A Fuzzy Hybrid Intelligent Model for Project Competencies and Performance Evaluation and Prediction in the Construction Industry

by

Moataz Nabil Omar

A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

In
Construction Engineering and Management

Department of Civil and Environmental Engineering
University of Alberta

Abstract

In contemporary construction environments, construction companies measure their performance against a set of predefined performance indicators. These performance indicators are governed by the ability of the company to maintain necessary sets of "competencies" that empower the successful execution of construction projects. Competencies in general are difficult to define and measure due to the multidimensional and subjective nature of their assessment. Additionally, there is little consensus on the performance indicators that capture the different critical aspects of how well a construction project is performing.

This thesis expands the body of knowledge on project competencies and performance by demonstrating the power of fuzzy logic combined with other artificial intelligence modeling (i.e., neural networks) in developing a model capable of identifying the relationship between the different project competencies and project performance on construction projects. First, this research identifies 41 project competencies with a total of 248 criteria for evaluating the different project competencies. Appropriate measurement scales are developed for the different project competencies' evaluation criteria. This research also identifies seven performance categories with 46 key project performance indicators. Second, a systematic framework and methodology are developed to measure project competencies and project key performance indicators on construction projects.

Finally, several state of the art techniques are developed and applied to model the relationship between project competencies and project performance namely: 1) a new prioritized aggregation method, 2) a dimensionality reduction technique, and 3) a fuzzy hybrid intelligent model incorporating fuzzy logic and artificial neural networks.

The new prioritized aggregation method is developed in this research to consider the prioritized relationship between criteria pertaining to the different project competencies. This prioritized aggregation method is developed for both crisp and fuzzy environments. Then, a dimensionality reduction technique, through the application of feature extraction, is applied to reduce the dimensionality of the model input (i.e., project competencies) and enhance its capability in providing more accurate outputs (i.e., key project performance indicators). Finally, granular AND/OR fuzzy neural networks are constructed using fuzzy logic and artificial neural networks to identify and map the relationship between the different project competencies and project key performance indicators. Data collected from seven construction projects are used to train and test the developed granular AND/OR fuzzy neural networks.

This thesis contributes to the current body of knowledge in project competencies and performance by establishing a standardized framework and methodology for evaluating the impact of construction project competencies on key project performance indicators. Furthermore, this thesis applies advanced modeling techniques through the application of fuzzy logic and artificial neural networks to identify and model the relationship between project competencies and project key performance indicators.

This thesis is dedicated to the memory of my father.

Acknowledgment

I would like to express my sincere gratitude to my supervisor, Dr. Aminah Robinson Fayek, for her guidance, invaluable ideas, intellectual support, and the time she dedicated to guiding me through the course of my research. She gave me a lot of motivation and support to work in this area of research and gave me a lot of guidance toward my academic goals.

I'm extremely grateful to the Strategic Construction Modeling and Delivery Industrial Research Chair partners for their valuable participation and support in facilitating data collection across their construction sites.

I'm grateful to my colleagues; Abraham Tsehayae, Mohamed Raoufi, Nima Gerami, Nasir Siraj, Andrea Wong, Dr. Mohamed Elbarkouky and, Dr. Adel Awad for their support.

Finally, I'm truly indebted to my lovely wife and mother's continuous support during my years of graduate studies.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. – Introduction[1]

1.1. Background

In today's dynamic construction industry, construction organizations encounter many challenges resulting from the increasing uncertainties in technologies, budgets, and development processes (Chan and Chan 2004). Hence, construction projects are completed as a result of merging many events and interactions, with varying participants and processes in a constantly changing environment (Sanvido et al. 1992). Many of these events and interactions can be quantified, and can be used to differentiate superior from average performance. Spencer and Spencer (1993) described the measurable events and interactions that are capable of differentiating between superior from average performance as "competencies".

Establishing a link between the different project competencies and project performance will identify project competencies that require further improvement and, will result in improved project performance (Antonacopoulou and FitzGerald 1996). Additionally, the ability to identify and enhance critical project competencies affecting project performance is expected to improve the competitiveness and profitability of construction organizations (Fayek 2012).

Project competencies in general are difficult to define and measure due to the multidimensional and subjective nature of their assessment. Project competencies exhibit subjective assessments that cannot be expressed by the traditional numerical approaches (Fayek 2012). A framework and methodology for identifying and measuring project competencies is required for the construction industry context (Omar and Fayek 2015). Performance measures,

[1] Parts of this chapter have been published in Construction Research Congress 2014. Omar, M. and Fayek, A. Robinson. (2014) A Framework for Identifying and Measuring Competencies and Performance Indicators for Construction Projects. Construction Research Congress 2014: pp. 2043-2052.

on the other hand, evaluate how well a construction project is producing its deliverables compared to its planned objectives. Construction organizations have suffered from the lack of a standard breakdown of project competencies and performance measures that are capable of capturing and anticipating continuous improvements or lack thereof in the execution of their projects. Additionally, relating project competencies to project performance measures has been an area of interest in previous research (Levenson et al., 2006; Isik et al., 2009).

Construction projects' competencies and performance requires a more comprehensive exploration to identify and formulate the different project competencies and their relationship to project performance. Defining the different project competencies, project performance measures and, the relationship between them is expected to result in a better understanding and identification of the requirements for successful execution of construction projects. A synopsis of previous research in the area of project competencies and project performance is essential to identify gaps in previous research and to formally provide a definition and quantification of the different project competencies and their relationship to project performance.

1.2. Project Competencies and Performance Research Gaps

Previous research has considered, in many situations, project competencies as a measure of project performance (Fayek 2012); it thus did not investigate project competencies as a prerequisite for project performance, or the fact that project competencies are leading indicators for project performance improvement.

Evaluation of project competencies has gained significant attention in the construction domain (Sparrow 1995; Kululanga et al., 2001; Walsh and Linton 2001; Markus et al., 2005; CII 2005; Levenson et al., 2006; Isik et al., 2009; Alroomi et al. 2011; Omar and Fayek 2014; Omar and Fayek 2015). Project performance measurements, on the other hand, are applied to assess organizational and project performance throughout the project life cycle. In order for a performance measurement to be effective, the measures must be accepted, understood, and owned across the construction organization and its different construction projects. Furthermore, the relationship of performance measures to project competencies needs to be identified when evaluating project performance. One motive behind investigating project competencies and performance is to establish the relationship between project competencies, as leading indicators for measuring project performance, and to identify their effect on project performance. A comprehensive framework and methodology for evaluating project competencies and identifying their relationship to project performance is developed in this thesis to overcome the limitations of previous research.

Another research gap identified in evaluating project competencies in the construction domain is in capturing the uncertainty associated with measuring project competencies (Fayek 2012). Traditionally, uncertainty has been treated as a random process (AbouRizk and Halpin 1990). However, most decisions in construction involve uncertainties that are subjective in nature and in many cases are expressed linguistically. When addressing project competencies, the identification and quantification of project competencies is not a random process, however, uncertainty and subjectivity has a significant effect on the inputs of such a study. In this thesis, the concept of project competencies is investigated using fuzzy set theory since project competencies are often characterized and assessed using linguistic terms that cannot be expressed by the traditional numerical approaches.

This thesis addresses two limitations existing in previous research namely: 1) Investigating project competencies as leading indicators to project performance (Fayek, 2012). Project competencies and project performance are investigated as two distinct measures. The relationship between project competencies and performance measurements is also investigated. 2) Capturing the uncertainty associated with measuring project competencies. The uncertainty associated with subjective measurements is modeled and analyzed using fuzzy set theory rather than traditional numerical methods. A fuzzy hybrid intelligent model is developed to evaluate and identify the relationship between project competencies and project performance measurements. This fuzzy hybrid intelligent model considers the uncertainty associated with measuring project competencies as well as the relationship between the different project competencies and project performance.

1.3. Project Competencies and Performance Research Objectives

The ultimate objective of this thesis is to present a fuzzy hybrid intelligent model for project competencies and performance evaluation and prediction in the construction industry. A standard breakdown of project competencies and key project performance measurements is identified. The relationship between project competencies and project performance is realized through fuzzy hybrid modeling. To achieve the objectives of this thesis, several state of the art techniques are considered as follows: 1) prioritized aggregation, 2) dimensionality reduction, 3) fuzzy set theory and, 4) artificial neural networks. Some of the ensuing research objectives are relevant to researchers and classified as academic objectives and other objectives are relevant to the construction industry and are classified as industrial objectives as follows:

1.3.1. Academic Research Objectives

Academic research objectives presented in this thesis are summarized as follows:

1. Explore prioritized aggregation. The notion of prioritized aggregation is considered to account for project competencies' evaluation criteria being assessed by experts and the prioritized relationship between these project competencies' evaluation criteria.
2. Present and apply a novel approach for prioritized aggregation. The new approach combines two well-known methods: 1) prioritized aggregation, where the aggregation accounts for the prioritization relationship between a set of criteria under investigation and, 2) the technique of order preference by similarity to ideal solution (TOPSIS), where the prioritized relationship between criteria is established using a distance measure. The new approach presented in this thesis accounts for the relative importance of a project competency evaluation criterion with respect to other evaluation criteria considered in the prioritized aggregation for the same competency, and its satisfaction relative to the most favourable satisfaction that a project competency's evaluation criterion can achieve. This relationship ensures that high satisfaction of lower priority project competencies' evaluation criteria does not compensate for low satisfaction of higher priority project competencies' evaluation criteria.
3. Develop a dimensionality reduction technique, suitable for fuzzy environments, to map high dimensional structures (i.e., project competencies) to lower dimensional structures (i.e., factor groups representing project competencies) with minimal loss of original information. The novel prioritized aggregation method –developed in this thesis- and factor analysis are presented and applied jointly as a preliminary step for developing the

fuzzy hybrid intelligent model for project competencies and performance evaluation and prediction.

4. Investigate and apply techniques of combining neural networks and fuzzy systems to improve the functionality and reliability of fuzzy hybrid intelligent models.
5. Develop a fuzzy hybrid intelligent model that accounts for: 1) the prioritized relationship between project competencies and, 2) the nonlinear relationship between project competencies and project performance. The fuzzy hybrid intelligent model combines prioritized aggregation, dimensionality reduction, fuzzy logic and, artificial neural networks in modeling. This fuzzy hybrid intelligent model is also transparent, traceable, and possesses learning capabilities (Gupta 1994, Pedrycz 2014). This fuzzy hybrid intelligent model will ultimately identify and quantify the relationship between project competencies and project performance. Furthermore, this fuzzy hybrid intelligent model will predict, after training and testing, the different project performance measures based on current project competencies.

1.3.2. Industrial Research Objectives

Industrial research objectives presented in this thesis are summarized as follows:

1. Identify a standardized breakdown of project competencies and performance suitable for the construction context.
2. Measure and evaluate project competencies and project performance in construction projects.
3. Predict project performance based on project competencies. The developed fuzzy hybrid intelligent model will allow construction practitioners to evaluate and predict project performance measures based on current project competencies.

4. Provide a software tool to evaluate project competencies and project performance for construction projects. This tool will allow construction practitioners to proactively evaluate their project competencies and projects performance at different points in the project life cycle.

1.4. Project Competencies and Performance Research Methodology

The research study presented in this thesis is conducted in four main phases as follows:

1.4.1. First Phase

The fuzzy hybrid intelligent model development starts with identifying the different project competencies and performance measures hierarchies. The developed project competencies and project performance hierarchies assist in the identification of the most relevant evaluation criteria for the different project competencies and project performance required when evaluating a construction project. Several data verification and validation methods (previous research review, questionnaires, one-on-one interviews, and interactive group workshops with highly experienced construction practitioners of varying level of expertise) are used to verify and validate the list of evaluation criteria for project competencies and project performance measures.

1.4.2. Second Phase

In this phase, data collected from seven construction projects are used to evaluate project competencies and identify their relationship to project performance. A novel prioritized aggregation method is developed to combine construction practitioners' evaluations of the different project competencies collected from different construction projects. The aim of the prioritized aggregation is to provide an informative evaluation of the different project competencies, which are subjective in nature, on the higher hierarchical level (i.e., project competency level) rather than the lower hierarchical levels (i.e., evaluation criteria of project competencies). This process provides a collective evaluation to be considered for the fuzzy hybrid intelligent model development as described later in the third phase of this research.

1.4.3. Third Phase

This phase commences with the application of a dimensionality reduction technique, using factor analysis, to combine project competencies into a fewer number of factor groups of similar statistical behaviour. The application of dimensionality reduction combines project competencies into a fewer number of factor groups that are more suitable for modeling. The factor groups are then used with the projects' performance measures for training and testing three types of neural networks: 1) traditional neural networks, 2) fuzzy neural networks using fuzzy arithmetic and, 3) fuzzy neural networks using fuzzy operations. The different networks are compared to identify the one with the best performance (i.e., expressed by the least global error). The identified network (i.e., with the least global error) is considered for the fuzzy hybrid intelligent model.

1.4.4. Fourth Phase

A software tool is developed to create an executable, stand-alone system that is connected to the user interface to evaluate project competencies and project performance. The software tool provides construction practitioners the ability to evaluate their project competencies and project performance respectively. The software tool also assists in generating the data required for the fuzzy hybrid intelligent model (i.e., neural networks) as described in the third phase of this research methodology.

1.5. Project Competencies and Performance Expected Contributions

This thesis presents several contributions in project competencies and project performance, some of which are relevant to researchers and classified as academic contributions and others that are industrial contributions to the construction industry.

1.5.1. Expected Academic Research Contributions

Expected academic research contributions presented in this thesis are summarized as follows:

1. Provide a standard hierarchy of project competencies and performance measures suitable for the construction context.
2. Develop a novel prioritized aggregation method for multiple-criteria decision making problems (MCDM) such as evaluation of project competencies. In this thesis, the developed prioritized aggregation method accounts for the interrelations between project competencies' evaluation criteria considered in the prioritized aggregation, and its satisfaction relative to the most favourable satisfaction that a given project competency evaluation criterion can achieve. This relationship ensures that the high satisfaction of a lower priority project competency's evaluation criterion does not compensate for the low satisfaction of a higher priority project competency's evaluation criterion. Furthermore, the developed method is extended to fuzzy environments to capture information that are subjective in nature.
3. Identify and group project competencies, through the application of the dimensionality reduction technique, of similar correlation relationship. Grouping project competencies into fewer groups enhances their evaluation, analysis and, improves project competencies and project performance modeling.

4. Develop a fuzzy hybrid intelligent model, that integrates state of the art techniques such as the developed prioritized aggregation method, dimensionality reduction, fuzzy logic and, artificial neural networks. Integrating these techniques in modeling enhances the interpretability, as explained later in this thesis, of the developed fuzzy hybrid intelligent model to identify and quantify the relationship between project competencies and project performance.

1.5.2. Expected Industrial Research Contributions

Expected industrial research contributions presented in this thesis are summarized as follows:

1. Provide a comprehensive, detailed list of project competencies' evaluation criteria and measurement scales for construction practitioners to measure and evaluate their projects' competencies.
2. Identify a standardized breakdown of performance measures for construction practitioners to evaluate their projects' performance.
3. Incorporate the evaluation of different project competencies and project performance measures into the developed fuzzy hybrid intelligent model to identify the effect of project competencies' improvement on project performance. The fuzzy hybrid intelligent model will assist construction practitioners to formalize and improve the evaluation of project competencies and project performance.
4. Deliver a software tool to evaluate project competencies and project performance. The software tool allows construction practitioners to evaluate their project competencies and project performance respectively at different points of project life cycle and identify trends of improvement in project competencies and performance.

1.6. Thesis Organization

Chapter 1 provides background, a brief literature review, and a statement of the problem. This chapter also describes the academic and industrial research objectives, research methodology and, expected academic and industrial contributions.

Chapter 2 presents a literature review of previous research in the areas of project competencies, project performance measures and, the relationship between project competencies and performance respectively. A standard hierarchy of competencies and performance measures with detailed evaluation criteria and measurement scales for each is presented. Data collection procedures are also presented in this chapter.

Chapter 3 presents the development and application of a new prioritized aggregation method in crisp and fuzzy environments.

Chapter 4 presents the development of a fuzzy hybrid intelligent model. The different components of the model (i.e., prioritized aggregation, dimensionality reduction, fuzzy logic and, neural networks) are introduced and their application is explained.

Chapter 5 presents the application, analysis, and results of the fuzzy hybrid intelligent model using data collected from seven construction projects.

Chapter 6 presents a software tool that has evaluative and predictive capabilities for the different project competencies and performance measures.

Chapter 7 describes the conclusions, contributions, and, limitations of this research. Also, recommendations for future research are also presented.

1.7. References

AbouRizk, S. and Halpin, D. (1990). ”Probabilistic simulation studies for repetitive construction processes.” *Journal of Construction Engineering and Management*, 116(4), 575–594.

Albert P.C. Chan, Ada P.L. Chan, (2004) "Key performance indicators for measuring construction success." *Benchmarking: An International Journal*, 11(2), pp.203 – 221.

Alroomi, A., Jeong, D., Oberlender, G. (2011). “Analysis of cost-estimating competencies using criticality matrix and factor analysis.” *Journal of Construction Engineering and Management*, 138(11), 1270–1280.

Antonacopoulou, E. P. and FitzGerald, L. (1996). “Reframing competency in management development.” *Human Resource Management Journal*, 6: 27–48.

Construction Industry Institute (CII) (2005). “Core competency toolkit.” Research Summary 111-3, Construction Industry Institute, Austin, Texas, September, 2005.

Fayek, A. Robinson. (2012). Advancing Fuzzy Hybrid Techniques for Competency Modeling of Construction Organizations, Natural Sciences and Engineering Research Council of Canada Discovery Grant Proposal, University of Alberta, Edmonton, AB.

Isik, Z., Arditi, D., Dikmen, I., and Birgonul, M. T. (2009). "Impact of corporate strengths/weaknesses on project management competencies." *Int.J.Project Manage*., 27(6), 629-637.

Kululanga, G. K., Edum-Fotwe, F. T., McCaffer, R. (2001). “Measuring construction contractors’ organizational learning.” *Building Research and Information*, 29(1), 21–29.

Levenson, A. R., Van der Stede, Wim A, and Cohen, S. G. (2006). "Measuring the relationship between managerial competencies and performance." *Journal of Management,* 32(3), 360-380.

Markus, L., Thomas, H. C., and Allpress, K. (2005). “Confounded by competencies? An evaluation of the evolution and use of competency models.” *New Zealand Journal of Psychology*, 34(2), 117.

Omar, M. and Fayek, A. (2014) A Framework for identifying and measuring competencies and performance indicators for construction projects. *Construction Research Congress,* 2043-2052.

Omar, M. and Fayek, A. Robinson (2015a). “Modeling and evaluating construction project competencies and their relationship to project performance” Manuscript submitted to *Journal of Automation in Construction*. September 1st, 2015.

Sparrow, P. (1995): “Organizational competencies: A valid approach for the future?” *International Journal of Selection and Assessment*, 3(3), 168–177.

Walsh, S. T., Linton, J. D. (2001). “The competence pyramid: A framework for identifying and analyzing firm and industry competence.” *Technology Analysis and Strategic Management.*, 13(2), 165–177.

Sanvido, V., Grobler, F., Parfitt, K., Guvenis, M. and Coyle, M. (1992) “Critical success factors for construction projects.” *Journal of Construction Engineering and Management*, 118(1), 94–111.

Spencer L.M & Spencer S.M. (1993). “Competence at work: Models for superior performance. New York: John Wiley & Sons, Inc.

CHAPTER 2. – Review of Project Competencies and Performance Frameworks and Models: Advancing Existing Challenges and Limitations[1]

2.1. Introduction

Construction projects are completed as a result of merging many events and interactions, with varying participants and processes in a constantly changing environment. Many of these events and interactions can be quantified and then used to differentiate superior from average performance. Spencer and Spencer (1993) described the measurable events and interactions that are capable of differentiating between superior and average performance as “competencies”. Performance measures, on the other hand, are vital to construction organizations and projects as they are used to manage the business and measure the success of projects (Chan and Chan 2004). Over the past few decades, researchers have shown interest in the areas of project competencies and performance.

Defining and measuring the different project competencies, as leading indicators to project performance, is expected to result in better understanding and identification of requirements for successful execution of construction projects. A synopsis of previous research is presented in this chapter to identify current research gaps in the areas of project competencies, their relationship to project performance and project performance. This synopsis will provide a basis for defining project competencies and performance measures, their hierarchies, evaluation and, data collection tools.

[1] Parts of this chapter have been submitted for publication in Journal of Automation in Construction. Omar, M. and Fayek, A. Robinson.(2015). “Modeling and Evaluating Construction Project Competencies and Their Relationship to Project Performance.” Manuscript, 53 pages.

2.2. Review of Project Competencies and Project Performance Frameworks and Models

An overview of previous research in the areas of project competencies, their relationship to project performance and project performance is presented next.

2.2.1. Project Competencies and Their Relationship to Project Performance

Project competencies in general are difficult to group and measure due to the multidimensional and subjective nature of their assessment. Project competencies exhibit subjective assessments that cannot be expressed by the traditional numerical approaches (Fayek 2012). Previous research has addressed project competencies in construction by describing project competencies, in many situations, as performance; it thus did not investigate projects competencies as a prerequisite for project performance evaluation, or the fact that project competencies are leading indicators for project performance improvement.

Hitt and Ireland (1986) used corporate level competencies and market return, as a performance measure, to evaluate the relationship between them. Corporate competencies were used as independent variables in a regression analysis and market return was used as a dependent variable. The results of the regression analysis suggested that a relationship exist between the different corporate competencies and market return, as a performance measure.

Spencer and Spencer (1993) developed an "Iceberg Model" that considers individuals qualities as one element of the model, and knowledge and skills as the second element. Spencer and Spencer (1993) concluded that in order to adequately measure competencies, the personal and professional competencies of individuals of an organization needs to be considered.

Provost and Leddick (1993) proposed a system that is divided into different components such as divisions, departments and functions. These components are unified by a common objective. The system, proposed by Provost and Leddick, measured and optimized overall performance by optimizing the different components of the system. Figure 2-1 displays how the family of measures were set as one system to measure overall performance. Provost and Leddick (1993) stated that the categories required for measuring performance are universal, but the "*specific measures for any one organization depend on factors of uniqueness*" (Provost and Leddick 1993, P479).

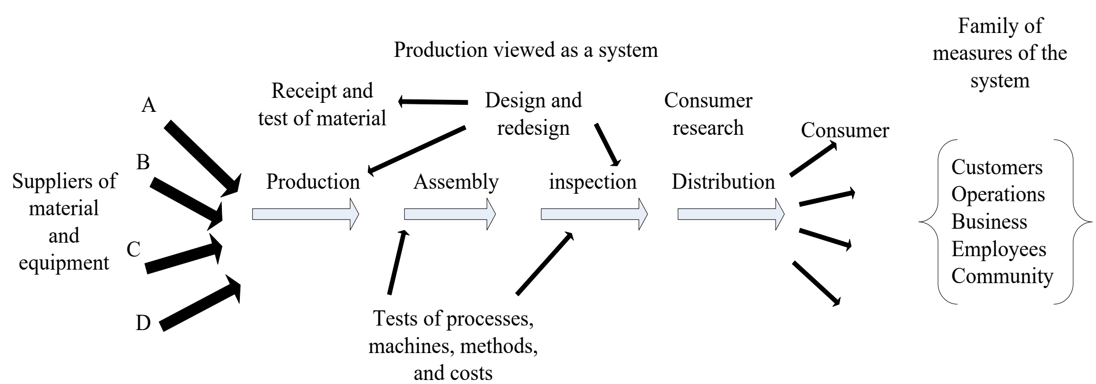


Figure 2-1 Concept of a Family of Measures of a System (Provost and Leddick 1993)

Sparrow (1995) attempted to integrate the different concepts of organizational competencies, described in previous research, through different levels of the organization. Three main approaches were described by Sparrow to measure organizational competencies. The "management competence" approach is introduced as an effective approach to measure effectiveness across different occupations and sectors within an organization. A "behavioural competence" approach was investigated to evaluate individuals and complement the "management competence" approach, across different occupations and management hierarchies within an organization. The third approach, "core competences", emerged to identify the resources and capabilities of the organization that are connected to overall performance. Sparrow concluded that in order for organizations to emerge from the current chaos in the business environment, then looking for ways to re-integrate the three approaches (i.e., management competence, behavioural competence and, core competence) in organizations and its Human Resources Management (HRM) systems is essential. "*Helping organizations create broad selection and assessment systems based around organizational-level behavioural competencies may offer an attractive way forward to compete in today's market*" (Sparrow 1995, P176).

