Prioritizing Labour Productivity Improvement Strategies by Integrating Hybrid Feature Selection, Fuzzy Multi-Criteria Decision-Making, and Fuzzy Cognitive Maps

by

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Abstract

Construction labour productivity (CLP), as a key performance index in the construction sector, is affected by various factors such as crew motivation and working conditions that are highly interconnected and vary on a project-by-project basis. CLP can be enhanced by properly practicing appropriate improvement strategies in terms of cost, duration, feasibility, and adaptability. Understanding factors that affect labour productivity is important for making strategic decisions and selecting appropriate CLP improvement strategies. However, identification of most-value-adding CLP factors is a challenging task, because CLP is situated in a high-dimensional feature space where a number interconnected quantitative factors (e.g., temperature) and qualitative factors (e.g., team spirit of crew) affect CLP directly or indirectly. Therefore, a research gap exists regarding methods for identifying the key factors affecting CLP by considering the dynamics, interconnection, and combined impact of the factors without dependency on expert knowledge. Another challenging task in the process of selecting improvement strategies is that budget, time, and resource restrictions force companies to implement only a limited number of CLP improvement strategies. Therefore, research gaps exist with respect to a model's ability to support selection and implementation of optimal CLP improvement strategies for a given project by quantifying the effect of strategies on CLP while simultaneously considering causal relationship among factors affecting CLP and project characteristics.

To bridge the existing gaps, this thesis aims at proposing a novel framework for prioritizing CLP improvement strategies by combining two models. First, a hybrid feature selection model is proposed to identify the most value-adding CLP factors for a given project based on the interconnection of CLP factors without dependency on expert knowledge. Second, a decision-support model is proposed for integrating fuzzy multi-criteria decision-making and fuzzy cognitive maps in order to rank CLP improvement strategies based on their impact on CLP, causal relationships among CLP factors, and project characteristics. The top three factors most influential on CLP include: (1) fairness of work assignment, (2) complexity of task, and (3) repetitiveness of task. The top three most effective CLP improvement strategies for concrete-pouring activities in building projects include: (1) providing clear instructions to craftspeople on how to complete tasks before their execution, (2) training labourers to achieve the latest concrete-pouring techniques, and (3) applying preventive maintenance to heating and air-conditioning systems to make sure they are in working order. The contribution of this study is to provide a systematic approach for identifying the most-value adding CLP factors and analyzing and selecting practical CLP improvement strategies by modeling the relationships among the key factors affecting CLP and quantifying the effect of various strategies on CLP. The findings of this study are expected to support construction practitioners in identifying influential CLP factors and effective improvement strategies to enhance the level of CLP in construction projects.

Preface

This thesis is an original work by Matin Kazerooni. Chapter 3 has been submitted for publication as Ebrahimi, S.; Kazerooni, M.; Sumati, V.; Fayek, A. R. (n.d.). "A Predictive Model for Construction Labour Productivity Using the Integration of Hybrid Feature Selection and PCA Methods," in review, submitted to *Canadian Journal of Civil Engineering*. Chapter 4 has been submitted for publication as Kazerooni, M.; Nguyen, P.; Fayek, A. R. (n.d.). "Prioritizing Construction Labour Productivity Improvement Strategies using Fuzzy Multi-Criteria Decision-Making and Fuzzy Cognitive Maps," in review, submitted to *Algorithms*. I was responsible for the major parts of the data collection, analysis, and composition of the manuscript. A. R. Fayek was the supervisory author and was involved with concept formation and manuscript composition and editing.

Dedication

I dedicate this research to my beautiful kind mother, who is always with me.

Acknowledgements

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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1. Background

The construction industry is one of the most important sectors in the economic development of a country. It contributes about 10% to the economy of various countries, providing employment to many people and acting as a link between the economy and other industries (Dixit et al. 2018). Thus, sustaining construction productivity is essential to economic growth (Barbosa et al. 2017). Based on Gouett et al. (2011), the most widely used construction productivity metrics include (1) unit rate (ratio of installed quantity of output to labour cost); (2) construction labour productivity (CLP) (ratio of installed quantity of output to labour work-hours); and (3) productivity factor (ratio of scheduled hours to actual work hours). Labour is a determinant resource in the construction sector, as many construction activities are labour dependent. Therefore, CLP as the most commonly used single-factor productivity measure has significant impact on the performance and profitability of construction projects (Heravi and Eslamdoost 2015; Kazaz 2016). Accordingly, this thesis focuses on CLP, which is defined as the ratio of units of output, expressed as installed quantity (in cubic meters), to units of input, expressed as total labour work-hours, and shown in Equation (1.1). The objective of measuring CLP is to obtain higher CLP values.

$$CLP = \frac{Output\ (Installed\ quantity)}{Input\ (labor\ work\text{-}hours)} \tag{1.1}$$

Because of the significant impact of CLP on time, cost, and quality of a construction project, improving CLP is pivotal for enhancing the overall performance of construction projects in multiple areas, such as reducing variances from the primary plan and keeping projects on time and within budget (Ghodrati et al. 2018). Therefore, construction companies require implementation of various CLP improvement strategies to enhance the level of factors influencing CLP and consequently improve CLP (Shan et al. 2016). In this thesis, a CLP improvement strategy is an individual management practice - working method, tactic or innovation - that construction managers use to improve CLP of their projects. Some examples of CLP improvement strategies include performing weekly reviews of crew compositions to ensure crew mix is per plan, providing clear instructions to craftspeople on how to complete tasks prior to execution, and scheduling regular inspections by the owner team to reduce interventions during project execution. However, budget, time, and resource constraints force construction companies to carry out only a limited number of CLP improvement strategies (Kazerooni et al. 2020). In addition, CLP is situated in a complex environment where it is either directly or indirectly affected by numerous objective and subjective factors (e.g., crew size, crew composition, crew motivation, working conditions, complexity of task, co-operation among craftsperson, location of work scope, weather condition). Also, the affecting factors are mostly interconnected and vary on a project-by-project basis (Tsehayae and Fayek 2016). Thus, actual impact on CLP can be only obtained by using a systematic approach that models the relationships among CLP factors (Caldas et al. 2015). However, most construction companies apply management practices, such as changing working times and switching workweek, based on the experience and knowledge of their managers (Shan et al. 2016).

Understanding the key factors that affects labour productivity is important for making strategic decisions and selecting appropriate CLP improvement strategies (Jalal and Shoar 2019). The factors that affect CLP are multi-level, ranging from the activity level to the project, national, and global levels (Gerami Seresht and Fayek 2019). Therefore, different opinions of the personnel of a construction company (e.g., project managers, craft workers, foremen) should be captured in order to determine the importance of CLP factors for CLP improvement (Tsehayae and Fayek 2014). Many previous studies have attempted to identify the key factors that affect CLP (Heravi and Eslamdoost 2015; Raoufi and Fayek 2018; Alaghbari et al. 2019; Johari and Jha 2020). Among these studies, the dominant method for ranking CLP factors is relative importance index (RII) (Kazaz et al. 2016; Jalal and Shoar 2019). Van Tam et al. (2021) identified 45 critical CLP factors that were ranked by collecting 203 samples from project managers and contractors using a survey questionnaire. Almamlook et al. (2020) developed a questionnaire containing 30 factors affecting CLP in Libya. Their results indicated that "Lack of labour supervision" and "Experience and skill of labour" are the most significant factors affecting CLP in Libyan construction projects. Alaghbari et al. (2019) structured a survey questionnaire of 52 predefined factors that were categorized into four primary groups: human/labour; management; technical and technological; and external. The identified groups and factors were then ranked using RII method.

Compared to CLP factor identification, very few studies have been conducted on identifying key CLP improvement strategies. According to the provided literature review, most techniques proposed for selecting key CLP improvement strategies, such as statistical models, are not able to quantify the impact of strategies on CLP. However, to effectively improve CLP, it is necessary to know the extent to which implemented improvement strategies affect CLP. Statistical methods are among the most widely used techniques for quantifying the impact of various strategies on CLP improvement, for example t-test and regression analysis (Ghodrati et al. 2018; Shan et al. 2016). The major limitation of statistical methods is their inability to capture causal relationships among CLP factors, improvement strategies, and CLP. In addition, statistical methods are not able to consider project characteristics. However, key CLP improvement strategies differ from one project to another. Consequently, investigating the relationship among key CLP factors and strategies and determining the impact of each strategy on CLP are crucial for prioritizing appropriate CLP improvement strategies for a given project.

1.2. Problem Statement

To select the most effective CLP improvement strategies, it is necessary to identify the key factors that affect CLP. However, identification of key CLP factors is a challenging task since CLP is set in a high-dimensional feature space where a number of interconnected factors directly or indirectly affect CLP. The importance of CLP on the performance of construction projects has prompted extensive research on the identification of key CLP factors. The majority of previous studies have relied on expert knowledge collected through questionnaire surveys to establish key factors that affect CLP, using evaluation index methods such as RII. Very few studies have attempted to identify the relative importance of CLP factors through the use of a data-driven approach such as correlation analysis or feature selection (Moselhi and Khan 2012). Data-driven approaches are not dependent on expert knowledge and consider the dynamics of CLP factors and the interconnected relationships among them. Commonly used data-driven approaches include statistical methods such as regression analysis or correlation-based feature selection, which are limited by the number of influencing factors and their capability to determine the combined impact of the influencing factors (Song and AbouRizk 2008). Therefore, the **first gap** related to identification of factors affecting CLP in the current construction literature is considering the dynamics, interconnection, and combined impact of these factors using a model that is not dependent on expert knowledge.

To achieve optimum productivity for projects, it is pivotal for management teams to identify the most effective CLP improvement strategies. Although several studies have been conducted on identifying key CLP improvement strategies in the construction domain, only a few attempted to quantify the impact of improvement strategies on CLP, and they relied on statistical methods, such as regression analysis and t-test. The **second gap** is that the applied statistical methods in previous studies did not consider the causal relationship among CLP improvement parameters, which are the affecting factors, improvement strategies, and CLP. CLP factors are mostly interconnected and affect each other. Thus, it is necessary to consider causal relationships among factors and strategies to achieve accurate values for the quantified impact of strategies on CLP. The **third gap** is that most previous studies did not consider a given project's characteristics when selecting CLP improvement strategies; they selected key improvement strategies based on previous research. However, CLP is a context-specific efficiency measure, as the identified factors and their degree of impact on CLP vary from project to project (Heravi and Eslamdoost 2015; Tsehayae and Fayek 2016). Therefore, key CLP improvement strategies also differ from one project to another, and a systematic approach is needed to capture project characteristics and construct the cause-and-effect relationships among CLP improvement parameters in order to identify the most effective CLP improvement strategies.

1.3. Research Objectives

The overall goal of this thesis is to develop a decision-support model for identifying the most effective CLP improvement strategies for a given project and quantify their impact on CLP by developing a decision-support model that integrates feature selection, fuzzy multi-criteria decision-making (fuzzy MCDM), and fuzzy cognitive maps (FCM). To achieve this overall goal, this thesis had the following detailed modelling objectives:

1. Identify the most value-adding factors affecting CLP by using a hybrid combination of two types of feature selection methods, namely filter and wrapper methods.
2. Identify the most effective CLP improvement strategies based on strategies selection criteria such as implementation feasibility, impact on CLP, implementation risk, and workers adaption by using fuzzy MCDM methods.
3. Quantify the impact of the most CLP effective improvement strategies by developing an FCM model that considers causal relationships among the most value-adding CLP factors as well as project characteristics.

1.4. Expected Contributions

This thesis is intended to provide contributions that will positively impact the selection of appropriate strategies for improving labour productivity of construction projects. Results of the thesis are expected to make several contributions to (1) the body of knowledge (Academic contributions) and (2) practitioners (Industrial contributions).

1.4.1. Academic Contributions

The expected academic contributions of this research are:

- Development of a combination of filter and wrapper methods as a hybrid feature selection (HFS) method for identifying the most value-adding factors that affect CLP.
- Development of a list of appropriate CLP improvement strategies that correspond to addressing the identified most value-adding CLP factors.
- Development of a ranking process for CLP improvement strategies with respect to various criteria by integrating fuzzy MCDM methods in order to determine the most effective CLP improvement strategies.
- Development of an FCM model that takes into account the imprecision and uncertainty of CLP factors in order to capture the causal relationships among CLP factors and quantify the impact of selected improvement strategies.

1.4.2. Industrial Contributions

The expected industrial contributions of this research are:

- Identification of the most value-adding factors affecting CLP, which helps construction companies accurately predict CLP and identify the corresponding improvement strategies that address identified CLP factors.
- Identification of the most effective CLP improvement strategies and quantification of their impact on CLP, which helps construction management teams allocate limited budget and resources to strategies that have the greatest positive impact on CLP.
- Development of a systematic approach for simulating the impact of various management practices on CLP for projects prior to their implementation. This helps construction companies avoid applying those management practices that have only subtle impact on CLP for a given project.

1.5. Research Methodology

The objectives of this thesis are achieved in three main stages of the proposed framework as shown in Figure 1.1 and described below.

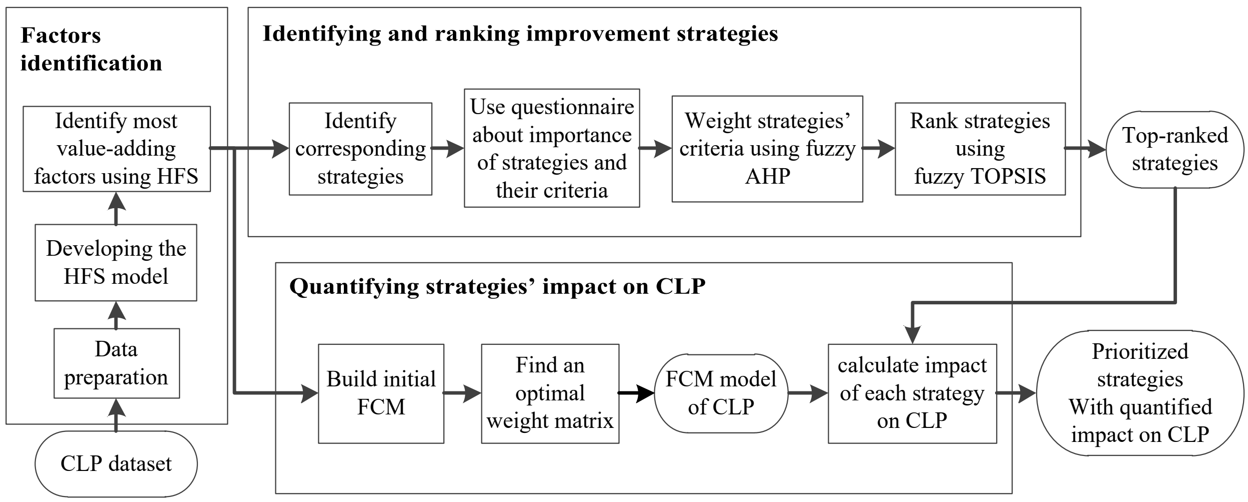

Figure 1.1. Framework for prioritizing CLP improvement strategies

1.5.1. The first stage: Factors and strategies identification

The first step in developing a CLP model and strategies selection is to determine the relevant factors that affect CLP within the studied context. Accordingly, for the purpose of this research, the most value-adding CLP factors are identified using the empirical data collected in a previous study by Tsehayae and Fayek (2014, 2016). First, the collected data are exposed to various preparation processes (i.e., normalization, removing useless factors, imputing missing values, and eliminating outliers) that transform the CLP data into a more informative form in order to make CLP modeling and analysis more efficient. Then, in order to determine the most value-adding CLP factors, an HFS model is developed by integrating a filter feature selection method with a wrapper feature selection method.

