it particularly successful in solving complex problems (Shitole et al. 2019). Some of these applications include works in the area of design and operations for water structures (Bertoni et al. 2020; Bhattacharya et al. 2003), transportation engineering (Genders and Razavi 2019; Medina and Benekohal 2011; Yin and Menendez 2019), and maintenance (Durango 2002). RL has been effectively applied to develop strategic conventional tunneling in construction, which provided optimal economic and safe policies with potential to discover new tunneling strategies (Erharter et al. 2021). RL is also emerging as a control technique (Wang and Hong 2020), and it is of growing interest in research, with demonstrated potential particularly in enhancing building performance (Berlink et al. 2015; Ruelens et al. 2017; Zhiang Zhang et al. 2019). Because RL uses an intelligent agent to learn to make a series of optimal decisions (Sutton and Barto 2018), it is a suitable approach for performing construction planning where a series of decisions (e.g., activity sequencing, resource allocation) are performed at different times throughout a project's lifecycle. In the area of scheduling, the majority of RL-based research has focused on production scheduling. Creighton and Nahavandi (2002) proposed an intelligent agent-based scheduling system that uses DES as a simulation engine with the goal of minimizing total production costs depending on job sequence and batch size. Cao et al. (2003) proposed an RL model using Monte Carlo simulation to solve a production planning problem that minimizes inventory and penalty costs. Wei and Zhao (2005) used Q-learning algorithm to schedule a dynamic job-shop problem that considers machine selection. Zhang et al. (2007) used an RL method coupled with heuristic method and simulation to perform parallel machine scheduling that minimizes mean flow time of jobs. Fonseca-Reyna et al. (2015) used RL to solve a scheduling problem that finds a permutation of operations that is processed sequentially on a set of machines with the objective of minimizing the completion time of all jobs. Bouazza et al. (2017) used an RL approach with Q-learning to solve a job-shop scheduling problem.

Unlike supervised and unsupervised learning approaches, RL is a machine learning technique that uses the environment for learning and is not dependent on a predefined dataset (Kurinov et al. 2020). Moreover, RL is particularly advantageous in the area of sequential decision making, which is a key challenge in artificial intelligence research (Moerland et al. 2020). When sequential decision making is formalized as Markov decision process (MDP) framework optimization problem, selecting the sequence of actions that produce optimal results (e.g., path planning) becomes complicated because of inherent key elements of the world (i.e., information about the environment and states; influence of actions on the environment; the notion of preferred actions now and in the future) (Moerland et al. 2020). In this regard, RL can offer an efficient solution for construction operation problems that may be viewed as a collection of recurring activities (Shitole et al. 2019) where the objective is to produce an optimal solution (i.e., optimal project performance measure such as minimum project duration or minimum cost) in a dynamic environment (i.e., changing project conditions) subject to constraints (i.e., limited resources). RL's capability also extends to solving large-scale dynamic optimization problems and complex multi-objective sequential decision-making problems (Moerland et al. 2020).

Even though there is growing research into RL-based optimization approaches that demonstrate the benefits of RL method in other fields within construction, most applications of RL for scheduling problems with respect to improving production have been limited to the manufacturing sector. In construction planning, decision makers analyze various activities to ensure optimal use of available resources and achieve required performance to meet project objectives with respect to cost, time, and quality. Establishing WBS and activity sequencing requires consideration of numerous interacting factors between the activities themselves, such as technology constraints, precedence relationships, available resources, conflicting objectives, and incomplete information. In this regard, RL enables a model to process optimization approaches that provide human-like intuitions and learning capabilities, which can enable decision makers to obtain better solutions that can adapt to changing environments.

6.2.5 Markov decision process (MDP)

Markov decision process (MDP) is a framework that describes the process of learning from interaction with the environment in order to achieve a goal. MDP has five components (Woo et al. 2019): 1) the set of possible actions ($A_t \in$ A) that can be taken by the agent or the decision-maker; 2) the set of all possible states ($S_t \in$ S) that can be experienced by the agent; 3) the immediate reward r that is received by the agent corresponding to the given state and action pair, defined in Equation (6.1); 4) the discount factor γ that signifies the relative importance future rewards have compared to the current immediate reward, defined in Equation (6.2), which denotes the discounted cumulative reward G_t following time t; and 5) the transition probability $p(s',\ r \mid s,\ a)$ of a state corresponding to past state and action, defined in Equation (6.3). The agent-environment interaction in MDP is summarized in Figure 6.1.

$$R(s,a) = E[r_{t+1} \mid S_t = s, A_t = a] \qquad (6.1)$$

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \qquad (6.2)$$

$$p(s',\ r \mid s,\ a) \doteq \mathrm{p}(S_t = s',\ R_t = r \mid S_{t-1} = s,\ A_{t-1} = a) \qquad (6.3)$$

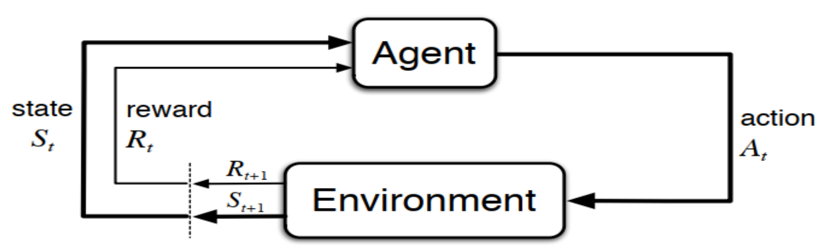

Figure 6.1 Agent-environment interaction in MDP (adopted from Sutton and Barto 2018).

In MDP, the optimal policy $\pi^*(a|s)$ can be the function that maps the current state s to the best action a^* while maximizing the expected future reward, as shown in Equation (6.4).

$$\pi^* = argmax\ \mathbb{E}[G_t|S_t = s, A_t = a] \qquad (6.4)$$

RL algorithms for solving an MDP problem can be implemented in two ways: through 1) action-value approximation or 2) policy approximation. Action-value methods directly learn the expected return of taking each action a in a specific state s (Sutton & Barto, 2018). The action-value function $q_\pi(s, a)$ is defined in Equation (6.5), and the optimal action-value function for the optimal policy (π^*) is defined in Equation (6.6) by considering the Bellman optimality equation, Equation (6.5), and Equation (6.3):

$$q_\pi(s, a) = \mathbb{E}_\pi[G_t|S_t = s, A_t = a] \qquad (6.5)$$

$$q_{\pi^*}(s, a) = \sum_{s',r} p(s', r|s, a)\,[r + \gamma \max_{a'} q_{\pi^*}(s', a')] \qquad (6.6)$$

On the other hand, in some MDPs, directly learning action-value functions is challenging in a big action space, and as a result, the policy function is used to calculate the preferences for each action in each state. The parameterized policy formula is defined in Equation (6.7).

$$\pi(a|s, \theta) = Pr[A_t = a|\ S_t = s, \theta_t = \theta] \qquad (6.7)$$

Equation (6.7) presents the probability of selecting an action as action preference. For example, this probability could be a linear function of any complex structure of deep learning, where θ is the weights or parameters of the function. Equation (6.8) and Equation (6.9) express the discrete action space for a linear parameterized policy with soft-max distribution (Dai et al. 2017). The objective in RL processes is to learn q^* or θ^* by interacting with the environment and receiving rewards. This learning is accomplished by updating a policy or set of action-value function parameters, which means learning the best values for each state or sub-problem, which leads to solving the MDP.

$$\pi(a|s,\theta) = \frac{e^{h(s,a,\theta)}}{\sum_b e^{h(s,b,\theta)}} \tag{6.8}$$

where

$$h(s,a,\theta) = \theta^T x(s,a) \tag{6.9}$$

6.3 Proposed Framework to Improve Construction Crew Productivity

In this section, two frameworks, namely: FSD-FABM-MCDM, and RL-FSD-FABM are introduced. The first framework (i.e., FSD-FABM-MCDM) is proposed to present a decision-making approach where selection of the best solution is made by comparing a given set of alternatives. The second framework (i.e., RL-FSD-FABM) is proposed to present a decision-making approach where selection of the best solution is made by performing optimization of input parameters. The input parameters used to demonstrate the proposed frameworks is shown in Table 6.1.