Kagioglou et al. (2001) provided a conceptual framework that integrated main themes of performance management, such as organizational strategy, and linked it to different project performance indicators. A conceptual framework was developed based on deploying a set of processes for performance management and improvement. The strategies were articulated in a set of processes that are monitored to improve different aspects related to project performance.

Walsh and Linton (2001) limited their investigation to core competencies, where, a distinction between competencies and capabilities was made. Competencies were defined as "firm specific technologies and production related skills" (Walsh and Linton 2001, P167), while capabilities were defined as "firm specific business practices, processes and culture" (Walsh and Linton 2001, P167). The implementation of the two concepts –as stated by Walsh and Linton- requires a deep understanding of what core competencies are. Core competencies are a "relative pursuit" where, companies and projects tends to gauge their competencies in terms of benchmarking. Accordingly, competencies are being assessed to achieve superior performance.

Markus et al. (2005) conducted an extensive review of previous competencies-related research. The benefits of applying competencies' models in New Zealand organizations, as described by Markus et al. (2005), were investigated in Human Resources (HR) systems and practices. Three approaches were identified for modeling competencies: the educational approach, psychological approach, and business approach. The educational approach is centred on the functional role analysis which is based on *"role outcomes, or knowledge, skills and attitudes, or both, required for role performance"* (Markus et al. 2005; P117). The psychological approach is based on identifying competencies based on *"the skilled behavioural repertoires of recognized star performers within particular organizations"* (Markus et al. 2005; P117). The business approach is most relevant to the construction domain, wherein inputs to the competency model consisted of organizational competencies for competitive advantage, including core competencies, capabilities, and practices; outputs of a business-based competency model were measured in terms of soft performance measures such as communication and interpersonal skills to assess organizational performance. Markus et al. (2005) concluded three fundamental issues related to competencies modeling, identified from previous research, as follows:

1. Construct validity: this is related to the validity of assessing whether the measures applied to quantify competencies are actually measuring the competencies. Another associated issue is that many competencies are evaluated using self and supervisor ratings, and sometimes by peers. Thus, the assessment of competencies is likely to suffer from reliability problems.
2. Model validity: validation of the model is important because competencies describe normative production-related competencies and individual behaviours.
3. Predictive validity: This is attributable to the issue of lack of evidence for benefits that result from adopting a competency approach. The underlying assumption of all competency initiatives is that the production-related competencies and individual behaviours, will lead to improved job performance.

The construction industry institute (CII) developed a project competencies toolkit (CII 2005) that assists owners to decide upon the most effective approach to outsourcing the different project competencies. The ultimate objective of the tool was to provide a systematic approach to determine key project competencies and their outsourcing for owners and contractors in construction projects. Furthermore, the project competencies toolkit assisted owners and contractors in the formation of optimal work relationships based on project competencies. Figure 2-2 details the nine processes steps included in the project competencies toolkit.

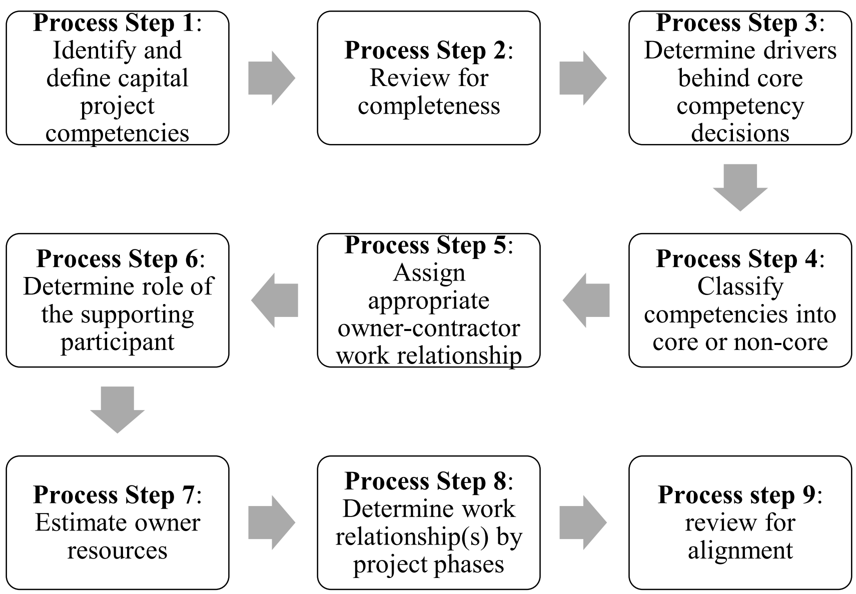


Figure 2-2 Project Competencies Toolkit (CII 2005)

The project competencies toolkit developed by CII (2005) assisted project management teams during the development of projects. The process provided a link between the strategic objectives of the company defined at an upper management level and the project level responsibilities (i.e., project competencies) defined on-site by the project management team.

Draganidis and Mentzas (2006) reviewed and summarized previous work in the area of competency-based management in human resources management systems. First, they identified the various definitions of competencies from previous research. Then, they derived competencies from observing satisfactory or exceptional employee performance for a specific occupation and developed a list of specific competencies to improve performance on work. An overview of 22 commercial competency management systems was reviewed in order to conclude common features. These common features were organizational competencies and individual-related abilities.

Levenson et al. (2006) applied descriptive statistics, factor analysis, correlation and regression analyses to identify the relationship between managerial competencies and then, managerial competencies and performance. First, correlation analysis was performed to measure the correlation relationship between the different managerial competencies. Then, factor analysis was performed to group the different competencies in order to conduct a regression analysis. Finally, regression analysis was performed to identify the relationship between the grouped competencies (i.e., from factor analysis) and performance.

Caupin et al. (2006) defined project management competencies as a set of 46 competence elements that cover the following: technical competences for project management (i.e., 20 elements); behavioural competences of project personnel (i.e., 15 elements); and contextual competences of projects, programmes and portfolios (i.e., 11 elements). Each of the elements was further divided into sets of evaluation criteria with predetermined 10 points measurement scale. Table 2-1 lists the competence elements for each category.

Table 2-1 Project Management Competencies Elements

Technical Competence	Behavioural Competence	Contextual Competence
• Project management success • Interested parties • Project requirements & objectives • Risk & opportunity • Quality • Project organization • Teamwork • Problem resolution • Project structures • Scope & deliverables • Time & project phases • Resources • Cost & finance • Procurement & contract • Changes • Control & reports • Information & documentation • Communication • Start-up	• Leadership • Engagement & motivation • Self-control • Assertiveness • Relaxation • Openness • Creativity • Results orientation • Efficiency • Consultation • Negotiation • Conflict & crisis • Reliability • Values appreciation • Ethics	• Project orientation • Program orientation • Portfolio orientation • Project programme & portfolio implementation • Permanent organization • Business • Systems, products & technology • Personnel management • Health, security, safety & environment • Finance • Legal

Isik et al. (2009) applied structural equation modeling to establish the relationship between different management competencies and organizational strengths/weakness as a performance measure. A strong relationship between the different management competencies and corporate strengths/weakness was identified as a result of applying structural equation modeling analysis.

Alroomi et al., (2011) proposed an estimating core-competency framework and methodology to prioritize cost estimators behavioural competencies on the basis of the combined effects of the level of importance of each competency and its associated gap between the ideal and actual level of competency. A correlation analysis between the different behavioural competencies was conducted to measure the degree of relationship between the different variables (i.e., behavioural competencies). Factor analysis was then used to group the predefined behavioural competencies into factor groups.

A 10-10 performance program was developed by CII (2013). The 10-10 performance program identified sets of leading indicators through the project life cycle to benchmark project performance. CII research identified ten sets of inputs (i.e., project competencies), as leading indicators, for evaluating project performance. The 10-10 performance program evaluated project competencies using simple statement-based questions. Ten leading indicators (i.e., input measures that represents project competencies) are obtained throughout the project's different phases that can act as leading indicators to the project management teams for possible improvement areas. This diagnostic capability aided in the development of corrective actions to improve project performance. As for output, ten outcome measures (i.e., lagging project KPIs) are used to determine if the project is proceeding as planned or not. This research distinguished between project competencies, as leading indicators for project performance, and project performance. The input and output metrics are listed in Table 2-2.

Table 2-2 10-10 Program Input – Output Metrics

Input Metrics	Output Metrics
1. Planning	1. Total project cost/capacity
2. Organizing	2. Total project schedule/capacity
3. Leading	3. Phase cost/capacity
4. Controlling	4. Phase schedule/capacity
5. Design efficiency	5. Phase cost growth
6. Human resources	6. Phase schedule growth
7. Quality	7. Capacity efficiency
8. Sustainability	8. FTE/Total project Cost
9. Partnering and supply chain	9. FTE/cost (includes complexity
10. Safety	10. Phase cost/Phase schedule

Omar and Fayek (2014) proposed a framework and methodology for measuring project competencies and performance. The proposed framework categorized the different project competencies into technical and behavioural project competencies. Technical project competencies stem from organizations, while behavioural project competencies are attained by individuals. The two project competencies' categories were assumed to contribute to better performance on construction projects.

Previous research synopsis identified contributions and limitations in modeling project competencies and their relationship to project performance. A summary outlining the main contributions of previous research and the limitations of each study, discussed earlier, is presented in Table 2-3.

Table 2-3 Summary of Previous Research in Project Competencies and Their Relationship to Project Performance

Study Description	Reference	Overview of the Study	Advancement to Project Competencies	Advancement to Project Performance	Limitations (i.e., Gaps)
Evaluating corporate competencies and performance	Hitt and Ireland (1986)	Evaluated corporate level competencies and performance using regression analysis	Developed a breakdown of corporate competencies	Identified a relationship between corporate competencies and market return, as a performance measure, statistically	• Considered simple statistical analysis to relate corporate competencies to performance • Considered one performance measure in the study
Project competencies measurement and evaluation	Spencer and Spencer (1993)	Developed an "Iceberg Model" that considers individuals qualities as one element of the model, and knowledge skills as the second element.	Developed a breakdown of individuals qualities and, knowledge and skills	Did not consider any performance measures	• Did not consider organizations roles • Did not identify any performance measures • Did not relate project competencies to project performance
Project competencies measurement and evaluation	Provost and Leddick (1993)	Developed a system with different components to represent competencies. These components are unified by a common objective which is project performance measures	Relied mainly on evaluating individuals attributes assisting in performing daily tasks	Considered a subset of performance measures in the evaluation	• Identified subset performance measures for a specific context (i.e., material supply) • Did not relate project competencies to project performance
Organizational competencies	Sparrow (1995)	Integrated three different concepts of organizational competencies, described in previous research, through different levels of the organization	Applied the three competence approaches to identify competences.	Considered organizational competencies evaluation to represent performance	• Did not consider performance measures • Did not relate organizational competencies to performance measures

Study Description	Reference	Overview of the Study	Advancement to Project Competencies	Advancement to Project Performance	Limitations (i.e., Gaps)
A framework that integrates main themes of performance management	Kagioglou et al. (2001)	deployed sets of processes (i.e., competencies) for performance management and improvement	Integrated organizational strategies to different construction performance indicators	Considered organizational processes as indicators for organizational performance	• The framework was conceptual (did not consider verification or validation) • Identified competencies and performance as two distinct entities, but did not investigate the relationship between them
A competency pyramid for the evaluation of organizational competencies	Walsh and Linton (2001)	Developed a competency pyramid to evaluate competencies for organizations	Developed a breakdown that categorized competencies into technical competencies and managerial capabilities	Did not consider performance measures in the evaluation and modeling	• The framework was considered as a guideline for practitioners • Did not identify specific performance measures to evaluate organizational performance • Did not relate competencies to performance
A critical review of previous competencies frameworks and models	Markus et al. (2005)	Identified three main approaches for modeling competencies	• Provided a comprehensive overview of the different competency models. • Identified fundamental issues that should be considered when modelling competencies	Considered – conceptually- the importance of differentiating between project competencies and performance	• The study was considered a guideline for developing and validating future competency models.

Study Description	Reference	Overview of the Study	Advancement to Project Competencies	Advancement to Project Performance	Limitations (i.e., Gaps)
Competencies toolkit	CII (2005)	A tool that assists owners to decide upon the most effective approach to outsourcing the different project competencies	Developed a detailed process to identify project competencies	Did not consider performance measures in evaluation	• Did not provide a standard structure for project competencies, definitions, functions and responsible members. Provided only the process. • Did not identify specific performance measures to evaluate project performance • The relationship between project competencies and project performance is not identified
Competency-based management systems	Draganidis and Mentzas (2006)	Summarized previous work in the area of competency-based management in human resources management systems	common features for competencies' models and systems are identified	Did not consider performance measures in evaluation	• Did not provide guidelines or a framework on how to improve project competencies and performance modeling.
Competence Baseline	Caupin et al. (2006)	Defined project management competencies	Developed detailed criteria for evaluating project management competencies	Did not consider performance measures in evaluation	• Did not identify specific performance measures to evaluate organizational performance • Did not relate competencies to organizational performance
Measuring the relationship between managerial competencies and performance	Levenson et al. (2006)	Identified the relationship between managerial competencies and then, managerial competencies and performance respectively	Identified criteria for evaluating managerial competencies	Applied statistical analysis to identify the relationship between managerial competencies and then, managerial competencies and performance respectively	• Considered simple statistical analysis to relate managerial competencies to performance • Considered few performance measures in the study

Study Description	Reference	Overview of the Study	Advancement to Project Competencies	Advancement to Project Performance	Limitations (i.e., Gaps)
Impact of corporate strengths/weaknesses on project management competencies	Isik et al. (2009)	Applied a structural equation modeling analysis to establish the relationship between the different management competencies and organizational strengths/weakness	Identified criteria for evaluating management competencies	Identified criteria for evaluating organizational strengths/weakness	• Considered simple statistical analysis to relate corporate competencies to performance • Considered only organizational strengths/weakness in the study as performance measure
Analysis of cost-estimating competencies	Alroomi et al., (2011)	Proposed core-competency framework and methodology for cost estimators	Considered the behavioural aspect for some project competencies. Identified criteria for evaluating cost estimators	Did not consider performance measures in evaluation	• Did not consider other project-competencies (i.e., identified in previous studies) in the evaluation • Did not relate competencies to performance
10-10 performance program	CII (2013)	Identified sets of leading indicators through the project life cycle to benchmark project performance	Identified criteria for evaluating project competencies	Identified criteria for evaluating project performance	• Acknowledged the relationship between project competencies and performance, but did not quantify the effect of project competencies improvement or lack off on project performance
Framework for Identifying and Measuring Competencies and Performance Indicators for Construction Projects	Omar and Fayek (2014)	Proposed a framework and methodology for measuring and evaluating construction project competencies.	Identified criteria for evaluating project competencies	Identified criteria for evaluating project performance	• The framework was conceptual (did not consider validation)

Previous research, as summarized in Table 2-3, addressed project competencies, in many situations, as project performance (Fayek 2012); it thus did not investigate a comprehensive structure of project competencies, the fact that project competencies are leading indicators to project performance and, the relationship between project competencies and project performance measures. Limitations in previous research can be categorized into three main limitations as described earlier by Markus et al. (2005): 1) the ability of existing competencies models to capture the different types of project competencies (i.e., organizational and individual competencies), 2) validity of existing competencies' models to measure and evaluate project competencies and, 3) lack of evidence for benefits (i.e., project performance improvement) that result from adopting a competency approach (i.e., ability to relate project competencies to project performance measures).

For previous research that related project competencies to project performance, applying simple statistical analyses to establish the relationship between project competencies and project performance is considered inadequate due to the nonlinear, multidimensional and subjective nature of project competencies assessment. Accordingly, in order to identify and establish this relationship between project competencies and project performance, project performance measures needs to be examined.

2.2.2. Project Performance

Performance measures are vital to construction organizations as they are used to manage the business and measure the success of construction projects (Chan and Chan 2004). Over the past two decades, researchers have shown interest in the area of project performance measures identification and quantification. The purpose of using project performance measures is to enable the assessment of project and organizational performance throughout the project life cycle. In order for performance measures to be effective, the measures or indicators must be accepted, understood, and owned across the construction organization and its different construction projects (Cheung et al. 2004; Navon 2005).

In the early 1990s, the evaluation of construction project success was tied to a few performance measures, which in turn were tied to the project objectives. These performance measures were a function of project duration, cost, and quality (Navarre and Schaan 1990). These three categories of project performance measures were described as insufficient by Ward et al. (1991). Pinto and Pinto (1991) stated that measures for enhanced project performance should also include project satisfaction with different project parties. Subjective performance measures such as participants' satisfaction level were known as soft performance measures. Kometa et al. (1995) used a comprehensive approach to evaluate projects performance by defining a set of project key performance indicators (KPIs). The project KPIs included: safety, construction cost, running/maintenance cost, time, and flexibility to users.

DuPont firm (Chandler 1977; Bassioni et al. 2004) presented the Return on Investment (ROI) measure and the pyramid of financial ratios in the early 20th century. Many of the financial performance methods and techniques developed by DuPont firm are used today in the construction industry and are implemented on the organizational and project levels (Chandler 1977; Kaplan 1984; Neely and Bourne 2000). However, a fundamental disadvantage of financial-based performance measures is the fact that financial information is lagging, in the sense that it describes the outcome of project performance after it occurs by at least one reporting period (Kaplan 1984; Eccles 1991; Letza 1996; Bourne et al. 2000; Norreklit 2000; Bassioni et al. 2004).

Recent research has focused on evaluating project performance through best practices and benchmarking programs. The construction best practice in UK introduced the project KPIs measurement program, where, sets of project KPIs are defined for different project and organizational levels that directly reflect the current performance and performance targets for organizations and projects (Egan 1998). Similarly, the Canadian Construction Innovation Council (CCIC), the Construction Industry Institute (CII) and, Construction Owner Association of Alberta (COAA) have each developed a benchmarking program that facilitates data collection and producing results pertaining to performance measures on projects (Rankin et al. 2008; Nasir et al. 2012; COAA 2010; CII 2013a, CII 2013b).

A comparative examination on benchmarking programs and project performance evaluation was also presented by Costa et al. (2006). Benchmarking programs related to construction industry in Brazil, Chile, United Kingdom, and the United States of America were assessed, and a set of recommendations were derived as follows: 1) a uniform classification of performance measures (i.e., project KPIs) needs to be established, 2) a framework is required to migrate from project KPIs to performance management systems and, 3) a collaborative learning processes is needed to devise new project measures (i.e., project KPIs) for construction projects' performance.

Following this literature review in the areas of project competencies, their relationship to project performance and, project performance measures, a breakdown of project competencies and project performance measures is needed to overcome the different project competencies frameworks and models limitations, as described in Table 2-3, and to relate them to project performance measures (i.e., project KPIs). The following section presents a detailed methodology to identify and evaluate project competencies and project performance measures.

Identifying and quantifying the relationship between project competencies and project performance measures is discussed in chapter four of this thesis.

2.3. Proposed Methodology to Evaluate Project Competencies and Project Performance for Construction Projects

This section presents a proposed methodology to identify and measure project competencies and project performance. The process of identifying the different project competencies, their evaluation criteria and measurements is first presented. Similarly, project performance categories, Project KPIs and their measures are presented as illustrated in Figure 2-3.

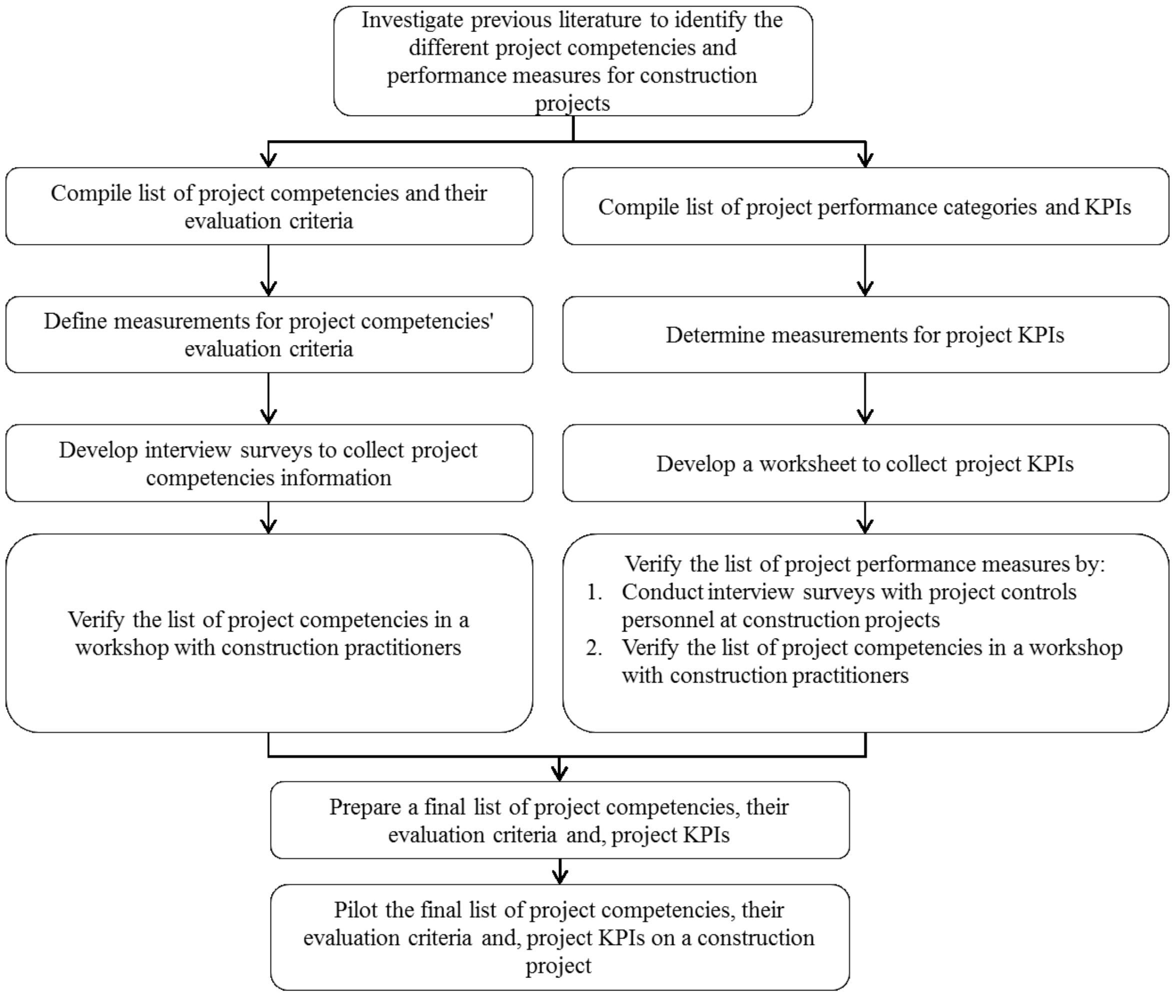


Figure 2-3 Process for Determining Project Competencies, Their Evaluation Criteria and, Project Performance Measures

2.3.1. Project Competencies: Categories, Evaluation Criteria and Measures

Two main categories of project competencies are identified from previous research (Provost and Leddick 1993; Sparrow 1995; Fleishman et al., 1995; Kululanga et al., 2001; Walsh and Linton 2001; Markus et al., 2005; CII 2005; Caupin et al., 2006; Edgar and Lockwood 2008; Alroomi et al. 2011; CII 2013a; CII 2013b; Omar and Fayek 2014). The first category is attributable to how an organization functions. The second category is attributable to individuals' attained competencies. The two categories contribute together to better construction project performance. Accordingly, the two categories of competencies identified are defined as: 1) functional competencies, which are knowledge and production related skills in a construction project. This knowledge and production related skills stem from the organization to assist in the execution of tasks in a construction project and, 2) behavioral competencies, which are a mixture of knowledge, skills, abilities, motivation, beliefs, values, and interests attained by individuals in a construction project and assist in the execution of tasks in a construction project.

Investigation of previous research led to identifying 21 functional competencies that consist of 162 evaluation criteria for measuring functional competencies. Table 2-4 lists the 21 functional competencies identified from previous research. Each functional competency is further divided into sets of evaluation criteria for measurement, examples of which is shown in Table 2-5. A detailed list of functional competencies' evaluation criteria is presented in Appendix 1.1.