1.5.2. The second stage: Strategies ranking

After identifying the most influential CLP factors, an extensive literature review of past studies is carried out to identify various CLP improvement strategies that correspond to the determined key factors and have the potential to improve CLP. The most appropriate strategy among the identified potential strategies is then determined for addressing each CLP factor using knowledge from three experts involved in the project under study. Thereafter, the identified strategies are exposed to a ranking process with respect to four qualitative criteria: impact on CLP, implementation feasibility, workers adaptation, and implementation risk. Due to advantages of fuzzy MCDM in dealing with qualitative criteria, the two widely used fuzzy MCDM methods of fuzzy analytic hierarchy process (fuzzy AHP) and fuzzy technique for order of preference by similarity to ideal solution (fuzzy TOPSIS) are integrated in order to rank the CLP improvement strategies per the mentioned criteria. The main advantages of these methods are that they mathematically represent uncertainty and vagueness in the decision-making process without involving cumbersome mathematics (Kahraman et al. 2004). Fuzzy AHP is used to determine the relative weights of SSCs based on fuzzy pairwise comparison, and fuzzy TOPSIS is applied to rank the strategies by determining the relative importance of each strategy. The inputs of the proposed decision-making methods are achieved by using two questionnaire surveys.

1.5.3. The third stage: Strategies modeling

An FCM model of CLP is developed for simulating the relationships among the most value-adding CLP factors and quantifying the impact on CLP of the selected top-ranked improvement strategies. FCM is a soft computing technique for modeling and simulating dynamic systems such as a CLP environment by mimicking the process of developing a cognitive map in a human mind (Ahn et al. 2015). When no expert is available or there is a large number of relationships within the model, an FCM cannot be developed through the manual process of using expert knowledge (Kokkinos et al. 2018). For such cases, learning processes can be applied to automatically determine near-optimal weights of the relations. The algorithms of FCM learning can be grouped into three types based on their underlying learning paradigm: (1) Hebbian-based, (2) error-driven, and (3) hybrid. A hybrid learning algorithm is developed in this research, since hybrid learning algorithms employ a combination of the first two FCM learning algorithms to take advantage of the fast speed and effectiveness of Hebbian-based methods and the global search and generalization ability of error-driven methods (Ren 2012). Using the developed learning algorithm, the impact of the strategies most effective on CLP is quantified and the strategies are prioritized accordingly. Finally, the developed model is evaluated using (1) structural validity, which evaluates the list of model parameters, and (2) extreme-conditions test that compares the generated behavior of CLP in the FCM model to the behavior of the real system of CLP under the same extreme conditions of CLP factors.

1.6. Thesis Organization

Chapter 1 provides background information on CLP research and identifies the gaps in the CLP research regarding selecting CLP factors and improvement strategies. This chapter also presents the research objectives, expected academic and industrial contributions, and research methodology of the thesis.

Chapter 2 presents an extensive literature review on the relevant topics, including identification of the factors influencing CLP, identification of CLP improvement strategies, and the utilized methods for quantifying the impact of strategies on CLP.

Chapter 3 presents the methodology of the proposed HFS model, which contains (1) CLP dataset overview, (2) data preparation, and (3) hybrid feature selection in order to identify the most value-adding CLP factors.

Chapter 4 presents the developed decision-support model for ranking CLP improvement strategies and quantifying their impact on CLP. The model integrates fuzzy AHP and fuzzy TOPSIS methods with an FCM model of CLP.

Chapter 5 describes the conclusions, contributions, and limitations of the study as well as recommendations for future research.

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Chapter 2. Literature Review

2.1. Identification of Factors that Affect CLP

Due to the importance of labour productivity in the overall performance of construction projects, a significant amount of research has been conducted to determine the most influential CLP factors and improve CLP (Heravi and Eslamdoost 2015; Raoufi and Fayek 2018; Alaghbari et al. 2019; Kedir et al. 2019). The factors that influence CLP are multi-level, ranging from the activity level to the organizational, national, and global levels (Tsehayae and Fayek 2014; Gerami Seresht and Fayek 2019). Therefore, different perspectives of project personnel (e.g., project managers, supervisors, craft workers, and foremen) are required to assess the importance of each factor in improving CLP. Several studies incorporated the opinions of different project participants through interview and questionnaire surveys and categorized the CLP factors under different groups. For example, Van Tam et al. (2021) identified 45 critical CLP factors categorized into 5groups including "Manpower," "Management," "Work condition," "Project," and "External." The factors were then ranked by collecting 203 samples from project managers and contractors who completed a survey questionnaire based on their previous participation in construction projects. Almamlook et al. (2020) developed a questionnaire containing 30 factors affecting CLP in Libya. Their results indicated that "Lack of labour supervision" and "Experience and skill of labour" are the most significant factors affect CLP in Libyan construction projects. Alaghbari et al. (2019) categorized 52 factors under four groups, "Human labour," "Technical and technological," "External," and "Management." The factors and the groups were then ranked per the opinions of experts from various construction positions. Kazaz et al. (2016) attempted to capture the perspectives of craft workers regarding about 37 CLP factors using a questionnaire survey. The factors were grouped under four categories and ranked according to their importance levels. Tsehayae and Fayek (2014) gathered 169 CLP factors from existing literature related to North American construction projects and investigated their influence on CLP by developing a protocol for collecting data from several construction companies. They not only focused on the impact of CLP factors on labour productivity, but also considered another criterion, frequency/agreement, when ranking the CLP factors. Frequency, or agreement, evaluates the extent to which each factor exists in a project setting. Kazerooni et al. (2020) developed a new evaluation index method by combining the previous two criteria with a new criterion, controllability, in order to rank factors with respect to their importance for CLP improvement. The criterion of controllability is defined as the extent to which each factor can be controlled by the construction company in terms of cost and time. For instance, a construction company has no control over oil prices, so Volatility of oil prices is an uncontrollable factor and no improvement strategy can improve it, whereas Job site orientation program for new craftspeople is a controllable factor to some extent and can be improved by allocating a reasonable amount of time and cost. In these studies, the most commonly used method for determining the rank of CLP factors is RII, which only considers one criterion, impact (I), when ranking factors. The main limitation of evaluation indices such as RII is their dependency on expert knowledge and their lack of ability to consider interconnections among CLP factors.

Very few studies have attempted to identify the relative importance of CLP factors through the use of a data-driven approach such as feature selection (Moselhi and Khan 2012). Data-driven approaches are not dependent on expert knowledge and consider the dynamics of CLP factors and the interconnected relationships among them. Commonly used data-driven approaches include statistical methods such as regression analysis or correlation-based feature selection, which are limited by the number of influencing factors and their capability to determine the combined impact of the influencing factors (Song and AbouRizk 2008). Feature selection methods as data-driven approaches for identifying the relative importance of CLP factors are divided into three categories: filter, wrapper, and hybrid. Filter methods offer less computational time to provide results, and they rank and select features based on statistical measures, such as correlation and regression analysis. Tsehayae and Fayek (2016) applied correlation-based feature selection to establish context-specific key CLP factors for the purpose of modeling concrete-pouring activity. correlation-based feature selection has been proven to perform very well in experiments with small data sets (Hall 1999). Filter feature selection methods are limited by the number of influencing factors and their capability to determine the combined impact of influencing factors (Song and AbouRizk 2008). Wrapper methods use the model prediction of artificial intelligence (AI) techniques to determine the set of most suitable features. AI techniques, such as fuzzy inference system, artificial neural network (ANN), and support vector machine (SVM), are appropriate for the identification of key CLP factors because of their ability to manage a high-dimensional feature space and learn from experience to improve their performance and their capability to determine the combined impact of the influencing factors (Mirahadi and Zayed 2016). Song and AbouRizk

(2008) presented a CLP model based on ANN and discrete-event simulation that analyzes historical data. El-Gohary et al. (2017) used ANN and hyperbolic tangent as a transfer function to determine key CLP factors and to quantify and map the relationship between CLP and identified influencing factors. The main limitation of wrapper methods is the high computational complexity when feature sets are wide (Piao and Ryu 2017).

To resolve the problem of high computational complexity, it can be helpful to merge a wrapper method with a suitable filter method to reduce the deficiencies of both methods, and thus HFS is generally more efficient than single filter or wrapper methods (Lu et al. 2017). The general HFS approach consists of two stages. In the first stage, a filter method refines and selects the top-*n* features, and in the second stage a wrapper method identifies the most discriminative subset of the top-*n* features (Ghosh et al. 2019). Researchers have proposed different HFS methods based on the problem and available data. Lee and Leu (2011) proposed a novel HFS method in microarray data analysis by using genetic algorithm (GA) with the χ^2-test as a feature ranking method to generate a number of subsets of genes and select the proper number of top-ranked features. Hsu et al. (2011) introduced an HFS method that used F-score and information gain as filter methods and SVM as a wrapper method for data reduction and feature selection. Tao et al. (2019) proposed an approach of feature selection and parameter optimization of SVM using GA for hospitalization expense modeling that includes binary data sets. Venkatesh et al. (2019) presented a novel HFS method combining mutual information as a filter method and recursive feature elimination as a wrapper method. The experimental results of these hybrid methods indicate HFS have the ability to reduce time complexity and improve classification accuracy.

Accordingly, this thesis proposes an HFS model for the identification of key factors affecting CLP. Due to the characteristics of HFS methods, the HFS model is not dependent on expert knowledge and is capable of modeling the dynamics of the CLP factors. In addition, the model considers the interconnected relationships and the combined impact of the influencing factors.

2.2. Identification of CLP Improvement Strategies

While new technologies and innovations provide construction companies with opportunities to improve CLP, their influence is insignificant if improvement strategies recognized as necessary for controlling and improving CLP are not utilized first (Shan et al. 2015). Consequently, project managers implement a wide range of improvement strategies to increase CLP in construction projects (Nasir et al. 2015; Shan et al. 2011, 2015; Caldas et al. 2015). The implemented strategies aim to boost CLP of a project by improving the factors affecting CLP and changing the work systems of the project (Ghodrati et al. 2018). However, more than half of nonproductive work hours are caused by implementing ineffective improvement strategies, since their actual impact on CLP is not evident (Thomas et al. 2003). Thus, to achieve optimum productivity in a project, it is pivotal for the construction management team to identify the most effective CLP improvement strategies. Several studies have been conducted on identifying key CLP improvement strategies in construction domain. Gurmu and Aibinu (2017) used two questionnaires and developed a scoring tool to identify and prioritize construction equipment management practices that increase productivity. Kazerooni et al. (2020) developed a systemic framework for ranking CLP factors according to their importance for CLP improvement by integrating fuzzy data clustering and MCDM, and they suggested various improvement strategies based on the identified key factors. In a different study, Shoar and Banaitis (2019) applied fuzzy fault tree analysis method to identify critical events that cause low productivity and find appropriate response strategies for addressing the identified events. Agrawal and Halder (2019) conducted two survey questionnaires and used RII to gauge the perception of construction workers on CLP factors and the practices leading to CLP improvement. Kermanshachi et al. (2021) developed a system dynamics model to analyze the effects of change orders on CLP, and based upon sensitivity analysis, established five policies to lessen their effects. Kedir et al. (2019) integrated fuzzy agent-based modeling and MCDM to analyze the implementation of different productivity improvement policies. In contrast to previous studies, Al-Rubaye and Mahjoob (2020) focused on the loss of labour productivity in Iraq by deploying cause and effect analysis, identifying factors that cause the loss of CLP and proposing various management practices to lower its impact. Hwang et al. (2018) developed an activity analysis method for site conditions and maintenance and shutdown activities at petrochemical plants in Singapore. The study was conducted over two cycles to assess the current trend in labour productivity, identify productivity barriers, and implement improvement solutions and assess their effectiveness. Javed et al. (2018) identified key drivers and constraints that concern construction productivity in Hong Kong, explored the interdependence of these factors, and suggested five productivity improvement strategies. Rojas and Aramvareekul (2003) presented the results of a survey instrument applied to determine the relative level of relevance of CLP drivers and opportunities. Various experts such as owners, general contractors, electrical contractors, and consultants responded to the survey. “Management skills” and “Manpower issues” were identified as the two areas with the greatest potential to affect productivity according to survey respondents, and based on that, the researchers suggested five strategies for improving CLP. Thomas et al. (2006) suggested various CLP improvement strategies for avoiding workspace congestion and increasing CLP by comparing the productivity rates measured in the field with the baseline productivity rates regarding historical data.

While previous studies investigated various CLP improvement strategies, only a few attempted to quantify the effect of improvement strategies on CLP. For instance, Ghodrati et al. (2018) attempted to quantify the effectiveness of nine widely implemented management strategies to improve labour productivity, such as incentive programs, training, resource scheduling, and communication. Each management strategy entails several management practices. To assess the implementation level of the management strategies, they developed a management strategy assessment index and interviewed experts from several New Zealand construction companies. They employed multiple regression analyses and t-test to determine the relationship between the strategies and CLP. Shan et al. (2015) aimed to identify the effectiveness of seven pre-defined key management programs in improving CLP. Through a series of t-tests, they examined the relationship between the management programs and labour productivity. The result of their analyses showed that CLP is positively correlated to the implementation of the management programs. Caldas et al. (2015) developed a statistical method and metric, called the best productivity practices implementation index for industrial projects (BPPII Industrial), for identifying key construction productivity practices and quantifying the relative importance of the identified practices. Their results indicated that projects with higher BPPII Industrial scores have a greater potential to achieve better construction productivity than was originally estimated.

The following are research gaps in the current literature of CLP improvement strategies. (1) The applied statistical methods do not consider the causal relationships among CLP improvement parameters, namely affecting factors, improvement strategies, and CLP. CLP factors are mostly interconnected and affect each other. Thus, it is necessary to consider the causal relationship among the factors and strategies in order to achieve accurate values for the quantified impact of strategies on CLP. (2) Most previous studies did not consider the project characteristics for selecting CLP improvement strategies, and instead selected the key improvement strategies based on previous research. However, CLP is a context-specific efficiency measure, as the identified factors and their degree of impact on CLP vary from project to project (Heravi and Eslamdoost 2015; Tsehayae and Fayek 2016). Hence, key CLP improvement strategies also differ from one project to another. Therefore, a systematic approach is needed to capture project characteristics and construct the cause-and-effect relationships among CLP improvement parameters in order to identify the most effective CLP improvement strategies.

To address these gaps, this thesis proposes a decision-support model to assist selection and implementation of optimal CLP improvement strategies for a given project. The proposed model consists of: (1) fuzzy MCDM methods for capturing experts' opinion about the ranking of strategies regarding various criteria in order to consider project characteristics and (2) an FCM model to consider the causal relationships among CLP factors for quantifying the impact of improvement strategies on CLP.