Table 6.1 Input parameters used for decision making (adapted from Kedir et al. 2020).

Alternative	Input	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	Initial percentage of low motivated crews	(0,1)	Percentage of crews with initial state of low motivation
6	Initial percentage of highly motivated crews	(0,1)	Percentage of crews with initial state of high motivation

6.3.1 FSD-FABM-MCDM Framework

When working to improve construction crew motivation and productivity, 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 SD and 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 framework for integrating FSD-FABM with MCDM to develop such a model. The FSD-FABM-MCDM has two major components, as highlighted in Figure 6.2. The first component is the MCDM analysis, in which the AHP is used to rank alternatives, which are the inputs to the model. The MCDM component is novel and is also developed based on collected field data. The second component is the FSD-FABM technique, in which a parametric study is applied to rank scenarios according to their outputs. The outputs are productivity, cost performance, and schedule performance. The FSD-FABM component is developed in Chapter 4. These two components (i.e., FSD-FABM, and MCDM) are described in the following section.

6.3.1.1 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 productivity will be ranked and used as parameters for the model's other component (i.e., FSD-FABM).

The analytic hierarchy process (AHP) is a widely used MCDM method. AHP decomposes a complex MCDM problem into a system of hierarchies. A collection of elements, or inputs, are compared using the AHP process. AHP uses pairwise comparisons and matrix algebra to weight criteria. The decision is made by using the derived weights of the evaluation criteria (Saaty 1990). Importance is measured on an integer-valued scale ranging from +/- 3 to +/- 9, depending on the desired consistency.

The inputs, shown in Table 6.1, are labeled "alternatives" (Alt.). Since the AHP was adopted for this chapter, pairwise comparisons are used to rank the alternatives according to their importance for three level 1 criteria (i.e., productivity criterion [C1], cost performance criterion [C2], and schedule performance criterion [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 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. [A] is the matrix of alternatives. Elements of this matrix correspond to the inputs of the FSD-FABM, which are ranked according to their importance in improving the model output. Each alternative is scored in terms of its relative importance in improving each of these performance measures (i.e., criteria) using the AHP to produce the alternatives matrix. The alternatives matrix consists of these relative scores of the pairwise comparison matrix, in the form of A_{ij} (=A_i/A_j). For example, a score of A_{ij} indicates the relative importance of alternative i when it is compared with another alternative j in terms of each criterion (C_1, C_2, or C_3). 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. Equation. (6.10) shows the pairwise comparison matrix, where m alternatives are compared in terms of a criterion.

$$Alternatives\ Matrix\ (A) = \begin{array}{c c} & \begin{array}{cccc} A_1 & A_2 & . & A_m \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ . \\ A_m \end{array} & \begin{bmatrix} \frac{A_1}{A_1} & \frac{A_1}{A_2} & . & \frac{A_1}{A_m} \\ \frac{A_2}{A_1} & \frac{A_2}{A_2} & . & \frac{A_2}{A_m} \\ . & . & . & . \\ \frac{A_m}{A_1} & \frac{A_m}{A_2} & . & \frac{A_m}{A_m} \end{bmatrix} \end{array} \qquad (6.10)$$

After the pairwise comparison 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 Equation (6.11), where E is the eigenvector and λ_{max} is the corresponding maximum eigenvalue.

$$[R] = \begin{bmatrix} \frac{A_1}{A_1} & \frac{A_1}{A_2} & . & \frac{A_1}{A_m} \\ \frac{A_2}{A_1} & \frac{A_2}{A_2} & . & \frac{A_2}{A_m} \\ . & . & . & . \\ \frac{A_m}{A_1} & \frac{A_m}{A_2} & . & \frac{A_m}{A_m} \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ . \\ . \\ A_m \end{bmatrix} = \lambda_{max} * E \qquad (6.11)$$

The resulting consistency index must be checked using Equation (6.12), and it must be less than 0.1 for the normalized eigenvector values to be used as weights for the criteria and alternatives (Saaty 1990). The consistency index is a measurement of the consistency of the performed comparisons throughout all alternatives. For example, if alternative A_1 is more important than A_2, and alternative A_2 is more important than A_3, then alternative A_1 needs to be more important than A_3 in a consistent reciprocal matrix.

$$\nu = \frac{\lambda_{max} - m}{m - 1} \tag{6.12}$$

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 Equation. (6.11) and Equation (6.12) are performed for all three criteria (i.e., C_1, C_2, and C_3). The criteria are also weighted using the same procedure, but instead of an alternative matrix, as shown in Equation (6.10), 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 Equation (6.13), in descending order.

$$For\ \ i = 1, m{:}\, Score\ (Alt_i) = \sum_{j=1}^{n} E_{ij} * C_j \quad where,\ j = 1, n \tag{6.13}$$

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 productivity.

6.3.1.2 FSD-FABM Component

The FSD-FABM component is the integration of FSD, and FABM in MATLAB and AnyLogic®. FSD-FABM simulates the effects of a combination of inputs (see Table 6.1) on three criteria (i.e., productivity, cost performance, and schedule performance). The main outputs of this model are variations in productivity, cost performance, and schedule performance 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 the given range.

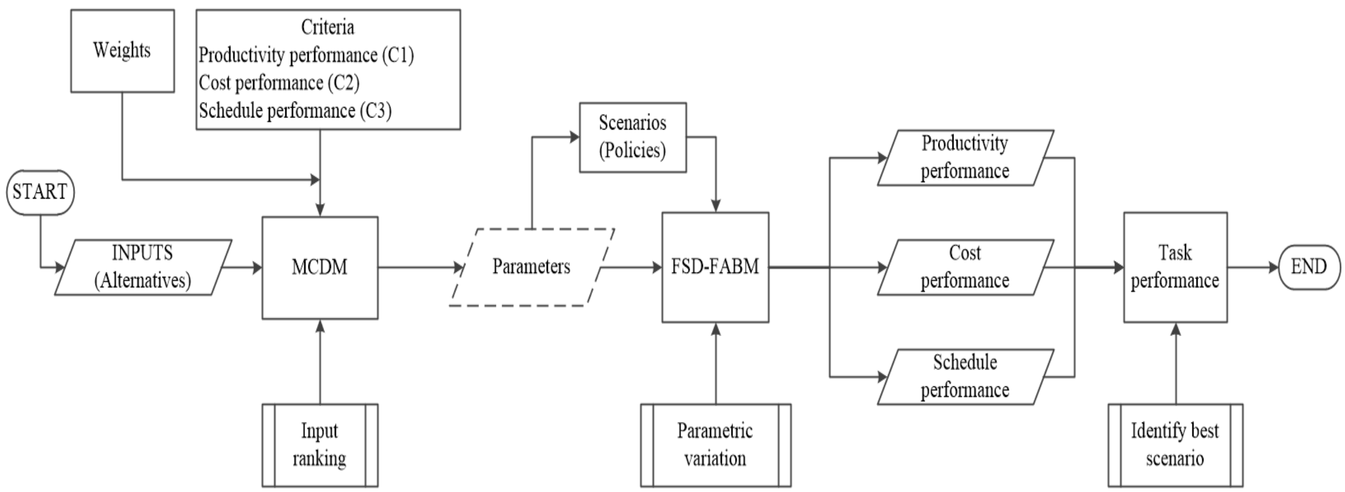

Figure 6.2 Proposed FSD-FABM-MCDM framework (adapted from Kedir et al. 2020).

6.3.2 RL-FSD-FABM Framework

The proposed framework consists of three steps: 1) development of the RL model, 2) problem definition, and 3) RL-FSD-FABM simulation process

6.3.2.1 Development of RL model

MDP states and actions

In the construction environment, formalizing productivity improvement as an MDP is described as follows. Possible actions ($A_t \in$ A) are alternatives that can be performed as actions, according to project state ($S_t \in$ S). The project state in this chapter is characterized by project time, the progress of each activity in the project, current productivity recorded in the project, and the budget spent for increasing the current productivity. Hence, the MDP environment starts by defining which actions are to be performed to maximize the objective function.