Table 2-4 Functional Competencies

1. Project Integration Management	12. Project Change Management
2. Project Scope Management	13. Project Stakeholders Management
3. Project Time Management	14. Project Environmental Management
4. Project Cost Management	15. Project Commissioning and Startup
5. Project Engineering and Procurement Management	16. Project Innovation
6. Project Resource Management	17. Project Workface Planning
7. Project Risk Management	18. Project Contract Administration
8. Project Communication Management	19. Project Team Building
9. Project Safety Management	20. Project Workforce Development
10. Project Human Resource Management	21. Project Technology Integration
11. Project Quality Management	

Table 2-5 Examples of Evaluation Criteria for "Project Safety Management" Functional Competency

9. Project safety Management
9.1. Policies and procedures for safety cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
9.2. Safety preplanning meetings are held, and a safety plan is established for the project
9.3. Safety meetings are conducted regularly on site for proper safety practices execution

Two scales are identified for measuring the different evaluation criteria. The first scale is the maturity scale. The maturity scale is developed based on the research work presented by Sarshar (2000) and Willis and Rankin (2011, 2012) in the area of construction industry maturity. Sarshar (2000) introduced a Structure Process Improvement for Construction Enterprise (SPICE) to measure the maturity of practices and processes. The SPICE framework evaluates the extent of how the different processes are measured, managed, and controlled. Willis and Rankin (2011, 2012) maturity assessment involves measuring the extent of existence of the different evaluation criteria. The integration of the two scales is used in this paper to benefit from the advantages of the two maturity models as described by Sarshar (2000) and Willis and Rankin (2011, 2012) respectively. The developed maturity scale is presented in Table 2-6.

Table 2-6 Maturity Scale for Functional Competencies

Scale value	Scale description
Not Applicable	Use of the practice is non-existent on this project
Level 1	Use of the practice is not consistently applied on this project
Level 2	A disciplined process exists for the practice on this project
Level 3	A disciplined process exists for the practice across the different projects within the same organization
Level 4	Quantitative process control is used across the organization to proactively manage the execution of the practice on this project
Level 5	Continuous process improvement is used across the organization to optimise the practice on this project

For example, when assessing the "Project Safety Management" competency, the maturity of the evaluation criterion "9.3. Safety meetings are conducted regularly on site for proper safety practices execution" can be evaluated using the proposed maturity scale described in Table 2-6 above. The developed scale captures two main aspects of the competency; the existence of the practice, and whether the practice is only applied or being proactively managed as described by Willis and Rankin (2011, 2012) and Sarshar (2000) respectively.

The second scale considered for measuring the evaluation criteria is the importance scale. The importance scale is used to prioritize the evaluation criteria pertaining to each functional competency. Five and seven point bipolar importance scales are commonly used to capture the importance of evaluated criteria. The five point importance scale is more advantageous as it tends to be a good balance between having enough points of discrimination without having to maintain too many options for respondents to choose from (Nunnally 1978). The importance scale allows the identification of the relative importance of an evaluation criterion compared to the set of evaluation criteria used to measure a given functional competency. A five point importance scale ranging from 1 "extremely unimportant" to 5 "extremely important" is identified for measuring the importance of the different evaluation criteria pertaining to the different functional competencies (Omar and Fayek 2014).

As for behavioural competencies, investigation of previous research led to identifying 20 behavioural competencies that consist of 86 evaluation criteria for measuring behavioural competencies. A detailed list of behavioural competencies identified from previous research is presented in Table 2-7. Each behavioural competency is further divided into sets of evaluation criteria for measurement, examples of which are shown in Table 2-8. A detailed list of behavioural competencies' evaluation criteria is presented in Appendix 1.2.

Table 2-7 Behavioural Competencies

1. Analytical Ability	11. Self-Control
2. Training	12. Reliability
3. Assessment Ability	13. Problem Solving
4. Decision Making	14. Commitment
5. Leadership	15. Adaptability
6. Teamwork	16. Building Trust
7. Consultation	17. Interpersonal Skills
8. Motivation	18. Influence (Assertiveness)
9. Negotiation and Crisis Resolution	19. Cultural Competence
10. Ethics	20. Initiative

Table 2-8 Examples of Evaluation Criteria for Teamwork Behavioural Competency

6. Teamwork
6.1. Members of this team participate as active and contributing members to achieve their team's daily goals.
6.2. Members of this team work cooperatively with other teams on their daily tasks.
6.3. Members of this team share information as appropriate to other teams.

Two scales are identified for measuring the different behavioural competencies. The first scale is the agreement scale. Ajzen (1991) suggested in his theory of planned behaviours to use a 7-point bi-polar scale ranging from a negative evaluation (e.g., strongly disagree) on one end to a positive evaluation on the other end (e.g., strongly agree) to form a bipolar continuum for evaluating human behaviours. The scale identified by Ajzen (1991) is used in this research to measure the degree of existence of the different evaluation criteria pertaining to behavioural competencies within teams performing work on a construction project. The second scale considered for measuring behavioural competencies, similar to the functional competencies evaluation criteria, is the importance scale.

2.3.2. Project Performance: Categories and Project KPIs Measures

Several frameworks and methodologies were presented earlier to identify project performance measures. These frameworks ranged from a theoretical concept to measurable sets of project KPIs. Reviewing the different frameworks and identifying the advantages of each, a framework and a detailed set of project KPIs are developed (CBPP-KPI 2002; Chan and Chan 2004; Rankin et al. 2008; COAA 2009; Nasir et al. 2012; CII 2013). The decision to merge these frameworks and project KPIs is based on their wide application in different industries and construction projects. The categorization of performance measures into sets of project KPIs provide a comprehensive overview of project performance through seven different performance categories and 46 project KPIs. Table 2-9 lists the seven project performance categories and a sample of project KPIs. A detailed list of project KPIs is presented in Appendix 1.3.

Table 2-9 Examples of Performance Metrics and Project KPIs

Performance Metric	KPI Number	KPI Description	KPI Definition	KPI Formula
Cost	1.1	Project Cost Growth	The variance between the actual total project cost to-date and the total project estimate to-date at tender stage, expressed as a ratio of the total project estimate to-date at tender stage	((actual total project cost- total project estimate at tender stage)/ total project estimate at tender stage)
Schedule	2.1	Project Schedule Growth	The variance between the actual total project duration to-date and the project duration to-date at tender stage, expressed as a ratio of the project duration to-date at tender stage	((actual total project duration – project duration at tender stage)/ project duration at tender stage)
Change	3.1	Total Change Cost Factor	The ratio between the total cost of scope changes (contractor and client) to-date and the actual total project cost to-date	(total cost of scope changes/actual total project cost)
Safety	4.1	Lost Time Rate	The ratio between the time lost to incidents in hours measured over 100,000 hours of work	(amount of lost time to incidents (in hours))/(100,000 hours of work))
Quality	5.1	Total Field Rework Cost Factor	The ratio between the total direct cost of field rework to-date, and the actual construction phase cost to-date	(total direct cost of field rework /actual construction phase cost)
Productivity	6.1	Construction Productivity Factor (Cost)	The ratio between the total installed work cost to-date and the total actual man-hours to-date	(total installed cost / total actual man-hours worked)

Performance Metric	KPI Number	KPI Description	KPI Definition	KPI Formula
Satisfaction	7.1	Satisfaction (Design team)	Owner/Contractor overall satisfaction with the design team	Rating from 1 to 7, where, 1 is extremely dissatisfied and 7 is extremely satisfied

2.4. Project Competencies and Project Performance: Data Collection Tools

Project competencies and project KPIs are used for evaluating construction projects. First, sets of interview surveys are developed for collecting data for the different project competencies. Second, a worksheet is developed to collect project KPIs (i.e., as presented in Table 2-9 and Appendix 1.3).

2.4.1. Project Competencies' Surveys

A set of interview surveys are developed for collecting the different functional and behavioural competencies. For functional competencies, a survey is designed to be completed by management staff who oversee the application of the different organizational practices on a construction project. A sample of the functional competencies' survey is presented in Appendix 1.4. For behavioural competencies, a set of surveys are designed to be completed by project personnel involved in the construction works on a construction project. Samples of the behavioural competencies' surveys are presented in Appendices 1.5 and 1.6 respectively. The structure of the different surveys is described next.

2.4.1.1. Functional Competencies Survey

The functional competencies survey has two sections. The first section collects information related to the construction company, project, and respondents. The second section evaluates the different functional competencies of a construction company on the project level. Each functional competency is divided into a set of evaluation criteria as described earlier, each of which is measured using (1) the importance scale and (2) the maturity scale. For the importance scale, an evaluation criterion pertaining to a given functional competency is evaluated using a five-point bipolar scale ranging from 1 “Extremely Unimportant” to 5 “Extremely Important”. For example, to evaluate the importance of the “Project Safety Management” competency to a given project, a survey respondent must assign an importance scale value from 1 to 5 to the competency’s evaluation criterion “9.2. Safety preplanning meetings are held, and a safety plan is established for the project”. The maturity scale is used to evaluate the extent of the application of a given evaluation criterion pertaining to a given functional competency on the construction project (Willis and Rankin 2012, 2011; Sarshar 2000). The maturity scale is based on a six point scale, as described in Table 2-6, ranging from 0 “Use of the practice is non-existent on this project” to 5 “Continuous Practice Improvement”. Accordingly, to evaluate the extent to which the “Project Safety Management” competency is applied on the project, a survey respondent must assign a maturity scale value from 0 to 5 to each evaluation criterion.

2.4.1.2. Behavioural Competencies Survey

The behavioural competencies survey has two sections. The first section collects information related to the respondent’s years of experience, position, and project complexity. The second section of the survey asks the respondent to evaluate the team’s different behavioural competencies at the project level. Each behavioural competency is further divided into a set of evaluation criteria, each of which is measured using (1) the importance scale and (2) the agreement scale. For the importance scale, an evaluation criterion pertaining to a given behavioural competency is evaluated using a five-point bipolar scale ranging from 1 “Extremely Unimportant” to 5 “Extremely Important”. For example, to evaluate the importance of the

"Teamwork" behavioural competency for a project team, a survey respondent must assign an importance scale value from 1 to 5 to the competency's evaluation criterion "6.2. Members of this team work cooperatively with other teams on their daily tasks". The agreement scale is used to evaluate the degree to which an evaluation criterion exists in the team performing work on the construction project pertaining to a given behavioural competency. The agreement scale ranges from 1 "Strongly disagree" to 7 "Strongly agree". Accordingly, to evaluate the extent to which the decision-making competency exists within a project team, a survey respondent must assign an agreement scale value from 1 to 5 to each evaluation criterion.

2.4.2. Project KPIs Worksheet

For project KPIs, data is collected, as described in Table 2-9, to calculate the different project KPIs at the same time the project competencies' surveys are conducted. A worksheet contains all required data to calculate the different project KPIs (listed in Appendix 1.3). For example the data required for calculating "1.1. Project Cost Growth" KPI are listed in Table 2-10.

Table 2-10 Example of Project KPI Data Collection Worksheet

KPI	KPI Required Data	KPI Formula	KPI Threshold
Project Cost Growth	1. Actual total project cost (i.e., to-date) 2. Total project estimate at tender stage (i.e., to-date)	((actual total project cost- total project estimate at tender stage)/ total project estimate at tender stage)	<0 Desirable value =0 Planned value >0 Undesirable value

The project KPIs values presents whether project performance, according to the project performance categories and project KPIs, are performing according to planned objectives or not? Furthermore, they quantify the amount of overrun, if any, for a given project KPI.

2.5. Project Competencies and Project Performance: Sample Size Determination and Data Collection

For the project competencies surveys, data collection commences with the identification of the different occupational clusters in a construction project. Initially, the occupational clusters are divided into management (e.g., project managers), superintendents, foremen, and tradespeople. Determination of sample size—or, the number of respondents to be surveyed from the different occupational clusters of workers—is essential to ensure the reliability and accuracy of results. The survey population, in terms of the total personnel, is stratified, as described earlier, into management, superintendents, foremen, and tradespeople. Once the population for each stratum is established, random sampling is taken. Stratified random sampling is an appropriate method in this situation, as the structure within the population of each stratum is assumed to be similar in terms of role and function, and adequate sample size is used to ensure proper representation of the population as a whole (Richard and Liu 2008). Additionally, random sampling ensures that respondents each have an equal chance of being selected, and thus avoids biased selection of respondents based on convenience (Montgomery and Runger 2003). The aim in this study is to achieve a 10% margin of error and 90% confidence interval. However, if the population numbers less than 30, all personnel in a stratum are considered for survey interviewing.

For the functional competencies' survey, the survey is designed to be completed by management staff who oversees the application of the different management practices on a given construction project. For the behavioural competencies' survey, an additional consistency analysis is required to ensure the reliability of the data collected (Cronbach, 1951) to capture behavioural attributes as described by Ajzen (1991) and to overcome current limitations in competencies models as described by Markus et al. (2005). First, main survey administration techniques are presented. Then a structured approach for behavioural competencies data collection is considered. Four different behavioural competencies survey administration techniques are identified from previous research. A brief description of each is presented.

1. 360-Degree feedback (Atkins and Wood 1999) is an evaluation system observing discrepancies or change in rating over time. It is based on rounds of survey instruments to measure a subject by acquiring evaluation from different sources (ex. team members and supervisors) related to that subject.
2. Supervisor evaluation (Hackman and Oldham 1976): A supervisor evaluation system observing discrepancies or changes in subordinates evaluation. It is considered a special case of 360-degree feedback.
3. Subordinate evaluation (Hater and Bass 1988): A subordinate evaluation system observing performance behaviour of managers and leaders by subordinates.
4. Peer evaluation (Fishbein and Ajzen 1975; Bandura, 1982; Ajzen 1991): An evaluation system measuring behaviours. It is based on capturing behaviours by the evaluation of peers. It is used to demonstrate general attitudes, personality traits and behavioural competencies.

Based on the four techniques outlined above, a hybrid technique, combining supervisor evaluation (i.e., point 2) and peer evaluation (i.e., point 4), is used for performing the behavioural competencies' evaluation. This hybrid technique ensures the reliability of the data collected from supervisors in evaluating their team members. The following structured approach for behavioural competencies' surveys data collection is considered.

1. Supervisors and their teams from each occupational cluster are identified, and a random sample is determined to select potential respondents to the behavioural competencies survey.
2. Each identified supervisor in an occupational cluster is asked to complete the behavioural competencies survey to evaluate a randomly selected number of teams working under his/her supervision. For each selected team, the supervisor performs a supervisor behavioural competencies' evaluation for the entire selected team.
3. Finally, from each selected team, a randomly selected number of team members are asked to perform a self-evaluation of their own team's behavioural competencies.

A Cronbach's alpha coefficient is used to examine the reliability of the data collected from different respondents (i.e., supervisor and his/her team members) participating in the behavioural competencies survey. This test, prior to data analysis, is used to measure the internal consistency of the data collected (Cronbach, 1951) from a supervisor and his/her randomly selected team members. Ranging between 0.0 and 1.0, the closer Cronbach's alpha coefficient is to 1.0 the greater the internal consistency of the data collected among the different respondents. George and Mallery (2003) stated that values below 0.5 are unacceptable. Accordingly, if the Cronbach's alpha coefficient is greater than that certain value (i.e., ≥ 0.5), then the supervisor behavioural competencies evaluation is considered for further analysis. Otherwise, the supervisor behavioural competencies evaluation is excluded from the analysis (i.e., <0.5).

2.6. Validation of Project Competencies Surveys, Project Performance Categories and Project KPIs

The different data collection tools (i.e., project competencies' surveys and Project KPIs worksheet) are validated as described next.

2.6.1. Project Competencies Surveys Validation

For the project competencies' surveys, a workshop was conducted at the annual Construction Owners Association (COAA) in May 2014. The workshop had 40 construction practitioners representing owners, consultants and, contractors. The construction practitioners were of different managerial positions ranging from field operations to senior management and, varying level of experience ranging from 5 to over 30 years of work experience. The different functional and behavioural competencies were presented to the audience to verify and provide additional functional and/or behavioural competencies and/or evaluation criteria that were not included. Construction practitioners' feedback was used to improve the functional and behavioural competencies' surveys.

2.6.2. Project Performance Categories and Project KPIs Validation

For the project performance categories and KPIs, first, project controls managers from five construction companies in residential, commercial and, industrial construction, and with varying years of experience, were asked to verify the project performance categories and KPIs, and identify the frequency of their use through an interview survey. A five-point scale was used to verify the project performance categories and measure the frequency of using the different project KPIs. Additionally, lines were intentionally left blank to add any project KPIs that were not included in the interview survey as presented in Appendix 1.7. A five-point scale ranging from 1 “never used” to 5 “always used” was assigned to the different project KPIs. The threshold value used to eliminate project KPIs from the list was set at scale value 1. The survey resulted in a total of 46 KPIs (i.e., none of the project KPIs were excluded from the original project KPIs worksheet) for evaluating project performance. Another validation of the project performance categories and project KPIs was conducted along with the different project competencies in the workshop conducted at the annual Construction Owners Association (COAA) in May 2014.

Finally, the data collection tools were piloted on a construction project to ensure suitability of data collection tools for use on different construction projects. Data collection tools were considered, by participating construction practitioners in the project, suitable and comprehensive enough to capture the different project competencies and project KPIs.

2.7. Concluding Remarks

This chapter presents a literature review of previous research in the areas of project competencies, the relationship between project competencies and project performance and, project performance measures respectively. Limitations of previous research are identified to enhance the existing body of knowledge in project competencies and project performance evaluation and modeling. Project competencies and detailed evaluation criteria and measurement scales are presented. Project performance categories and project KPIs measurements are also presented. Data collection tools and sample size determination are identified for data collection on construction projects. Finally, the developed data collection tools (i.e., for project competencies and, performance categories and project KPIs) are validated using workshops, interview surveys and, a pilot project. Integral to the findings of this chapter, a need to develop an information fusion method that is capable of producing informative evaluation of the different project competencies on the higher hierarchical level (i.e., project competency level) rather than the lower hierarchical levels (i.e., evaluation criteria of project competencies) is vital. This process provides a collective evaluation to be considered for modeling the relationship between project competencies and project performance as described in the next two chapters.

2.8. References

Alroomi, A., Jeong, D. H. S., and Oberlender, G. D. (2011). "Analysis of cost-estimating competencies using criticality matrix and factor analysis." *J.Constr.Eng.Manage.,* 138(11), 1270-1280.

Ajzen, I. (1991). "The theory of planned behavior." *Organ.Behav.Hum.Decis.Process.,* 50(2), 179-211.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American psychologist*, *37*(2), 122.

Bassioni, H. A., Price, A. D., and Hassan, T. M. (2004). "Performance measurement in construction." *J.Manage.Eng.,* 20(2), 42-50.

Bourne, M. , Mills, J. , Wilcox, M. , Neely, A. , and Platts, K. (2000). "Designing, implementing and updating performance measurement systems." *Int. J. Operat. Product. Manage.* , 20 (7), 754–771.9

Caupin, G., Knöpfel, H., Morris, P., Motzel, E., Pannenbäcker, O. (2006). ICB-IPMA Competence Baseline, International Project Management Association, Netherlands.

Chan, A. P., & Chan, A. P. (2004). Key performance indicators for measuring construction success. *Benchmarking: an international journal*, 11(2), 203-221.

Chandler, A. (1977). The visible hand: the managerial revolution in American business. Cambridge. *Massachusetts.*

Cheung, S. O., Suen, H. C., & Cheung, K. K. (2004). PPMS: a web-based construction project performance monitoring system. *Automation in construction*, *13*(3), 361-376.

Construction Industry Institute (CII). (2005). Competencies toolkit, The Univ. of Texas at Austin, Austin, Tex.

Construction Industry Institute (CII). (2013). 10-10 performance program. Accessed August 1, 2015, from http://10-10program.org/overview.htm

Construction Industry Institute (CII). (2013). CII benchmarking and metrics data report 2013, The Univ. of Texas at Austin, Austin, Tex.

Costa, D. B., Formoso, C. T., Kagioglou, M., Alarcón, L. F., & Caldas, C. H. (2006). Benchmarking initiatives in the construction industry: lessons learned and improvement opportunities. *Journal of Management in Engineering*, *22*(4), 158-167.

Cronbach, L. J. (1951). "Coefficient alpha and the internal structure of tests." *Psychometrika,* 16(3), 297-334.

Eccles, R. (1991). “The performance measurement manifesto.” Harvard Bus. Rev. 69 (1), 131–137.

Edgar, W. B., & Lockwood, C. A. (2008). Organizational competencies: clarifying the construct. *Journal of Business*, *22*, 21-32.

Fayek, A. Robinson. (2012). Advancing fuzzy hybrid techniques for competency modeling of construction organizations. *NSERC Discovery Grant Application* 2013-2017.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wesley

George, D., & Mallery, M. P. (2003). *Using SPSS for Windows Step by Step: A Simple Guide and Reference*. Allyn & Bacon: Boston, MA.

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational behavior and human performance*, *16*(2), 250-279.

Hater, J. J., & Bass, B. M. (1988). Superiors' evaluations and subordinates' perceptions of transformational and transactional leadership. *Journal of Applied psychology*, *73*(4), 695.

Hitt, M. A., and Ireland, R. D. (1986). "Relationships among corporate level distinctive competencies, diversification strategy, corporate structure and performance." *Journal of Management Studies,* 23(4), 401-416.

Isik, Z., Arditi, D., Dikmen, I., and Birgonul, M. T. (2009). "Impact of corporate strengths/weaknesses on project management competencies." *Int.J.Project Manage*., 27(6), 629-637.

Kagioglou, M., Cooper, R., & Aouad, G. (2001). Performance management in construction: a conceptual framework. *Construction management and economics*, *19*(1), 85-95.

Kululanga, G. K.; Edum-Fotwe, F. T.; McCaffer, R. (2001): Measuring construction contractors' organizational learning. In *Building Research & Information* 29 (1), pp. 21–29.

Kaplan Robert S.; Norton David P. (2005): The balanced scorecard: Measures that drive performance. Boston, MA, ETATS-UNIS: Harvard Business School Publishing Corporation (Harvard business review, 83) (7).

Kometa, S. T., Olomolaiye, P. O., and Harris, F. C. (1995). "An evaluation of clients' needs and responsibilities in the construction process." *Engineering, Construction and Architectural Management,* 2(1), 57-76.

Letza, S. R. (1996). “The design and implementation of the balanced scorecard.” *Bus. Process Re-engineering Manage. J.*, 2 (3), 54–76.

Levenson, A. R., Van der Stede, Wim A, and Cohen, S. G. (2006). "Measuring the relationship between managerial competencies and performance." *Journal of Management,* 32(3), 360-380.

Markus, L., Thomas, H., and Allpress, K. (2005). Confounded by competencies? An evaluation of the evolution and use of competency models. *New Zealand Journal of Psychology,* 34(2), 117.

Nasir, H., Haas, C. T., Rankin, J. H., Fayek, A. Robinson, Forgues, D., and Ruwanpura, J. (2012). "Development and implementation of a benchmarking and metrics program for construction performance and productivity improvement." *Canadian Journal of Civil Engineering, Special Issue on Construction Engineering and Management,* 39(9), 957-967.

Navarre, C. and Schaan, J.L. (1990). Design of project management systems from top management's perspective. *Project Management Journal*, Vol. 21 No. 2, pp. 19-27.

Navon, R. (2005). Automated project performance control of construction projects. *Automation in Construction*, *14*(4), 467-476.

Neely, A., Bourne, M., (2000). Why measurement initiatives fail", *Measuring Business Excellence*, Vol. 4 Iss: 4, pp.3 – 7

Norreklit, H. (2000). The balance on the balanced scorecard—A critical analysis of some of its assumptions." *Manage. Account. Res.*, 11 (1), 65–88.

Nunnally JC (1978) *Psychometric Theory*, 3rd edition. McGraw-Hill, New York.

Omar, M., and Fayek, A. Robinson (2014). "A Framework for Identifying and Measuring Competencies and Performance Indicators for Construction Projects." *J.Constr.Eng.Manage.*, 2043-2052.

Pinto, M.B. and Pinto, J.K. (1991), Determinants of cross-functional cooperation in the project implementation process. *Project Management Journal*, Vol. 22 No. 2, pp. 13-20

Provost, L., & Leddick, S. (1993). How to take multiple measures to get a complete picture of organizational performance. *National Productivity Review*,12(4), 477-490.