2.3. Summary

This chapter provides a literature review on the identification of key factors affecting labour productivity and key strategies for improving labour productivity in construction. The majority of previous studies relied on expert knowledge collected through questionnaire surveys to establish key factors that affect CLP using evaluation index methods such as RII. Very few studies have attempted to identify the relative importance of CLP factors through the use of a data-driven approach such as correlation analysis or feature selection (Moselhi and Khan 2012). Data-driven approaches are not dependent on expert knowledge and consider the dynamics of CLP factors and the interconnected relationships among them. Commonly used data-driven approaches include statistical methods, such as regression analysis or correlation-based feature selection, which are limited by the number of influencing factors and their capability to determine the combined impact of influencing factors (Song and AbouRizk 2008). Therefore, the **first gap** is that the applied methods in previous studies for identification of the factors affecting CLP are dependent on expert knowledge and not able to consider the dynamics, interconnection, and combined impact of the factors that affect CLP. Although several studies have been conducted on identifying key CLP improvement strategies in the construction domain, only a few attempted to quantify the impact of improvement strategies on CLP. The existing literature on quantifying the impact of CLP improvement strategies have relied on statistical methods, such as regression analysis and t-test.

The **second gap** related to the identification of CLP improvement strategies in current construction literature is the inability of applied statistical methods to consider causal relationships among CLP improvement parameters. The **third gap** is the inability of previous construction studies to capture characteristics of a given project when selecting CLP improvement strategies. The previous studies selected the key improvement strategies based on previous research and results that exist in the construction literature.

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Chapter 3. Identification of the Most Value-adding CLP Factors[1]

3.1. Introduction

Understanding factors that affects labour productivity is important for making strategic decisions and selecting appropriate CLP improvement strategies (Jalal and Shoar 2019). However, identification of most-value CLP factors is a challenging task since CLP is set in a high-dimensional feature space where a number of factors which are mostly interconnected affect CLP directly or indirectly. There is an extensive research on the identification of key CLP factors due to the importance of CLP on the performance of construction projects. Majority of past studies have relied on expert knowledge through factor surveys and a group of experts to establish key factors that affect CLP. The established key factors were then used to either suggest further improvements or to carry out further data collection for analysis and modeling. Among these studies, the dominating method for ranking CLP factors is RII. Very few studies have attempted to identify the relative importance of the CLP factors through the use of a data-driven approach such as correlation analysis or feature selection (Moselhi and Khan 2012). Data-driven approaches are not dependent on expert knowledge and consider the dynamics of CLP factors and the interconnected relationships among them. The commonly used data-driven approaches are statistical methods like regression analysis or correlation-based feature selection. The statistical approaches are limited by the number of influencing factors and their capability to determine the combined impact of the influencing factors (Song and AbouRizk 2008). Therefore, a research gap exists regarding methods for identifying the key factors affecting CLP by considering the dynamics, interconnection, and combined impact of the factors without dependency on expert knowledge.

To address this gap, an HFS method is utilized to assist selection of the most value-adding CLP factors for a given project based on the dynamics, interconnection of CLP factors without dependency on expert knowledge.

[1] The contents of this chapter have been submitted for publication Ebrahimi, S.; Kazerooni, M.; Sumati, V.; Fayek, A. R. (n. d.). "A predictive model for construction labour productivity using the integration of hybrid feature selection and PCA methods." *Canadian Journal of Civil Engineering*, under review.

3.2. Research Methodology

This section discusses the methodology of the proposed model for identifying the most value-adding CLP factors in a high-dimensional feature space where numerous factors affect CLP. Fig. 3.1 shows a general view of the proposed methodology, which includes two main phases: data preparation and data analysis. In the data preparation phase, the most valuable data are sorted out from the less important. In the data analysis phase, the HFS method is applied for analysis of the prepared dataset. The following sections are an overview of the CLP dataset used in this thesis and the stages of processing the CLP data.

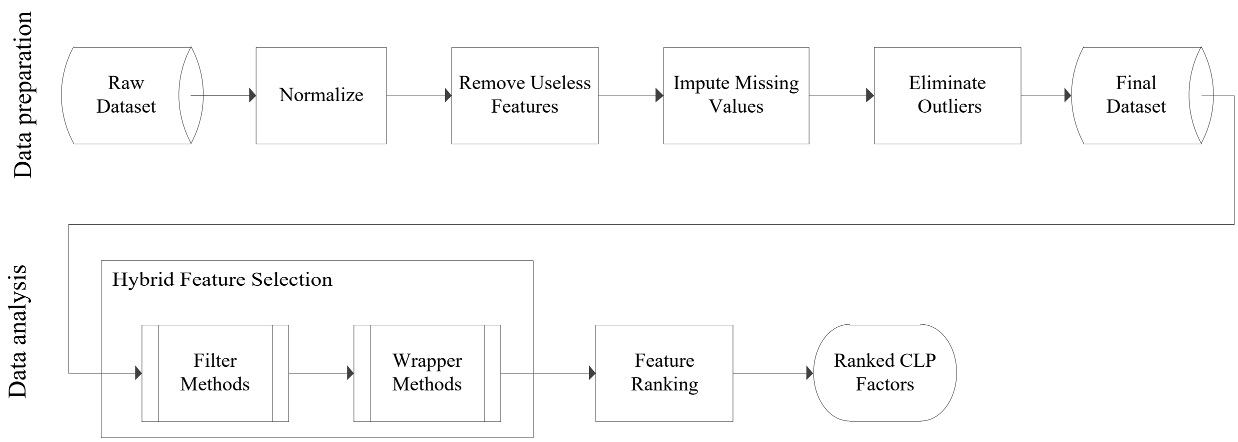

Figure 3.1. Overview of methodology for identifying key CLP factors.

3.2.1. CLP dataset overview

The data used in this thesis are based on the dataset developed by Tsehayae and Fayek (2014, 2016) for identifying the key factors affecting CLP. As a result, 112 influential factors on CLP were identified as shown in Appendix A and measured for a total of 92 days. Therefore, the utilized CLP dataset in this thesis has 10,856 tuples consisting of 92 instances and 113 attributes including the class attribute, which is CLP. The class attribute has positive real values due to CLP definition.

3.2.2. Phase 1: Data preparation

Data preparation is the initial stage of processing data, with the goal of sorting out the most valuable data from the less important. A CLP dataset is prepared as a raw dataset and transformed to a more informative form per the following data preparation stages, in order to make CLP data modeling and analysis more efficient.

3.2.2.1. Normalization

By adjusting the value range, normalization can lead to stable convergence and prevent biases in predictive models (Golnaraghi et al. 2020). The normal distribution, which subtracts the mean of the data from all values and divides them by the standard deviation, helps preserve the original distribution of the data (Frigerio et al. 2019). Thus, normalization with respect to normal distribution is used in the developed model to scale CLP data into an organized range.

3.2.2.2. Remove useless features

Standard deviation as the square root of the variance is a measure of how spread out the values of each feature are in the dataset. In this thesis, 8 CLP features with standard deviation equal to zero were removed from the CLP dataset, and the total number of CLP factors was reduced to 104.

3.2.2.3. Impute missing values

Imputation is a technique of estimating the missing values of a dataset by applying various machine learning algorithms. Imputation methods based on K-nearest neighbors (KNN) use classification capacity to identify a subset of instances having the most similarity to the instances with missing values (Ma and Zhong 2016). Hence, in the presented model a KNN-based imputation method is utilized to impute missing values of the CLP dataset.

3.2.2.4. Eliminate outliers

Outliers in a dataset can significantly affect the performance of data analysis. The Tukey Test method is a commonly used outlier detector, in which a confidence interval is defined for each feature by calculating the distance between the median of the feature observations divided by the distance of the lower/upper Tukey Test boundary to the median (Sandbhor and Chaphalkar 2019). In this thesis, after applying the Tukey Test method to the CLP dataset, 10 observations were identified as outliers. Hence, the total number of instances in the CLP dataset was reduced to 82.

3.2.3. Phase 2: Data analysis

The second phase of developing a model for identifying the most value-adding CLP factor is analyzing the final CLP dataset resulting from phase 1. The following subsections explain the preliminary concepts used in the HFS method and describe the stages of key CLP factors identification.

3.2.3.1. Preliminaries

The main concepts used in the data analysis phase of the proposed methodology are as follows.

ReliefF algorithm (RFA): The Relief algorithm as an individual evaluation filtering feature selection method assigns weights to each feature based on correlation between features, and it selects all features with greater weight compared with the threshold. Although Relief is an efficient method with satisfactory results, an important limitation of this algorithm is that it can handle only two-class classification problems. To manage this limitation and handle multi-class problems, RFA was proposed by Kononenko (1994). Equation (3.1), which is ReliefF function (RFF), shows the evaluation criteria of RFA, where n is the total number of features, D is distance measurement, $f_{t,j}$ is the value of instance x_j on feature f_j, and $f_{s(x_j)}$ and $f_{d(x_j)}$ denote the value of jth feature of the nearest point to x_j in the same and different class, respectively.

$$RFF(f_j) = 0.5 \sum_{j=1}^{n} \left(D\left(f_{t,j} - f_{s(x_j)}\right) - D\left(f_{t,j} - f_{d(x_j)}\right) \right) \tag{3.1}$$

SVM: A SVM is a supervised learning model that can solve two-class binary classification problems. SVMs are used for classification and regression analysis. The learning algorithm of SVM is based on statistical learning theory and structural risk minimization. Theoretically, SVMs experience less overfitting and better generalization than traditional techniques such as ANN. The main approach of SVM is using the maximum margins between support vectors to build an optimal hyperplane. SVM shows great generalization performance, which represents the desired accuracy in classification and prediction of unseen samples (Fernández-Delgado et al. 2014). SVM is used for solving linear and non-linear problems. For non-linear classification, the mapping function is utilized to convert low-dimensional data to a high-dimensional dataset, which changes the non-linear problem to a linear and separable problem. Kernel functions are employed to make this process easier. There are various types of kernel function, namely, linear, polynomial, sigmoid, and Gaussian function. Gaussian function, presented in Equation (3.2), is the most common kernel function for solving classification problems, as it requires just one parameter, γ, which is a free parameter and has a significant influence on classification accuracy (Pai et al. 2021). Another important parameter in SVM is penalty factor C, which is the cost of misclassification. Based on the importance of these two parameters on the result of SVM, C and γ needed to be optimized for achieving the desired accuracy, which is accomplished by GA.

$$K(x, x') = \exp(-\gamma \parallel x - x' \parallel^2) \quad (3.2)$$

GA optimization: GA is a stochastic searching process based on the mechanism of natural selection and natural genetics, thus imitating the process of natural evolution. GA is a good approach to exploring feature space and can produce many alternative feature subsets through reproduction operations to obtain the best subset that includes the most important features. GA uses a fitness function to evaluate each candidate solution's fitness. The crossover and mutation functions randomly transfer chromosomes as two major operators with the key impact on the fitness value. The crossover is a randomizing mechanism that exchanges features between two chromosomes using single-point, two-point, or homologue crossover (RazaviAlavi and AbouRizk 2017). The three criteria for designing a fitness function are: the number of selected features, classification accuracy, and cost. Based on these criteria, a chromosome with a small number of selected features, high classification accuracy, and low cost can produce a high fitness value. The GA optimization method maximizes the value of the fitness function, shown in Equation (3.3) where SVM_Error is a root mean square error (RMSE) of SVM classifier, W_f is a weight value for the number of features (n_f), f_i represents '1' if the feature i is selected or '0' if the feature i is not selected, and c_i is cost of feature i.

$$Fitness = (SVM\_Error \times (1 + W_f \times (\sum_{i=1}^{n_f} c_i \times f_i)))^{-1} \quad (3.3)$$

3.2.3.2. HFS method

An overview of the proposed HFS method is shown in Figure 3.2, which presents the process of integrating RFA as a filter method with GA and SVM as the wrapper method.

The detailed explanation of the steps for developing the HFS method are as follows.

Step 1 – The RFA filter method evaluates the weight of each feature according to the correlations between features and ranks them in terms of their weights. After the RFA process is complete, feature weights (w_r) are normalized from 0 to 1 to make the wrapper process more effective; by using a defined threshold (τ) in the range 0–1, any features with a weight $w_r \geq \tau$ are selected.

Step 2 – GA generates the random initial population of chromosomes. Each chromosome in the population represents an available solution to the feature subset selection problem.

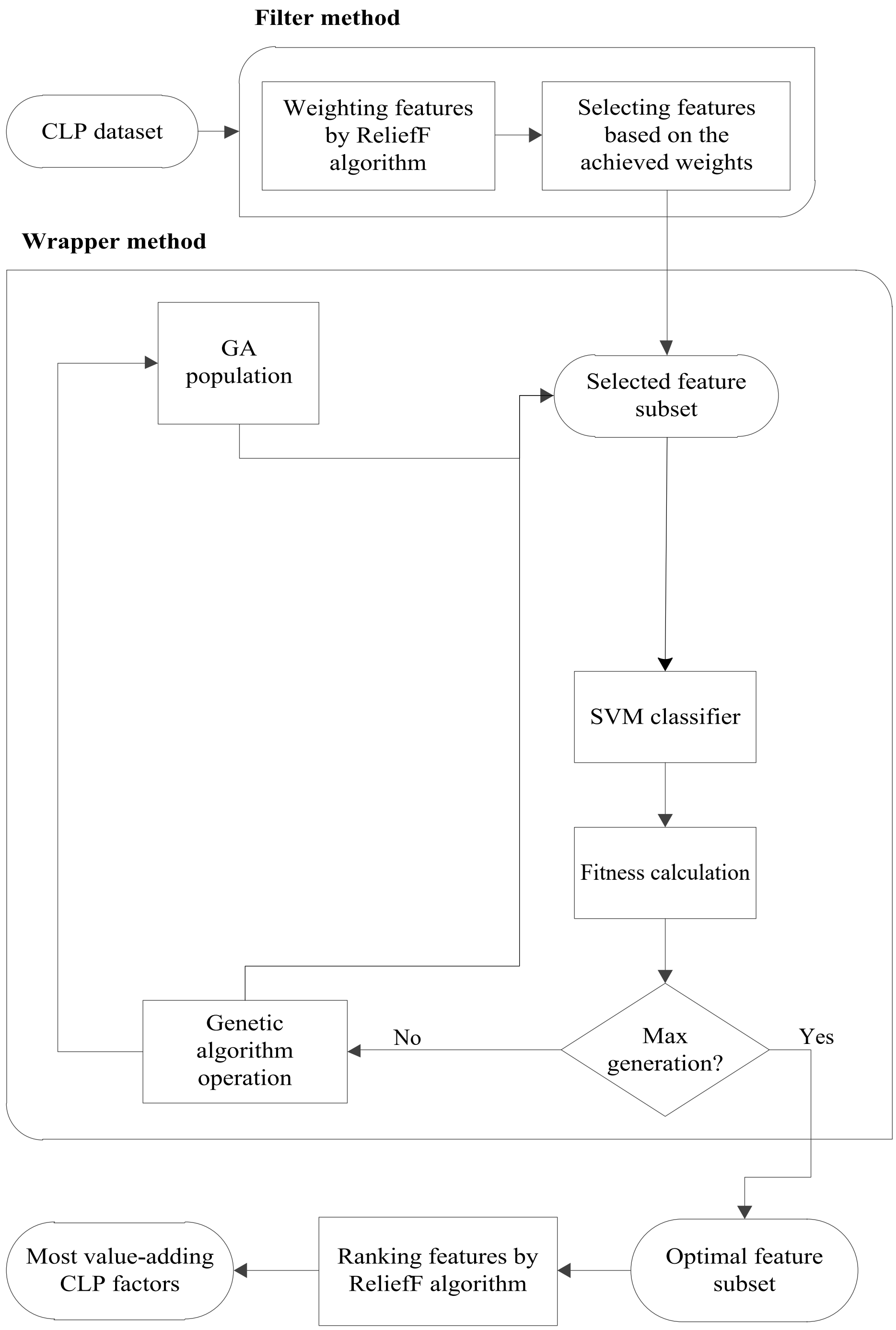

Figure 3.2. Overview of the HFS method

Step 3 – Selected features that have weights greater than the threshold are the inputs of SVM.