The reward is considered as a cost function, described as a function of the monetary value of incurred delay due to lower-than-expected productivity, and the budget spent to increase productivity. The objective is to minimize the long-term negative reward. In this sense, minimizing over negative value results in minimizing the value of the cost function. The "state" and "action" pairs, which are the two major components in the MDP, are described below.

State: The productivity problem is formulated as an MDP problem with RL algorithms that use an MDP framework to derive optimal strategies. Each state in the RL algorithms is represented in a structure format as an input to calculate future values according to possible actions in the current state. Each state S represents the outcome of a previous action and comprises the following information:

i. Activities states in simulation: These can be obtained from the simulation model at each timestep per a corresponding numeric value, as shown in Table 6.2.

Table 6.2 Description of state.

State	State description
Project time	Number of days (t) elapsed in the project
Work progress	Units of work performed per time t
Cost	Budget spent for increasing productivity at time t

Action: For each state, the agent selects an action from the available inputs shown in Table 6.1, which affects the simulation output. Hence, selecting an action results in changing the project state, and the agents use updated information to select the next action. In other words, agents select one action per state. In the RL component, the RL agents select an environment action ($A_t \in$ A) that affects the work progress. This production rate is also translated into the time needed to complete the activity in the project. Moreover, the action taken by the RL agent is also associated with the cost of taking such action. For example, increasing the *contact rate* between crews requires that working time is taken away to ensure crews have an increased contact using methods such as tailgate meetings, briefings, trainings.

Q- function

The RL agents learn to make the optimal sequence of decisions that can meet the predefined objective by maximizing the received reward for a given action while also exploring the decision space to avoid local solutions, as shown in Equation (6.14).

$$q_\pi(s,a) = \mathbb{E}_\pi[G_t|S_t = s, A_t = a] q_{\pi^*}(s,a) = \sum_{s',r} p(s',r|s,a)\,[r + \gamma \max_{a'} q_{\pi^*}(s',a')\pi(a|s,\theta)$$

$$= Pr[A_t = a|\, S_t = s, \theta_t = \theta]$$

$$\pi(a|s,\theta) = \frac{e^{h(s,a,\theta)}}{\sum_b e^{h(s,b,\theta)}}\; h(s,a,\theta) = \theta^T x(s,a) \qquad (6.14)$$

The value function therefore learns to calculate the value of each possible action taken, based on receiving rewards and tries to estimate the prioritization of actions to take based on the project state.

Optimizing the value function

The optimization problem in the RL component can be defined as selecting the optimal combination of input parameters in order to complete the activities in the construction project with improved productivity, leading to minimal cost.

$$minimize \qquad C = \{d_i + p_i\,|i = 1, 2, \ldots, n\} \quad (6.15)$$

where C = total cost to be optimized d_i = cost of delay which is incurred due to unfinished activity$i$, and p_i = cost incurred due to selecting an action as a strategy.

6.3.2.2 FSD-FABM Component

The FSD-FABM component is the integration of FSD, and FABM in MATLAB and AnyLogic®. The FSD-FABM is presented in Chapter 4 of this thesis and is used to capture the construction environment while performing the optimization procedure in RL. The RL model uses the simulation outputs of FSD-FABM to evaluate the reward of taking a specific action. The results of FSD-FABM simulation are daily productivity, and the duration taken to complete an activity based on optimized parameters. These values are used by the RL model during optimization, which is achieved by maximizing the value function to obtain the best possible reward throughout the project duration.

6.4 Chapter Summary

In this chapter, two frameworks are presented to propose a decision-making methodology for improving crew productivity. These frameworks were proposed to address the need for decision support tools for use in construction, where problems exist in a dynamic environment with subjective uncertainties. The first framework proposes a decision-making framework by integrating the simulation capacity of FSD-FABM to address dynamic and subjective problems, with MCDM's capacity to address multiple, sometimes conflicting, expert opinions. The second framework proposes an optimization solution by integrating the simulation capacity of FSD-FABM to address dynamic and subjective problems, with RL's computational efficiency and adaptability to learn optimal solutions.

This chapter has three contributions: First, it proposed a methodology to integrate FSD-FABM with MCDM to improve decision-making processes in construction. Second, it proposed a framework to integrate the simulation of dynamic construction processes using FSD-FABM, with the optimization capabilities of RL, to improve decision-making processes in construction. Third, it developed two frameworks, that can individually be used to construction practitioners adopt economically feasible strategies by improving the productivity of construction crews. The developed frameworks are able to offer an applicable and representative approach to the overall process of decision making in construction by solving scenario selection, and optimization problems separately. The frameworks proposed in the study can also be adapted to other construction problems to help decision makers optimize, prioritize or select from several strategies intended to improve different crew performance measures.

Chapter 7: Conclusions and Recommendations for Future Work[7]

7.1. Introduction

This chapter presents a summary of the work conducted in this dissertation and outlines the academic and industrial contributions. Furthermore, limitations of this research and recommendations for future research are presented.

7.2 Research Summary

Viewing productivity as a complex system whose inputs are continuously interacting both with themselves and the environment, the approach to simulate it using a FSD approach (that considers productivity as a dynamic system, whose behaviour is captured over time) and an FABM approach (whose individual components interact with each other and the environment according to a given

[7] Parts of this chapter have been published in *Journal of Management in Engineering*: Kedir, N. S., Raoufi, M., and Fayek, A. R. (2020). "Fuzzy agent-based multicriteria decision-making model for analyzing construction crew performance." *Journal of Management in Engineering*, 36(5), 04020053; submitted for publication in *Automation in Construction*: Kedir, N. S., and Fayek, A. R. (2022)." Integrated Fuzzy System Dynamics–Fuzzy Agent-Based Modeling of Crew Motivation and Productivity in Construction." *Automation in Construction*, 61 manuscript pages, submitted Oct. 2022; submitted for publication in *Advances in Civil Engineering*: Kedir, N., Siraj, N.B., and Fayek, A. R. (2022), "Application of System Dynamics in Construction Engineering and Management: Content Analysis and Systematic Review." *Advances in Civil Engineering*, 49 manuscript pages, submitted Oct. 2022; submitted for publication in *Canadian Journal of Civil Engineering*: Kedir, N., and Fayek, A. R. (2020), "Integrated FAHP-FDEMATEL for Determining Causal Relationships in Construction Crew Productivity Modeling." *Canadian Journal of Civil Engineering*, 39 manuscript pages, submitted Oct. 2022.

set of rules) is crucial to formulate an efficient abstraction of the productivity problem. However, there is a gap in the literature regarding methods that can capture the dynamic causal relationships between factors affecting CLP, and also the emergent nature of some variables, while addressing subjective uncertainty in the modeling and predictive processes. This research addresses the compounded problem of human behaviour modeling (such as crew motivation, using FABM), dynamic interactions between inputs (such as CLP, using FSD) in addition to proposing a decision-making framework that enables feedback mechanisms to improve productivity metrics in an environment of subjective and probabilistic uncertainties.

The research in this dissertation was conducted using five main stages: 1) conducting a literature review to identify factors affecting CLP, and modeling techniques used to model CLP, 2) conducting a systematic review, and content analysis of SD research to identify hybrid FSD as a feasible technique to capture dynamic causal relationships between the variables affecting CLP; 3) development of a systematic and structured methodology that integrates fuzzy system theory with the modeling approaches FAHP, and FDEMATEL, to capture causal relationships in dynamic modeling of CLP; 4) development of a novel FSD-FABM to capture subjective variables, dynamic relationships, and complex systems for a more comprehensive modeling CLP; 5) development of FSD-FABM-MCDM, and RL-FSD-FABM, to address the strategic decision-making aspect of productivity improvement

7.2.1 First Stage

In the first stage, a comprehensive literature review on productivity was conducted. Several definitions of productivity and different levels of productivity measurements were presented.