Rankin, J., Fayek, A. Robinson., Meade, G., Haas, C., and Manseau, A. (2008). "Initial metrics and pilot program results for measuring the performance of the Canadian construction industry." *Canadian Journal of Civil Engineering,* 35(9), 894-907.

Sarshar, M., Haigh, R., Finnemore, M., Aouad, G., Barrett, P., Baldry, D., and Sexton, M. (2000). "SPICE: a business process diagnostics tool for construction projects." *Engineering Construction and Architectural Management,* 7(3), 241-250.

Sparrow, P. (1995). Organizational competencies: a valid approach for the future? *International Journal of Selection and Assessment,* 3(3), 168-177.

Spencer, M. L. S. (1993). *Competence at work models for superior performance.* John Wiley & Sons, New York.

Stuart, R. (1983). Problems of training design, Industrial & Commercial Training, August, 239-40.

The Alberta Report: COAA Major Projects Benchmarking Summary". Construction Industry Institute. (n.d.). Accessed August 1, 2015, from https://www.construction-institute.org/nextgen/publications/COAA/COAA_Alberta_Report.pdf

Walsh, Steven T., Linton, Jonathan D. (2001). The competence pyramid: A framework for identifying and analyzing firm and industry Competence. In *Technology Analysis & Strategic Management* 13 (2), pp. 165–177.

Ward, P. T., Duray, R., Leong, G. K., & Sum, C. C. (1995). Business environment, operations strategy, and performance: an empirical study of Singapore manufacturers. *Journal of operations management*, *13*(2), 99-115.

Willis, C. J., and Rankin, J. H. (2010). "Measuring the Maturity of Guyana's Construction Industry Using the Construction Industry Macro Maturity Model (CIM3)." *Journal of Construction in Developing Countries,* 15(2), 87-116.

Willis, C. J., and Rankin, J. H. (2012). "The construction industry macro maturity model (CIM3): theoretical underpinnings." *International Journal of Productivity and Performance Management,* 61(4), 382-402.

Wood, R. E., Atkins, P. W., & Bright, J. E. (1999). Bonuses, goals, and instrumentality effects. *Journal of Applied Psychology*, *84*(5), 703.

CHAPTER 3. – Information Fusion: A New Prioritized Aggregation Method for Multi-Criteria Decision-Making Problems [1, 2]

3.1. Introduction

Information fusion is defined as the process of integrating information from different sources to describe the overall behavior of a specific system (Dubois and Prade 2004). The process of information fusion aims to support decisions and actions relating to a certain system. Interest in information fusion has grown over the past few decades. Dubois and Prade (2004) highlighted four main concepts that information fusion aims to fulfil separately or jointly: 1) improve available knowledge about the current state of the world, 2) update current information on cases of interest, 3) capture the global point of view of a group of experts, and 4) improve the generic knowledge by means of data. Hence, aggregation is central to information fusion.

Aggregation, in general, is defined as a "mathematical object that has the function of reducing a set of numbers into a unique representative value" (Detyniecki 2001). The primary application of aggregation is to combine information from a group of sources to reach a collective value representing all the different sources. This chapter presents a new method for prioritized aggregation. The objective of the new prioritized aggregation method is to establish and dynamically quantify the relationship between the various criteria during aggregation.

This chapter enhances the existing body of knowledge by capturing the relationship between different data sources (i.e., criteria) during the aggregation process through a new

---

[1] Parts of this chapter have been accepted for publication in international journal of multi-criteria decision analysis. Omar, M. and Fayek, A. Robinson. (2015a). "A TOPSIS–based approach for prioritized aggregation in multiple-criteria decision-making problems." Manuscript, 20 pages.
[2] Parts of this chapter have been submitted for publication in fuzzy sets and systems journal. Omar, M. and Fayek, A. Robinson. (2015b). "A TOPSIS–based method for prioritized aggregation in fuzzy environments." Manuscript, 18 pages.

prioritized aggregation method. This method is capable of considering the prioritized relationship between the different criteria considered for aggregation, thereby ensuring that poor satisfaction of higher-priority criteria is not compensated for by high satisfaction of lower-priority criteria. The relationship between criteria is modeled using the technique of order preference by similarity to ideal solution (TOPSIS) to account for the importance of higher-priority criteria as well as the degree to which these criteria are satisfied. The presented method is then extended to fuzzy environments to account for the subjective nature of measuring evaluation criteria using linguistic terms.

3.2. Overview of the Aggregation Problem

When performing aggregation, ensuring that the data are properly combined into one collective value can be challenging. The collective value, in many instances, needs to account for the relationship between the individual data considered for aggregation; in many instances, this relationship is one of prioritization. Recent research has focused on defining and quantifying prioritized relationships (Detyniecki 2001; Yager 2004, 2009; Yager et al. 2011a, 2011b; Yan et al. 2011; Bisdorff et al. 2014; Emrouznejad and Marra 2014) during aggregation.

Aggregation methods have numerous real-world applications. One is the multi-criteria decision-making (MCDM) problem. In MCDM problems, it is vital to analyze the different criteria considered to reach a collective value representing all criteria for decision making (Shih et al. 2007). In the construction domain, many decisions are based on the evaluation of multiple related criteria (Yager 1988; Ulubeyli and Kazaz 2009; Razmak and Aouni 2014). For example, the evaluation of a contractor bidding for a construction project requires an investigation of a set of criteria such as years of experience, bonding capacity, and budget and track record of the contractor for previous projects (Choo et al. 1999). The relationship between these criteria needs to be considered before a decision can be made.

Another application of aggregation is the optimization problem. In construction contexts, an optimization problem requires the investigation of several criteria that contribute to the optimization result. For example, the optimization of mass concrete construction requires an analysis of concrete composition, equipment used, and temperature control. Foremost to this problem is the application of an aggregation method that allows the determination of an index representative of the entire set of related criteria being considered.

3.3. Aggregation Methods, Classifications and, Properties

Before aggregation can be applied, the most suitable aggregation method must be identified. The aggregation methods, described in previous research, can be divided into two main categories: 1) crisp aggregation methods that are used to aggregate real values and 2) fuzzy aggregation methods that are used to aggregate linguistic labels (Xu and Yager 2006). The classification of different aggregation functions—and their properties—within each of the two categories of aggregation methods has been explored in previous research (Detyniecki 2001; Yager 2004, 2009; Yager et al. 2011; Wei and Tang 2012). These explorations have led to the aggregation functions, for each category, being classified as illustrated in Table 3-1.

Table 3-1 Aggregation Functions Classes (Omar and Fayek 2015a)

Aggregation Function Class	Aggregation Function Class Description	Aggregation Function Example
1. Conjunctive functions	This class of functions considers criteria that have a logical union "or" relationship.	t-norm
2. Disjunctive functions	This class of functions considers criteria that have a logical intersection "and" relationship.	t-conorms
3. Compensative/compromise functions	This class of functions considers operators that are comprised between the union "or" and intersection "and" relationship. They are neither conjunctive nor disjunctive.	Arithmetic mean, median, and order statistic
4. Non compensative functions	This class of functions encompasses the compensative class, but extends beyond the minimum and maximum functions.	Symmetric sums, combined t-norm, and t-conorm
5. Weighted functions	This class is considered an extension to the compensative functions. The weighted functions class aims to eliminate the neutrality of the criteria being aggregated.	Ordered weighted arithmetic, weighted sum, ordered weighted average

Now that the different categories and classifications of aggregation functions have been identified, an investigation into the main properties of these aggregation functions is presented. Six mathematical properties relevant to an aggregation function have been identified from previous research: boundary, cummutativity, continuity, monotonicity, idempotence, and associativity conditions (Marichal 1998; Yager 2004, 2009; Pedrycz and Gomide 2007; Shih et al. 2007). Each of these is explained below.

Boundary Condition

A vital property of aggregation functions is the boundary condition. The boundary condition constrains the result of an aggregation function $f(x)$ to the minimal and maximal boundaries of possible outputs. In other words, if we have only one minimal (maximal) possible input then we should obtain the minimal (maximal) possible output. Hence, for an aggregation function $f(x)$:

$$f(0,\ldots,0) = 0 \text{ and } f(1,\ldots,1) = 1, \text{ where } x \in [0, 1] \tag{3-1}$$

Cummutativity Condition

The cummutativity property implies that the ordering or ranking of arguments does not matter. This property is valid when there is equal importance or no relationship considered between the different criteria to be aggregated. For an aggregation function $f(x)$ to be commutative, then:

$$f(x_1, x_2, \ldots, x_n) = f(x_2, x_1, \ldots, x_n) = f(x_n, x_1, x_2, \ldots), x \in \mathrm{S} \tag{3-2}$$

Continuity Condition

The continuity property suggests that the aggregation function does not show a chaotic reaction to a small change in the attributes considered for aggregation. In other words, a "small" error in the inputs will not cause a "big" error in the resulting output (Marichal 1998). For an aggregation function $f(x)$:

$$\cup_{x \in \mathrm{S}} [0,1]^x \rightarrow [0,1] \text{ is a continuous aggregation function if } f(x)\text{: } [0,1]^x \rightarrow [0,1] \tag{3-3}$$

Monotonicity Condition

Aggregation functions are monotonic, which means they exhibit a "non-decreasing" relationship between the criteria and the output of the aggregation operation. An aggregation function $f(x)$ is strictly non-decreasing and its result increases when any of the attributes under aggregation increase:

$$x_i' > x_i, \text{ then } f(x_i') > f(x_i) \text{ where } x \in \mathrm{S} \tag{3-4}$$

Idempotence Condition

Idempotence is an algebraic property related to a binary operation *, wherein if x is an idempotent element with respect to an operation *, then $x * x = x$. Extending this notion to aggregation functions, an aggregation function $f(x)$ is idempotent if:

$$f(x, x, \ldots, x) = x \text{ where } x \in \mathrm{S} \quad (3\text{-}5)$$

Associativity Condition

Another property of aggregation functions is the ability to aggregate by groups, or "associations". According to the associativity condition, the choice of the group should not influence the overall result. The associativity property can be described for an aggregation function $f(x)$ as:

$$f(f(x_1, x_2, \ldots), x_n) = f(f(x_1, x_2), \ldots, x_n),\ x \in \mathrm{S} \quad (3\text{-}6)$$

3.4. Prioritized Aggregation

In MCDM problems, decision makers are required to evaluate criteria while considering the interrelations between these criteria. For example, when a group of decision makers are required to evaluate the importance of a set of criteria, an importance scale of x_m ordered alternatives is provided, where x_1 corresponds to the least important evaluation alternative and x_m corresponds to the most important evaluation alternative. Several aggregation methods that require the processing of multiple interrelated criteria have been proposed (Tong and Bonissone 1980; Tanino 1984; Bardossy et al. 1993; Hsu and Chen 1996; Ralescu et al. 1997; Wei 2009 2010, 2012). These aggregation methods combine decision makers' opinions in MCDM problems while considering the interrelations (e.g., prioritized relationship) between them.

In many situations, the satisfaction of a higher-priority criterion affects the overall evaluation of the entire set of criteria under investigation (Yager 2004; Ulubeyli and Kazaz 2009; Yager et al. 2011; Zhao et al. 2013; Chen and Xu 2014; Chen et al. 2014). Here, satisfaction implies the degree to which a criterion is adjacent to its most favourable setting. In MCDM problems, where a prioritized relationship exists between criteria, aggregation must include information related to the importance of each criterion. Yager (2004) describes importance information to be fundamentally advantageous in aggregation because it allows alternatives to be combined while overseeing trade-offs between the respective satisfactions of the different criteria. For example, in selecting a bicycle for a child based upon the criteria of safety and cost, a lower cost of the bicycle does not offset a loss in its safety (Yager 2009; Yager et al. 2011). The advantage of including importance information in aggregation is also exemplified, for example, by the construction contractor selection process. Consider that a contractor is to be selected based on safety records, experience, and cost. In this situation, the high experience and low cost of a contractor does not compensate for his/her poor safety record.

Yager has comprehensively investigated prioritized aggregation (1988, 1996, 2004, 2008, 2009, 2011), and first introduced a prioritized scoring operator (2004) to account for the satisfaction of higher-priority criteria considered for aggregation. The prioritized scoring operator is used to establish a dynamic relationship between the various ordered criteria considered for aggregation. Yager (2009) stated that the application of a prioritized scoring operator allows poor satisfaction of any higher-priority criteria to reduce the ability for compensation by lower-priority criteria. This is the fundamental characteristic of the prioritization relationship established by the prioritized scoring operator. However, in Yager's work, the determination of the prioritized scoring operator was limited in that it was based mainly on the use of the least satisfied criteria within a given category. The new prioritized aggregation method, presented in this chapter, extends Yager's prioritized aggregation by introducing a structured process, using TOPSIS, for calculating the prioritized scoring operator.

3.5. A TOPSIS-Based Method for Prioritized Aggregation in Multi-Criteria Decision-Making Problems in Crisp Environments (Omar and Fayek 2015a)

This section extends Yager's work in prioritized aggregation by utilizing TOPSIS in prioritized aggregation. TOPSIS is an approach that originates from the geometric concept of the displaced ideal point, according to which a criterion under investigation is seen to be situated in relation to its ideal positive (most favourable) and negative (least favourable) locations (Chu 2002). Each criterion under investigation is assigned an index—called the relative closeness index—that represents how close it is to its positive ideal solution (*PIS*) and how far it is from its negative ideal solution (*NIS*). The relative closeness index is then used to calculate a prioritized scoring operator to establish the dynamic relationship between the various ordered criteria considered for prioritized aggregation.

According to Chu (2002), using TOPSIS is advantageous for several reasons: it applies a sound logic that represents satisfaction levels of criteria by their proximity to their most favourable satisfaction; it employs a simple and effective computational process, where a scalar value that accounts for both the best and worst alternatives is calculated; and it provides users with the ability to visualize the different alternatives on at least any two dimensions (Chu 2002). The application of TOPSIS in the presented prioritized aggregation method enables the calculation of a prioritized scoring operator that incorporates each criterion's relative importance compared to other criteria, as well as the satisfaction of each criterion toward its most favourable satisfaction.

A prioritization process is first introduced to rank and prioritize the different criteria prior to aggregation. Following the ranking, TOPSIS is applied to generate the prioritized scoring operator to adjust the criteria's existing relative weights prior to aggregation. The final stage in this method is to apply a weighted aggregation function to provide an overall aggregated value representing the set of criteria under consideration.

3.5.1. Prioritized Scoring Operator Using TOPSIS

The calculation of the prioritized scoring operator for the presented method uses the prioritized relationship between criteria and the satisfaction levels of the different criteria. The satisfaction scale represents the degree to which a criterion meets its most favourable satisfaction level. In the previously considered example where a bicycle is to be purchased for a child, a satisfaction scale for the safety feature reflects to what extent the safety of the bicycle meets the buyer's requirements. An ordinal scale with x_m alternatives is assigned for the set of predefined criteria C. A set of alternatives $x_m = \{x_1, \dots, x_m\}$ represents, in order, the different satisfaction levels that a given criterion can achieve.

The set of alternatives x_m obtained from the satisfaction scale are normalized to avoid a situation where criteria with greater numerical satisfaction values dominate those of smaller numeric values (Shih et al. 2007). Thus, the satisfaction alternative x_i obtained for the different criteria is normalized prior to the application of TOPSIS. After normalization, the satisfaction alternative assigned for each criterion C_i is denoted by $C_i(x)$. Table 3-2 lists some of the commonly used normalization methods presented in past literature and applied as a prerequisite to TOPSIS (Hwang and Hwang 1992; Milani et al. 2005; Yoon and Hwang 1995).

Table 3-2 Common Normalization Methods for TOPSIS (Shih et al., 2007)

Normalization Method	Formula
Vector normalization	$C_i(x) = \frac{x_i}{\sqrt{\sum_{i=1}^{m} x_i^2}}$, $x_i = x_1, \ldots, x_m$
Linear normalization	(a) $C_i(x) = \frac{x_i}{x_m}$, $x_i = x_1, \ldots, x_m$
	(b) $C_i(x) = \frac{x_i^{\sim}}{x_i}$, $x_i = x_1, \ldots, x_m$; $x_i^{\sim} = min\{x\}$
	(c) $C_i(x) = 1 - \frac{x_i}{x_m}$, $x_i = x_1, \ldots, x_m$
	(d) $C_i(x) = \frac{x_i - x_i^{\sim}}{x_m - x_i^{\sim}}$, $x_i = x_1, \ldots, x_m$; $x_i^{\sim} = min\{x\}$
	(e) $C_i(x) = \frac{x_i}{\sum_{i=1}^{m} x_i}$, $x_i = x_1, \ldots, x_m$

Considering a relative importance score (RIS) for a criterion C_i and its associated satisfaction level $C_i(x)$ for TOPSIS application, the $C_i(RIS)$ and the related normalized satisfaction alternatives $C_i(x)$ for the various criteria are used as attributes for the TOPSIS application to calculate the prioritized scoring operator. It is important to highlight that the ideal positive solution for a given criterion C_i is $\{C_i(RIS)_{Max}, C_i(x)_{Max}\}$ and the ideal negative solution for the same criterion is $\{C_i(RIS)_{Min}, C_i(x)_{Min}\}$. The coordinates assigned as the ideal positive (which represents the most favourable *RIS* and satisfaction of a given criterion) and those assigned as the ideal negative (which represents the least favourable *RIS* and satisfaction of all criteria) solutions geometrically demonstrate a quantification of the relative closeness of a given criterion assigned a higher priority (i.e., expressed in its *RIS*) to the rest of the criteria considered in the aggregation. The coordinates also consider the satisfaction level achieved by a criterion in relation to its most favourable satisfaction levels.

It is important also to note that to measure the respective distances between a given criterion and its ideal positive and negative solutions, several methods are presented in previous research (Berberian 1998; Steuer 1989; Jones and Mardle 2004); that are listed in Table 3-3. Of these methods, the Euclidean distance measure is the most commonly used method in TOPSIS (Shih et al. 2007) and hence it is applied in this method.

Table 3-3 Common Distance Measures for TOPSIS (Chu, 2002)

Distance Measure	Formula
(i) Minkowski's S_p metrics (a) Manhattan (city block) distance p = 1 (b) Euclidean distance p = 2 (c) Tchebycheff distance p = α	$S_p(x,y) = \{\sum_{j=1}^{n} \lvert x_j - y_j \rvert^p\}^{\frac{1}{p}}$, Where p≥1 and with n dimensions
(ii) Weighted S_p metrics	$S_p(x,y) = \{w_j \sum_{j=1}^{n} \lvert x_j - y_j \rvert^p\}^{\frac{1}{p}}$, Where p$\epsilon$\{1,2,3,…\} $\cup\{\alpha\}$; w_j is the weight on the j^{th} dimension or direction

In order to determine the prioritized scoring operator for the proposed prioritized aggregation method using TOPSIS, the positive ($^+$) and negative ($^-$) distances S_i for a criterion C_i are calculated. Calculating the distances is a preliminary step to determine where a criterion C_i is located relative to the most and least favourable *RIS* and satisfaction values it can achieve. A relative closeness index can then be calculated to be used for calculating the prioritized scoring operator.

Following this overview, criteria ranking and weight determination for the different criteria is described next. Then the application of TOPSIS is presented to calculate the prioritized scoring operator. Finally a prioritized aggregation function is used to provide a collective value representing the different interrelated criteria.

3.5.1.1. Criteria Ranking and Weight Determination in Crisp Environments

Several ranking and weight determination methods are identified in previous research (O'Hagan 1988, 1990; Choo 1999; Lootsma 2000; Yager 2006, 2009; Bisdorff 2014):

1. Direct choice of weight: This method is based upon the assignment of weights to the different criteria prior to aggregation. Weights are mainly determined from consensus among a group of experts.
2. Learn weights from data: This method depends on the availability of data to generate weights for the different criteria considered for aggregation.
3. Select a notable type of aggregation: This method depends on the use of simple operators such as t-norms and s-conorms to rank the different criteria.
4. Maximum entropy method: O'Hagan (1988, 1990) suggested an offline, nonlinear, geometric program to develop weights using a mathematical algorithm. The algorithm is initiated by a coefficient, α, provided by the decision maker.
5. Linguistic-functional specification: Yager (1996) introduced a method for generating the weights for an OWA aggregation operation using basic unit monotonic (BUM) functions for the different criteria considered for aggregation. A BUM function is a mapping f:[0,1] → [0,1] such that $f(0) = 0$, $f(1) = 1$ and $f(x) \geq f(y)$ if $x > y$.

The "learn weights from data" method is applied in the presented prioritized aggregation method to prioritize criteria and generate relative weights for the criteria considered for aggregation. The application of the "learn weights from data" method is usually preceded by a data collection phase (e.g., interview surveys completed by experts) to measure the relative importance and satisfaction of each criterion. The different criteria are each assigned values on two scales: an importance scale to determine the relative importance of a given criterion compared to other criteria, and a satisfaction scale to measure the satisfaction of a given criterion towards its most favourable satisfaction.

For the presented prioritized aggregation method using TOPSIS, a set of criteria $C = \{C_1, \dots, C_n\}$ represents the set of criteria considered for a prioritized aggregation. An ordinal importance scale with n alternatives represents the different importance alternatives. The set of alternatives $n = \{n_1, \dots, n_i\}$ represents the importance of a given criterion; a_i is the number of respondents who assigned an importance scale alternative n_i. Assuming that J respondents provide their evaluation of the importance—expressed by the n_i importance scale assigned—of each criterion in the set, then a relative importance score (*RIS*) for a criterion C_i is calculated using Eq. (3-7):

$$C_i\,(RIS) = \frac{\mathrm{a}_1 n_1 + \mathrm{a}_2 n_2 \dots + \mathrm{a}_i n_i}{n_i * J} \quad C_i\,(RIS) \in [0, 1] \qquad (3\text{-}7)$$

The application of the *RIS* provides a data-driven approach that, via the results of the interview surveys completed by experts, elicits experts' knowledge in determining the relative importance of the different criteria. The relative importance of the criteria, measured by the *RIS* of each criterion, is then used as a method of ranking the criteria. Furthermore, the application of *RIS* enables the quantification of a relative weight for each criterion compared to the other criteria. The relative weight w_i, using Eq. (3-8), is capable of quantifying the significance of a criterion C_i compared to other criteria and to perform aggregation.

$$w_i = \frac{C_i(RIS)}{\sum_1^i C_i(RIS)}, \quad w_i \in [0, 1] \qquad (3\text{-}8)$$

Where:

$C_i(RIS)$ is the relative importance score of a given criterion and,

$\sum_1^i C_i(RIS)$ is the sum of *RIS* for the set of criteria being considered for aggregation.

3.5.1.2. TOPSIS Application

Considering the most and least favourable distances for each criterion are considered prerequisites to calculating the relative closeness index. First, the most favourable distance is calculated using the Euclidean distance measure, as presented in Eq. (3-9) and (3-10), respectively.

$$S_i^+ = ((C_i(x)_{Max} - C_i(x))^2 + (C_i(RIS)_{Max} - C_i(RIS))^2)^{\frac{1}{2}} \tag{3-9}$$

Where:

S_i^+ is the most favourable distance of C_i to the ideal positive C_i,

$C_i(x)_{Max}$ is the maximum normalized satisfaction for C_i,

$C_i(x)$ is the normalized satisfaction for C_i,

$C_i(RIS)_{Max}$ is the maximum relative importance score for C_i, and

$C_i(RIS)$ is the relative importance score for C_i.

$$S_i^- = ((C_i(x) - C_i(x)_{Min})^2 + (C_i(RIS) - C_i(RIS)_{Min})^2)^{\frac{1}{2}} \tag{3-10}$$

Where:

S_i^- is least favourable distance of C_i to the ideal negative C_i,

$C_i(x)$ is the normalized satisfaction for C_i,

$C_i(x)_{Min}$ is the minimum satisfaction for all criteria,

$C_i(RIS)$ is the relative importance score for C_i, and

$C_i(RIS)_{Min}$ is the minimum relative importance score for all criteria.

The relative closeness index of a criterion C_i to the ideal positive (most favourable) solution is then calculated in Eq. (3-11), where $0 \leq C_i \leq 1$.

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)} \tag{3-11}$$

A larger relative closeness index indicates that the criterion is located closer to its most favourable location in terms of both priority and satisfaction.