Step 4 – The fitness calculation process is completed using the calculated RMSE for SVM classification, based on Equation (3.4).

$$SVM\_Error = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - T_i)^2} \quad (3.4)$$

where n is the number of outputs, A_i is the actual output value of the ith output, and T_i is the target output value of the ith output. In this paper, there is one output, which is CLP. Note that a better fitness of the SVM requires a smaller error.

Step 5 – If termination criteria are satisfied, the process ends; otherwise, the process goes to the next generation by GA.

Step 6 – GA searches for better solutions by using crossover, mutation, elitism, and replacement. In this thesis, single-point binary crossover and binary mutation were performed. Also, per the elitism process the three best chromosomes are selected to be part of the population in the next generation. Once the final generation meets termination criteria, the iteration stops, and the selected feature subset is the one that has the best predictor of CLP among all feature subsets. The termination criteria include either the generation number reaches a determined value, or the fitness value does not improve during a specified number of generations. For this thesis, maximum generation was 150 and specified number of generations was 50.

Step 7 – RFA is used one more time to rank the selected features and adjust features' weights.

For this thesis, features that satisfied the threshold of 0.2 in Equation (3.1) were selected as essential features for the next stage of HFS. Of the 110 features in the final CLP dataset, RFA selected 35 as essential features. The termination criteria for the GA-SVM method applied in this thesis were: a maximum generation of 150, or no improvement of the fitness value during the last 50 generations. SVM parameters C and σ were both set to 20, kernel type was radial, and kernel cache was 200. The parameter settings for GA were population size of 100, crossover rate of 0.7, mutation rate of 0.02, one-point crossover, and tournament selection scheme. To reduce bias selection of the optimal feature subset, 15 different local seeds were examined in order to identify the best possible subset of CLP factors. Considering these parameters, the proposed wrapper feature selection was developed, which selected 19 factors out of the 35 CLP factors specified by RFA. Finally, RFA was used one more time to rank the selected features and adjust features' weights. Table 3.1 shows RFA ranking of the 19 features selected as the most value-adding CLP factors.

Table 3.1. RFA ranking of the most value-adding CLP factors

Factor index	CLP Factor	Normalized importance	RFA rank
2	Fairness of work assignment	1.000	1
6	Complexity of task	0.793	2
7	Repetitiveness of task	0.706	3
16	Owner staff on site	0.568	4
10	Congestion of work area	0.535	5
19	Structural element	0.527	6
18	Concrete placement technique	0.476	7
1	Team spirit of crew	0.295	8
13	Weather (precipitation)	0.233	9
3	Crew participation in foreman's decision-making process	0.231	10
9	Location of work scope (distance)	0.229	11
5	Material movement practices (horizontal)	0.217	12
17	Availability of labour	0.199	13
12	Weather (temperature)	0.172	14
14	Variability of weather	0.168	15
4	Job security	0.071	16
8	Working conditions (dust and fumes)	0.041	17
15	Ground conditions	0.002	18
11	Cleanliness of work area	0.000	19

3.3. Summary

This chapter presents an HFS model for identifying the most value-adding CLP factors in a high-dimensional feature space where numerous factors affect CLP. The HFS model is consists of two major phases, data preparation and data analysis. In the first phase, the utilized CLP dataset is prepared as a raw dataset and transformed to a more informative form in order to make CLP data modeling and analysis more efficient. In this manner, normalization with respect to normal distribution, imputing missing values with KNN, removing factors with zero deviation, and eliminating outliers by Tukey Test method are applied to improve the efficiency of CLP data analysis. In the second phase, the final CLP dataset resulting from phase 1 is analyzed in order to determine the key factors affecting CLP. To achieve this aim, RFA method as a filter method and SVM-GA as a wrapper method are integrated as an HFS model to identify the most value-adding CLP factors. RFA method evaluates the weight of each feature according to the correlations between features and ranks them in terms of their weights. GA-SVM method is utilized to search for an optimum solution using crossover, mutation, elitism, and replacement with respect to SVM error. As a result, the top three most influential factors include (1) fairness of work assignment, (2) complexity of task, and (3) repetitiveness of task. The most value-adding CLP factors resulting from this chapter is used to develop the decision-support model of improvement strategies selection as discussed in Chapter 4.

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Chapter 4. Prioritizing CLP Improvement Strategies[2]

4.1. Introduction

Maximizing CLP is pivotal for enhancing the overall performance of construction projects in multiple areas, such as reducing variances from the primary plan and keeping the projects on time and within budget. So, construction companies are required to implement various CLP improvement strategies to enhance the level of influencing CLP factors and consequently improve CLP. In this thesis, a CLP improvement strategy is an individual management practice - working method, tactic or innovation - that construction managers use to improve CLP of their projects. Some examples of CLP improvement strategies include performing weekly reviews of crew compositions to ensure crew mix is per plan, providing clear instructions to craftspeople on how to complete tasks prior to execution, and scheduling regular inspections by the owner team to reduce interventions during project execution. However, budget, time, and resource constraints force construction companies to carry out only a limited number of CLP improvement strategies (Kazerooni et al. 2020). In addition, in the complex environment of construction, CLP is affected by numerous factors that are mostly interconnected (Ebrahimi et al. 2021; Tsehayae and Fayek 2016). Thus, the actual impact of various factors on CLP can be only obtained using a systematic approach that models the causal relationship among them (Caldas et al. 2015). However, most construction companies apply management practices, such as changing working times and switching workweek, based on the experience and knowledge of their managers (Shan et al. 2016).

Compared to CLP factors identification, very few studies have been conducted for identifying key CLP improvement strategies. According to the provided literature review, most techniques proposed for selecting key CLP improvement strategies lack the ability to quantify the impact of strategies on CLP. However, to effectively improve CLP, the extent to which the implemented improvement strategies affect CLP needs to be known. Widely used techniques for quantifying the impact of various strategies on CLP improvement include statistical methods such as t-test and regression analysis (Ghodrati et al. 2018; Shan et al. 2016). The major limitation of statistical methods is their inability to capture the causal relationships among CLP factors, improvement strategies, and CLP. In addition, such methods lack the ability to consider project characteristics.

2 The contents of this chapter have been published for publication Kazerooni, M.; Nguyen, P.; Fayek, A.R. (2021) "Prioritizing Construction Labor Productivity Improvement Strategies Using Fuzzy Multi-Criteria Decision Making and Fuzzy Cognitive Maps." *Algorithms*, 14, 254. https://doi.org/10.3390/a14090254.

However, key CLP improvement strategies differ from one project to another. Consequently, determining the relationships among key CLP factors and strategies and determining the impact of each strategy on CLP is crucial for prioritizing appropriate CLP improvement strategies for a given project.

To address the mentioned gaps, this study proposes a decision-support model to assist selection and implementation of optimal CLP improvement strategies for a given project. The proposed model consists of: (1) the combination of fuzzy AHP and fuzzy TOPSIS methods in order to deal with the uncertainty and vagueness in the decision-making process of selecting CLP improvement strategies and capture experts' opinion about the ranking of strategies regarding various criteria in order to consider project characteristics and (2) an FCM model to consider the causal relationships among CLP factors for quantifying the impact of improvement strategies on CLP and capture the imprecision and uncertainty of CLP factors for CLP modeling. Accordingly, the proposed methodology is expected to achieve more accurate results than previous studies that utilized statistical methods to quantify the impact of CLP improvement strategies without taking into account imprecision of CLP factors, causal relationships among CLP factors, and project characteristics.

4.2. Methodology

This thesis proposes a decision-support model for identifying and prioritizing the most effective CLP improvement strategies by integrating fuzzy MCDM methods with FCM. Fuzzy MCDM methods, including fuzzy AHP and fuzzy TOPSIS, are operations research tools for ranking various parameters regarding multiple criteria in complex decision-making problems (Taylan et al. 2014). In the problem of improvement strategy selection, fuzzy AHP is used to weight the criteria, and fuzzy TOPSIS is used to rank the strategies based on the criteria. FCM is a causal cognition tool for modeling and simulating dynamic systems (Nápoles, Leon, et al. 2018). In this thesis, FCM is utilized to quantify the impact of strategies on CLP by modeling a CLP environment. Figure shows a general view of the framework for selecting CLP improvement strategies, which includes three phases: identifying factors and strategies, ranking strategies, and quantifying strategies' impact on CLP.

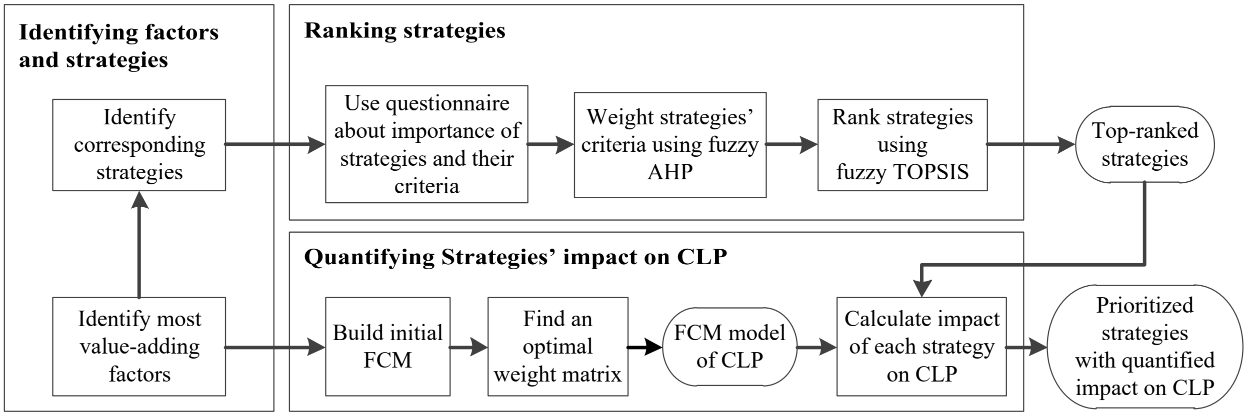

Figure 4.1. Overview of the decision-support model of CLP

In the first phase, the key CLP factors were determined in chapter 3 as shown in Table 3.1. Then, various CLP improvement strategies that correspond to key factors (i.e., strategies that could be used to address each factor) are identified through a comprehensive background review of the literature. In the second phase, two fuzzy MCDM methods are integrated and used to rank the identified improvement strategies by capturing experts' opinions of the importance of each strategy versus various criteria. In the third phase, an FCM model is developed based on the identified factors and top-ranked strategies for analyzing the effects of factors on each other and determining the impact of each strategy on CLP improvement. Finally, the most effective CLP improvement strategies are prioritized, or ranked, according to their quantified impact on CLP. Two validation approaches, structural validity, and behavioral validity, are used in this thesis to validate the developed decision-support model. The structural validity approach is utilized to evaluate the list of model components (factors influencing CLP and CLP improvement strategies) and the relationships among them. Behavioral validity of the FCM model is evaluated using the extreme conditions test, as utilized by Kumar and Yamaoka (2007). The extreme conditions test compares the behavior of a developed model to the behavior of the real system under the same extreme conditions of input factors (Nojedehi and Nasirzadeh 2017). According to Gerami Seresht and Fayek (2018), common validation tests such as the statistical hypothesis test are not suitable for FCM models, which simulate dynamic systems. Therefore, both utilized validation approaches compare the structure and behavior of the model with a real-world system empirically, using case studies, and theoretically, using the literature. An overview of the utilized case study is presented below.

4.2.1. Case study and CLP dataset overview

The CLP dataset used in this research was provided from a previous study conducted by Tsehayae and Fayek (2014, 2016). They defined CLP as the ratio of units of output, expressed as installed quantity (in cubic meters), to units of input, expressed as total labour work-hours, and the data were collected for concrete-pouring activities in building projects in Alberta, Canada. They studied concrete-pouring in three data collection cycles between June 2012 and October 2014 in collaboration with two partnering companies. Thus, the proposed decision-support model in this thesis is developed for identifying, ranking, and implementing improvement strategies for the CLP of concrete-pouring activities in building projects. The following sections present the details of each phase of CLP improvement strategy selection by implementing them in the case study model.

4.2.2. Identifying factors and strategies

Past studies have shown that key CLP factors vary from one construction project to another (El-Gohary et al. 2017). In this regard, the first step in developing a CLP model is to determine the relevant surrounding factors that affect CLP within the studied context. Accordingly, for the purpose of this research, the most value-adding CLP factors identified in Table 3.1 of chapter 3 are considered since the same empirical data are utilized.

After the most value-adding CLP factors were determined, an extensive literature review of past studies was conducted to identify various CLP improvement strategies that correspond to the determined key factors. As a result, 54 strategies with the potential to improve CLP were identified for 19 factors. The most appropriate strategy among the identified potential strategies were then determined for addressing each CLP factor using three experts involved in the project under study. As a result, 16 different strategies were determined. Table 4.1 shows the factors and their corresponding improvement strategies. The linguistic descriptors of the factors are given under the factors in order to give a clear understanding of the factors' definitions. The linguistic descriptors of F6 are categorical, and it is not possible to replace a category (e.g., columns) with another category (e.g., slabs) in the project, so no improvement strategy corresponds to this factor.

Table 4.1. Key CLP factors and their corresponding improvement strategies.