Discussions on techniques used to model productivity were also presented. Moreover, the definition of productivity that was used in this research was also presented and discussed.

7.2.2 Second Stage

In the second stage, the study of SD as a technique to model complex and dynamic problems in the area of construction engineering was performed. The study covered articles spanning more than 25 years to get a comprehensive picture of SD research in CEM. peer-reviewed journals with important impact and prominence in the field of CEM and which hosted published research works in the area of SD between 1995 and 2021. Relevant articles from the selected journals were selected and indexed. After the selected articles were profiled, a systematic review of SD research in the main CEM application areas was performed to identify strengths, and gaps in the state-of-the-art.

The study found that that a significant number of articles only provided either qualitative SD models, or SD models without application on real projects. Even though SD has had relative success in terms of its application to project management compared with other SD works, SD's practical application in construction management was found to be relatively less and confined to individual projects. This highlights the significant challenge to use SD modeling for CEM problems, stemming from either the lack of data or the reluctance by construction stakeholders to apply SD methods. In this regard, there is a need to produce more SD models that can be generalized, and at the organizational level.

A critical review of the literature also identified the possible areas of improvement regarding SD hybridization with traditional methods and with other modeling approaches. Analysis of the literature indicates that more work needs to be done in integrating SD with the more traditional tools, which can help facilitate a better understanding of SD among construction practitioners and increase SD's applicability and presence across a vast spectrum of projects. There is also potential for further research in SD hybridization with other methods, especially in the areas of: SD-ABM modeling to capture the spatial natures of construction environments and emerging nature arising from individual interactions; and SD-BIM to facilitate a more collaborative decision making process in dynamic construction environments. Moreover, there is a potential to improve the qualitative and quantitative modeling process in SD using modeling approaches such as machine learning, ANN, neuro-fuzzy inference systems, FDEMATEL, and SEM. This chapter also identified the added complexity that may result from hybrid SD modeling owing to system abstraction, aggregation, and model verification. Another identified of SD modeling issue was the lack of much research on incorporating feedback delay in SD models.

7.2.3 Third Stage

In the third stage, the causal relationships between factors affecting productivity were investigated for dynamic modeling of CLP by proposing FAHP-FDEMATEL method. Expert weight assignment was performed using the FAHP part of the model, while causal relationship mapping was performed using the FDEMATEL part of the model. Related findings corresponding to the FAHP indicate that, *productivity-related project and construction management practices* was identified amongst the list of criteria which can be considered unique for assessing decision makers' inputs in the area of productivity; with sub-criteria of: *average hours of work in productivity-related work per week*, *level of management training related to productivity*, *experience in conferences related to productivity management, and functional skills related to productivity management.* Moreover, in the stage corresponding to FDEMATEL, results indicate that *ability to perform, reliability, work progress, visibility of outcome,* and *project scheduling* make-up the top-five factors with highest prominence, representing the most relationship with the other factors. Hence, the top factors have a higher strength of interrelationship with the other factors and strongly influence the other factors in terms of their causal relationship.

7.2.4 Fourth Stage

In the fourth stage of this research, a novel FSD-FABM was developed to capture subjective variables, dynamic relationships, and complex systems for a more comprehensive modeling CLP. The proposed methodology is then demonstrated using a case study based on a real industrial construction project in Alberta, Canada. The FSD-FABM proposed in this chapter predicts the CLP of multiple work packages that make up a construction project. The proposed CLP model was also able to predict the motivation of the crews working on the different work packages on the project, and the impact of crews' motivation states on their productivity. Moreover, the proposed model was able to simulate the dynamic interrelationships between situational/contextual variables to assess the impact of situational/contextual average on daily productivity of crews. The results indicate that the proposed FSD-FABM expanded the scope of applicability of the individual methods of FSD and FABM, and showed more comprehensive modeling capabilities.

7.2.5 Fifth Stage

In the fifth stage, two models were presented to address the strategic decision-making aspect of productivity improvement. The proposed modeling methods were FSD-FABM-MCDM, and RL-FSD-FABM respectively.

In the FSD-FABM-MCDM, the construction environment was captured using FSD-FABM, and parametric variation was used in the proposed model to effectively simulate varying sets of input combinations to obtain scenario analysis results. The results indicated that FSD-FABM-MCDM can be used to offer applicable and representative approach to the process of decision making in construction. In the RL-FSD-FABM, the FSD-FABM was used to simulate the construction environment, while the RL was used to facilitate solving of optimization algorithm. The results of the RL-FSD-FABM indicate that RL-FSD-FABM is a computationally efficient approach to perform optimization process for decision making.

7.3 Research Contributions

The academic and industrial contributions of this research relevant to academic researchers and construction industry practitioners, respectively are presented in the following subsections.

7.3.1 Academic Contributions

The main academic contributions of this research are summarized as follows:

1. *Providing a state-of-the-art on SD research, by presenting a detailed content analysis and comprehensive review of SD literature and assessing the potential for SD hybridization with other modeling and simulation approaches in order to identify modeling issues related to the use of SD in CEM and productivity modeling.* This research provides a comprehensive state-of-the-art literature review and content analysis on the topic of system dynamics (SD), as a viable tool to capture the dynamic nature of system variables and their complex causal relationships for CLP modeling. This chapter provides researchers a more focused resource in SD research and incorporates different approaches to structure the systematic review by defining major areas of CEM research areas, and analyzing the trends of SD research in those research areas. For researchers interested in the use of SD modeling, this chapter also provides a comprehensive review to identify modeling issues

related to the use of SD in CEM, and also assesses the potential for SD hybridization with other modeling paradigms. This research identified major potential areas of future research in different CEM application areas, which can be used to guide researchers to further SD's application within the proposed research areas. This chapter also presented in detail the added complexity that may result from hybrid SD modeling owing to system abstraction, aggregation, and model validation.

2. *Proposing a novel FAHP-FDEMATEL method in order to provide a systematic and structured methodology to define causal relationships between the most significant factors that affect productivity and analyze their interrelated impacts.* This research addresses the lack of systematic and structured methodology to establish causal relationships in the dynamic productivity modeling process, which involves: assessing the importance of, and causalities between the situational/contextual factors, and constructing the CLDs, which illustrate the dynamic relationships between system variables. The proposed methodology expands the scope of current research in the area of dynamic productivity modeling, and provides researchers a methodology to better define causal relationships between factors affecting productivity and analyze their impacts.

3. *proposing a novel hybrid FSD-FABM technique that can capture and assess complexities arising from non-linear behaviors, and dynamic causal interactions between multiple factors in modeling and predicting CLP.* This research expands the scope of applicability of current FABM, by integrating FSD to produce a FSD-FABM, which is able to assess causalities between different system variables of the construction environment. This research also expands the scope of applicability of current FSD models by integrating

FABM to produce FSD-FABM, which allows to capture complex adaptive systems, and emerging nature of variables such as crew motivation, congestion, and fatigue. In effect, this research provides researchers with a novel FSD-FABM to perform a more comprehensive productivity modeling.

4. *Proposing a novel methodology that will help improve decision-making processes in construction by expanding the scope of MCDM through integration with FSD-FABM.* This research provides researchers with a methodology to integrate FSD-FABM with MCDM, and expands the scope of applicability of the individual modeling methods for a more effective decision-making process.

5. *Proposing a novel RL framework that can be used in support decision making, to propose strategic productivity improvement solutions*. This research provides researchers with a novel framework to hybridize RL and FSD-FABM, that is computationally efficient while performing complex optimization problems.

7.3.2 Industry Contributions

The expected industry contributions of this research are as follows:

1. *Providing construction practitioners useful perspective by presenting practical applications of SD in the construction industry, which serves as a useful reference in facilitating the effective implementation of SD modeling in construction projects.* Construction practitioners will be unable to implement SD in their projects if they are not aware of the value of SD, stemming from either the lack of knowledge about the concept, seldom use of SD in their organizations, or the misconception that SD is impractical. In this regard this research provides construction practitioners with the state-of-the-art in SD

research and application within the construction industry, to provide a guideline regarding implementation of SD modeling technique in construction projects.