3.5.1.3. Prioritized Scoring Operator Calculation

After calculating the relative closeness, the prioritized scoring operator is calculated, as in Eq. (3-12).

$$T_i = \ C_{i-1}\, T_{i-1} \tag{3-12}$$

The highest ranked criterion in a set of criteria considered for an aggregation operation is assigned a value of T_1=1 (Yager 2004, 2008, 2009). The prioritized scoring operator T_i is used to adjust the original weight assigned to a given criterion as shown in Eq. (3-13).

$$w'_i = T_i * \ w_i \tag{3-13}$$

Where:

w'_i is the adjusted criterion weight,

T_i is the prioritized scoring operator, and

w_i is the relative criterion weight.

3.5.1.4. Weighted Aggregation Function

Once the prioritized scoring operator T_i has been determined for the different criteria, a weighted aggregation function is applied and the newly adjusted weights w'_i for the criteria are applied using Eq. (3-14).

$$F_w = \sum_{i=1}^{n} w'_i * \ C_i(x) \tag{3- 14}$$

Where:

F_w is the weighted aggregation variable,

w'_i is the adjusted criterion weight, and

$C_i(x)$ is the normalized satisfaction scale value for a criterion C_i.

The relationship between the evaluation of a higher-priority criterion and successive criteria is established through the incorporation of the prioritized scoring operator in the adjusted criterion weight. The prioritized scoring operator considers the importance level and the satisfaction level of the criteria considered for aggregation. The prioritized scoring operator thus reduces the ability of lower-priority criteria to compensate for poor satisfaction of higher-priority criteria—even if lower-priority criteria achieve higher satisfaction levels than higher-priority criteria. The ability to establish this relationship between criteria through the application of TOPSIS is the central feature associated with the application of new prioritized aggregation presented in this chapter.

Juxtaposing the new prioritized aggregation method using TOPSIS to other prioritized aggregation methods (Omar and Fayek 2015a), the presented prioritized aggregation exhibits greater sensitivity towards lower-priority criteria as a result of the relative importance that the different criteria possess—even with minor/no satisfaction of higher-priority criteria. If a higher-priority criterion is not being satisfied does not lead to the full exclusion of subsequent criteria to be excluded from aggregation, but significantly decreases their effect on the overall aggregated value. Other prioritized aggregation methods (e.g., Prioritized OWA) does not consider subsequent criteria in the event that a higher-priority criterion is unsatisfied.

3.5.2. Illustrative Case Study (Crisp Environments)

Consider the following construction-related aggregation problem: A survey was conducted on a construction site with all 19 tradespeople on site to measure the tradespeople's evaluation of the effect of different construction practices on construction labour productivity. The tradespeople identified four safety-related criteria—unsafe work conditions, frequency of accidents and personal injury, provision of protective gear, and stringent safety rules—as having an effect on construction labour productivity; all four are considered in this case study.

Two scalar values are assigned for each of the safety-related criteria identified through the survey to capture the importance of a given criterion relative to the others and the given criterion's effect on construction labour productivity (i.e., satisfaction). A seven-point Likert importance scale indicates to what extent a given criterion is important in relation to the other criteria in the same category (in this case, safety-related criteria). Another seven-point Likert scale evaluates the effect of a given criterion on construction labour productivity.

The *RIS* for each of the four safety-related criteria is calculated using the first scale (i.e., importance scale) using Eq. (3-7). For example, the *RIS* for the "frequency of accidents and personal injury" criterion is calculated as follows:

$$C_1(RIS) = \frac{0*1+0*2+0*3+1*4+1*5+1*6+16*7}{7*19} = 0.96 \tag{3-15}$$

The *RIS*s for the remaining safety-related criteria are also calculated using Eq. (3-7). The criteria are then reordered based on their *RIS* values as shown in Table 3-4.

Table 3-4 *RIS* for Safety-Related Criteria

Safety-related Criterion	***RIS***
(i) Frequency of accidents and personal injury	0.96
(ii) Unsafe working conditions	0.34
(iii) Provision of protective gear	0.22
(iv) Stringent safety rules	0.10

Once the *RIS*s for the different criteria are calculated, a relative weight is derived for each criterion based on its calculated *RIS*. For example, the relative weight for "frequency of accidents and personal injury" is calculated using Eq. (3-8), as:

$$w_1 = \frac{0.96}{(0.96+0.34+0.22+.10)} = 0.59 \quad (3\text{-}16)$$

The relative weights for the four safety-related criteria are listed in Table 3-5.

Table 3-5 Relative Weights for Safety-Related Criteria

Safety-related Criterion	Relative Weight
(i) Frequency of accidents and personal injury	0.59
(ii) Unsafe working conditions	0.21
(iii) Provision of protective gear	0.14
(iv) Stringent safety rules	0.06

An average value of the 19 responses is used to represent the effect of each of the four safety-related criteria on construction labour productivity; the results are listed in Table 3-6.

Table 3-6 Mean Safety-Related Criteria Effects on Construction Labour Productivity

Safety-Related Criteria	Average Effect on Construction Labour Productivity
(i) Frequency of accidents and personal injury	0.85
(ii) Unsafe working conditions	0.67
(iii) Provision of protective gear	0.65
(iv) Stringent safety rules	0.59

After calculating the *RIS*s and relative weights for the four safety-related criteria and ranking them, TOPSIS is applied to calculate the prioritized scoring operator T_i—as explained earlier—for each criterion considered for aggregation. The application of TOPSIS defines the degree of fulfillment each safety-related criterion has achieved, in terms of its relative importance and effect on construction labour productivity, in relation to its most favourable location. For example, the prioritized scoring operator for "frequency of accidents and personal injury" is calculated based on this criterion's proximity to its most favourable location as shown in Figure 3-1.

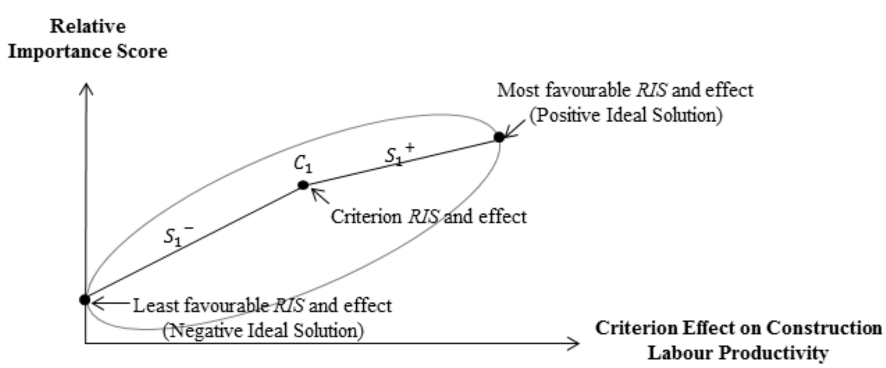


Figure 3-1 TOPSIS Application to Calculate Prioritized Scoring Operator (Omar and Fayek 2015a)

As illustrated in Figure 3-1, the most favourable effect and *RIS* coordinate for the "frequency of accidents and personal injury" criterion is (1, 0.96). The least favourable effect and *RIS* coordinate is (0, 0.10). Accordingly, the positive and negative distance measures for the "frequency of accidents and personal injury" criterion are calculated in Eqs. (3-17) and (3-18) using the Euclidean distance as presented in Eqs. (3-9) and (3-10), respectively.

$$S_1^+ = ((1-0.85)^2 + (0.96-0.96)^2)^{\frac{1}{2}} = 0.15 \tag{3-17}$$

$$S_1^- = ((0.85-0.0)^2 + (0.96-0.10)^2)^{\frac{1}{2}} = 1.21 \tag{3-18}$$

Next, a relative closeness index is calculated using Eq. (3-11).

$$C_1 = \frac{1.21}{(0.15 + 1.21)} = 0.88 \tag{3-19}$$

Finally, the prioritized scoring operator is calculated using Eq. (3-12).

$$T_2 = C_1 * T_1 = 1 * 0.88 = 0.88 \tag{3-20}$$

Note that the "frequency of accidents and personal injury" criterion is not fully satisfied. Accordingly, the subsequent criterion "unsafe working conditions" will be adjusted to reflect the fact that it will not be fully considered in the aggregation process. This adjustment is carried out using the prioritized scoring operator as described later in this section. Table 3-7 lists the prioritized scoring operator for each of the four criteria.

Table 3-7 Prioritized Scoring Operator for Safety-related Criteria

Safety-Related Criteria	$\mathbf{C}_i$	$\boldsymbol{T_i = C_{i-1}\, T_{i-1}}$
(i) Frequency of accidents and personal injury	0.88	1
(ii) Unsafe working conditions	0.62	0.88
(iii) Provision of protective gear	0.57	0.54
(iv) Stringent safety rules	-	0.31

The original relative weights of the safety-related criteria are then adjusted using the calculated prioritized scoring operator. For example, the "unsafe working conditions" criterion pertaining has an original relative weight of 0.21 to the set of criteria. However, since the higher-priority criterion "frequency of accidents and personal injury" is not fully satisfied and produced a prioritized scoring operator of 0.88, then the adjusted weighted for "unsafe working conditions" is calculated using Eq. (3-13), as in Eq. (3-21).

$$w_1' = 0.88 * 0.21 = 0.18 \tag{3-21}$$

The final stage of aggregation is to apply the weighted aggregation function $f(x)$ to provide an overall value representing the four safety-related criteria's combined effect on construction labour productivity. Table 3-8 lists the adjusted relative weights w_i' for the four safety-related criteria.

Table 3-8 Adjusted Weights for the Safety-Related Criteria

Safety-Related Criteria	$\boldsymbol{W'_i}$
(i) Frequency of accidents and personal injury	0.59
(ii) Unsafe working conditions	0.18
(iii) Provision of protective gear	0.08
(iv) Stringent safety rules	0.02

The weighted aggregation function $f(x) = \sum_{i=1}^{n} w_i' * C_i(x)$ is used to provide an overall aggregated value representing the four safety-related criteria. Accordingly, the aggregated value for the four safety-related criteria is calculated by multiplying the adjusted weight for each criterion by its normalized satisfaction value (see Table 3-6). The resulting aggregated value becomes 0.59*0.85+0.18*0.67+0.08*0.65+0.02*0.59 = 0.68. This value represents the overall opinion of tradespeople on the combined effect of the four safety-related criteria on construction labour productivity. An aggregated value of 0 indicates that safety-related criteria have no effect on construction labour productivity, while an aggregated value of 1 indicates that safety-related criteria have the maximum effect on construction labour productivity.

The presented method describes a new approach using TOPSIS for performing prioritized aggregation that considers the importance and degree of satisfaction of each criterion. A fundamental issue that relates to aggregation of criteria where a prioritized relationship exists was modeled using TOPSIS. The presented method extends the earlier work presented by Yager (2004, 2008, 2009, 2011) for prioritized aggregation. This relationship ensures that the high satisfaction of lower-priority criteria does not compensate for the low satisfaction of higher-priority criteria. The application of TOPSIS provides a means of developing a systematic prioritized scoring operator dependent on both the relative importance of criteria and their satisfaction.

The presented prioritized aggregation method is extended to fuzzy environments as described next. The utilization of fuzzy numbers, linguistic label quantifiers, and fuzzy TOPSIS is applied to consider the subjective nature of using linguistic terms, thereby extending the concept of prioritized aggregation using TOPSIS into fuzzy environments.

3.6. A TOPSIS-Based Method for Prioritized Aggregation in Multi-Criteria Decision-Making Problems in Fuzzy Environments (Omar and Fayek 2015b)

In many MCDM problems, some of the criteria considered for the decision to be made are linguistically measured and thus exhibit a considerable amount of uncertainty and imprecision in their measurement. Additionally, these criteria are interrelated, and a prioritized relationship exists between them. The entire set of criteria is combined using aggregation to provide one collective opinion. In such MCDM problems, criteria undergoing aggregation can be divided into: 1) imprecise criteria that are represented directly on a given linguistic scale or 2) imprecise subset criteria that are represented on a given linguistic scale. Following the first alternative, to measure a customer's satisfaction with the overall quality of a new bicycle, the measurement could be captured through a given linguistic satisfaction scale ranging from "extremely unsatisfied" to "extremely satisfied". Following the second alternative, imprecise subset criteria are represented on a given linguistic scale and therefore require an aggregation process to provide a collective value that can be represented on the linguistic scale. For the same example stated earlier, assume that the overall quality of the new bicycle is measured through three interrelated criteria—namely, safety, price, and warranty. In this case, the three criteria (i.e., safety, price, and warranty) require an aggregation process prior to their representation as a collective value of overall quality of bicycle satisfaction represented on the linguistic scale.

To begin with, this section provides an overview of fuzzy set theory, fuzzy numbers and the different characteristics of aggregating fuzzy numbers in MCDM problems. The application of fuzzy relative importance scores *(FRIS)*, fuzzy relative weights *(FRW)*, and the fuzzy technique for order preference by similarity to ideal solution (TOPSIS) is presented as prerequisites for performing a fuzzy prioritized aggregation due to their advantages in capturing the uncertainty and imprecision associated with linguistic measurements (Bardossy et al. 1993; Lee 1999). The application of fuzzy TOPSIS has been successful in various research areas such as prioritization and optimization (Chu 2002; Steuer 2004; Shih et al., 2007), yet its application in prioritized aggregation is to be considered (Pedrycz and Gomide 2007; Omar and Fayek 2015a). Fuzzy TOPSIS is beneficial in this application, as it features a sound logic that geometrically considers the relationship between interrelated criteria to account for the best and worst alternatives in fuzzy environments. Fuzzy TOPSIS also provides decision makers with the ability to visualize the relationship between different fuzzy prioritized alternatives on at least any two dimensions (Yu and Xu 2013). Thus, in this section, fuzzy numbers and fuzzy TOPSIS are considered to perform fuzzy prioritized aggregation that is capable of considering the prioritized relationship between criteria that are measured using linguistic scales.

3.6.1. Prioritized Scoring Operator Using Fuzzy TOPSIS

Prior to applying fuzzy TOPSIS, fuzzy set theory, fuzzy numbers and, characteristics of aggregating fuzzy numbers for MCDM problems are presented.

3.6.1.1. Fuzzy Set Theory and Fuzzy Numbers

Fuzzy set theory was first presented by Zadeh in 1965. Zadeh defined fuzzy sets as “a class of objects with a continuum of grades of membership” (Zadeh 1965). These grades of a membership range from zero to one, where zero indicates full exclusion of the object from a given continuum and one indicates full inclusion of the object in a given continuum. The application of fuzzy sets was recognized through previous research as to mimic human (i.e., particularly decision makers) judgment and reasoning (Bardossy et al. 1993; Carlsson and Fullér 1996; Lee 1999; Wei 2009, 2010. 2012).

Fuzzy Numbers

Fuzzy numbers are subsets of fuzzy sets and are defined by membership functions. A fuzzy number models an imprecise quantity represented linguistically by a real line *X*. In MCDM, a fuzzy number is used to represent the decision makers' opinions for criteria measured on a linguistic scale. A fuzzy number must satisfy at least three properties (Pedrycz and Gomide 2007) as follows:

1. Must be of a normal fuzzy set *A***:** this requirement means that there is at least one point in the membership function $f_A(x)$ with a membership value of 1: $\sup\{f_A(x)\} = 1$ $x \in X$.

   Where:

   $\sup\{f_A(x)\}$ is the supremum or the maximum $f_A(x)$

2. Must be bounded: a fuzzy number is of a closed interval: $f_A(x) \in$ [a, b], a, b $\in X$

3. Must be unimodal**:** a fuzzy number must be represented by a monotonically non decreasing function $f(x)$

Triangular membership functions have been commonly used in previous research to represent fuzzy numbers (Laarhoven and Pedrycz 1983; Pedrycz 1994; Lee 1999). Accordingly, the application of fuzzy numbers represented by triangular membership functions is further investigated here. First, for a fuzzy number A_i defined by a triangular membership function $fA_i(x)$, a triplet $({a_i}^l,\ {a_i}^m,\ {a_i}^u)$ defines its location on a real line *X*. Accordingly, $fA_i(x)$ can be defined as shown in Eq. (3-22).

$$fA_i(x) = \begin{cases} 0, & x < a_i{}^l \\ \frac{x-a_i{}^l}{a_i{}^m - a_i{}^l}, & a_i{}^l \le x < a_i{}^m \\ \frac{x-a_i{}^l}{a_i{}^u - a_i{}^m}, & a_i{}^m \le x \le a_i{}^u \\ 0, & x > a_i{}^u \end{cases} \tag{3-22}$$

The function principle introduced by Chen (1984) preserves the original type of membership function and simplifies the arithmetic operations of fuzzy numbers. Accordingly, the function principal is considered to define the basic operations considered between any two triangular fuzzy numbers A_1 and A_2. Each fuzzy number is defined by triplets: ($a_1{}^l$, $a_1{}^m$, $a_1{}^u$) and ($a_2{}^l$, $a_2{}^m$, $a_2{}^u$) respectively (Nagoor and Mohamed 2012). Fuzzy arithmetic can therefore be carried out as demonstrated in Eqs. (3-23) to (3-26).

Addition

$$A_1 \oplus A_2 = [a_1{}^l, a_1{}^m, a_1{}^u] \oplus [a_2{}^l, a_2{}^m, a_2{}^u] = [a_1{}^l + a_2{}^l, a_1{}^m + a_2{}^m, a_1{}^u + a_2{}^u] \tag{3-23}$$

Subtraction

$$A_1 \ominus A_2 = [a_1{}^l, a_1{}^m, a_1{}^u] \oplus [a_2{}^l, a_2{}^m, a_2{}^u] = [a_1{}^l - a_2{}^u, a_1{}^m - a_2{}^m, a_1{}^u - a_2{}^l] \tag{3-24}$$

Multiplication

$$A_1 \otimes A_2 = [a_1{}^l, a_1{}^m, a_1{}^u] \otimes [a_2{}^l, a_2{}^m, a_2{}^u] = [a_1{}^l a_2{}^l, a_1{}^m a_2{}^m, a_1{}^u a_2{}^u] \tag{3-25}$$

Division

$$\frac{A_1}{A_2} = (\min(\frac{a_1{}^l}{a_2{}^l}, \frac{a_1{}^l}{a_2{}^u}, \frac{a_1{}^u}{a_2{}^l}, \frac{a_1{}^u}{a_2{}^u}), \frac{a_1{}^m}{a_2{}^m}, \max(\frac{a_1{}^l}{a_2{}^l}, \frac{a_1{}^l}{a_2{}^u}, \frac{a_1{}^u}{a_2{}^l}, \frac{a_1{}^u}{a_2{}^u})) \tag{3-26}$$

Following the application of fuzzy arithmetic, main characteristics of aggregating fuzzy numbers in MCDM problems is presented next.

Characteristics of Aggregating Fuzzy Numbers in Multi-Criteria Decision-Making Problems

When aggregating fuzzy numbers in MCDM problems, the result of this aggregation requires maintaining a set of characteristics that are relevant to the decision to be made. For example, if all decision makers provide the same evaluation for a given problem, then it is expected that the result of aggregating the associated fuzzy numbers would be the common evaluation provided by the decision makers. Accordingly, six main characteristics are defined, in previous research (Bardossy et al. 1993; Lee 1999), for the aggregation of fuzzy numbers in MCDM problems. These properties may or may not be desirable in prioritized aggregation operators (Bardossy et al. 1993) such as the ordered weighted average (OWA) (Yager 1988).

Agreement preservation

This property is a consistency requirement that ensures if all decision makers provide the same evaluation, then the aggregated result should be the common evaluation. For a group of decision makers evaluating a criterion C_i, if the evaluation of each decision maker is identical and represented by a fuzzy number A_j, then the aggregated fuzzy number A resulting from the aggregation of all decision makers for criterion C_i on the real line X is illustrated by Eq. (3-27).

$$A = A_j, A \in \mathrm{X} \tag{3-27}$$

Order independence

This property ensures that the order of aggregation of the set of interrelated criteria does not matter. For a set of fuzzy numbers denoted by $[A_1, A_2 \dots A_i]$, the result of aggregation does not depend on the order of the criteria evaluation by the decision makers, as in Eq. (3-28) where if T is the aggregation operator of an ordered group of fuzzy numbers, then

$$T(A_1, A_2 \dots A_i) = T(A_i, A_2 \dots A_1), A \in \mathrm{X} \tag{3-28}$$

Note that in the case of aggregation with a set of interrelated criteria that have a prioritized relationship between them, this property is not satisfied since the aggregation of fuzzy numbers in prioritized aggregation is order-dependent (Yager 1988, 2004, 2008, 2009, 2011).

Transformation invariance

This property ensures that the transformation of the outcome space does not affect the results as illustrated by Eq. (3-29), where if *f* is an invertible, continuous mapping on the real line *X*, then

$$T\,(fA_1, fA_2 \dots fA_i) = f\,(T\,(A_1, A_2 \dots A_i)),\ A \in \mathrm{X} \qquad (3\text{-}29)$$

Possibility conservation

This property implies that if a fuzzy number is considered as an evaluation value for a criterion C_i, then it should remain as a possible overall evaluation value for the aggregation output according to Eq. (3-30).

$$fA_i(x) > 0 \text{ implies that } fA(x) > 0 \text{ for } A \in \mathrm{X} \qquad (3\text{-}30)$$

Possibility interval conservation

This property implies that any fuzzy number in a space of possible outputs is also considered as a possible aggregation output according to Eq. (3-31).

$$\cap_{i=1}^{i} A_i \subseteq A,\ A \in \mathrm{X} \qquad (3\text{-}31)$$

Individual versus overall uncertainty

For an uncertainty measure denoted by $H(A_i)$, the uncertainty of decision makers' evaluation represented by a fuzzy number A_i is defined as the area under its membership function, as illustrated by Eq. (3-32).

$$H(A) = \int_{-\infty}^{+\infty} fA_i(x)\,dx \qquad (3\text{-}32)$$

For example, if the decision makers have comparable backgrounds and knowledge, then the aggregated value of criteria based on the decision makers' evaluations should be $H(A) \leq sup_i H(A_i)$, where, $sup_i H(A_i)$ is the supremum or the maximum $H(A)$. Conversely, if the decision makers have widely diverging backgrounds and knowledge, then the aggregated value of the criteria based on the decision makers' evaluations should be $H(A) \geq sup_i H(A_i)$. Finally, if an "average" uncertainty is considered, then the relationship will be $inf_i H(A_i) \leq H(A) \leq sup_i H(A_i)$, where $inf_i H(A_i)$ is the infimum or the minimum $H(A)$ (Bardossy et al. 1993).

Now that fuzzy numbers and their characteristics in MCDM problems are presented, a description of the application of fuzzy TOPSIS for prioritized aggregation in fuzzy environments is presented next.

3.6.1.2. Criteria Ranking and Weight Determination in Fuzzy Environments

The first step in the proposed method is to establish and quantify the prioritization relationship between the criteria considered for a prioritized aggregation in MCDM problems. The criteria considered in the MCDM problem are usually measured by means of linguistic scales and thus encompass a considerable amount of uncertainty and imprecision in their measurements. Accordingly, a fuzzy relative importance score (*FRIS)* is calculated to account for the uncertainty and imprecision associated with the use of linguistic measurement scales. The "learn weights from data" approach, described earlier in this chapter, is applied in the presented prioritized aggregation method to prioritize criteria and generate relative weights for the criteria considered for aggregation. The *FRIS* is used in the method presented in this paper to prioritize and rank the different criteria and generate a fuzzy relative weight (*FRW)* (Bardossy et al. 1993) for each criterion. Furthermore, the *FRIS* is considered as an attribute in the fuzzy TOPSIS application to generate the prioritized scores for the different criteria, as explained earlier.