No.	Most value-adding CLP factor	No.	CLP improvement strategy
F1	Fairness of work assignment (Poor, Fair, Good)	S1	Perform weekly reviews of crew compositions to ensure crew mix is per plan

F2	Complexity of task (Low, Average, High)	S2	Provide clear instructions to craftspeople on how to complete tasks prior to execution
F3	Repetitiveness of task (Low, Medium, High)	S3	Have the same person perform a task several times rather than making personnel changes along the way
F4	Owner staff on site (Low, Average, High)	S4	Schedule regular inspections by the owner team to reduce interventions during project execution
F5	Congestion of work area (Low, Average, High)	S5	Establish staggered working-hours of labourers
F6	Structural element (Columns, Footings, Grade beams, Pile caps, Slabs, Walls)	N/A	N/A
F7	Concrete placement technique (Pump, Crane and bucket, Direct chute)	S6	Train labourers to achieve the latest concrete-pouring techniques
F8	Team spirit of crew (Poor, Fair, Good)	S7	Perform project team activities
F9	Weather – precipitation (Low, Medium, High)	S8	Cover working area to protect from wind effects and precipitation
F10	Crew participation in foreman's decision-making process (Without explanation, Joint, With)	S9	Hold regular meetings with labourers about schedule and remaining tasks
F11	Location of work scope – distance (Very close, Close, Far)	S10	Design processes to eliminate repetitive motion and reduce manual labour
F12	Material movement practices – horizontal (Poor, Fair, Good)	S11	Develop clear instructions about the equipment used to transport materials
F13	Availability of labour (Low, Medium, High)	S12	Offer internship and scholarship programs to trade and vocational schools to help company's future workers
F14	Weather – temperature (Low, Medium, High)	S13	Apply preventive maintenance to heating and air-conditioning systems to make sure they are in working order
F15	Variability of weather (Low, Medium, High)	S8	Cover working area to protect from wind effects and precipitation
F16	Job security (Poor, Fair, Good)	S14	Hold meetings during later project stages to discuss transfer of project team to future projects of the company
F17	Working conditions – dust and fumes (Low, Average, High)	S13	Apply preventive maintenance to heating and air-conditioning systems to make sure they are in working order

F18	Ground conditions (Poor, Fair, Good)	S15	Use a down-hole vibrator that is lowered into the ground to compact soils at depth
F19	Cleanliness of work area (Poor, Fair, Good)	S16	Hire cheap labour for daily housekeeping tasks

4.2.3. Ranking strategies

In this phase, the identified 16 strategies are ranked with respect to four criteria, which were identified by reviewing the current literature around strategy selection (Chatterjee et al. 2018; Efe 2016; Mathiyazhagan et al. 2019; Tamošaitiene et al. 2017; Taylan et al. 2014). These strategy selection criteria (SSCs) are described as follows:

- Impact on CLP (IC) is the impact of a strategy on CLP improvement in the project under study.
- Implementation feasibility (IF) is the degree to which the strategy can be implemented in the project with respect to economic, technical, and scheduling constraints, including required time and cost of implementation.
- Workers' adaption (WA) is the ease with which workers can adapt to each strategy.
- Implementation risk (IR) is the potential for each strategy to encounter development or deployment failure. (The term describes risks related to strategy launch.)

Due to advantages of fuzzy MCDM in dealing with qualitative criteria as stated in the introduction section, two widely used fuzzy MCDM methods – fuzzy AHP and fuzzy TOPSIS – are integrated to rank the CLP improvement strategies meeting the above criteria. The main advantages of these methods are that they mathematically represent uncertainty and vagueness in the decision-making process without involving cumbersome mathematics (Kahraman et al. 2004). According to Taylan et al. (2014), the combination of fuzzy AHP and fuzzy TOPSIS shows better performance compared to using each method separately. Accordingly, fuzzy AHP is used to determine the relative weights of SSCs based on fuzzy pairwise comparison, and fuzzy TOPSIS is applied to determine the relative importance of each strategy and rank the strategies. Figure 4.2 presents the hierarchical structure of the decision-making process for CLP improvement strategy selection. Inputs of the proposed decision-making methods are achieved by using two questionnaire surveys, described in the next section. The following sections demonstrate the development of fuzzy AHP and fuzzy TOPSIS to identify the top-ranked CLP improvement strategies.

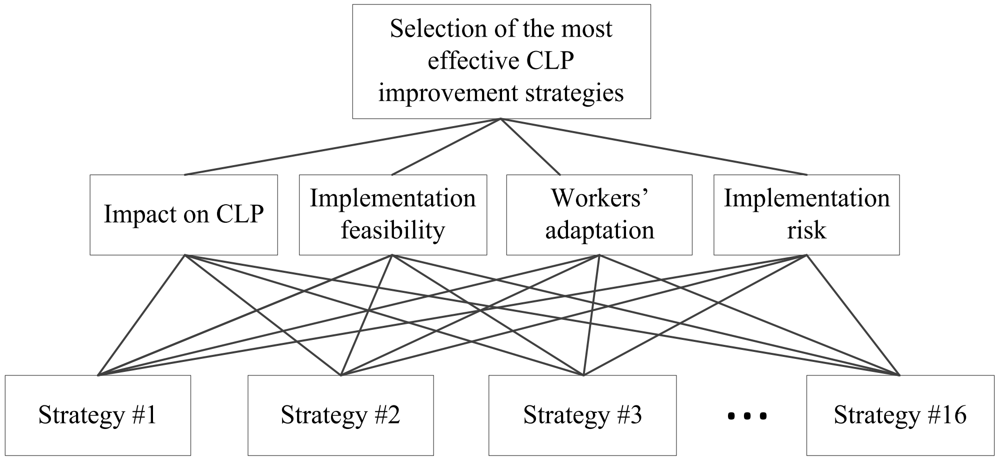

Figure 4.2. Hierarchical structure of decision-making for improvement strategy selection.

4.2.3.1. Questionnaire surveys

A major task in constructing the proposed model is determining the relative importance of each SSC to the final goal of selecting the most effective CLP improvement strategies. How the weights are determined can affect the outcome of the decision-making process. A well-designed weighting mechanism serves two purposes: (1) it identifies the solution that best meets the decision makers' needs, and (2) it quantifies the differences between the solutions. Accordingly, two questionnaire surveys were designed, and 10 experts with an average of 7 years of experience in construction responded. In the first questionnaire, as shown in Figure 4.3, experts were asked to weight SSCs by selecting a preference term from "Equal" to "Absolute" when comparing the relative importance of one criterion to another. Similar to Efe (2016), Mathiyazhagan et al. (2019), and Kabak et al. (2014), a symmetric triangular fuzzy number (TFN) is used to represent each preference term in order to compute the SSC weights in the next phase. The numbers under the importance levels to the left of "Equal" show that the left SCC is more important than the matching one on the right in the same row. The numbers to the right of "Equal" show the opposite statement. For example, 4 experts indicated that the relative importance of IF to the problem of selecting CLP improvement strategies is "Fairly Strong" compared to the relative importance of IR. However, 2 experts responded that the importance of IR is "Fairly Strong" compared to the importance of IF.

SSC	**Left** Criterion is more important				Equal (1, 1, 1)	**Right** Criterion is more important				SSC
	Absolute (4, 5, 6)	Very Strong (3, 4, 5)	Fairly Strong (2, 3, 4)	Weak (1, 2, 3)		Weak (1, 2, 3)	Fairly Strong (2, 3, 4)	Very Strong (3, 4, 5)	Absolute (4, 5, 6)	
IC		2	2	1	3		2			IF
IC		2	2	1	1	1	2	1		WA
IC		3	3	1			2	1		IR
IF		2	2	2	1		2	1		WA
IF		1	4	1	2		2			IR
WA				4	2	2	1	1		IR

Figure 4.3. Survey questionnaire for weighting SSCs.

In the second questionnaire survey as shown in Appendix B, the same 10 experts indicated their opinions on the importance of the selected strategies to CLP improvement with respect to SSCs. They indicated their responses using the seven-value linguistic scale presented in Table . Figure 4.4 shows the membership functions of linguistic terms, which are based on Özdağoğlu and Güler (2016).

Table 4.2. Linguistic scale for ranking the improvement strategies.

Linguistic term	Membership function
Very Low (VL)	(0, 0, 1, 2)
Low (L)	(1, 2, 2, 3)
Fairly Low (FL)	(2, 3, 4, 5)
Moderate (M)	(4, 5, 5, 6)
Fairly High (FH)	(5, 6, 7, 8)
High (H)	(7, 8, 8, 9)
Very High (VH)	(8, 9, 10, 10)

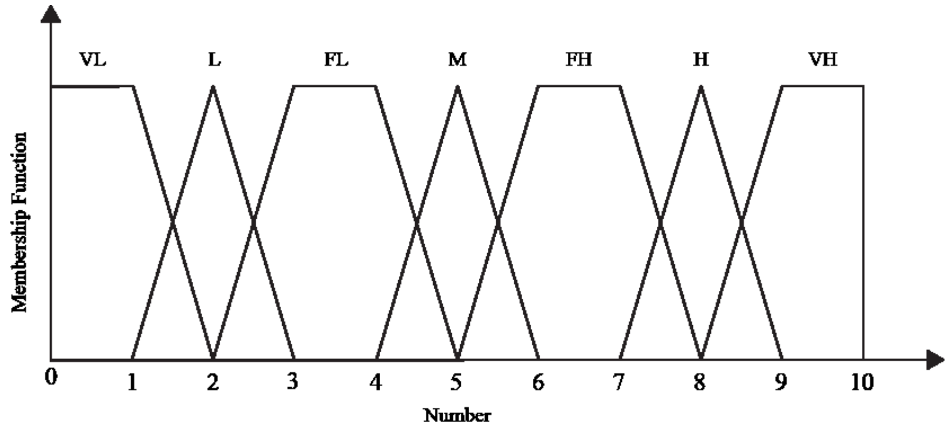

Figure 4.4. Membership functions of the linguistic variables.

4.2.3.2. Fuzzy AHP

AHP is a broadly applied method for determining the weights of criteria in a structured manner based on pairwise comparison (Liu et al. 2020). To handle subjective judgements in comparison, fuzzy sets are combined with AHP. Thus, fuzzy AHP assigns membership degrees to exact numbers in order to describe to what extent these numbers belong to a linguistic expression. The relative weight of an SSC is assessed by processing the triangular fuzzy preference numbers elicited from the questionnaire survey of Figure 4.3, through fuzzy AHP method in a manner similar to that presented by Perçin and Aldalou (2018). The triangular fuzzy preference of the ith SSC over the jth SSC is shown as (L_{ij}, M_{ij}, U_{ij}), where the parameters L, M and U denote the smallest possible value, the most promising value, and the largest possible value that describe the relative importance of the ith SSC over the jth SSC, respectively. The steps of the proposed fuzzy AHP can be described as follows.

Step 1: Calculate the fuzzy sum. The fuzzy sum value with respect to the ith SSC, which is a TFN, is defined as:

$$FS_i = \left(L_{FS_i}, M_{FS_i}, U_{FS_i}\right) = \left(\sum_{j=1}^{4} L_{ij}, \sum_{j=1}^{4} M_{ij}, \sum_{j=1}^{4} U_{ij}\right) \tag{4.1}$$

Step 2: Calculate the fuzzy synthetic extent. The S value with respect to the ith SSC, which is a TFN, is defined as:

$$S_i = \left(L_{S_i}, M_{S_i}, U_{S_i}\right) = \left(\frac{L_{FS_i}}{\sum_{j=1}^{4} U_{FS_j}}, \frac{M_{FS_i}}{\sum_{j=1}^{4} M_{FS_j}}, \frac{U_{FS_i}}{\sum_{j=1}^{4} L_{FS_j}}\right) \tag{4.2}$$

where S_1, S_2, S_3 and S_4 are the fuzzy synthetic extent of IC, IF, WA, and IR, which equal (0.1891, 0.3092, 0.4936), (0.1697, 0.2743, 0.4317), (0.1314, 0.2120, 0.3489), and (0.1291, 0.2046, 0.3408), respectively.

Step 3: Calculate the degree of possibility (*V*). The *V* value with respect to the ith SSC is defined as:

$$V_i = \min_{j \neq i} \left(v(S_i > S_j) \right) \tag{4.3}$$

where $v(S_i > S_j)$ is calculated as follows:

$$v(S_i > S_j) = \begin{cases} 1, & if\ M_{S_i} \geq M_{S_j} \\ 0, & if\ L_{S_j} \geq U_{S_i} \\ \frac{L_{S_j} - U_{S_i}}{(M_{S_i} - U_{S_i}) - (M_{S_j} - L_{S_j})}, & otherwise \end{cases} \tag{4.4}$$

Step 4: Calculate the relative weight of SSCs (*W*). The *W* value with respect to the ith SSC is determined by normalizing V_i as follows:

$$W_i = V_i / \sum_{j=1}^{4} V_j \quad \forall i = 1\ to\ 4 \tag{4.5}$$

where W_1, W_2, W_3 and W_4 are the relative weights of IC, IF, WA, and IR, which equal 0.324, 0.283, 0.201, and 0.192, respectively.

Step 5: Assess the consistency ratio (CR). The consistency of the respondents' pairwise comparisons in the questionnaire survey (see Figure 4.3) is assessed to determine whether any re-examination of the survey pairwise judgments is required. This is done by computing the CR of the matrix $\widetilde{A}$, which includes the fuzzy preference numbers of the relative importance of each SSC versus another. Based on the approach used by Kazerooni et al. (2020), matrix $\widetilde{A}$ is defuzzified into two crisp matrices. The first matrix, A_1, includes the most promising value of the fuzzy numbers of matrix $\widetilde{A}$, and the second matrix, A_2, includes the geometric mean of the lower and upper bounds of the fuzzy numbers. Then, the CR for matrices A_1 and A_2 is evaluated: $CR_{A_1} = 0.0155$, and $CR_{A_2} = 0.0426$. Since both CRs are less than 0.1, no re-examination of the survey pairwise responses, shown in Figure 4.3, is required.

4.2.3.3. Fuzzy TOPSIS

Fuzzy TOPSIS, as another fuzzy MCDM technique, is used for determining the relative importance of each strategy to CLP improvement. TOPSIS is one of the most widely used MCDM methods that works satisfactorily in various application areas (Yavuz 2016). However, it is often difficult for decision makers to assign accurate values to alternatives for the criteria under consideration (Perçin and Aldalou 2018). Fuzzy TOPSIS allows decision makers to assign linguistic performance ratings to the alternatives instead of precise numbers. This method ranks CLP strategies according to their distance to the fuzzy positive-ideal solution, $\tilde{A}^*$, and the fuzzy negative-ideal solution, $\tilde{A}^-$. According to Singh et al. (Singh et al. 2016), $\tilde{A}^*$ can be obtained by maximizing the benefit criteria IC, IF, and WA. $\tilde{A}^-$ can be reached by minimizing the cost criterion, which is IR. Considering a set of K decision makers as $\{D_1;\ D_2; \dots;\ D_K\}$ and a set of m CLP improvement strategies as $\{S_1;\ S_2; \dots;\ S_m\}$, the steps of fuzzy TOPSIS for determining the importance of the CLP improvement strategies are given below.

Step 1: Construct the fuzzy decision matrix.

The linguistic value given by the kth decision maker to each improvement strategy regarding each SSC is transformed into a trapezoidal fuzzy number as $\tilde{R}_k = (a_k;\ b_k;\ c_k;\ d_k)$, using the membership functions in Table 4.2. The responses of the decision makers are then aggregated as $\tilde{R} = (a;\ b;\ c;\ d)$ using the following detailed computations:

$$a = \min_k\{a_k\} \qquad b = \frac{1}{K}\sum_{i=1}^{k} b_K \qquad c = \frac{1}{K}\sum_{i=1}^{k} c_K \qquad d = \max_k\{d_k\} \tag{4.6}$$

The fuzzy decision matrix is built with m rows and K columns. Each cell of the matrix is shown by $\tilde{R}_{ij} = (r_{ij1};\ r_{ij2};\ r_{ij3};\ r_{ij4})$, which is the fuzzy number of the ith strategy with respect to the jth criterion.

Step 2: Compute the normalized fuzzy decision matrix.

For the benefit criteria IC, IF, and WA, normalized $\tilde{R}_{ij}$ is computed as:

$$\widetilde{N}_{ij} = \left(\frac{r_{ij1}}{r_j^*};\ \frac{r_{ij2}}{r_j^*};\ \frac{r_{ij3}}{r_j^*};\ \frac{r_{ij4}}{r_j^*}\right) \tag{4.7}$$

where r_j^* is calculated as:

$$r_j^* = \max_i\{r_{ij4}\} \tag{4.8}$$

For the cost criterion IR, normalized $\tilde{R}_{ij}$ is calculated as:

$$\tilde{N}_{ij} = \left(\frac{r_j^-}{r_{ij4}}; \frac{r_j^-}{r_{ij3}}; \frac{r_j^-}{r_{ij2}}; \frac{r_j^-}{r_{ij1}}\right) \tag{4.9}$$

where r_j^- is calculated as:

$$r_j^- = \min_i\{r_{ij1}\} \tag{4.10}$$

Step 3: Weight the normalized fuzzy decision matrix.