2. *Providing a hybrid FSD-FABM approach that can help construction practitioners identify reasons for CLP loss, and track the causal relationships between factors affecting CLP, to facilitate a more proactive planning.* The proposed model is capable of simulating the effect of variables with emerging behaviours (e.g., congestion, fatigue, crew motivation) using FABM, and capturing the overall dynamic system of construction environments using FSD. Therefore, in addition to the increased performance in model accuracy; the FSD-FABM offers a more comprehensive method to understand the effect of specific variables on the overall system. Consequently, this research facilitates for a more informed and strategic decision making to improve KPIs such as CLP by enabling construction practitioners to select various input scenarios, discern system drivers, and select the best productivity improvement measures.

3. *Providing construction practitioners with the framework to make informed decisions, and adopt economically feasible strategies for improving the motivation and productivity of construction crews.* This research provides construction practitioners with a framework to make informed decisions and adopt economically feasible strategies for improving the CLP of their 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.

7.4. Research Limitations and Recommendations for Future Research

The following subsections discuss the limitations of this research and recommendations for future research.

7.4.1. Content Analysis and Systematic Review of Application of SD in Construction Engineering and Management

The content analysis and systematic review indicated that SD application in CEM has mostly been confined to research purposes, owing to some underlying challenges in SD implementation. Although models are a very important part of communicating results and conclusions, more work should be done in communicating the modelling process to end users, because much of the learning comes from such processes. In this regard, future research will investigate methodologies to overcome the challenges which contributed to a restricted use of SD method in the construction industry. Analysis of the literature indicates that there is a potential to improve the qualitative and quantitative modelling processes in SD using modelling approaches such as machine learning, ANN, NFIS, FDEMATEL, and SEM. In this regard, future research should investigate state-of-the-art methodologies that could be integrated with SD, to propose better approaches in the qualitative and quantitative modeling stages.

7.4.2. Integration of FAHP and FDEMATEL for Establishing Causal Relationships in Dynamic Modeling of CLP

This research proposed a systematic and structured methodology that integrates FAHP and FDEMATEL, for use in dynamic modeling of productivity. Future works in this chapter can be summarized in two parts. Firstly, the FAHP method that is developed in this research to perform expertise level assessment considers no dependency between the elements in the hierarchy (i.e., criteria and sub-criteria). For example, there is evident dependence between experience (criteria 1) and knowledge (criteria 2), as explored in behavioral studies (Duerden and Witt 2010). Hence, the FAHP method should be improved to consider the dependence between multiple criteria and/or sub-criteria using other approaches (e.g., fuzzy analytic network process). Secondly, the effect of varying threshold selection approaches (i.e., higher percentile thresholds, average of the elements in the matrix, expert inputs) while developing the CLD from the defuzzified values of the TRM, will also be explored in future studies.

7.4.3. Integration of FSD and FABM for Modeling of CLP

This research proposed a hybridization of FSD-FABM, which can capture the causalities between crew motivation, and situational/contextual factors that impact CLP and address subjective uncertainties in the predictive modeling process. The proposed model is capable of simulating the effect of variables with emerging behaviors (e.g., congestion, fatigue, crew motivation) using FABM, and capturing the overall dynamic system of construction environments using FSD. However, only crew motivation is studied in this research due to data availability constraints. In this regard, future studies will investigate the effect of congestion and crew movements on CLP to further demonstrate the potential of the proposed FSD-FABM. Future studies will also investigate the effect of fatigue on CLP of crews. The proposed FSD-FABM methodology is able to predict productivity at the project level by aggregating the productivity values obtained at the work package level. However, system variables at the higher level (i.e., project level situational/contextual factors, organization related factors) must first be assessed, and their feedback relationships must be incorporated in the current CLD. In this regard, future studies will define system variable relationships at the project level to provide a project-level prediction of productivity. Future studies will define system variable relationships at the project level to provide a project-level prediction of productivity. Moreover, the proposed model is capable to incorporate abstraction at lower levels by defining agents within the Workpackage and Crew agents to define smaller tasks, and individual crew members respectively. In this regard, the model should be extended to model individual crew members' behavior while performing their tasks, to propose a more accurate model. In the area of decision making, the proposed FSD-FABM should be used to propose strategies to improve the CLP measure. This can be achieved by combining the features of decision making approaches, such as MCDM with the FSD-FABM. Moreover, the proposed FSD-FABM should be hybridized with RL approach to propose a strategic, and automated decision-making scheme, that is capable of performing dynamic optimization to align with the dynamic nature of construction systems.

7.4.4. FSD-FABM-MCDM to Propose Productivity Improvement Strategies

This research proposed a methodology for the development of an FSD-FABM-MCDM, to address the need for decision support tools in construction, where decision making problems exist in a dynamic environment with subjective uncertainties. However, the model may not perform in different contexts. In the future, sensitivity analysis of the MCDM model component should be performed to analyze which alternatives have the most influence on the decision-making process. When AHP is used in decision-making, the effect of minor variations in the data (i.e., changes in an individual data point or minor variations in the weights of criteria) can have an influence on the ranking of inputs, and thereby on the strategies that are adopted at the company level. This should be studied in more detail by performing sensitivity analysis of the model, to variations in the input-data. The high sensitivity of AHP results to minor variations in data can cause problems, such as producing multiple interpretations in the way alternatives have been selected. Therefore, it is important to determine how sensitive the selected criteria be to the expert inputs, and to what extent the selected criteria are important. Furthermore, the applicability of the developed decision support model, to propose CLP improvement strategies should be validated with data from real construction project in other contexts (e.g., building construction) to ensure the model can be applied to develop strategies for CLP improvement in other sectors of the construction industry. In this research, the proposed FSD-FABM-MCDM was demonstrated to provide improvement strategies for overall crew performance. However, this is a general approach, and would not enable identification of improvement strategies specific to CLP. In the future, the developed model should be applied on a real construction project to assess the model's capabilities to propose CLP improvement solutions.

7.4.5. Reinforcement Learning to Propose Optimal Productivity Improvement Strategies

This research proposed a framework to which can provide optimization and dynamic simulation using RL-FSD-FABM technique. The proposed framework is capable of providing optimal productivity improvement solutions by performing optimization using RL, while the FSD-FABM simulates the construction environment. However, the proposed approach has some limitations. First, system variables affecting CLP were not incorporated to demonstrate the methodology, as more focus was given to presenting how the model works compared with other previous studies. Future research will implement the proposed framework on a real construction project, intended to optimize the predicted CLP. Second, the research is limited to addressing single-objective optimization problems, subject to single or multiple constraints. Optimization of multiple objectives using multiple RL-agents was not performed in this chapter. In future work, the proposed model should also be extended to perform multi-objective optimizations with more constraints which have direct relations with CLP, such as time, cost, and quality, by incorporating multi agent RL.

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Appendices

Appendix A. Survey to perform expert weight assessment

Instruction: Please assess the degree of importance of criterion ***I*** (**row**) over criterion ***j*** (**column**), using the linguistic terms provided.