For calculating the *FRIS* and *FRW*, a linguistic scale with x_m alternatives is assigned for the set of predefined criteria C. A set of alternatives $x_m = \{x_1, \ldots, x_m\}$ represents the different ordered priority levels that a given criterion can have. The set of alternatives x_m obtained from the linguistic importance scale are each represented by a triangular fuzzy number with membership functions $f_{A_i}(x_m)$ (Laarhoven and Pedrycz 1983; Pedrycz 1994; Lee 1999). For example, a linguistic importance scale ranging from one, "extremely unimportant", to m, "extremely important", is assigned to determine the relative importance of a given criterion compared to other criteria. Accordingly, the *FRIS* can be calculated for a given criterion as in Eq. (3-33):

$$FRIS_i = \frac{(n_1 \otimes x_1) \oplus (n_2 \otimes x_2) \oplus \ldots \oplus (n_{\mathrm{j}} \otimes x_m)}{n * (x_1 \oplus x_2 \oplus \ldots \oplus x_{\mathrm{m}})} \tag{3-33}$$

Where:

n_{j} is the number of respondents who chose an importance alternative x_m

x_m is the linguistic importance scale—each linguistic scale value is represented by a triangular fuzzy number

The application of *FRIS* provides a reliable approach to capture decision makers' opinions in determining a given criterion's importance relative to other criteria (Omar and Fayek 2015a). The relative importance of the criteria, measured by the *FRIS* of each criterion, is then used for ranking the criteria (Grzegorzewski 2004). Additionally, the application of *FRIS* enables the quantification of a *FRW* for each criterion compared to other criteria. The calculated *FRW* is capable of quantifying the significance on the overall aggregated value of a criterion C_i compared to other criteria in the same category, and is calculated as in Eq. (3-34).

$$FRW_i = \frac{FRIS_i}{\sum_{\mathrm{i}=1}^{i} FRIS} \tag{3-34}$$

Where:

$FRIS_i$ is the fuzzy relative importance score for a criterion C_i

$\sum_{\mathrm{i}=1}^{i} FRIS$ is the summation of fuzzy relative importance score for all criteria

Once the *FRIS* and *FRW* for the different criteria is calculated, fuzzy TOPSIS is applied to calculate a prioritized scoring operator. First, fuzzy TOPSIS is presented.

3.6.1.3. Fuzzy TOPSIS Application

Fuzzy TOPSIS is a systematic method that enables the evaluation of a set of criteria using distance measures, where each criterion is measured against its fuzzy positive ideal solution *(FPIS)* and fuzzy negative ideal solution *(FNIS)*. Using fuzzy TOPSIS in MCDM aggregation problems is advantageous as it provides decision makers with the ability to geometrically define the relationship between different prioritized criteria, through fuzzy distance measures, on at least any two dimensions. Fuzzy TOPSIS features a simple and effective computational process where each interrelated criterion takes into account the positive and negative fuzzy ideal solutions respectively (Chen 1984; Shih et al. 2007).

For a criterion C_i, in a category H_i, represented by a fuzzy number A_i , the calculation steps for fuzzy TOPSIS to determine the most and least favourable fuzzy distances for this criterion are considered prerequisites to calculating the closeness coefficient (CC_i) for a criterion C_i.

The *FPIS* in a category H_i is calculated using Eq. (3-35), and is expressed as a triplet (${a_{max}}^l$, ${a_{max}}^m$, ${a_{max}}^u$).

$$A_i^+ = Max\ (A_1, A_2, \ldots, A_i) \tag{3-35}$$

The *FNIS* in a category H_i is calculated using Eq. (3-36), and is expressed by a triplet (${a_{min}}^l$, ${a_{min}}^m$, ${a_{min}}^u$).

$$A_i^- = Min\ (A_1, A_2, \ldots, A_i) \tag{3-36}$$

The positive distance (d^+) and negative distance (d^-) are calculated respectively, as in Eqs. (3-37) and (3-38).

$${d_i}^+ = \sum_{i=1}^{i} d(A_i, A_i^+) \tag{3-37}$$

$${d_i}^- = \sum_{i=1}^{i} d(A_i, A_i^-) \tag{3-38}$$

Where:

$d(A_i, A_i^+)$ is the distance between a criterion C_i and its *FPIS*

$d(A_i, A_i^-)$ is the distance between a criterion C_i and its *FNIS*

Several normalized distance measures are presented in previous research (See Table 3-2). Normalized distance measures are used to avoid a situation where criteria with greater levels of satisfaction values dominate those of smaller values (Omar and Fayek 2015a). Of these measures, the Euclidean distance is the most commonly used method as listed in Table 3-2.

Finally, a closeness coefficient CC_i is calculated as follows:

$$CC_i = \frac{{d_i}^-}{{d_i}^+ + {d_i}^-} \tag{3-39}$$

The closeness coefficient (CC_i) measures the location of a criterion C_i to its ideal positive location, where $0 \leq CC_i \leq 1$. It is important to note that a larger CC indicates that the criterion is located at a closer distance to its *FPIS*. To illustrate the application of fuzzy TOPSIS using one of the distance measures, we present the following example using the Euclidean method. Assume three fuzzy triangular numbers represented by triplets are A, A^{+}, and A^{-}.

$A = (0.25, 0.38, 0.50)$ represents the criterion whose distance from the *FPIS* and *FNIS* we are trying to measure

A^{+} = (0.75, 0.88, 1.00) represents the *FPIS* for criterion A

A^{-} = (0.00, 0.13, 0.25) represents the *FNIS* for criterion A

The distance between criterion A and its *FPIS* is denoted by d^{+} and is calculated using Eq. (3-40).

$$d^{+} = \sqrt{\frac{1}{3}\left[(0.25 - 0.75)^2 + (0.38 - 0.88)^2 + (0.50 - 1.00)^2\right]} = 0.50 \tag{3-40}$$

The distance between criterion A and its *FNIS* is denoted by d^{-} and is calculated using Eq. (3-41).

$$d^{-} = \sqrt{\frac{1}{3}\left[(0.25 - 0.00)^2 + (0.38 - 0.13)^2 + (0.50 - 0.25)^2\right]} = 0.25 \tag{3-41}$$

Finally, the CC is calculated Eq. (3-42).

$$CC = \frac{0.25}{0.50+0.25} = 0.33 \tag{3-42}$$

The calculated closeness coefficient (*CC*) represents the relative closeness of criterion *A* towards its *FPIS* or, in other words, the extent to which criterion *A* is satisfied compared to its most favourable level of satisfaction. After applying fuzzy TOPSIS, the determination of the fuzzy prioritized scoring operator is calculated as presented next.

3.6.1.4. Fuzzy Prioritized Scoring Operator Calculation

In order to aggregate the different criteria into one collective value, a prioritized score (T_i) is required. Fuzzy TOPSIS is employed to generate the T_i for the criteria considered for prioritized aggregation. The T_i determines the degree to which a given criterion is located relative to its most favourable level of satisfaction. The *FRIS* and satisfaction levels are considered as fuzzy coordinates (each represented by a fuzzy number) in the course of applying fuzzy TOPSIS to generate the T_i. The positive and negative distances d_i^+ and d_i^- for a criterion C_i are first calculated using Eq.s (3-37) and (3-38), respectively. Then, the CC_i is generated using Eq. (3-39) to determine where a criterion C_i is located relative to the most favourable *FRIS* and satisfaction level it can achieve in a given category H_i and to the least favourable *FRIS* and satisfaction level it can achieve in the same category H_i. The calculated CC_i is then used to generate the T_i for adjusting the prioritized criterion's FRW_i using Eq. (3-12). An adjusted FRW is calculated using Eq. (3-43)

$$FRW'_i = T_i \otimes FRW_i \tag{3-43}$$

Where:

FRW'_i is the adjusted criterion's fuzzy relative weight

FRW_i is the criterion's fuzzy relative weight

Once the new adjusted weights (FRW'_i) are calculated, an aggregation operator is used to provide a collective value representing the different criteria as described next.

3.6.1.5. Weighted Fuzzy Aggregation Function

Once the different prioritized scores have been calculated for the different ordered criteria and the new weights have been generated, a weighted aggregation operator (e.g., FPWA operator) can be used to provide a collective value representing the different criteria. Depending on the choice of the weighted aggregation operator (see Table 3-1), the aggregated value representing the different criteria considered is generated and is also expressed as a fuzzy number to account for the uncertainty and imprecision associated with using linguistic measures in evaluating the different criteria. Eq. (3-43) shows the calculation of the aggregated value using the FPWA.

$$FPWA = (FRW_1' \otimes S_1) \oplus (FRW_2' \otimes S_2) \oplus \dots \oplus (FRW_i' \otimes S_m) \tag{3-44}$$

Where:

FRW_i' is the adjusted weight for a criterion C_i

S_m is the satisfaction level for a criterion C_i

The presented method establishes a dynamic relationship, through the application of fuzzy TOPSIS, to include the level of satisfaction of higher priority criteria in the overall aggregation. This relationship is defined through the generation of a prioritized score T_i that is a function of both the criterion's *FRIS* and its satisfaction level. The generated prioritized score T_i is then used to adjust the different criteria when performing the prioritized aggregation based on their importance and level of satisfaction. In the next section, the illustrative case study, described earlier in this chapter, is presented but considering the imprecision associated with using linguistic terms to measure the criteria.

3.6.2. Illustrative Case Study (Fuzzy Environments)

For the illustrative case study presented earlier in this chapter, Tables 3-9 and 3-10 present symmetric triangular fuzzy numbers representing the different linguistic importance and impact scales respectively.

Table 3-9 Fuzzy Numbers Representing Linguistic Importance Scale

Importance	Triangular Fuzzy Number
Extremely unimportant	(0.00, 0.14, 0.29)
Unimportant	(0.14, 0.29, 0.43)
Slightly unimportant	(0.29, 0.43, 0.57)
Neither unimportant nor important	(0.43, 0.57, 0.71)
Slightly important	(0.57, 0.71, 0.86)
Important	(0.71, 0.86, 1.00)
Extremely important	(0.89, 1.00, 1.00)

Table 3-10 Fuzzy Numbers Representing Linguistic Impact Scale

Impact	Triangular Fuzzy Number
Extremely low	(0.00, 0.14, 0.29)
Low	(0.14, 0.29, 0.43)
Slightly low	(0.29, 0.43, 0.57)
Neither low nor high	(0.43, 0.57, 0.71)
Slightly high	(0.57, 0.71, 0.86)
High	(0.71, 0.86, 1.00)
Extremely high	(0.89, 1.00, 1.00)

First, the *FRIS* is calculated based on the number of respondents who completed the survey. For the "unsafe working conditions" criterion, the *FRIS* is calculated using Eq. (3-33) as demonstrated in Eq. (3-45).

$$FRIS = \frac{\begin{array}{c}(0\otimes(0.14,0.14,0.29))\oplus(0\otimes(0.14,0.29,0.43))\oplus\\(0.05\otimes(0.29,0.43,0.57))\oplus(0.16\otimes(0.43,0.57,0.71))\oplus(0.16\otimes(0.57,0.71,0.86))\oplus(0.64\otimes(0.71,0.86,1.00))\oplus(0.04\otimes(0.86,1.00,1.00))\end{array}}{(0.14,0.14,0.29)\oplus(0.14,0.29,0.43)\oplus(0.29,0.43,0.57)\oplus(0.43,0.57,0.71)\oplus(0.57,0.71,0.86)\oplus(0.71,0.86,1.00)\oplus(0.86,1.00,1.00)}$$

$$FRIS = (0.46, 0.62, 0.77). \tag{3-45}$$

Table 3-11 presents the *FRIS* for each safety-related criterion. Figure 3-2 presents the *FRIS* for each safety-related criterion graphically.

Table 3-11 *FRIS* Values for Safety-Related Criteria

Safety-Related Criteria	*FRIS*
Frequency of accidents and personal injury	(0.66, 0.81, 0.95)
Unsafe working conditions	(0.46, 0.61, 0.77)
Provision of protective gear	(0.34, 0.48, 0.62)
Stringent safety rules	(0.21, 0.35, 0.50)

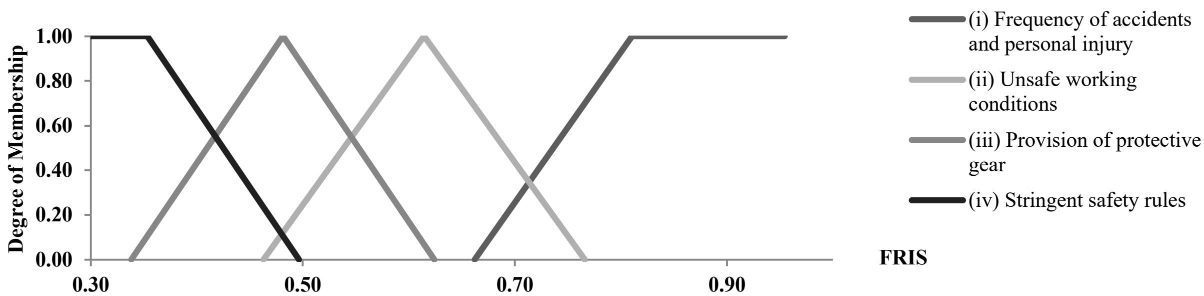


Figure 3-2 Graphical Representation of FRIS Values for Safety-Related Criteria

Once the *FRIS* for each criterion is calculated, the *FRW* is calculated using Eq. (3-34). For "unsafe working conditions", the *FRW* is calculated accordingly in Eq. (3-46).

$$FRW = \frac{(0.46,0.62,0.77)}{(0.62,0.81,0.96)\oplus(0.46,0.62,0.77)\oplus(0.34,0.48,0.62)\oplus(0.21,0.35,0.50)}$$

$$FRW = (0.16, 0.27, 0.46). \tag{3-46}$$

Table 3-12 presents the *FRW* for each ranked safety-related criterion (based on the *FRIS* values presented in Table 3-11). Figure 3-3 presents the *FRW* for each safety-related criterion graphically.

Table 3-12 *FRW* Values for Safety-Related Criteria

Safety-Related Criteria	*FRW*
Frequency of accidents and personal injury	(0.23, 0.36, 0.57)
Unsafe working conditions	(0.16, 0.27, 0.46)
Provision of protective gear	(0.12, 0.21, 0.37)
Stringent safety rules	(0.07, 0.16, 0.30)

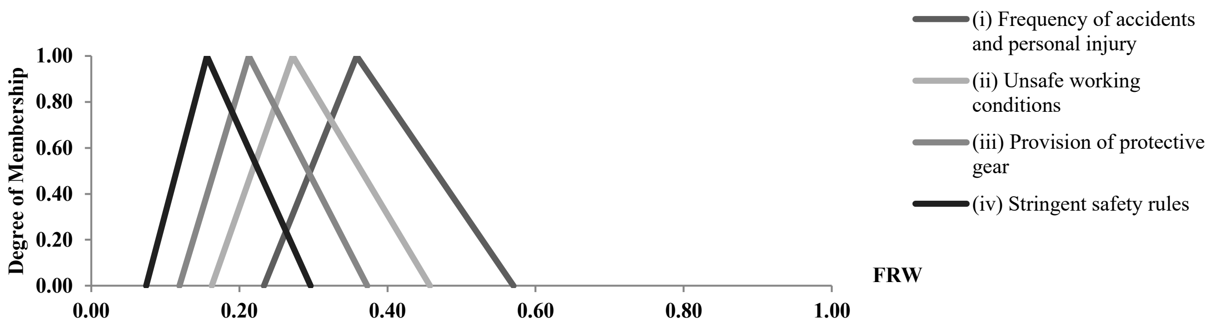


Figure 3-3 Graphical Representation of *FRW* Values for Safety-Related Criteria

Once the *FRW* values for the different safety-related criteria are calculated, the average decision makers' impact scores (IS) are calculated for each safety-related criterion. Table 3-13 lists the average decision makers' scores for each safety-related criterion.

Table 3-13 Average Decision Makers' -Derived Impact Scores

Safety-Related Criteria	Average Effect on Construction Labour Productivity
Frequency of accidents and personal injury	(0.49, 0.64, 0.78)
Unsafe working conditions	(0.64, 0.79, 0.92)
Provision of protective gear	(0.62, 0.76, 0.89)
Stringent safety rules	(0.85, 0.99, 1.00)

The two sets of scores (*FRIS* and *IS*) are considered as fuzzy coordinates; each is represented by a fuzzy number. Fuzzy TOPSIS is applied to determine the T_i and generate the adjusted *FRW* to be used with the prioritized aggregation operator.

First, each criterion is measured against its *FPIS* and *FNIS*. The *FPIS* for the four safety-related criteria is calculated according to Eq. (3-37), with the result that A^{+} = [(0.85, 0.99, 1.00), (0.66, 0.81, 0.95)]. The *FNIS* for the four safety-related criteria is calculated according to Eq. (3-38), with the result that A^{-} = [(0.62, 0.76, 0.89), (0.21, 0.35, 0.50)].

For the "unsafe working conditions" criterion, the fuzzy coordinates representing impact score and *FRIS* respectively are [(0.64, 0.79, 0.93), (0.46, 0.61, 0.77)]. The positive distance (d^{+}) and negative distance (d^{-}) are calculated following the Euclidian method in Eq.s (3-37) and (3-38), respectively. The positive distance calculation is illustrated by Eq. (3-47) and the negative distance calculation by Eq. (3-48).

$$d_i^{+} = \sqrt{\frac{1}{3}\,[(0.64-\ 0.85)^2 +\ (0.79-\ 0.99)^2 + (0.93-\ 1.00)^2] + \frac{1}{3}\,[(0.46-\ 0.66)^2 +\ (0.61-\ 0.81)^2 + (0.77-\ 0.95)^2]} \tag{3-47}$$

The result of this calculation indicates that $d_i^{+} = 0.26$.

$$d_i^{-} = \sqrt{\frac{1}{3}\,[(0.64-\ 0.62)^2 +\ (0.79-\ 0.76)^2 + (0.93-\ 0.89)^2] + \frac{1}{3}\,[(0.46-\ 0.21)^2 +\ (0.61-\ 0.35)^2 + (0.77-\ 0.50)^2]} \tag{3-48}$$

The result of this calculation indicates that $d_i^{-} = 0.01$.

Next, using Eq. (3-39), a *CC* for "unsafe working conditions" is calculated in Eq. (3-49).

$$CC = \frac{0.01}{0.26+0.01} = 0.04 \tag{3-49}$$

The *CC* for each of the four safety-related criteria is listed in Table 3-14.

Table 3-14 CC Values for Safety-Related Criteria

Safety-related criteria	***CC***
Frequency of accidents and personal injury	0.15
Unsafe working conditions	0.04
Provision of protective gear	0.01
Stringent safety rules	0.05

For the "unsafe working conditions" criterion, the T_i and adjusted FRW$'$ are calculated using Eq.s (3-12) and (3-43), respectively. The T_i is calculated in Eq. (3-50) and the FRW$'$ in Eq. (3-51).

$$T_2 = 1 * 0.15 = 0.15 \tag{3-50}$$

$$FRW' = 0.15 \otimes (0.16, 0.27, 0.46) = (0.02, 0.04, 0.07) \tag{3-51}$$

The T_i and adjusted FRW'calculated for the four safety-related criteria is presented in Table 3-15. Figure 3-4 presents graphically the FRW$'$ for each safety-related criterion.

Table 3-15 $\mathbf{T_i}$ and FRW' Values for Safety-Related Criteria

Safety-Related Criteria	$\boldsymbol{T_i}$	$\boldsymbol{FRW'}$
Frequency of accidents and personal injury	1.00	(0.23, 0.36, 0.57)
Unsafe working conditions	0.15	(0.02, 0.04, 0.07)
Provision of protective gear	0.00	(0.00, 0.00, 0.00)
Stringent safety rules	0.00	(0.00, 0.00, 0.00)

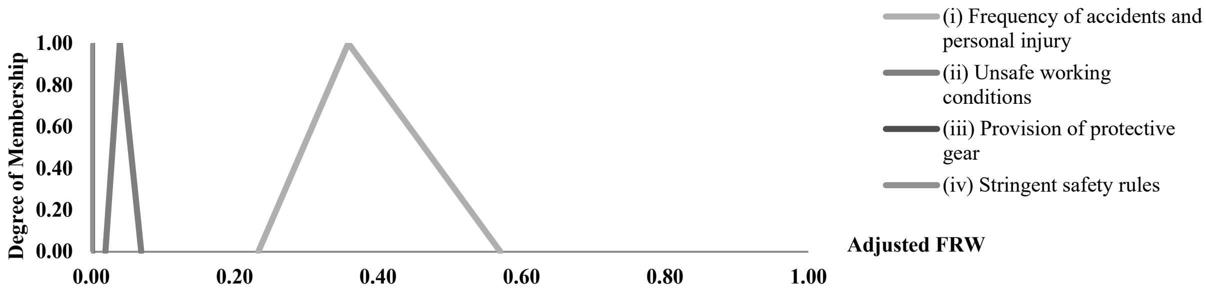


Figure 3-4 Adjusted FRW for Safety-Related Criteria

The poor satisfaction of higher priority criteria "frequency of accidents and personal injury" and "unsafe working conditions" has reduced the ability for compensation by lower priority criterion "provision of protective gear and stringent safety rules" in the overall aggregated value. This reduced ability for compensation by lower priority criteria was emphasized in the adjusted FRW values for "provision of protective gear and stringent safety rules", as displayed in Table 3-15 and Figure 3-4.

The $FPWA$ is used to combine the four safety-related criteria into one collective value representing the impact of the four safety-related criteria on construction labour productivity as shown in Eq. (3-52).

$$FPWA = [(0.23, 0.36, 0.57) \otimes (0.49, 0.64, 0.78)] \oplus [(0.02, 0.04, 0.07) \otimes (0.64, 0.79, 0.93)] \oplus [(0.00, 0.00, 0.00) \otimes (0.62, 0.76, 0.89)] \oplus [(0.00, 0.00, 0.00) \otimes (0.85, 0.99, 1.00)]$$

$$FPWA = (0.13, 0.26, 0.51). \quad (3\text{-}52)$$

The aggregated value for the effect of safety-related criteria on construction productivity can be presented as a fuzzy number as shown in Eq.3-52. This value—also shown in Figure 3-4—presents the overall aggregated impact of safety-related criteria on construction labour productivity. It can be observed in Figure 3-5 that the use of a fuzzy number has captured the uncertainty and imprecision associated with the use of linguistic measures of the impact of safety-related practices on construction labour productivity. The aggregated value in this case study can be related to more than one linguistic term ranging from "extremely low" to "neither low nor high". The relationship between the aggregated value and the different linguistic terms can be further determined using a distance measure (e.g., fuzzy similarity measure) to determine to which linguistic term the aggregated value corresponds—in this case, it is "low" (Hung and Yang 2004).

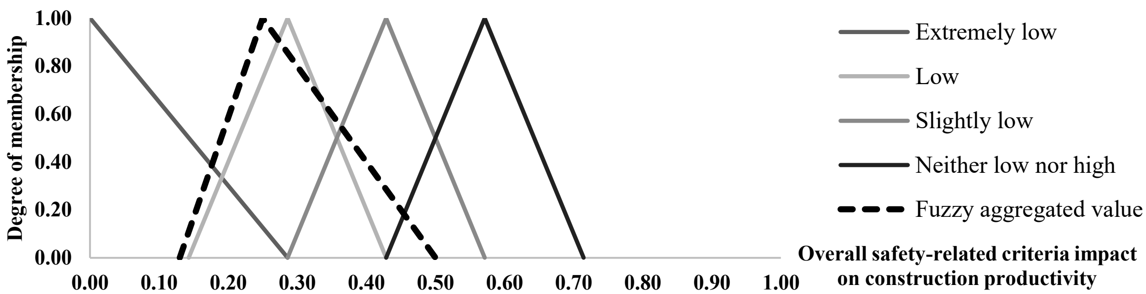


Figure 3-5 Overall Aggregated Safety-Related Criteria Impact on Construction Productivity

On the other hand, the aggregated value can, further, be defuzzified to provide a crisp value representing the impact of safety-related criteria on construction productivity. Defuzzifying the value obtained in Eq. (3-53) using a defuzzification method, such as the centroid method, yields a crisp value of 0.28. This single crisp value represents the combined opinion of decision makers for the impact of the four safety-related criteria on construction labour productivity. A defuzzified aggregated value of 0 indicates that safety-related criteria have no impact on construction labour productivity, and a defuzzified aggregated value of 1 indicates that safety-related criteria have a high impact on construction labour productivity.

It can be observed that the consideration of the linguistic nature of the scales has reduced the overall prioritized aggregated value from one crisp value 0.68, as presented in the first part of this chapter (i.e., subheading 3.5.2) to 0.28. This variance is a result of the subjective nature of the measurement scales used for quantifying the impact of safety-related criteria on construction labour productivity.