The weighted $\tilde{N}_{ij}$ is determined by following formula:

$$\tilde{V}_{ij} = W_j \times \tilde{N}_{ij} \tag{4.11}$$

where $\tilde{V}_{ij}$ is the weighted fuzzy number of the ith strategy with respect to the jth criterion and is depicted as $(v_{ij1};\ v_{ij2};\ v_{ij3};\ v_{ij4})$.

Step 4: Calculate the distance of each improvement strategy from $\tilde{A}^*$ and $\tilde{A}^-$.

First, $\tilde{A}^*$ and $\tilde{A}^-$ are determined by the following formulas:

$$\tilde{A}^* = (\tilde{V}_1^*, \tilde{V}_2^*, \tilde{V}_3^*, \tilde{V}_4^*) \tag{4.12}$$

$$\tilde{A}^- = (\tilde{V}_1^-, \tilde{V}_2^-, \tilde{V}_3^-, \tilde{V}_4^-) \tag{4.13}$$

where $\tilde{V}_j^*$ and $\tilde{V}_j^-$ are trapezoidal fuzzy numbers, defined as:

$$\tilde{V}_j^* = (\max_i\{v_{ij1}\}; \max_i\{v_{ij2}\}; \max_i\{v_{ij3}\}; \max_i\{v_{ij4}\}) \tag{4.14}$$

$$\tilde{V}_j^- = (\min_i\{v_{ij1}\}; \min_i\{v_{ij2}\}; \min_i\{v_{ij3}\}; \min_i\{v_{ij4}\}) \tag{4.15}$$

Then, the distance of the ith improvement strategy from $\tilde{A}^*$ and $\tilde{A}^-$ is calculated by:

$$d_i^* = \sum_{j=1}^4 d_v(\tilde{V}_{ij}, \tilde{V}_j^*), \qquad d_i^- = \sum_{j=1}^4 d_v(\tilde{V}_{ij}, \tilde{V}_j^-) \tag{4.16}$$

where $d_v(.,.)$ is the vertex distance measurement between two trapezoidal fuzzy numbers, such as $\tilde{x}$ and $\tilde{y}$, that is computed by following formula:

$$d_v(\tilde{x}, \tilde{y}) = \sqrt{\frac{(x_1-y_1)^2+(x_2-y_2)^2+(x_3-y_3)^2+(x_4-y_4)^2}{4}} \tag{4.17}$$

Step 5: Compute the closeness coefficient.

The closeness coefficient of each CLP improvement strategy is computed by:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{4.18}$$

The higher the CC_i of the strategy, the closer to $\tilde{A}^*$ and farther from $\tilde{A}^-$. Table 4.3 shows the closeness coefficient of the CLP improvement strategies along with their rank compared to each other.

Based on the data in Table 4.3, the average closeness coefficient equals 0.7090. Therefore, the first seven top-ranked strategies are S11, S2, S13, S7, S6, S9, and S16, which have closeness coefficients greater than the average, and were selected as the most effective CLP improvement strategies for the project under study.

Table 4.3. CLP improvement strategy ranking.

Strategy	Closeness coefficient	Rank
S11	0.8496	1
S2	0.8341	2
S13	0.8026	3
S7	0.7899	4
S6	0.7665	5
S9	0.7201	6
S16	0.7099	7
S12	0.6991	8
S8	0.6961	9
S14	0.6900	10
S1	0.6875	11
S3	0.6644	12
S15	0.6418	13
S10	0.6215	14
S5	0.6005	15
S4	0.5704	16

4.2.4. Quantifying strategies' impact on CLP

An FCM model of CLP is developed for simulating the relationships among the most value-adding CLP factors and quantifying the impact on CLP of the selected top-ranked improvement strategies. FCM is a soft computing technique for modeling and simulating dynamic systems such as a CLP environment by mimicking the process of developing a cognitive map in a human mind (Ahn et al. 2015). Generally, the manual process for developing an FCM is using expert knowledge to evaluate the strength of causal relationships in terms of weights using linguistic variables such as "Low," "Medium," and "High." During the simulation, the value of CLP factor C_j at time t is calculated using Equation (4.19), as proposed by Papageorgiou (2012):

$$A_j^{(t)} = f\left(\sum_{\substack{i=1 \\ j\neq i}}^{M} w_{ij}\left(2A_i^{(t-1)} - 1\right) + \left(2A_j^{(t-1)} - 1\right)\right) \tag{4.19}$$

where w_{ij} is the strength of the casual relation between two CLP factors C_i and C_j and denoted via a causal edge from C_i to C_j; w_{ij} ranges from -1 (absolute negative causality) to 0 (no causality) and 1 (absolute positive causality).

In Equation (4.20), f(.) is an activation function that is formulated as sigmoid threshold function in this thesis:

$$f_{(x)} = \frac{1}{1+e^{-\lambda(x-h)}} \tag{4.20}$$

where λ and h are real positive numbers that control slope and offset of the function, respectively. Higher values of λ make the function more sensitive to the fluctuations of x (Felix et al. 2017).

When no expert is available or is the model contains a large amount of relationships, an FCM cannot be developed through the manual process of using expert knowledge (Kokkinos et al. 2018). For such cases, learning processes can be applied to automatically determine near-optimal weights of the relationships. FCM learning algorithms can be grouped into three types based on their underlying learning paradigm: (1) Hebbian-based, (2) error-driven, or (3) hybrid. Hebbian-based learning algorithms, such as nonlinear Hebbian learning (NHL), are unsupervised methods, which do not require historical data. Their main drawback is their dependency on expert knowledge, since they require initial weight of causal relationships (Stach et al. 2008). Error-driven learning algorithms, such as the real-coded genetic algorithm (RCGA), generates weight matrices by attempting to fit the FCM model to a set of historical data. Several studies illustrated that these algorithms increase the FCM robustness, functionality, and generalization abilities (Chen et al. 2015). Hybrid learning algorithms employ a combination of the other two types to take advantage of the fast speed and effectiveness of Hebbian-based methods and the global search and generalization ability of error-driven methods (Ren 2012).

In the proposed method, an initial FCM model is developed based on the importance of the most-value adding CLP factors, then the strength of a causal relation between two factors C_i and C_j is quantified by a numerical weight $w_{ij} \in [-1, 1]$. Three types of causal relation among the factors exist: (1) positive causality ($w_{ij} > 0$), which means an increase or decrease in C_i causes the same result in C_j; (2) negative causality ($w_{ij} < 0$); and (3) no causality (w_{ij} = 0). After the strengths of all relationships are assessed, each improvement strategy is considered in the model, one at a time, in order to determine the quantitative effect of each strategy on construction productivity.

FCM Expert, developed by Nápoles, Espinosa, et al. (2018), is used as a software platform for modeling the proposed FCM model of CLP. Figure 4.5 shows the flow chart of the proposed framework of constructing the FCM model, which consists of three major tasks, described below.

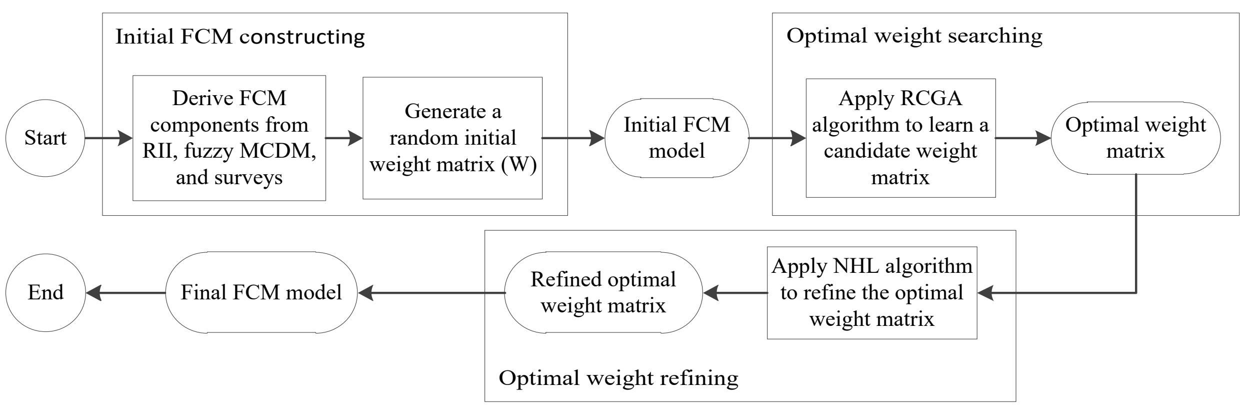

Figure 4.5. Flow chart of constructing the FCM model.

Initial FCM constructing included causal relationships among the initial FCM parameters (i.e., the most value-adding factors and CLP) and initial states of the parameters according to the dataset, surveys results, and past studies.

Optimal weight searching entails applying RCGA algorithm to find an optimal weight matrix based on its global search and generalization ability. The weight matrix comprises the causal relationships among the factors. The data used in RCGA is based on the dataset of Tsehayae and Fayek (2014, 2016) discussed above in the methodology section. The dataset including the value of factors and CLP is normalized between 0 and 1 in order to be used in the FCM model. Figure 4.6 shows the real-time visualization of the error curve of searching the optimal weight matrix by performing 50 iterations.

Optimal weight refining applies NHL algorithm in order to fine-tune the optimal weight matrix and get closer to the optimized structure. The output of RCGA is used as the input of NHL algorithm, thus no expert knowledge is required for conducting NHL.

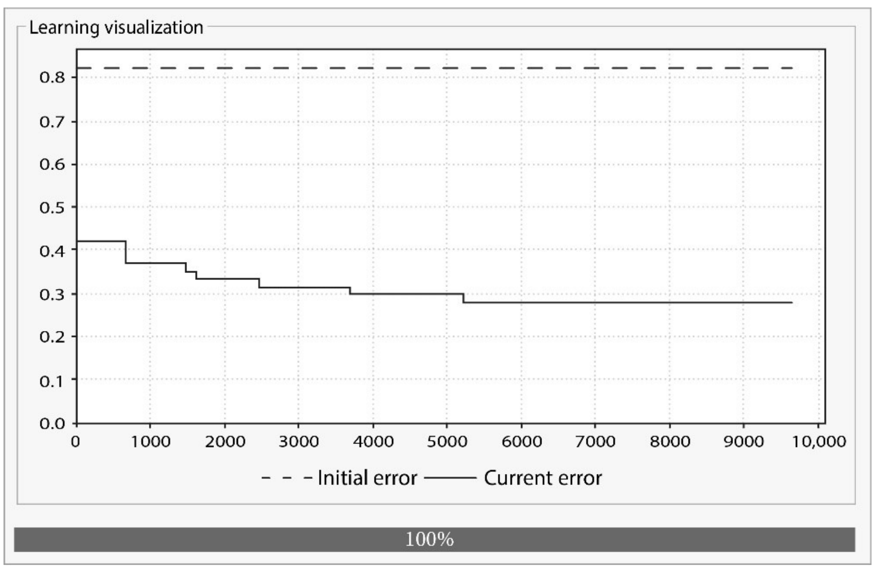

Figure 4.6. Visualization of error curve in the process of finding the optimal weight matrix.

Based on the refined optimal weight matrix, the final FCM model of CLP is developed as shown in Figure 4.7. F1, F2, and so on through F19 are the identified most value-adding CLP factors (listed in Table 4.1), and the directions and values of the arrows demonstrate the direction and strength of causalities among the factors. For example, the strength of causality from factor 4 (F4) “Owner staff on site” toward the factor 5 (F5) “Congestion of work area” is + 0.8, which means F4 has a strong positive influence on F5; and the strength of causality from factor 19 (F19) “Cleanliness of work area” toward factor 2 (F2) “Complexity of task” is – 0.2, which means F19 has a weak negative influence on F2.

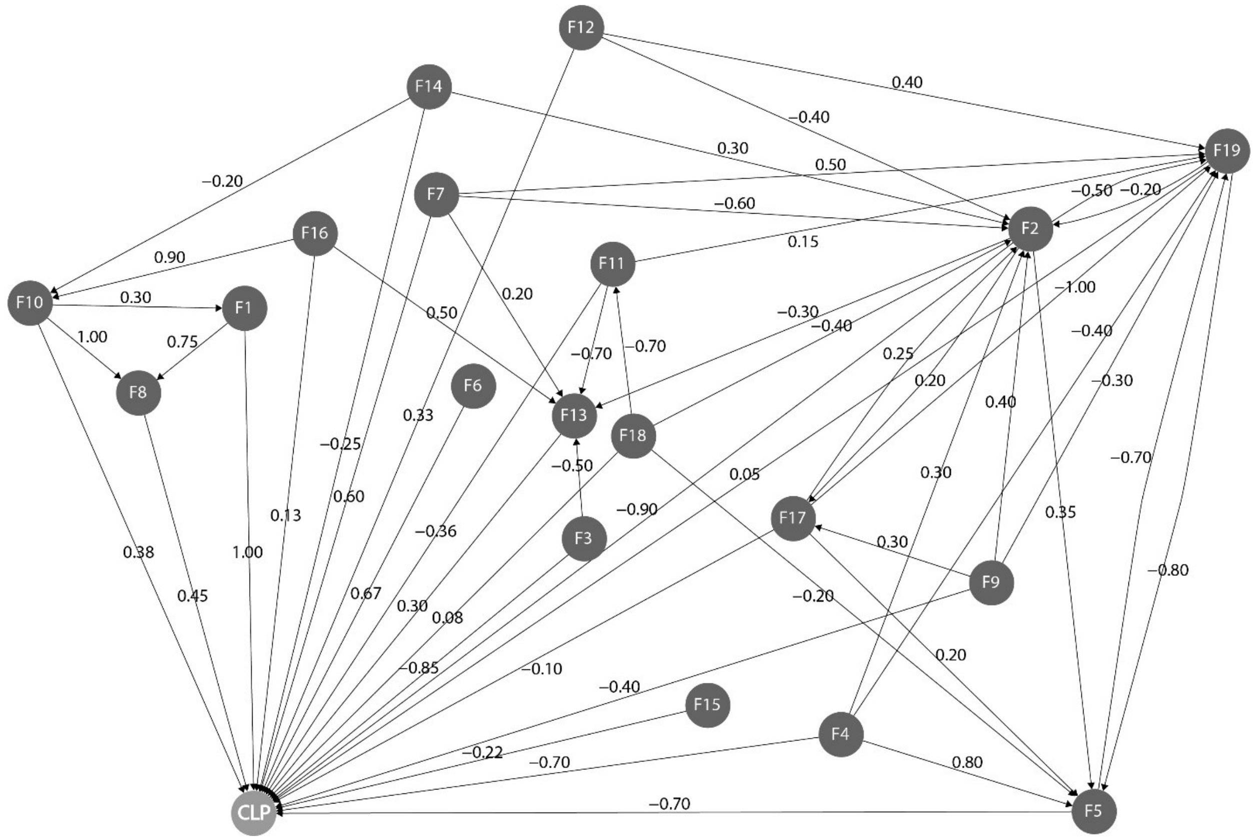

Figure 4.7. The FCM model of CLP with refined optimal weights.