Degree of Causal Relationship	Degree of importance between criteria for ranking of expertise	Acronym
Equally important	Criterion ***i*** and criterion ***j*** are **equally important**.	EI
Weakly important	Criterion ***i*** is **weakly important** than criterion ***j***.	WI
Fairly strong important	Criterion ***i*** is **fairly strong important** than criterion ***j***.	FSI
Very strongly important	Criterion ***i*** is **very strongly important** than criterion ***j***.	VSI
Absolutely important	Criterion ***i*** is **absolutely important** than criterion ***j***.	AI

PART 1: PAIRWISE COMPARISON FOR CRITERIA

No.	Criteria	Experience	Knowledge	Professional performance	Productivity-related project management practices	Project Specifics	Reputati on	Personal Attribut es and Skills
1	**Experience**	**EI**						
2	**Knowledge**		**EI**					
3	**Professional performance**			**EI**				
4	**Productivity-related project management practices**				**EI**			
5	**Project Specifics**					**EI**		
6	**Reputation**						**EI**	

7	**Personal Attributes and Skills**							**EI**

PART 2: PAIRWISE COMPARISON FOR SUB-CRITERIA

Criteria	**Sub-criteria**	**1.1 Total years of experience**	**1.2 Relevant experience**	**2.1 Academic knowledge**	**2.2 Education level**	**2.3 On the job training**	**..**	**7.1 Level of communication skills**	**7.2 Level of teamwork skills**	**7.3 Level of leadership skills**	**7.4 Level of analytical skills**	**7.5 Level of ethics**
Experience	1.1 Total years of experience	**EI**										
	1.2 Relevant of experience		**EI**									
Knowledge	2.1 Academic knowledge			**EI**								
	2.2 Education level				**EI**							
	2.3 On the job training					**EI**						

Criteria	Sub-criteria	1.1 Total years of experience	1.2 Relevant experience	2.1 Academic knowledge	2.2 Education level	2.3 On the job training	..	7.1 Level of communication skills	7.2 Level of teamwork skills	7.3 Level of leadership skills	7.4 Level of analytical skills	7.5 Level of ethics
..												
Personal Attributes and Skills	7.1 Level of communication skills							**EI**				
	7.2 Level of teamwork skills								**EI**			
	7.3 Level of leadership skills									**EI**		
	7.4 Level of analytical skills										**EI**	
	7.5 Level of ethics											**EI**

Appendix B. Survey to perform expert profiling, and assessment of causal interrelationships between crew motivation, and contextual/situational factors

PART 1: PROFILING OF EXPERTS

1) ***BACKGROUND***

1.1. Please indicate your position:

□ Construction Manager	□ Project Manager	□ Technical Coordinator
□ Contracts Administrator	□ Project Control	□ Other (please specify):
□ Field Engineer	□ Superintendent	________________________

1.4. How long have you worked in the stated occupation? ____ Year(s) ____ Month(s)

1.5. Current employer: ____

1.6. How long have you been employed by your current employer?

________ Year(s) _________ Month(s)

1.7. How long have you been employed by your current employer on this project?

________ Year(s) _________ Month(s)

1.9. Your demographic information:

Age: □ 20–30 □ 31–40 □ 41–50 □ 51–60 □ Over 60

Education (please select ALL categories that apply to you):

□ High school	□ Master's degree
□ Vocational or technical or trade school	□ Other (please specify): ____________
□ College diploma	__________________________________

□ Bachelor’s degree

1.9. Please indicate the number of courses/trainings taken in your current discipline: _________

2. <u>Productivity related project management practices:</u>

□ How many hours per week are you engaged in productivity-related work? ______________

□ Please indicate the number of certificates obtained from training sessions or workshops that can be applied to productivity management (e.g., lean construction, trainings, etc.) _________

□ Please indicate the number of conferences you attended that focused on productivity management practices (e.g., productivity tracking, productivity improvement, best practices in the industry etc.) _______________

□ Please rate your experience with developing and executing policies, procedures and practices related to productivity management; identification of factors affecting productivity, planning activities to manage productivity, mitigating problems contributing to productivity loss.

Scale	**Rating**
1	**NO** development and execution of policies, procedures and practices related to productivity management, **VERY POOR** identification of factors affecting productivity, **VERY POOR** planning of activities to manage productivity and mitigate problems contributing to productivity loss.
2	**NO** development and execution of policies, procedures and practices related to productivity management, **POOR** identification of factors affecting productivity, **POOR** planning of activities to manage productivity and mitigate problems contributing to productivity loss.
3	**SOME** development and execution of policies, procedures and practices related to productivity management, **FAIR** identification of factors affecting productivity, **FAIR** planning of activities to manage productivity and mitigate problems contributing to productivity loss.

Scale	Rating
4	**SOME** development and execution of policies, procedures and practices related to productivity management, **GOOD** identification of factors affecting productivity, **GOOD** planning of activities to manage productivity and mitigate problems contributing to productivity loss.
5	**DETAILED** development and execution of policies, procedures and practices related to productivity management, **VERY GOOD** identification of factors affecting productivity, **VERY GOOD** planning of activities to manage productivity and mitigate problems contributing to productivity loss.

3. __Project Specifics:__

□ Please indicate monetary value of the largest project you have worked on in current company__

□ Please indicate the percentage of projects finished on time by all projects you involved in____

□ Please indicate the percentage of projects finished on budget by all projects you have been involved in ___________________

□ Please indicate the number of projects you have worked in with zero incident rates __________

□ Please indicate number of different project locations that you have worked on _____________

4. __Reputation:__

□ Please indicate your perceived level of social acclimation by others based on the scale indicated below

1	**VERY LOW** social acclimation
2	**LOW** social acclimation
3	**AVERAGE** social acclimation
4	**HIGH** social acclimation
5	**VERY HIGH** social acclimation

□ Please indicate your attitude and willingness towards participating in research survey based on the scale indicated below

1	**COMPLETELY** Unwilling
2	**SOMEWHAT NOT** Willing
3	**SOMEWHAT** Willing
4	Willing
5	**COMPLETELY** Willing

□ Please indicate your perceived level of credibility of expert based on consistency and reasonableness (use of engineering judgement) of previous decisions based on the scale indicated below

1	**VERY INCONSISTENT** professional decisions and **VERY UNRESONABLE** professional decisions
2	**INCONSISTENT** professional decisions and **UNRESONABLE** professional decisions
3	**SOMEWHAT CONSISTENT** professional decisions and **SOMEWHAT RESONABLE** professional decisions
4	**CONSISTENT** professional decisions and **RESONABLE** professional decisions
5	**VERY CONSISTENT** professional decisions and **VERY RESONABLE** professional decisions

5. Personal Attributes and Skills

□ Please indicate your perceived level of communication skills based on the scale indicated below

1	**VERY POOR** interpersonal skills, **NO** eloquence, and **VERY POOR** vertical communication
2	**POOR** interpersonal skills, **NO** eloquence and **POOR** vertical communication

3	**AVERAGE** interpersonal skills, **SOME** eloquence, and **AVERAGE** vertical communication
4	. **GOOD** interpersonal skills, **CLEAR** eloquence, and **GOOD** vertical communication
5	**VERY GOOD** interpersonal skills, **CLEAR** eloquence, and **VERY GOOD** vertical communication

□ Please indicate your perceived level of teamwork skills based on the scale indicated below

1	**VERY INACTIVE** team member and **NO** contribution to team's goals
2	**INACTIVE** team member and **NO** contribution to team's goals
3	**AVERAGE ACTIVE** team member and **SOME** contribution to team's goals
4	**ACTIVE** team member and **FAIR** contribution to team's goals
5	**VERY ACTIVE** team member and **FAIR** contribution to team's goals

□ Please indicate your perceived level of leadership skills based on the scale indicated below

1	**VERY POOR** training, **NO** support tools to team members, **VERY POOR** communication of objectives and progress, **COMPLETELY** Unwilling to mentor
2	**POOR** training, **NO** support tools to team members, POOR communication of objectives and progress, **SOMEWHAT NOT** Willing to mentor
3	**AVERAGE** training, **SOME** support tools to team members, **AVERAGE** communication of objectives and progress, **SOMEWHAT** Willing to mentor
4	**GOOD** trainings, **FAIR** support tools to team members, **GOOD** communication of objectives and progress, Willing to mentor
5	**VERY GOOD** training, **FAIR** support tools to team members, **VERY GOOD** communication of objectives and progress, **COMPLETELY** Willing to mentor

□ Please indicate your perceived level of analytical skills based on the scale indicated below

1	**VERY POOR** anticipation and **VERY POOR** identification of problems
2	**POOR** anticipation and **POOR** identification of problems

3	**AVERAGE** anticipation and **AVERAGE** identification of problems
4	**GOOD** anticipation and **GOOD** identification of problems
5	**VERY GOOD** anticipation and **VERY GOOD** identification of problem

□ Please indicate your perceived level of ethics based on the scale indicated below

1	**VERY POOR** compliance to legal and regulatory framework, and **VERY POOR** level of morality
2	**POOR** compliance to legal and regulatory framework, and **POOR** level of morality
3	**AVERAGE** compliance to legal and regulatory framework, and **AVERAGE** level of morality
4	**GOOD** compliance to legal and regulatory framework, and **GOOD** level of morality
5	**VERY GOOD** compliance to legal and regulatory framework, and **VERY GOOD** level of morality

PART 2: CAUSAL INTERRELATIONSHIP ASSESSMENT OF THE FACTORS

Instruction: Please assess the degree of causal influence of factor ***i*** (**row**) over factor ***j*** (**column**), using the linguistic terms provided.