3.7. Concluding Remarks

This chapter presents a new prioritized aggregation method that relates to the fusion of information (i.e., criteria) in crisp and fuzzy environments. To provide sufficient background, different methods and classifications of aggregation functions were described and properties of aggregation functions were explained. A fundamental issue that relates to aggregation of criteria, where a prioritized relationship exists, is modeled using TOPSIS. The presented method extends the earlier work presented by Yager (1988, 2004, 2008, 2009, 2011) for prioritized aggregation. The presented prioritized aggregation method using TOPSIS considers the relative importance of a criterion with respect to other criteria, and its satisfaction relative to the most favourable satisfaction that it can achieve. This relationship ensures that the high satisfaction of lower-priority criteria does not compensate for the low satisfaction of higher-priority criteria.

The presented new prioritized aggregation method is extended to fuzzy environments. This extension to fuzzy environments provides a way for capturing and representing the uncertainty and imprecision associated with the use of linguistic terms, by expressing them as fuzzy numbers, rather than the use of numerical values. This extension assists in solving aggregation-related problems in fuzzy environments—such as MCDM problems—that require the consideration of the prioritized relationship and satisfaction levels between the different criteria that are expressed linguistically and are considered for aggregation.

The new prioritized aggregation method, presented in this chapter, is used to produce informative evaluation of the different project competencies on the higher hierarchical level (i.e., project competency level) rather than the lower hierarchical levels (i.e., evaluation criteria of project competencies) as presented in chapter two of this thesis. This reduction of the number of variables (i.e., 41 project competencies rather than 248 project competencies' evaluation criteria) is complemented by a new fuzzy feature extraction method to produce inputs for the granular AND/OR fuzzy neural networks as presented in the next chapter.

3.8. References

Bardossy, A., Duckstein, L., and Bogardi, I. (1993). Combination of fuzzy numbers representing expert opinions. *Fuzzy Sets and Systems* 57.2: 173–181.

Berberian SK. (1998). *Fundamentals of Real Analysis*. Springer: New York, New York, USA.

Bisdorff R, Meyer P, and Veneziano T. (2014). Elicitation of criteria weights maximising the stability of pairwise outranking statements. *Journal of Multi-Criteria Decision Analysis* 21: 113–124.

Calvo T, Mayor G, and Mesiar R (eds). (2002). *Aggregation Operators: New Trends and Applications*. Springer: New York, New York, USA.

Carlsson, C., and Fullér, R. (1996). Fuzzy multiple criteria decision making: Recent developments. *Fuzzy Sets and Systems* 78.2: 139–153.

Chen S.H. (1984). On the theory of operating, ranking, and estimating fuzzy numbers and its application. Doctor of Science thesis, Tamkang University, Taipei University, Taiwan, 1984.

Chen LH and Xu ZS. (2014). A prioritized aggregation operator based on the OWA operator and prioritized measure. *Journal of Intelligent and Fuzzy Systems* 27: 1297–1307.

Chen L, Xu Z, and Yu X. (2014). Prioritized measure-guided aggregation operators. *Fuzzy Systems, IEEE Transactions on* 22: 1127–1138.

Chen SJ and Hwang CL . (1992). *Fuzzy Multiple Attribute Decision Making.* Springer-Verlag: New York, New York, USA.

Cholewa, W. (1985). Aggregation of fuzzy opinions—an axiomatic approach. *Fuzzy Sets and Systems* 17.3 (1985): 249–258.

Choo EU, Schoner B, and Wedley WC. (1999). Interpretation of criteria weights in multicriteria decision making. *Computers and Industrial Engineering* 37: 527–541.

Chu TC. (2002). Facility location selection using fuzzy TOPSIS under group decisions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 10: 687–701.

Delgado, M., J. L. Verdegay, and M. A. Vila. (1993). On aggregation operations of linguistic labels. *International Journal of Intelligent Systems* 8.3: 351–370.

Detyniecki M. (2001). Fundamentals on aggregation operators. Manuscript based on PhD thesis, Berkeley Initiative in Soft Computing, Computer Science Division, University of California, Berkeley, California, USA. Available at: http://www.poleia.lip6.fr/~marcin/papers/Detynieck_AGOP_01.pdf (accessed June 16, 2014).

Dubois D and Prade H. (2004). On the use of aggregation operations in information fusion processes. *Fuzzy Sets and Systems* 142: 143–161.

Emrouznejad A, and Marra M. (2014). Ordered weighted averaging operators 1988–2014: A citation-based literature survey. *International Journal of Intelligent Systems* 29: 994–1014.

Grabisch M, Orlovski SA, and Yager RR. (1998). Fuzzy aggregation of numerical preferences. *Fuzzy Sets in Decision Analysis, Operations Research and Statistics*, R Slowiński (Ed). Springer: New York, New York, USA; 31–68.

Grzegorzewski, P. (2004). Distances between intuitionistic fuzzy sets and/or interval-valued fuzzy sets based on the Hausdorff metric. *Fuzzy Sets and Systems* 148.2 (2004): 319–328.

Hsu, H. M., and Chen, C. T. (1996) Aggregation of fuzzy opinions under group decision making. *Fuzzy Sets and Systems* 79.3: 279–285.

Hung, W. L., and Yang, M. S. (2004). Similarity measures of intuitionistic fuzzy sets based on Hausdorff distance. *Pattern Recognition Letters*, 25.14: 1603–1611.

Jones DF and Mardle SJ. (2004). A distance-metric methodology for the derivation of weights from a pairwise comparison matrix. *Journal of the Operational Research Society* 55: 869–875. doi: 10.1057/palgrave.jors.2601745.

Lee, H. (1999). An optimal aggregation method for fuzzy opinions of group decision. *IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics* Vol. 3.

Li, D., and Yang, J. (2004). Fuzzy linear programming technique for multi attribute group decision making in fuzzy environments. *Information Sciences* 158 (2004): 263–275.

Lootsma FA. (2000). Distributed multi-criteria decision making and the role of the participants in the process. *Journal of Multi-Criteria Decision Analysis*, 9(1–3): 45–55.

Marichal JL. (1998). Aggregation operators for multicriteria decision aid. PhD thesis, Institute of Mathematics, University of Liège, Belgium.

Milani AS, Shanian A, Madoliat R, and Nemes JA. (2005). The effect of normalization norms in multiple attribute decision making models: A case study in gear material selection. *Structural and Multidisciplinary Optimization* 29: 312–318.

Nagoor, G. A. and Mohamed Assarudeen, S. N. (2012). A New operation on triangular fuzzy number for solving fuzzy linear programming problem. *Applied Mathematical Sciences* 6.11: 525–532.

Narukawa Y. (2007). *Modeling Decisions: Information Fusion and Aggregation Operators*. Springer: New York, New York, USA.

O'Hagan M. (1988). Aggregating template or rule antecedents in real-time expert systems with fuzzy set logic. In Proceedings of the 22nd Annual IEEE Asilomar Conference on Signals, Systems and Computers, October 31–November 2, Pacific Grove, California, USA; 681–689.

O'Hagan M. (1990). A fuzzy neuron based on maximum entropy ordered weighted averaging. In Proceedings of the 24th Annual IEEE Asilomar Conference on Signals, Systems and Computers, October 5–November 7, Pacific Grove, California, USA; 618–623.

Omar, M. and Fayek, A. Robinson. (2015a). "A TOPSIS–based approach for prioritized aggregation" *Manuscript accepted for publication in the International Journal of multi-criteria decision analysis*.

Pedrycz, W. (1994). Why triangular membership functions? *Fuzzy Sets and Systems* 64: 21–30.

Pedrycz, W., and Gomide, F. (2007). *Fuzzy Systems Engineering: Toward Human-Centric Computing*. John Wiley and Sons, Toronto, 2007.

Ralescu, Anca L., and Dan A. Ralescu. (1997). Extensions of fuzzy aggregation. *Fuzzy Sets and Systems* 86.3: 321–330.

Razmak J and Aouni B. (2014). Decision Support System and Multi-Criteria Decision Aid: A state of the art and perspectives. *Journal of Multi-Criteria Decision Analysis* (pre-publication online version).

Shih HS, Shyur HJ, and Lee ES. (2007). An extension of TOPSIS for group decision making. *Mathematical and Computer Modelling* 45: 801–813.

Steuer RE. (1989). *Multiple Criteria Optimization: Theory, Computation, and Application*. Krieger: Malabar, Florida, USA.

Tanino, T. (1984). Fuzzy preference orderings in group decision making. *Fuzzy Sets and Systems* 12: 117–131.

Tong, R. M., and Bonissone P. P. (1980). A linguistic approach to decision making with fuzzy sets. *IEEE transactions on Systems, Man and Cybernetics* 10.11: 716–723.

Ulubeyli S and Kazaz A. 2009. A multiple criteria decision-making approach to the selection of concrete pumps. *Journal of Civil Engineering and Management* 15: 369–376.

Van Laarhoven, P. J. M., and Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy sets and systems* 11.1: 199–227.

Wei, G. (2009). Some geometric aggregation functions and their application to dynamic multiple attribute decision making in the intuitionistic fuzzy setting. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 17.2: 179–196.

Wei, G. (2010). Some induced geometric aggregation operators with intuitionistic fuzzy information and their application to group decision making. *Applied Soft Computing* 10.2: 423–431.

Wei C and Tang X. (2012). Generalized prioritized aggregation operators. *International Journal of Intelligent Systems* 27: 578–589.

Wei, G. (2012). Hesitant fuzzy prioritized operators and their application to multiple attribute decision making. *Knowledge-Based Systems* 31: 176–182.

Xu Z and Yager RR. (2006). Some geometric aggregation operators based on intuitionistic fuzzy sets. *International Journal of General Systems* 35: 417–433.

Yager RR. (1988). On ordered weighted averaging aggregation operators in multicriteria decision making. *Systems, Man and Cybernetics, IEEE Transactions on* 18*:* 183–190.

Yager RR. (1996). Quantifier guided aggregation using OWA operators. *International Journal of Intelligent Systems* 11: 49–73. doi: 10.1002/(SICI)1098-111X(199601)11:1<49::AID-INT3>3.0.CO;2-Z

Yager RR. (2004). Modeling prioritized multicriteria decision making. *Systems, Man, and Cybernetics, IEEE Transactions on—Part B: Cybernetics* 34: 2396–2404.

Yager RR. (2008). Prioritized aggregation operators. *International Journal of Approximate Reasoning* 48: 263–274.

Yager RR. (2009). Prioritized OWA aggregation. *Fuzzy Optimization and Decision Making* 8: 245–262.

Yager, RR, Gumrah G, and Reformat MZ. (2011). Using a web personal evaluation tool PET for lexicographic multi-criteria service selection. *Knowledge-Based Systems* 24: 929–942.

Yager RR, Kacprzyk, J, and Beliakov G. (2011). *Recent developments in the ordered weighted averaging operators: Theory and practice* 265. Springer-Verlag: Berlin, Germany.

Yan, H. B., Huynh, V. N., Nakamori, Y., & Murai, T. (2011). On prioritized weighted aggregation in multi-criteria decision making. *Expert Systems with Applications*, *38*: 812-823.

Yoon K and Hwang CL. (1985). Manufacturing plant location analysis by multiple attribute decision making: Part I—Single-plant strategy. *International Journal of Production Research* 23: 345–359.

Yoon KP and Hwang CL (eds). (1995). *Multiple Attribute Decision Making: An Introduction*. Sage: London, UK.

Yu, D., Wu, Y., and Lu, T. (2012). Interval-valued intuitionistic fuzzy prioritized operators and their application in group decision making. *Knowledge-Based Systems* 30: 57–66.

Yu, D. (2012). Group decision making based on generalized intuitionistic fuzzy prioritized geometric operator. *International Journal of Intelligent Systems* 27.7: 635–661.

Yu, X., and Xu, Z. (2013). Prioritized intuitionistic fuzzy aggregation operators. *Information Fusion* 14.1: 108–116.

Zhao XF, Lin R, and Wei GW. (2013). Fuzzy prioritized operators and their application to multiple attribute group decision making. *Applied Mathematical Modelling* 37: 4759–4770.

Zadeh L. A. (1965): "Fuzzy sets." Information and Control 8.3 338–353.

CHAPTER 4. – A Fuzzy Hybrid Intelligent Model for Evaluating Construction Project Competencies and Their Relationship to Project Performance [1]

4.1. Introduction

Despite the suitability of applying the principals of fuzzy logic in developing highly interpretable construction systems, systems that are based on fuzzy logic alone are limited, mainly due to their lack of learning capability and their inability to reflect the high complexity of some model structures. These shortcomings in fuzzy logic require combining it with other modeling techniques. The combination of one or more modeling techniques with fuzzy models in a single model is referred to as a fuzzy hybrid model. For example, incorporating the learning capability of artificial neural networks (ANNs) into fuzzy models can be achieved through hybridization (Jang, 1993; Hawas, 2004; Mahabir et al., 2006; Yu et al., 2006; Pedrycz and Gomide 2007; Li et al., 2009; Yu and Skibniewski, 2010; Pedrycz 2014; Omar and Fayek 2015)

Hybridization of fuzzy models with other techniques, such artificial intelligence techniques, has improved the learning capability of fuzzy logic-based models (Gupta 1994, Pedrycz and Gomide 2007; Pedrycz 2014). The principal mechanism by which fuzzy logic-based models have been hybridized focuses on optimization. Using data and other artificial intelligence techniques, the different parameters of fuzzy logic-based models are optimized; thereby providing a learning capability, improving model interpretability, and making the developed fuzzy hybrid models more intelligent.

[1] Parts of this chapter have been submitted for publication in Journal of Automation in Construction. Omar, M. and Fayek, A. Robinson. (2015). “Modeling and Evaluating Construction Project Competencies and Their Relationship to Project Performance.” Manuscript, 53 pages.

As described earlier in chapter two of this thesis, project competencies are difficult to group and measure due to the multidimensional and subjective nature of their assessment. Project competencies exhibit subjective assessments that cannot be expressed by traditional numerical approaches (Fayek 2012). Capturing the multidimensional and subjective nature of project competencies evaluation requires the utilization of fuzzy logic (i.e., capture subjective human reasoning in measuring and evaluating project competencies) and artificial neural networks (i.e., improve fuzzy logic models by incorporating ANNs' capacity for mapping the nonlinear relationship between project competencies and project KPIs by learning from actual data sets). The application of fuzzy hybrid intelligent models will better evaluate project competencies and quantify the nonlinear relationship between project competencies and project KPIs.

For evaluating project competencies and their relationship to project KPIs, a new fuzzy hybrid intelligent model considering the new prioritized fuzzy aggregation, presented in chapter three of this thesis, a new fuzzy feature extraction technique and a granular AND/OR fuzzy neural network is presented in this chapter. The presented fuzzy hybrid intelligent model is capable of identifying and quantifying the relationship between project competencies' evaluation criteria and project KPIs.

4.2. Overview of the Fuzzy Hybrid intelligent Model Processing Units

The fuzzy hybrid intelligent model, presented in this chapter, is divided into three main processing units namely; 1) Information fusion processing unit. An information fusion is carried out using the new fuzzy prioritized aggregation method presented in chapter three of this thesis. 2) Dimensionality reduction processing unit. A new fuzzy feature extraction technique is applied to perform an intermediate grouping and structuring of project competencies. Additionally, the ranking of the different project competencies within a given group is realized. The application of the new fuzzy feature extraction technique reduces the project competencies into fewer fuzzy factor groups suitable for modeling while preserving their fuzziness. 3) Granular AND/OR Fuzzy neural networks (Pedrycz and Gomide 2007; Pedrycz 2014) processing unit. Granular AND/OR fuzzy neural networks are used to identify the relationship between project competencies, expressed by fuzzy factor groups, and project KPIs. Granular AND/OR fuzzy neural networks are transparent and traceable constructs that have learning and prediction capabilities (Gupta 1994, Pedrycz and Gomide 2007; Pedrycz 2014), and are capable of admitting formalism in modeling non-linear relationships between inputs and outputs (Pedrycz 2014). Figure 4-1 displays the structure (i.e., processing units) of the fuzzy hybrid intelligent model.

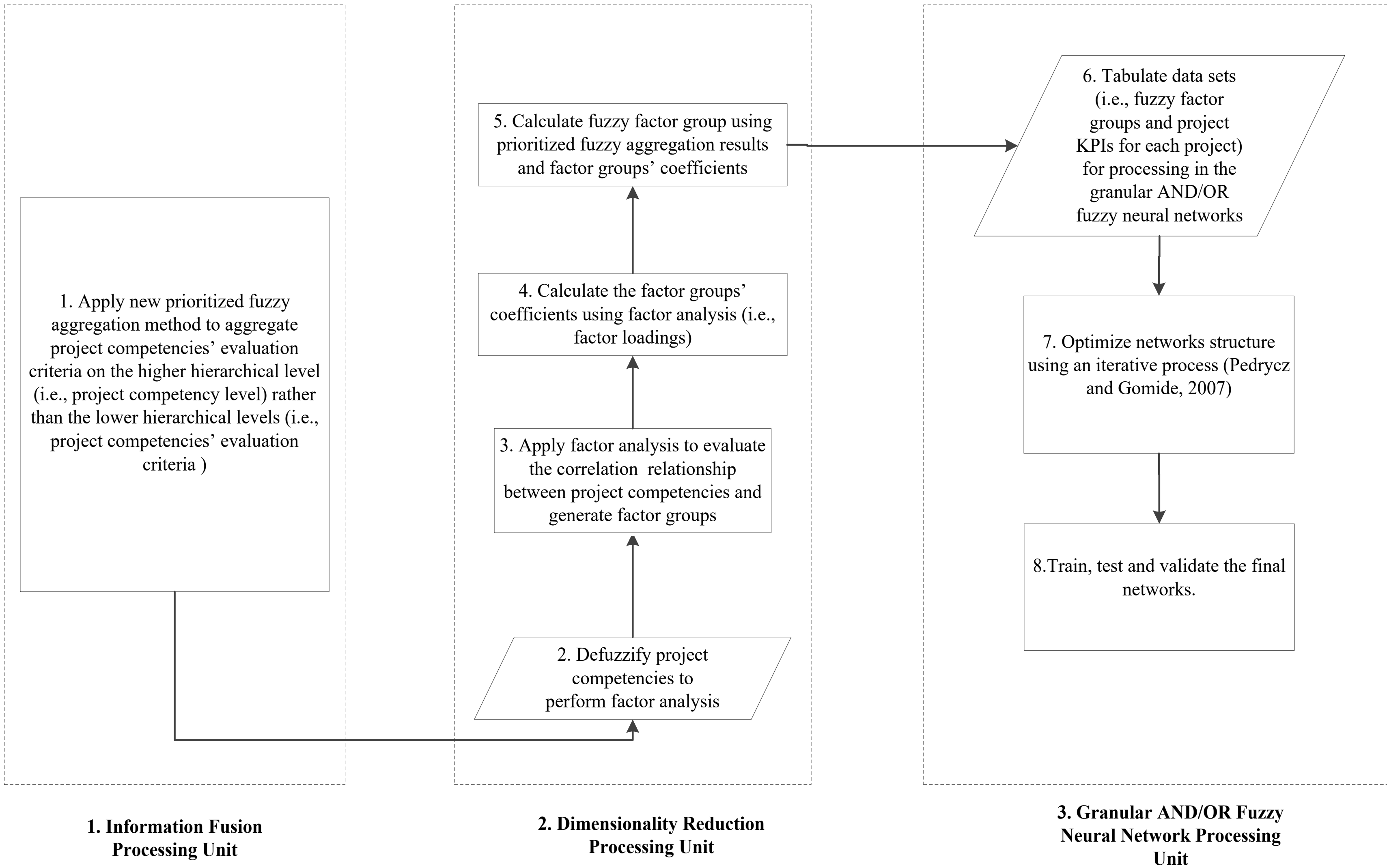


Figure 4-1 Fuzzy Hybrid Intelligent Model Processing Units

The fuzzy hybrid intelligent model units perform the analysis as follows. First, the data collected from construction projects is tabulated. The project competencies' evaluation criteria are combined using the new fuzzy prioritized aggregation method described in chapter three of this thesis. The fuzzy prioritized aggregation method calculates project competencies' evaluations on the higher hierarchical levels (i.e., project competency level) rather than the lower hierarchical levels (i.e., project competencies' evaluation criteria level) for each respondent. Second, the results of the fuzzy prioritized aggregation method are defuzzified, for the application of a dimensionality reduction technique (i.e., factor analysis). The dimensionality reduction technique identify a set of fewer factor groups that represents the different project competencies and calculate coefficients representing the contribution of each project competency towards the factor group it belongs to. Third, the calculated coefficients, using factor analysis, are used jointly with the project competencies' prioritized fuzzy aggregation results to calculate fuzzy factor groups. Finally, the calculated fuzzy factor groups and project KPIs are used jointly in a granular AND/OR fuzzy neural network to identify and quantify the relationship between project competencies, expressed by fuzzy factor groups, and project KPIs. A detailed overview of each of the fuzzy hybrid intelligent model processing units is presented next.

4.2.1. Information Fusion Processing Unit: New Prioritized Fuzzy Aggregation Method

As described in chapter two of this thesis, a methodology for project competencies and project KPIs evaluation and data collection is first applied to collect project competencies and project KPIs from construction projects. Project competencies' evaluation criteria, collected from project personnel across the different construction projects, are collected using a stratified random sampling approach to achieve a 10% margin of error and 90% confidence interval. The collected data is, therefore, suitable for representing project competencies on the project level.

Once data collection is complete, the following four steps are considered for calculating overall project competencies' evaluations:

1. Step one: Use all respondents (i.e., from construction projects) importance scores to generate a fuzzy relative importance score for each evaluation criterion used to evaluate a project competency.
2. Step two: Rank the different project competencies' evaluation criteria for the different project competencies.
3. Step three: Calculate overall project competencies' assessments on the higher hierarchical levels (i.e., project competency level) rather than the lower hierarchical levels (i.e., project competencies' evaluation criteria level) for each respondent using the prioritized fuzzy aggregation method presented in chapter three of this thesis.
4. Step four: Calculate an average project competency value based on all respondents project competencies' evaluations for a given project.

The previous four steps produce an informative evaluation, based on the stratified random sampling and the new prioritized fuzzy aggregation method, explained in chapter three of this thesis, for the different project competencies on a construction project. Following this reduction in the number of variables (i.e., 41 project competencies rather than 248 project competencies' evaluation criteria), a new fuzzy feature extraction technique is applied to cluster and group the project competencies into fewer fuzzy factor groups suitable for use in the granular AND/OR fuzzy neural network as described later in this chapter.

4.2.2. Dimensionality Reduction Processing Unit: New Fuzzy Feature Extraction Technique

Dimensionality reduction techniques have been widely used for visualization and analysis of high-dimensional data sets to overcome the curse of high dimensionality of data. Dimensionality reduction techniques reduce the number of variables considered for analysis and modeling. In general, dimensionality reduction techniques functions either by transforming the existing features to a new reduced set of features or by selecting a subset of the existing features (Devijver and Kittler 1982; Kumar 2009; Alroomi et al. 2011). Two main categories of dimensionality reduction techniques are presented in previous research namely; 1) Supervised dimensionality reduction techniques and, 2) Unsupervised dimensionality reduction techniques. Supervised dimensionality reduction techniques require a training set with the class label information to learn the lower dimensional representation according to some criteria and then predict the class labels on unknown data. Unsupervised dimensionality reduction techniques project the original data to a new lower dimensional space without utilizing a training set (Kumar 2009). Each of the abovementioned techniques is further classified based on the processing approach. Examples of dimensionality reduction techniques are Latent Semantic Indexing (LSI): truncated SVD, Independent Component Analysis (ICA), Factor Analysis (FA), Principal Component Analysis (PCA), Canonical Correlation Analysis (CCA) and, Linear Discriminant Analysis (LDA) (Dumais 2004; Comon 1994; Hyvärinen et al., 2004; Thompson 2004; Izenman 2008).

One of the most commonly used methods in dimensionality reduction techniques is factor analysis (Rencher 2002; Thompson 2004; Costello and Osborne 2005; DiStefano et al. 2009; Alroomi et al. 2011). Factor analysis is a feature extraction method that reduces the number of variables (e.g., project competencies) into a smaller number of factor groups.

One essential aspect in conducting a factor analysis is determining an adequate sample size. A study was conducted by Costello and Osborne (2005) to determine the minimum sample size required for performing factor analysis. A ratio representing the number of variables (e.g., project competencies) and number of data points, known as subject-to-item ratio, was used for comparative purposes. A large percentage of researchers were reported to use factor analyses with relatively small subject-to-item ratio as listed in Table 4-1.