By considering the importance of improvement strategies derived from fuzzy TOPSIS, the quantified impact of each strategy on CLP is achieved through the steps shown in Figure 4.8.

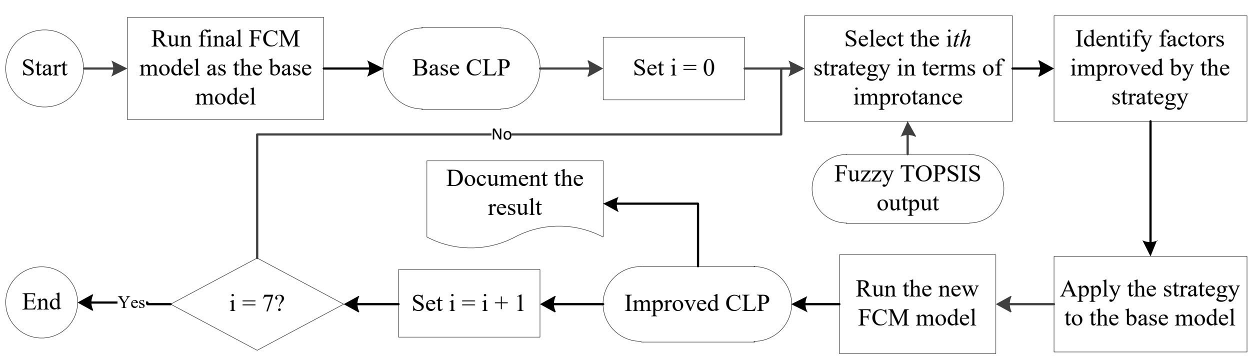

Figure 4.8. Flow chart of determining the impact of improvement strategies on CLP.

As shown in Figure 4.8, the final FCM model is run one time without applying any strategies in order to determine the base CLP that equals 0.5310 for the project under study. The base CLP is the current value of the project's CLP. Then, a single strategy is applied to the model according to its rank as shown in Table 4.3. In the case study, strategy 11, "Develop clear instructions about the equipment used to transport materials," is selected first. The model is run and the resulting CLP is called the "improved CLP," since it is obtained from applying the CLP improvement strategy to the FCM model. The improved CLP is 0.5452 for strategy 11. Other strategies are selected one by one according to their rank as shown in Table 4.3, and their improved CLPs are determined, as shown in Table 4.4.

Table 4.4. Quantified impact and rank of the most effective strategies.

No.	CLP improvement strategy	Improved CLP	Rank
S2	Provide clear instructions to craftspeople on how to complete tasks before their execution	0.5516	1
S6	Train labourers to achieve the latest concrete-pouring techniques	0.5478	2
S13	Apply preventive maintenance to heating and air-conditioning systems to make sure they are in working order	0.5460	3
S11	Develop clear instructions about the equipment used to transport materials	0.5452	4
S9	Hold regular meetings with labourers about schedule and remaining tasks	0.5451	5
S7	Perform project team activities	0.5446	6
S16	Hire cheap labour for daily housekeeping tasks	0.5420	7

4.3. Results and Discussion

The case study provided the application of the presented decision-support model to identify the most effective CLP improvement strategies and quantify their impact on CLP for concrete-pouring activities in the building construction project. Experts' opinion and historical data were collected to model the complex CLP environment including the relationships among the factors affecting CLP that are mostly interconnected. According to SSCs' weights derived from the responses of 10 experts to the questionnaire survey of Figure 4.3, the most critical criteria for selecting CLP improvement strategies for the project under study are IC and IF, respectively. It means that the first priority of the company is to implement strategies that have greater impact on CLP compared to other strategies. The second priority of the company is to implement strategies, which takes less time and cost compared to project's scheduled duration and budget.

In Table 4.3, strategy 11, “Develop clear instructions about the equipment used to transport materials,” has the highest value of closeness coefficient. This strategy along with strategies – S2, S13, S7, S6, S9, and S16 have closeness coefficients above the average. This means these strategies are the most effective CLP improvement strategies with respect to SSCs. The impact of these seven most effective strategies was quantified by developing an FCM model for CLP, implementing each strategy in the model, and determining improved CLP for each strategy. According to Table 4.4, strategy 2, “Provide clear instructions to craftsmen on how to complete tasks before their execution,” improves CLP by 0.0206 and has the greatest impact on CLP. Recall that CLP is defined as the ratio of installed quantity (in cubic meters) to total labour work-hours, therefore if the concrete pouring requires 100 labour work-hours per week, implementing this improvement strategy will increase the installed quantity of concrete by 100 × 0.0206, or 2.06 cubic meters per week. This strategy is supported by Tsehayae and Fayek (2014) and Gurmu and Aibinu (2017), whose work identified “Availability of clear work front,” “Adequate job instruction,” and “Clear readability of drawings and specifications” as top strategies for improving CLP. Strategy 6, “Train labourers to achieve the latest concrete-pouring techniques,” improves CLP by 0.0168 and is the second most effective in terms of impact on CLP. This strategy is supported by Archana Menon and Varghese (2018) and Hammad et al. (2011) who found “Training crew” and “Expanding skilled labourers” to be important strategies for improving construction productivity. Strategy 13, “Apply preventive maintenance to heating and air-conditioning systems to make sure they are in working order,” strategy 11, “Develop clear instructions about the equipment used to transport materials,” strategy 9, “Hold regular meetings with labourers about schedule and remaining tasks,” strategy 7, “Perform project team activities,” and strategy 16, “Hire cheap labour for daily housekeeping tasks,” are the next most effective strategies, improving project CLP by 0.0150, 0.0142, 0.0141, 0.0136, and 0.0101, respectively.

The proposed decision-support model was evaluated using structural validity and behavioral validity, as discussed in the methodology section above. Structural validity was conducted by evaluating the list of model parameters (i.e., factors influencing CLP, CLP improvement strategies) with respect to the relevant literature and the panel of experts who completed surveys in various phases of the study. Regarding behavioral validity, behavior of the system was validated by the extreme-conditions test that compares the generated behavior of CLP in the FCM model before applying any strategies to the behavior of the real system of CLP under the same extreme conditions of CLP factors. First, the upper and lower bounds of factors and CLP need to be defined. Since the utilized dataset was normalized between 0 and 1, the upper bound for the factors and CLP is 1 and the lower bound is 0. Second, the FCM model is run twice. In the first run, factors that positively impact CLP took the extreme high value of 1, and the factors with negative impact on CLP took the extreme low value of 0. In this case, the resulting CLP was 0.984, which is close to 1, as anticipated. In the second run, positive factors took the extreme low value of 0 and negative factors took the high value of 1. The resulting CLP in this case was 0.088, which is close to 0, as anticipated. Therefore, the FCM model of CLP revealed a logical behavior when extreme values were assigned to the factors affecting CLP. Accordingly, behavioral validity of the proposed FCM model of CLP is determined.

Since CLP is affected by various interconnected factors, such as crew motivation and working conditions, it is necessary to consider the causal relationships among the factors and strategies to achieve accurate values for the quantified impact of strategies on CLP (Gerami Seresht and Fayek 2019). Another issue that affects the accuracy of the quantified impact of improvement strategies is the consideration of project characteristics in modeling CLP. CLP is a context-specific efficiency measure, because the identified factors and their degrees of impact on CLP vary from project to project (Heravi and Eslamdoost 2015; Tsehayae and Fayek 2016). Hence, key CLP improvement strategies also differ from one project to another. Since statistical methods such as t-test and regression analysis lack the ability to capture project characteristics and causal relationships among various factors, considering the project characteristics and the causal relationships among CLP factors made the results of this research more accurate than previous studies that used statistical methods to quantify the impact of improvement strategies on CLP.

4.4. Summary

This chapter presents the decision-support model for selection the most effective CLP improvement strategies. The proposed model is developed through the five following steps: factors and strategies identification, ranking strategies, quantifying the strategies' impact on CLP. In the first phase, 16 CLP improvement strategies that correspond to the determined key factors of Chapter 3, are determined by expert knowledge. In the second phase, the identified 16 strategies are ranked with respect to four criteria, including IC, IF, WA, and IR by integrating two fuzzy MCDM methods – fuzzy AHP and fuzzy TOPSIS. In the third phase, An FCM model of CLP was developed for simulating the relationships among the most value-adding CLP factors and quantifying the impact on CLP of the selected top-ranked improvement strategies. First, an initial FCM model was constructed based on the importance of the most-value adding CLP factors, then the strength of causal relation among the factors are quantified by applying RCGA algorithm to find an optimal weight matrix based on its global search and generalization ability. Then, each improvement strategy is considered in the model, one at a time, in order to determine the quantitative effect of each strategy on construction productivity. As a result, the top three most effective CLP improvement strategies for concrete activities in building project include (1) providing clear instructions to craftspeople on how to complete tasks before their execution, (2) training labours to achieve the latest concrete pouring techniques, and (3) applying preventive maintenance to heating and air-conditioning systems to make sure they are in working order. Finally, the decision-support model is validated by evaluates the list of model parameters, and extreme-conditions test.

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Chapter 5. Conclusions and Recommendations

5.1. Introduction

This chapter provides the research summary and the academic and industrial contributions of this research. This chapter also discusses the limitations of this research and provides recommendations for future research and development.

5.2. Research Summary

This thesis aimed to fill gaps in construction research regarding prioritizing CLP improvement strategies and quantifying their impact on CLP. An extensive review of past research on developing systematic models for selection and quantification of CLP improvement strategies revealed several gaps: The majority of previous studies have relied on expert knowledge through questionnaire surveys and evaluation index methods such as RII to establish the factors that affect CLP significantly. Very few studies have attempted to identify the relative importance of CLP factors through the use of a data-driven approach such as correlation analysis or feature selection (Moselhi and Khan 2012). Data-driven approaches are not dependent on expert knowledge and do consider the dynamics of CLP factors and the interconnected relationships among them. Widely used data-driven approaches include statistical methods such as regression analysis or correlation-based feature selection, which are limited by the number of influencing factors and their capability to determine the combined impact of influencing factors (Song and AbouRizk 2008). The **first gap** in the current literature of identifying factors affecting CLP is considering the dynamics, interconnection, and combined impact of the factors that affect CLP by developing a model which is independent on expert knowledge. To achieve optimum productivity in construction projects, it is pivotal for management teams to identify the most effective CLP improvement strategies. Although several studies have been conducted on identifying key CLP improvement strategies in the construction domain, only a few attempted to quantify the impact of improvement strategies on CLP. The **second gap** is that the statistical methods applied in previous studies, such as t-test and regression analysis, were not able to consider the causal relationship among CLP improvement parameters such as affecting factors, improvement strategies, and CLP. CLP factors are mostly interconnected and affect each other. Thus, it is necessary to consider the causal relationship among the factors and strategies to achieve accurate values for the quantified impact of strategies on CLP. The **third gap** is that previous studies selected CLP improvement strategies without considering a given project's characteristics; instead, they selected key improvement strategies based on previous research. However, CLP is a context-specific efficiency measure, as the identified factors and their degree of impact on CLP vary from project to project (Heravi and Eslamdoost 2015; Tsehayae and Fayek 2016). Therefore, key CLP improvement strategies also differ from one project to another, and a systematic approach is needed to capture the project characteristics and construct the cause-and-effect relationships among CLP improvement parameters in order to identify the most effective CLP improvement strategies for a given project.

To fill the mentioned gaps, the objectives of this research were achieved in four stages as follows.

5.2.1. The first stage: Literature review

An extensive literature review was conducted on relevant topics, as described in Chapter 2. First, previous studies on developing different methods such as regression techniques, correlation analysis, evaluation index methods, and feature selection for identifying the key factors that affect CLP were reviewed. Then, previous studies on identifying CLP improvement strategies and quantifying the impact of strategies on improving CLP was reviewed.

5.2.2. The second stage: Identifying the most value-adding CLP factors

Understanding the factors that affect labour productivity is important for making strategic decisions and selecting appropriate CLP improvement strategies (Jalal and Shoar 2019). Chapter 3first discusses how data preparation steps including normalization, imputing missing values, removing factors with zero deviation, and eliminating outliers were applied to improve the efficiency of CLP data analysis. Normalization with respect to normal distribution was used to scale CLP data into an organized range, and KNN-based imputation method was utilized to impute missing values. The Tukey test method was used to detect and eliminate outliers. After the CLP data were prepared, the integration of ReliefF algorithm as a filter method and SVM-GA as a wrapper method was presented as an HFS model for identifying the most value-adding CLP factors.

5.2.3. The third stage: Identifying and ranking CLP improvement strategies

After the most value-adding CLP factors were determined, an extensive literature review of past studies was conducted to identify various CLP improvement strategies that correspond to the determined key factors. As a result, 54 strategies with the potential to improve CLP were identified for 19 factors. The most appropriate strategy among the identified potential strategies was then determined for addressing each CLP factor using the knowledge of three experts involved in the project under study. As a result, 16 different strategies were identified. These 16 strategies were then ranked with respect to four criteria: impact of CLP (IC); implementation feasibility (IF); workers' adaptation (WA); and implementation risk (IR). Thereafter, two fuzzy MCDM methods – fuzzy AHP and fuzzy TOPSIS – were integrated in order to rank the CLP improvement strategies. Fuzzy AHP was used to determine the relative weights of the four criteria based on fuzzy pairwise comparison, and fuzzy TOPSIS was applied to determine the relative importance of each strategy and rank the strategies. The combination of fuzzy AHP and fuzzy TOPSIS captures experts' opinion and represents uncertainty and vagueness in the decision-making process of CLP improvement strategies selection without involving cumbersome mathematics. In addition, the utilized fuzzy MCDM methods support FCM by reducing the number of improvement strategies needed for FCM modeling according to various criteria including impact on CLP, implementation feasibility, workers' adaptation, and implementation risk.

5.2.4. The fourth stage: Quantifying strategies' impact on CLP

An FCM model of CLP was developed for simulating the relationships among the most value-adding CLP factors and quantifying the impact on CLP of the selected top-ranked improvement strategies. First, an initial FCM model was constructed based on the importance of the most-value adding CLP factors; the strength of causal relation among the factors were then quantified using numerical weights. The weights were determined by applying RCGA algorithm to find an optimal weight matrix based on its global search and generalization ability. After the strengths of all relationships were assessed, each improvement strategy was considered in the model, one at a time, in order to determine the quantitative effect of each strategy on construction productivity. The developed FCM model takes into account the imprecision and uncertainty of CLP factors as well as the causality among them. The proposed methodology considers the causal relationships among CLP improvement parameters and captures the perspective of construction experts to consider project characteristics and address existing gaps in the CLP improvement strategies literature. Therefore, the results of this research are more accurate than previous studies that used statistical methods to quantify the impact of improvement strategies on CLP without considering the project characteristics and causal relationships among CLP factors. Finally, the proposed model was evaluated using (1) structural validity, which evaluates the list of model parameters, and (2) extreme-conditions test that compares the generated behavior of CLP in the FCM model to the behavior of the real system of CLP under the same extreme conditions of CLP factors.

5.3. Research Contributions

Results of the thesis are expected to make several contributions to (1) the body of knowledge (Academic contributions) and (2) practitioners (Industrial contributions), as follows.