Degree of Causal Relationship	Degree of Causal Relationship between factors affecting Crew Performance
No	No causal influence
Very Low	The degree of causal influence of factor ***i*** over factor ***j*** is **Very Low**
Low	The degree of causal influence of factor ***i*** over factor ***j*** is **Low**
Medium	The degree of causal influence of factor ***i*** over factor ***j*** is **Medium**
High	The degree of causal influence of factor ***i*** over factor ***j*** is **High**
Very High	The degree of causal influence of factor ***i*** over factor ***j*** is **Very High**

FACTOR ID	Factors affecting Crew Performance	1.1 Task repetition	1.2 Task identity	1.3 Visibility of outcome	.	.	.	6.8 Temperature	7.1 Safety procedures	7.2 Safety trainings
1.1	Task repetition	**No**								
1.2	Task identity		**No**							
1.3	Visibility of outcome			**No**						
1.4	Rework									
2.1	Crew composition									
2.2	Crew experience									
2.3	Ability to perform									
2.4	Material handling									
2.5	Hazards identification & mitigation									
2.6	Teamwork									
2.7	Reliability									
2.8	Crew motivation									
3.1	Foreman knowledge									
3.2	Foreman experience									
3.3	Safety facilitation and implementation									

FACTOR ID	Factors affecting Crew Performance	1.1 Task repetition	1.2 Task identity	1.3 Visibility of outcome	.	.	.	6.8 Temperature	7.1 Safety procedures	7.2 Safety trainings
3.4	Performance monitoring									
3.5	Communication									
3.6	Goal-setting (crew level)									
3.7	Change in weather conditions									
4.1	Work progress									
5.1	Project scheduling									
5.2	Safety management									
5.3	Fairness									
5.4	Goal-setting (project level)									
5.5	Project time management									
5.6	Project cost management									
5.7	Project safety management									
5.8	Project environmental management									

FACTOR ID	Factors affecting Crew Performance	1.1 Task repetition	1.2 Task identity	1.3 Visibility of outcome	.	.	.	6.8 Temperature	7.1 Safety procedures	7.2 Safety trainings
6.1	Location of washrooms									
6.2	In-site transportation									
6.3	Cleanness									
6.4	Congestion									
6.5	Noise									
6.6	Pollution									
6.7	Access points									
6.8	Temperature							**No**		
7.1	Safety procedures								**No**	
7.2	Safety trainings									**No**

Appendix C. List of Identified Factors for Survey Administration

1) ***LABOUR AND CREW-RELATED:***

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
2.1	Crew size is adequate for the task at hand.											
2.2	Crew is given adequate training before project or work package start											
2.3	Crew is experienced and has the necessary technical skills to perform the tasks.											
2.4	Crew has a well-balanced composition (Journeymen and Apprentices).											
2.5	Work is fairly assigned between crews.											
2.6	Crew team spirit is high.											
2.7	Efforts are taken to minimize crew turnover.											
2.8	Craftspeople's skills are fully utilized.											
2.9	Craftspeople trust the skills and judgment of their supervisors.											
2.10	Craftspeople are always involved in decision-making process.											
2.11	Performance of craftspeople is regularly evaluated.											
2.12	Clear goals are given to crafts.											
2.13	There is a good cooperation between craftspeople.											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
2.14	Craftspeople are flexible in accommodating task changes.											
2.15	This crew has experience working in project conditions similar to the current project.											
2.16	Changes are effectively communicated to craftspeople.											
2.17	Crew members are highly motivated to complete their tasks.											
2.18	There are few unscheduled breaks during work hours.											
2.19	The high crew size is well-managed to avoid crowding.											
2.20	Craftspeople have shown acceptable learning speed.											
2.21	For new craftspeople, job site orientation program is carried out.											
2.22	In this project, craftspeople have acceptable job security.											
2.23	This crew is a close one.											
2.24	The members of this crew feel confident that they can successfully perform difficult tasks.											
2.25	The members of this crew can usually concentrate on performing the tasks.											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
2.26	The members of this crew strongly identify with the other members of the crew.											
2.27	The members of this crew feel a strong sense of "belonging" to this company.											
2.28	The members of this crew are efficient in using materials to perform their tasks.											
2.29	I feel confident that I can successfully perform difficult tasks.											
2.30	I strongly identify with the other members of my crew.											
2.31	I feel a strong sense of "belonging" to my company.											

List other ***labour and crew related*** factors that affect productivity and evaluate each of them on the same scales.

2) ***MATERIALS AND CONSUMABLES:***

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
3.1	Material is always delivered on time.											
3.2	Delivered materials are always of high quality.											
3.3	Temporary material storage areas are properly planned.											
3.4	There is a reporting system for tracking material shortages											
3.5	Consumables (e.g., nails, duct tape, drill bits, blades) are adequately provided											
3.6	A clear process is laid out for crewmembers whereby they can easily and timely get consumables.											
3.7	Work package documents include the material list.											
3.8	Material unloading practices are effective.											
3.9	Material movement practices are well planned											

List other ***materials and consumables*** factors that affect productivity and evaluate each of them on the same scales.

3) ***EQUIPMENT AND TOOLS:***

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
4.1	Work equipment is readily available.											
4.2	Transport equipment is readily available.											
4.3	The frequency of equipment breakdown is low.											
4.4	Delays that occur in obtaining equipment after it breaks down are low.											
4.5	There is sufficient supply of critical work-tools (e.g., pipe cutters, welding machines).											
4.6	The work (powered) tools are of desired quality.											
4.7	The tool room attendant is efficient in delivering tools in timely fashion.											
4.8	Tools are seldom misplaced, avoiding wasted time in locating them.											
4.9	There are no interruptions due to power outage.											
4.10	Extension cords are readily available.											
4.11	Quality maintenance of tools is performed.											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
4.12	Equipment operators have the necessary experience and skills for the job											
4.13	Equipment operators get the necessary training where and when required											

List other ***equipment and tools*** factors that affect productivity and evaluate each of them on the same scales.

4) TASK-RELATED:

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
5.1	The scope of the tasks (i.e., total work volume) is appropriate.											
5.2	In this project, the tasks are repetitive.											
5.3	The construction methods used for the different project tasks are appropriately selected for the project conditions.											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
5.4	Frequency of requests for information (RFIs) in this project is low.											
5.5	Rework usually requires less time and effort.											
5.6	There is a good balance between the crew size and available equipment for the current task.											
5.7	Tasks that this crew is performing have a significant impact on the work of others (i.e., task significance is high).											
5.8	The level of interruption while performing tasks is low.											
5.9	Members of this crew have a high degree of freedom in scheduling their tasks.											
5.10	The members of this crew have a high degree of freedom in selecting the procedures to be used in carrying out their tasks.											
5.11	The waste-disposal process has little/no impact on productivity.											
5.12	The frequency of reworks due to contractor's fault is low											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
5.13	In this project, the types of reworks are very similar.											
5.14	In this project, the types of tasks are very labour intensive.											
5.15	In this project, performing the tasks requires various skills											

List other ***task-related*** factors that affect productivity and evaluate each of them on the same scales.