5.3.1. Academic contributions

The expected academic contributions of this research are:

- Development of an HFS model by combining ReliefF as a filter method and SVM-GA as a wrapper method in order to identify the most value-adding factors that affect CLP. The developed HFS model considers the dynamics, interconnection, and combined impact of the factors without dependency on expert knowledge.
- Development of a list of appropriate CLP improvement strategies that correspond to addressing the identified most value-adding CLP factors through an extensive literature review of past studies in the construction domain.
- Development of a ranking process for CLP improvement strategies with respect to various criteria by integrating two fuzzy MCDM methods – fuzzy AHP and fuzzy TOPSIS – in order to determine the most effective CLP improvement strategies for a given project.
- Development of an FCM model that quantifies the impact of various management strategies on improving CLP. The proposed model takes into account project characteristics and the imprecision and uncertainty of CLP factors in order to capture the causal relationships among CLP factors. Thus, the results of this model are more accurate than previous studies that used statistical methods to quantify the impact of improvement strategies on CLP.

5.3.2. Industrial contributions

The expected industrial contributions of this research are:

- Identification of the most value-adding factors affecting CLP, which helps construction companies identify the improvement strategies that correspond to and can address specific identified CLP factors. In addition, this finding provides construction practitioners with information about factors that have the highest level of influence on predicting CLP.

- Identification of the most effective CLP improvement strategies and quantification of their impact on CLP, which helps construction management teams allocate their limited budget and resources to those strategies that have the greatest impact on CLP. In addition, this finding assists construction managers in improving CLP for their projects in an optimum manner to reduce variances from the primary plan and keep projects on time and within budget. Quantifying the impact of an improvement strategy helps construction companies determine the cost savings and time savings achieved by implementing that strategy.
- Development of a systematic approach for simulating the impact of various management practices on CLP of specific projects prior to their implementation. This helps construction companies avoid applying management practices that have only subtle impact on CLP for given projects.

5.4. Research Limitations and Recommendations for Future Research

The following limitations were encountered in the research study, and some recommendations are suggested for future work:

1. The developed HFS model utilizes field data collected for concrete-pouring activities in building projects. However, in order to develop a generic model of CLP for different types of labour-dependent activities and industrial projects, new data need to be collected. Additional investigation with other labour-intensive activities, such as welding, piping, and scaffolding, is recommended to further improve the developed HFS model.
2. The proposed decision-support model that was developed for labour-intensive activities, so it cannot accurately quantify the impact of management practices on improving the productivity of equipment-intensive activities. Therefore, future research can focus on using the proposed methodology to develop an FCM model of multi-factor construction productivity, which includes labour, equipment, and materials.
3. The FCM model of CLP was built using FCM Expert software. Since the results depend on the performance of the utilized software, developing the FCM model using other software platforms such as Mental Modeler and FCM Tool are recommended.

4. Future studies may use structural simplification methods such as clustering of nodes in order to simplify the FCM model of CLP and reduce computational complexity.
5. The decision-support model of this thesis determines the effect of each improvement strategy on CLP without considering the existence of other strategies. However, improvement strategies are interconnected and synergy among them is expected to exist. To overcome the aforementioned limitation, future research may consider the impact of improvement strategies on each other using simulation techniques such as fuzzy system dynamics to achieve results that are more precise.
6. A limited number of experts were used to carry out various phases of the developed decision-support model. In order to have a more generalized and representative results, future studies may utilize a larger sample size in terms of experts.
7. As a future research, more criteria, such as impact on a company's key performance indicators, schedule risk, and budget risk, can be considered for ranking the CLP improvement strategies. Although adding more criteria increases the computational complexity of fuzzy MCDM methods and increases the time spent on the survey questionnaire, it is expected that the model delivers more accurate results for prioritizing improvement strategies as more criteria are considered in the strategy selection process. Adding more criteria can also increase the applicability of the proposed decision-support model within a broader context, such as the selection of the most effective improvement strategies on multi-factor productivity, which includes labour, equipment, and material.
8. In a future study, researchers may implement the top-ranked improvement strategies to a real case study to validate and refine the FCM model of CLP by comparing the generated behavior of CLP in the FCM to the behavior of the real system of CLP.
9. According to the quantified impact of strategies on CLP using the proposed model, future studies may focus on comparing the cost of implementing an improvement strategy and the cost savings achieved by implementing the same strategy.

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Appendix A. CLP Factors of the Dataset

Table A. CLP factors of the dataset

	No.	Factors	Linguistic Descriptors	Scale of Measure
Activity level	1	Crew size	small, average, large	Integer (Total number of crew members)
	2	Craftsperson education	Elementary (1), High School (2), Technical (3), College (4), University (5)	Categorical (Most frequent category)
	3	Craftsperson on job training	poor, fair, good	Real number (No. trainings attended x Duration of Training, hrs)
	4	Craftsperson technical training	poor, fair, good	Real number (No. trainings attended x Duration of Training, hrs)
	5	Crew composition	poor, fair, good	Proportion (Ratio Journeyman to Apprentice to Helper) (1 JR/2 AP)
	6	Crew experience (seniority)	poor, fair, good	Real number (Crew average years of experience)
	7	Number of languages spoken	low, medium, high	Integer (Number of languages spoken, total for a crew)
	8	Co-operation among craftsperson	poor, fair, good	1–5 Predetermined rating
	9	Treatment of craftsperson by foreman	poor, fair, good	1–5 Predetermined rating
	10	Craftsperson motivation	low, average, high	1–5 rating
	11	Craftsperson fatigue	low, average, high	Real number (Total worked hours per week to Regular work hour per week)
	12	Craftsperson trust in foreman	poor, fair, good	1–5 Predetermined rating
	13	Team spirit of crew	poor, fair, good	1–5 Predetermined rating
	14	Level of absenteeism	low, medium, high	Percentage (% average number of absent crew members to total crew size, daily average)
	15	Crew turnover	low, medium, high	Turnover rate (% of crew)
	16	Discontinuity in crew makeup	small, medium, large	Real Number (Average occurrence of crew member change)
	17	Level of interruption and disruption	low, medium, high	Integer (Number of interruption and disruption per day)

	18	Fairness of work assignment	poor, fair, good	1–5 Predetermined rating
	19	Crew participation in foreman decision-making process	Without explanation (1), Joint (2), With (3)	Categorical (Decision Type)
	20	Crew flexibility	low, average, high	1–5 rating
	21	Job site orientation program	No (0), Yes (1)	Categorical
	22	Job security	poor, fair, good	Integer (Average length of unemployment period, months)
	23	Availability of craftsperson	poor, fair, good	Integer (Average number of unmet labour demand per crew for a given task)
	24	Availability of task materials	poor, fair, good	Real number (Average waiting time for getting materials, man-hours)
	25	Quality of task materials	poor, fair, good	1–5 Predetermined rating
	26	Material unloading practices	poor, fair, good	Real Number (average unloading time, min)
	27	Material movement practices (horizontal)	poor, fair, good	Real Number (average distance, m)
	28	Material movement practices (vertical)	poor, fair, good	Real Number (average distance, m)
	29	Availability of work equipment (crane, forklift)	poor, fair, good	1–5 rating
	30	Availability of transport equipment (man lift)	poor, fair, good	1–5 rating
	31	Equipment breakdown	infrequent, frequent, very frequent	Integer (Equipment Type and Average number of breakdown occurrence per week)
	32	Availability of tools	poor, fair, good	Real number (Average waiting time, min)
	33	Sharing of tools	low, average, high	Real number (Number of crews sharing a tool)
	34	Quality of tools	poor, fair, good	Real Number (Average no. of tool breakdown per week)
	35	Misplacement of tools	infrequent, frequent, very frequent	Real Number (Average no. of misplacement per day)
	36	Availability of electric power	poor, fair, good	Real number (Average waiting time, min)

	37	Availability of extension cords	poor, fair, good	Real number (Average waiting time, min)
	38	Complexity of task	low, average, high	1–5 Predetermined rating
	39	Repetitiveness of task	low, medium, high	Real number (ratio of identical work tasks qty to the total work task qty)
	40	Total work volume	small, medium, large	Real number (Approved quantity for construction)
	41	Level of Rework	low, average, high	Real number (Construction Filed Rework Index)
	42	Frequency of Rework	infrequent, frequent, very frequent	Real number (No. of rework occurrence per scope of work)
	43	Task change orders – Extent	low, average, high	Real number (Ratio of approved total volume of change order to total work volume)
	44	Task change orders – Frequency	few, some, many	Real number (No. of occurrence per scope of work)
	45	Working condition (noise)	low, average, high	1–5 Predetermined rating
	46	Working condition (dust and fumes)	low, average, high	1–5 Predetermined rating
	47	Location of work scope (distance)	very close, close, far	Real number (distance, m)
	48	Location of work scope (elevation)	very close, close, far	Real number (distance, m)
	49	Congestion of work area	low, average, high	Real number (ratio of actual peak manpower to actual average manpower)
	50	Cleanliness of work area	poor, fair, good	Integer (Number of cleaning operations per day)
	51	Foreman Skill and Responsibility	poor, fair, good	1–5 rating
	52	Fairness in performance review of crew by foreman	poor, fair, good	1–5 Predetermined rating
	53	Change of foremen	infrequent, frequent, very frequent	Turnover rate (No. of turnovers per month)
	54	Span of control	low, medium, high	Integer (Average total number of crews per foreman)
	55	Response rate with RFI's	poor, fair, good	Real number (Response time, hrs)

Project level	56	Concrete placement technique	Pump (1), Crane and Bucket (2), Direct chute (3)	Categorical
	57	Structural element	Columns (1), Footings (2), Grade Beams (3), Pile Caps (4), Slabs (5), Walls (6)	Categorical
	58	Change in design drawings	infrequent, frequent, very frequent	Real number (Ratio of number of changed drawings to total number of drawings per discipline)
	59	Change in specifications	infrequent, frequent, very frequent	Real number (Ratio of number of changed specifications to total number of specification clauses on specific scope)
	60	Changes in contract conditions	infrequent, frequent, very frequent	Real number (Ratio of number of contract conditions changes to total number of contract clauses on specific scope)
	61	Lack of information	infrequent, frequent, very frequent	Real number (Number of RFI's per month per discipline)
	62	Approval for building permit	poor, fair, good	Real number (average process time for work or permit approval, months)
	63	Year of construction (to identify relation)	Year	Integer (Year of Construction)
	64	Project level rework	infrequent, frequent, very frequent	Real number (Project Overall CFRI)
	65	Project level change order	low, average, high	Real number (Ratio approved total cost of change order over all project to original approved project cost)
	66	Weather (temperature)	low, medium, high	Real number (˚C)
	67	Weather (precipitation)	low, medium, high	Real number (mm)
	68	Weather (humidity)	low, medium, high	Real number (%)
	69	Weather (wind speed)	low, medium, high	Real number (km/hr)
	70	Variability of weather	low, medium, high	1–5 rating
	71	Ground conditions	poor, fair, good	1–5 Predetermined rating
	72	Site congestion	low, medium, high	Real number (Ratio free site space to total site area)
	73	Width of site access	low, medium, high	Real number (Width of access, m)
	74	Queue time to access site	low, medium, high	Real number (Average queue time to access time, minutes)
	75	Project work times	poor, fair, good	1–5 rating
	76	Owner staff on site	low, average, high	Integer (Total number of owner staff on site)

	77	Approval of shop drawings and sample materials	poor, fair, good	Real number (Average time taken to approve, days)
	78	Support and administrative staff	poor, fair, good	Real number (Ratio of support to technical staff)
	79	Level of paper work for work approval	low, medium, high	1–5 rating
	80	Treatment of foremen by superintendent and project manager	poor, fair, good	1–5 Predetermined rating
	81	Uniformity of work rules by superintendent	poor, fair, good	1–5 Predetermined rating
	82	Availability of labour	low, medium, high	Real number (Unmet labour requirement, for the given trade)
	83	Labour Disputes (legal cases between a worker on a project)	low, medium, high	Real number (Average number of cases per project)
	84	Project cost control	poor, fair, good	1–5 rating
	85	Labour productivity measurement practice	poor, fair, good	1–5 Predetermined rating
	86	Quality audits	low, average, high	Real number (Number of inspections per month)
	87	Inspection delay	poor, fair, good	Real number (Average delay for inspection, min)
	88	Interference	poor, fair, good	Real number (Average number of interruption due to interference)
	89	Out of sequence inspection or survey work	poor, fair, good	Real number (Number of occurrence per week)
	90	Project Safety plan execution	poor, fair, good	1–5 rating
	91	Safety training	poor, fair, good	Real number (No. trainings attended x Duration of Training, hrs)
	92	Safety Inspections	low, average, high	Real number (Number of inspections per month)
	93	Safety Audits	low, average, high	Real number (Number of audits per month)
	94	Safety Incidents	low, average, high	1–5 Predetermined rating
	95	Equipment/Property Damage	infrequent, frequent, very frequent	Integer (Number of reported equipment/property damage incident per month)
	96	Safety Incident investigation	poor, fair, good	1–5 rating

	97	Project Safety administration and reporting	poor, fair, good	1–5 Predetermined rating
	98	Risk monitoring and control	poor, fair, good	1–5 Predetermined rating
	99	Crisis management	poor, fair, good	1–5 Predetermined rating
	100	Communication between different trades	poor, fair, good	1–5 Predetermined rating
	101	Availability of communication devices	poor, fair, good	Real number (ratio of communication radio to number of crews, %)
	102	Hiring practices (open shop)	poor, fair, good	1–5 Predetermined rating
	103	Project team development	poor, fair, good	1–5 rating
	104	Project team closeout	poor, fair, good	1–5 rating
	105	Project Environmental Assurance	poor, fair, good	1–5 Predetermined rating
	106	Environmental audits	low, average, high	Real number (Number of inspections per month)
	107	Sorting of waste materials	poor, fair, good	1–3 Predetermined rating
	108	Project Environmental Control	poor, fair, good	1–5 Predetermined rating
Global level	109	Oil price	low, average, high	Real number (Dollar / barrel)
	110	Oil price fluctuation	low, average, high	Real number (Weekly price change, %)
	111	Natural gas price	low, average, high	Real number (Dollar / GJ)
	112	Natural gas fluctuation	low, average, high	Real number (Weekly price change, %)

Appendix B. Survey Questionnaire for Importance of Strategies

Table B. Survey questionnaire for determining importance of the selected strategies.

Improvement Strategy	**IC**	**IF**	**WA**	**IR**
Perform weekly reviews of crew compositions to ensure crew mix is per plan				
Provide clear instructions to craftspeople on how to complete tasks before their execution				
Have the same person perform a task several times rather than making personnel changes along the way				
Schedule regular inspections by the owner team to reduce interventions during the project execution				
Establish staggered working-hours of labours				
Train labours to achieve the latest concrete pouring techniques				
Perform project team activities				
Cover working area to protect from wind effects and precipitation				
Hold regular meetings with labours about schedule and remained tasks				
Design the processes to eliminate repetitive motion and reduce manual labour				
Develop clear instructions about the equipment used to transport materials				
Offer internship and scholarship programs to trade and vocational schools to help company's future worker				
Apply preventive maintenance to heating and air-conditioning systems to make sure they are in working order				
Hold meetings in later project stages to discuss transfer of project team to future projects of the company				
Use a down-hole vibrator that is lowered into the ground to compact soils at depth				
Hire cheap labour for daily housekeeping tasks				