5) <u>LOCATION-RELATED:</u>

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
6.1	The project site has the necessary space for completing tasks without limiting crew size or type of equipment that may be used.											
6.2	Site restrictions do not affect the project progress											
6.3	Measures are taken to minimize weather (temperature, wind, humidity, precipitation) effects.											
6.4	Noise level of equipment and activities is at the appropriate level											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
6.5	The level of air pollution (e.g. dust and fumes) is at an appropriate level in the work area.											
6.6	Work area is usually not congested.											
6.7	Work area is usually clean.											
6.8	Conditions of site facilities (e.g. lunchrooms) are appropriate.											
6.9	Facilities (e.g., offices, recreation places) are provided for crew members to rest during shift breaks											

List other ***location related*** factors that affect productivity and evaluate each of them on the same scales.

6) ***ENGINEERING AND INSTRUCTIONS:***

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
7.1	Drawings and specifications are made available well ahead											
7.2	Drawings and specifications are often complete, and the frequency of revisions is low											
7.3	Engineering department responds in a timely manner to inquiries.											
7.4	The information required to perform tasks can be easily derived from drawings and specifications.											
7.5	The waiting time for inspections is acceptable.											

List other ***engineering and instructions*** factors that affect productivity and evaluate each of them on the same scales.

7) SAFETY:

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
8.1	The project working conditions are safe.											
8.2	Proper Personal Protective Equipment (PPE) is used on site											
8.3	Project safety plans are properly executed.											
8.4	Safety incidents are rare on this project.											
8.5	Safety procedures are uniform among different crews.											
8.6	There is a good culture of project safety planning, administration and reporting in the project.											
8.7	The crew is provided with the appropriate PPE.											
8.8	The project team is provided with appropriate safety training.											
8.9	Daily job hazard assessment forms are filled-in properly.											

List other ***safety*** factors that affect productivity and evaluate each of them on the same scales.

8) PROJECT MANAGEMENT PRACTICES:

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
9.1	Initial project planning practices (e.g., detailed front-end planning, constructability review, etc.) have led to increased productivity											
9.2	Time management: Work packages in this project are properly defined, planned, scheduled, and assigned to workers.											
9.3	Quality management: Quality requirements are identified and planned.											
9.4	Quality management: Quality control is practiced properly.											
9.5	Communications management: There is good communication among the supervisory team members.											
9.6	Communications management: There is appropriate communication among the different crews and trades at the project site.											

9.7	Scope management: Project scope is properly defined and verified.											
9.8	Scope management: Project scope is properly updated and captures project changes.											

List other ***project management practices*** factors that affect productivity and evaluate each of them on the same scales.

9) PROJECT NATURE AND PROJECT CONDITIONS:

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
10.1	Project complexity is low.											
10.2	There is adequate support and administrative staff for the project.											
10.3	The level of paperwork needed for work approval in the project is low.											
10.4	The project camp (if available) is in good condition.											
10.5	There are an adequate number of parking spots within close distance to the project site.											
10.6	Proper project site access planning contributed to increased project productivity.											

No.	Factor	N/A	Agreement					Impact on Productivity				
			Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*	*Strongly Negative*	*Negative*	*No Impact*	*Positive*	*Strongly Positive*
10.7	The project site is located far from urban areas.											
10.9	Congestion in the project site is low.											
10.10	Daily working hours are long and cause physical/mental fatigue for the workers.											
10.11	The working cycle (number of consecutive days on the job) is long and causes physical/mental fatigue for the workers.											
10.12	Project level rework frequency is low on this project.											

List other ***safety*** factors that affect productivity and evaluate each of them on the same scales.

Appendix D. System Variables for the FSD-FABM

System variable	Description	Type (Endo vs Exo)	Type (Subjective vs Objective)
Task repetition	Percentage (% No. of identical tasks in work package to total No. of tasks in work package)	Endogenous	Objective
Task identity	Rating - To what extent do crews identify with the tasks at hand	Endogenous	Subjective
Visibility of outcome	Rating - To what extent does performing the tasks provide crew members with visibility of the outcomes of the work.	Endogenous	Subjective
Rework	The measure of the total reworked volume in relation to the total volume of work.	Endogenous	Objective
Crew composition	The ratio of journeyman to apprentice	Endogenous	Objective
Crew experience	Number (Average years of experience in current position)	Endogenous	Objective
Crew motivation	Motivation of the crews performing the task at hand.	Endogenous	Objective
Baseline productivity	Best productivity observed while performing similar tasks.	Exogenous	Objective
Ability to perform	Rating - Ability of the crew to perform tasks	Endogenous	Subjective
Material handling	Rating - Ability of the crew to move, protect, and/or store materials throughout the construction process.	Endogenous	Subjective
Hazards identification & mitigation	Rating - Using daily job Hazard assessment forms, and mitigation of identified hazard.	Endogenous	Subjective
Teamwork	Rating - Putting team objectives over own personal interests.	Endogenous	Subjective
Reliability	Rating - The crew member can be relied on to perform tasks.	Endogenous	Subjective
Foreman knowledge	Rating - Knowledge of work methods, procedures, and requirements	Endogenous	Subjective

System variable	Description	Type (Endo vs Exo)	Type (Subjective vs Objective)
Foreman experience	Number (years of experience in current position)	Endogenous	Objective
Safety facilitation and implementation	Rating - Knowing, understanding, communicating and ensuring compliance with safety regulation; Providing answers to safety related questions; Participating and completing safety incident reports.	Endogenous	Subjective
Performance monitoring	Rating - Assessing competency and capability of crew members to meet quality requirements.	Endogenous	Subjective
Communication	Rating - Forman's communicating to and with crew.	Endogenous	Subjective
Goal-setting	Rating - Clarity in and specificity in assignment of goals.	Endogenous	Subjective
Change in weather conditions	Rating - changes in weather conditions during daily work.	Endogenous	Subjective
Work progress	Amount of work performed per unit time.	Endogenous	Objective
Project scheduling	Rating - Scheduling of work packages.	Endogenous	Subjective
Safety management	Rating - Knowing, understanding, communicating and ensuring compliance with safety regulation; Providing answers to safety related questions	Endogenous	Subjective
Fairness	Rating - Consistency (same policy), Reasonableness (use of common sense)	Endogenous	Subjective
Project time management	Rating - Development execution, and monitoring of Project Schedule	Endogenous	Subjective
Project cost management	Rating - Development and monitoring of project cost estimates; identifying project budget; and development and monitoring of Project Cash Flow	Endogenous	Subjective
Project safety management	Rating - Development, execution, and monitoring of safety plan; identifying safety requirements; and conducting safety trainings	Endogenous	Subjective

System variable	Description	Type (Endo vs Exo)	Type (Subjective vs Objective)
Project environmental management	Rating - development, execution, and monitoring of environmental management system; providing required legal permits; and performing of Environmental Impact Assessment	Endogenous	Subjective
Location of washrooms	Real number (average distance, m)	Endogenous	Objective
In-site transportation	Integer (Number of transportation vehicle on site)	Endogenous	Subjective
Cleanness	Integer (Number of cleaning operations per week)	Endogenous	Subjective
Congestion	Real Number (number of people per 100 square meter in working area)	Endogenous	Subjective
Noise	Rating - Noise sources (equipment's); Intrusiveness of noise; Voice levels in normal conversation	Endogenous	Subjective
Pollution	Rating - Dust and fume source; Level of exposure; Length of exposure	Endogenous	Subjective
Access points	Integer (number of access points to working area)	Endogenous	Objective
Temperature	Real number (˚C)	Exogenous	Objective
Safety procedures	Rating - Development and implementation of safety procedures	Endogenous	Subjective
Safety trainings	Rating - Conduction of safety trainings	Endogenous	Subjective
Work to do	Number- Measurement of Work planned to be executed by the crews	Exogenous	Objective
Crew productivity	Number-Ratio of work performed (units) per worked hours (person hours)	Endogenous	Objective
Fatigue	Rating- Exhaustion of crew members resulting from mental or physical exertion	Endogenous	Subjective
Daily work hours	Number - Planned hours allocated for crews to perform their activities.	Exogenous	Objective