Table 4-1 Current Practice in Factor Analysis (Costello and Osborne 2005)

Subject-to-item Ratio	Percentage of Studies (%)	Cumulative Percentage (%)
2:1 or less	14.70%	14.70%
>2:1, ≤5:1	25.80%	40.50%
>5: 1, ≤10:1	22.70%	63.20%
>10: 1, ≤20:1	15.40%	78.60%
>20:1, ≤100:1	18.40%	97.00%
>100:1	3.00%	100.00%

Costello and Osborne (2005) review concluded that "*strict rules regarding sample size for factor analysis have mostly disappeared*" (Costello and Osborne 2005, P4). Additionally, Costello and Osborne determined that previous research has shown that adequate sample size is partly determined by the nature of the research problem and type of data collected (Fabrigar et al., 1999; MacCallum et al. 1999) rather than strict sample size requirements for performing factor analysis.

Several commercial software packages are used to perform factor analysis. In this thesis, SPSS 22 is used to; 1) test the suitability of data to perform factor analysis, 2) perform factor analysis to cluster and group the different project competencies into factor groups and, 3) calculate associated factor groups' coefficients representing the contribution of each project competency towards its factor group. Finally, fuzzy factor groups are calculated using the prioritized fuzzy aggregation results (i.e., information fusion processing unit) and the factor groups' coefficients (i.e., dimensionality reduction processing unit) to be used for the granular fuzzy neural networks (i.e., granular AND/OR fuzzy neural networks processing unit) described later in this chapter.

4.2.2.1. Determination of Factor Groups Using Factor Analysis

For performing the factor analysis, first, the results of the prioritized fuzzy aggregation are defuzzified. The centroid method is one of the most common defuzzification methods (Pedrycz and Gomide 2007). The centroid method determines the centre of area of a given membership function $f_A(x)$ (i.e., fuzzy number) and is calculated as shown in Eq. (4-1).

$$\bar{x} = \frac{\sum_{x\,min}^{x\,max} \mu_A(x) * x}{\sum_{x\,min}^{x\,max} \mu_A(x)} \tag{4-1}$$

Where:

$\bar{x}$ = defuzzified value using the centroid method

$\mu_A(x)$ = membership degree of x

x = values representing the evaluation (i.e., project competency assessment)

The single value calculated from the centroid method is used to perform the intermediate grouping and structuring of project competencies using factor analysis.

Second, eigenvalues are determined. Eigenvalues are used to determine the number of factor groups to be retained. The minimum eigenvalue criteria, known as the Kaiser's criteria (Alroomi et al. 2011) is the most commonly used method to determine the number of factor groups to be retained. The Kaiser's criteria requires ranking the eigenvalues from largest to smallest and then selecting the eigenvalues greater than 1.0 as the number of factor groups to be retained. The varimax rotation is used to maximize high correlations and minimize low correlations. The varimax rotation method is a commonly used method to enhance the interpretability of the factor analysis results (Alroomi et al. 2011).

4.2.2.2. Factor Groups' Coefficients

Factor loadings (i.e., calculated after the varimax rotation method) are used to calculate the factor groups' coefficients. Factor loadings provide a ranking of the different variables within a factor group. Additionally, factor loadings quantify the contribution of each variable, based on the correlation relationship between variables, towards its factor group. Factor loadings are used to derive factor group's coefficients. Several factor groups' coefficients methods are described in previous research (DiStefano et al. 2009). The "sum scores-above cut-off value" method (DiStefano et al. 2009) is a commonly used method to quantify the contribution of each variable (i.e., project competency) towards the factor group it belongs to. This method suggests that a cut-off value is first set using the factor group loading calculated from the factor analysis. Rencher (2002) suggests that factor group loadings less than ±0.40 be removed because they are considered insignificant for factor group interpretation. Then, variables within a factor group with loading values above the predefined cut-off value (i.e., ±0.40) are included in the computation of the factor group coefficients. The variables' factor loadings for a given factor group are used to calculate the factor groups' coefficients. The factor groups' coefficients are calculated by dividing a factor loading of each variable in the factor group by the sum of the factor group loadings of all variables within the same factor group. An advantage of applying this method is that a variable with the highest factor loading in a given factor group would have the largest effect on the factor group value.

4.2.2.3. Fuzzy Factor Groups' Calculation

Once the different variables (i.e., project competencies) are clustered into factor groups and the contribution of each variable (i.e., project competency) towards its factor group is calculated (i.e., factor groups' coefficients), the results are used along with the results of the prioritized fuzzy aggregation generated from the first processing unit (Step four, Page 5), to generate fuzzy factor groups using Eq. (4-2).

$$Fuzzy\ Factor\ Group = \sum_{1}^{n}[\lambda * a_i{}^{l}, \lambda * a_i{}^{m}, \lambda * a_i{}^{u}] \tag{4-2}$$

Where:

A_i is a fuzzy number (i.e., representing an overall evaluation of a project competency for a project) defined by a triplet ($a_i{}^{l}$, $a_i{}^{m}$, $a_i{}^{u}$).

λ is a crisp number representing the factor group coefficient for a given project competency (i.e., identified from factor groups' coefficients).

The new fuzzy feature extraction technique, presented in this chapter, combines the advantages of fuzzy logic and dimensionality reduction techniques. Fuzzy logic captures the uncertainty and subjectivity associated with human reasoning using the notion of graded memberships (Zadeh 1965; Pedrycz and Gomide 2007). Graded memberships are used to model human reasoning associated with the linguistic assessment of project competencies' evaluation criteria. Dimensionality reduction techniques (i.e., factor analysis) are used to transform the existing set of project competencies to a new reduced set of factor groups (i.e., representing the different project competencies) while considering the correlation relationship between the original set of project competencies. The final calculated fuzzy factor groups are constructs of graded memberships (i.e., fuzzy numbers) that capture subjective human reasoning associated with the linguistic assessment of project competencies' evaluation criteria and are of reduced dimensionality (i.e., without compromising the original set of project competencies' evaluations) suitable for modeling.

Finally, the calculated fuzzy factor groups, representing project competencies, are used with project KPIs as inputs and outputs for the third processing unit (i.e., granular AND/OR fuzzy neural networks). The third processing unit is then used to determine the relationship between project competencies (i.e., expressed by fuzzy factor groups) and project KPIs as described next.

4.2.3. Granular Fuzzy Network Processing Unit: Granular AND/OR Fuzzy Neural Networks

The notion of Fuzzy Neural Networks (FNNs) is used to develop constructs of fuzzy hybrid systems that combine the technologies of fuzzy set theory and neuro-computing. FNNs contribute in developing hybrid systems that are transparent, traceable, and with learning and prediction capabilities (Gupta 1994, Pedrycz and Gomide 2007; Pedrycz 2014). FNNs demonstrated, in previous research, its ability to model complex and non-linear relationships between inputs and outputs (Pedrycz 2014). The advancement of artificial neural networks and fuzzy logic to fuzzy neural networks is first presented to highlight its merits. Then, the application of granular AND/OR FNNs is presented to highlight its advantages of capturing and interpreting the nonlinear and complex relationship between inputs and outputs when a limited set of data is available (Pedrycz 2014).

4.2.3.1. Overview of Artificial Neural Networks (ANNs)

The flexibility associated with the learning and adaptation of biological neuronal mechanisms has been a motivation for the design of artificial intelligent systems. Unlike conventional systems, biological neuronal mechanisms are non-model based mechanisms, and such non-model based mechanisms are quite successful in dealing with the complexity and approximate nature of some research problems (Gupta 1994). Artificial Neural Networks (ANNs) have received particular attention because of their ability to analyze complex nonlinear data sets and establish the nonlinear and complex relationship between inputs and outputs.

The human brain, for example, is composed of networks of billions of biological neurons. These biological neurons receive input from other neurons in the same network and across different networks, which may lead to either excitation or inhibition of the network. When the network excitation achieves a threshold value, some neurons fire a signal to produce an output. As such, a neuron's output always bears the same relationship to its input. This being the case, the ability to adapt and learn is induced by a change in the strength of the relationship (i.e. connections weights) between the different biological neurons. Thus, the effectiveness of one neuron in exciting another is not constant but varies with "experience" and/or "learning". In one network that consists of a number of neurons, the outputs are still considered as a function of the inputs, but because the strength of the connections within the network can change, the relationship of the network's outputs to its inputs can be altered by experience and/or learning. Therefore, it is the connections strength between the neurons that determine a neural network's behavior and how that behavior varies over time (Gupta 1994; Drew and Monson 2000).

Error back propagation (BP) algorithms provide the learning capability (i.e., similar to biological neurons) to ANNs. Learning algorithms tend to adapt a NN by adjusting its synaptic weights to improve the network output. Two main categories of learning algorithms are presented in previous research (Gupta 1994; Li et al. 2009; Yu and Skibniewski 2010) as presented in Figure 4-2.

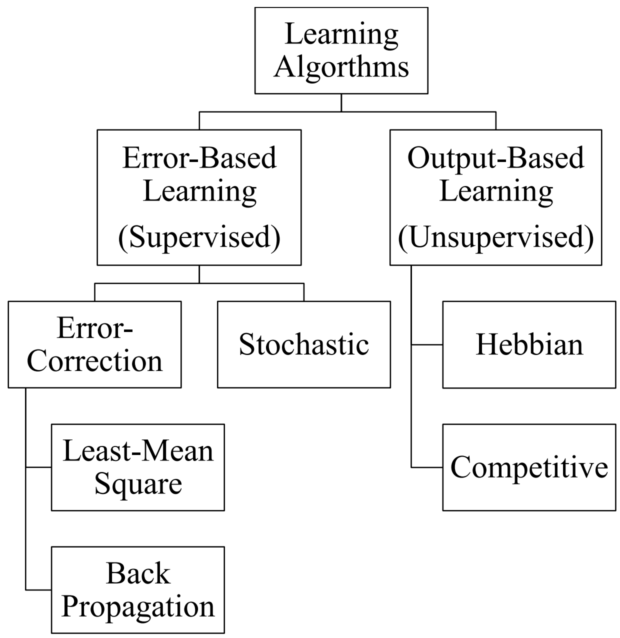


Figure 4-2 Flow Diagram for Learning Algorithms for ANNs

Error-based learning (i.e., supervised) algorithms employ an external reference (i.e., actual output) and generates an error signal by comparing the external reference with the obtained response (i.e., network output). Based on the error signal, a neural network modifies its synaptic connections (i.e., weights) to improve the system performance. System performance is then measured by means of a global error as shown in Eq. (4-3).

$$Global\ Error = \frac{1}{2}\sum_{1}^{n}(Z_{i\ network} - Z_{i\ actual})^2 \qquad (4\text{-}3)$$

Where:

n is number of actual data points

$Z_{i\ network}$ is obtained response (i.e., network output) for a given data set

$Z_{i\ actual}$ is the external reference (i.e., actual output) for a given data set

Note that the effect of weak connections with small values can be masked (eliminated) as they are interpreted to be of minimal or no contribution (i.e., no connection strength) towards the network architecture. Also note that the different connections (i.e., weights) serve as annotations (quantifications) of their corresponding component (i.e., inputs) (Pedrycz and Gomide 2007 P361).

Output-based learning (unsupervised) algorithms do not employ an external reference, and generally involve self-organization principles that rely only upon local information and internal control mechanisms in order to discover collective properties. Two forms of output-based learning are the Hebbian learning and the competitive learning. Hebbian learning involves the adjustment of synaptic weights according to the correlation of the response of the neurons that adjoin it. Competitive learning is a variant of Hebbian learning. Competitive learning functions by increasing the knowledge of each node in the network (Gupta 1994). A common application of the competitive learning algorithms is data clustering.

The application of ANNs was further complemented by the use of fuzzy set theory and fuzzy logic. Fuzzy set theory introduces graded membership in order to provide a mathematical precision to approximate human reasoning capabilities described linguistically. Traditional binary set theory describes crisp events as events that either do or do not occur. Fuzzy set theory extends crisp events using the notion of graded memberships (Zadeh 1965). Graded memberships model imprecise and ambiguous data. Imprecise and ambiguous data is often encountered in real life problems (Gupta 1994; Pedrycz and Gomide 2007; Pedrycz 2014). Hybridization of fuzzy set theory with ANNs improves systems performance by enhancing the application of each domain (i.e., fuzzy set theory and ANNs) while eliminating, to a certain extent, the limitation of each domain separately as described next.

4.2.3.2. Overview of Fuzzy Neural Networks (FNNs)

ANNs structures are of limited ability when dealing with imprecise data and ill-defined activities (Gupta 1994; Pedrycz and Gomide 2007; Yu and Skibniewski 2010). However, subjective phenomena such as reasoning are regarded beyond the ability of traditional ANNs. Hence, fuzzy set theory is applied to overcome such limitation. Fuzzy neural networks (FNNs) are constructs of fuzzy hybrid modeling that combine the technologies of fuzzy set theory and neuro-computing in developing models that are transparent, traceable, and with learning and prediction capabilities (Gupta 1994, Pedrycz 2014). Two main FNNs models are presented in previous research. The first modeling type of FNNs provides a fuzzy interface for the neural network to process subjective information such as approximate human reasoning. The second modeling type applies traditional NNs, in general, to optimize a predefined knowledge-base in a fuzzy inference. Figure 4-3 and Figure 4-4 presents the two types of FNNs (Gupta 1994).

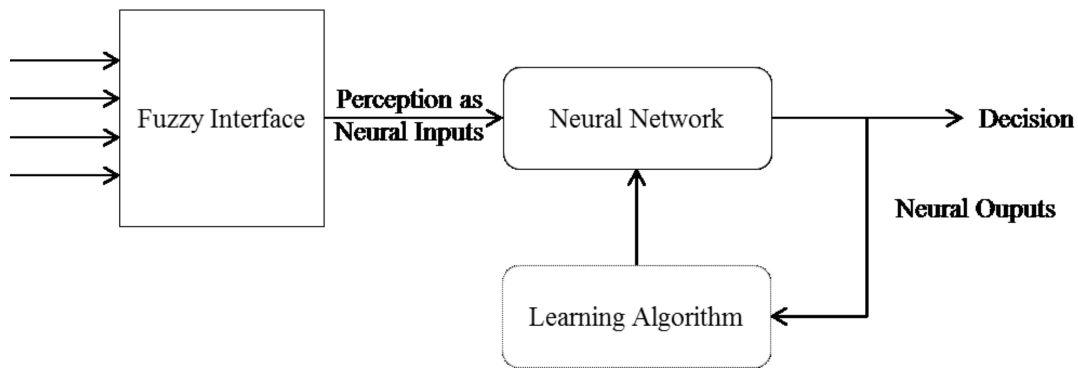


Figure 4-3 Type 1: Fuzzy Input Vector to a Multi-Layered Neural Network

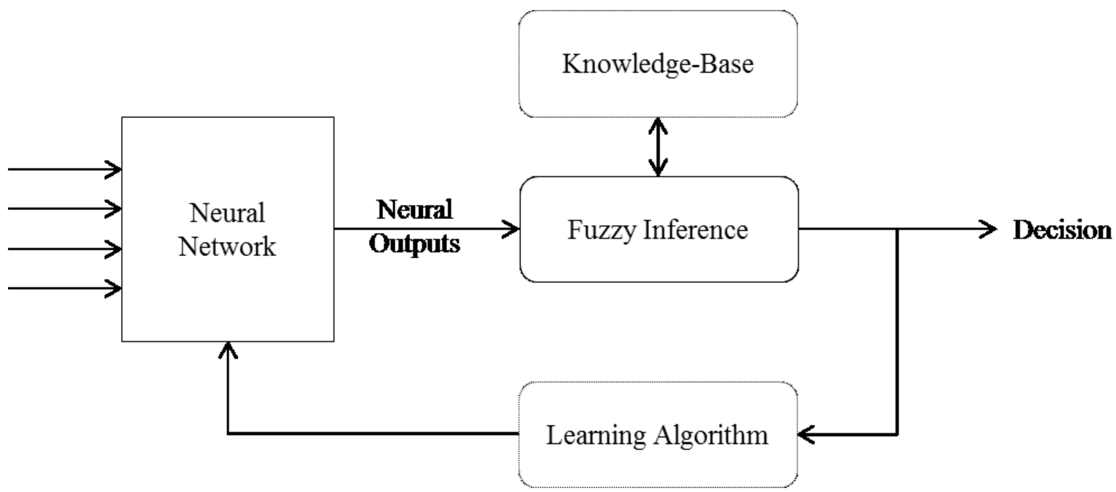


Figure 4-4 Type 2: Crisp Input Vector to a Fuzzy Inference

The two modeling types of FNNs (i.e., Figure 4-3 and Figure 4-4) were applied in several evaluation and prediction models in previous research. Table 4-2 summarizes some of the main studies that incorporated the two modeling types of FNNs.

Table 4-2 Summary of Previous Research in FNNs

Study	Reference	Overview of the Study	Application Area
FNNs theory and application	Gupta (1994)	Application of FNNs as evaluative and predictive models	Illustrative examples
Dynamic FNNs	Wu and Er (2000)	Dynamic fuzzy neural networks (D-FNN) implementing Takagi-Sugeno-Kang (TSK) fuzzy systems based on extended radial basis function (RBF) neural networks (NNs)	Function approximation
Evolving FNNs	Kasabov (2001)	Implementation of the evolving connectionist systems (ECOS) that is aimed at building online, adaptive intelligent systems (i.e., (Evolving FNNs)	Supervised/Unsupervised online knowledge-based learning
Forecasting FNNs	Pinson and Kariniotakis (2003)	A prediction system that integrates models based on adaptive fuzzy-neural networks configured for short and long terms forecasting	Wind power forecasting
Self-Organizing FNNs	Leng et al. (2005)	A self-organising fuzzy neural network (SOFNN), to extract fuzzy rules from the training data	Extraction of fuzzy rules
Dynamic FNNs for chaotic systems	Lin et al. (2010)	A model that incorporates fuzzy logic and neural adaptive backstepping control for an uncertain chaotic system	Fault diagnosis system of a rotary machine
FNNs for water level and discharge forecasting with uncertainty	Alvisi and Franchini (2011)	A water level (or discharge) forecasting model (i.e., under uncertainty) using artificial neural networks (ANNs) where, uncertainty is expressed in the form of a fuzzy number	Forecasting water levels
FNNs for estimation of triethylene glycol purity	Ghiasi et al. (2014)	An intelligent model based on standard feed-forward back-propagation neural network (NN) for accurate prediction of triethylene glycol purity based on operating conditions of reboiler	prediction of triethylene glycol purity on operating conditions of reboiler
Granular FNNs	Pedrycz (2014)	Extending traditional FNNs to Fuzzy FNNs	Illustrative examples

The first modeling type of FNNs (i.e., Figure 4-3) was considered for problems that are highly dimensional and/or based on composite variables (e.g., fuzzy factor groups). In such problems, a predefined knowledge-base is not available to capture the relationship between inputs and outputs. The second modeling type of FNNs (i.e., Figure 4-4) was considered for problems that are of relatively low dimensionality and/or have a predefined knowledge-base that requires an optimization process to capture the relationship between inputs and outputs. Reviewing the two modeling types of FNNs along with their application in previous research (i.e., see table 4-2); the first modeling type of FNNs (i.e., Figure 4-3) is considered in the fuzzy hybrid intelligent model presented in this chapter. The first modeling type of FNNs is capable of identifying and quantifying the relationship between project competencies, expressed by fuzzy factor groups, and project KPIs where, a predefined knowledge-base is not available and, composite variables (e.g., fuzzy factor groups) are used.

Two main computational processes are also considered with the application of FNNs in previous research. Figure 4-5 classifies the calculations with respect to the two types presented in Figure 4-3, Figure 4-4 and Table 4-2.

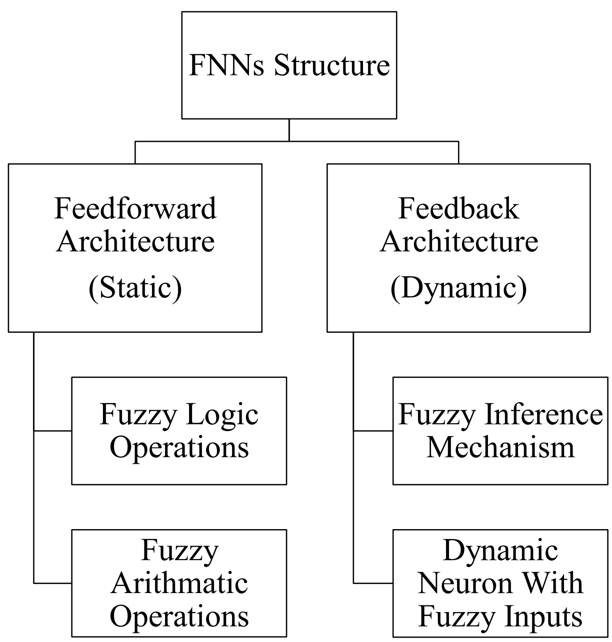


Figure 4-5 Calculations for FNNs

As stated earlier, the first modeling type of FNNs (i.e., Figure 4-3) is considered in the fuzzy hybrid intelligent model presented in this chapter. For the feedforward (static) architecture, the neurons respond to the input (i.e., fuzzy input vectors) using either fuzzy arithmetic or fuzzy logic operations. In the feedback (dynamic) architecture, a learning algorithm is applied to provide robust computing characteristics. This computation either enhances the weight associated to the fuzzy neurons, as shown in Figure 4-3, to generate outputs directly or, to the fuzzy inference input, as shown in Figure 4-4, to improve the predefined knowledge-base for the fuzzy inference.

For FNNs calculations, Chen (1984) introduced the function principle to preserve the original type of membership function and simplifies the arithmetic operations in the network. Accordingly, the application of fuzzy arithmetic provide a simple method to process fuzzy signals (i.e., expressed by their membership functions) using fuzzy arithmetic and fuzzy operations.

The underlying topology of FNN, using fuzzy arithmetic operations, is processing fuzzy signals (e.g., fuzzy numbers) as described in Eq. (4-4) to (4-8).

Fuzzy Addition (two fuzzy numbers): $A_1 + A_2 = [{a_1}^l, {a_1}^m, {a_1}^u] + [{a_2}^l, {a_2}^m, {a_2}^u] = [{a_1}^l + {a_2}^l, {a_1}^m + {a_2}^m, {a_1}^u + {a_2}^u]$ (4-4)

Fuzzy Multiplication (two fuzzy numbers): $A_1 * A_2 = [{a_1}^l, {a_1}^m, {a_1}^u] * [{a_2}^l, {a_2}^m, {a_2}^u] = [{a_1}^l * {a_2}^l, {a_1}^m * {a_2}^m, {a_1}^u * {a_2}^u]$ (4-5)

Fuzzy Multiplication (crisp number and fuzzy number): $\lambda * A_1 = = [\lambda * {a_1}^l, \lambda * {a_1}^m, \lambda * {a_1}^u]$ (4-6)

Fuzzy Division (two fuzzy numbers): $\frac{A_1}{A_2} = (\min(\frac{{a_1}^l}{{a_2}^l}, \frac{{a_1}^l}{{a_2}^u}, \frac{{a_1}^u}{{a_2}^l}, \frac{{a_1}^u}{{a_2}^u}), \frac{{a_1}^m}{{a_2}^m}, \max(\frac{{a_1}^l}{{a_2}^l}, \frac{{a_1}^l}{{a_2}^u}, \frac{{a_1}^u}{{a_2}^l}, \frac{{a_1}^u}{{a_2}^u}))$ (4-7)

Fuzzy Division (crisp number and fuzzy number): $\frac{A_1}{\lambda} = (\frac{a_1{}^l}{\lambda}, \frac{a_1{}^m}{\lambda}, \frac{a_1{}^u}{\lambda})$ (4-8)

Where:

A_1 and A_2, are fuzzy numbers defined by triplets $(a_1{}^l,\ a_1{}^m, a_1{}^u)$ and $(a_2{}^l,\ a_2{}^m, a_2{}^u)$ respectively.

λ is a crisp number

Accordingly, conventional arithmetic operations performed in traditional ANNs can be transformed to FNNs.

As for FNNs that incorporates fuzzy operations, the underlying topology is to use fuzzy operations such as AND and OR operations rather than fuzzy arithmetic. AND and OR logic neurons provides aggregative functions suitable for performing calculations in FNNs (Pedrycz and Gomide 2007; Pedrycz 2014). AND logic neurons realizes an *or* logic aggregation for a set of fuzzy inputs x = $[x_1, x_2, x_3,\dots x_n]$ with corresponding connections (weights) w = $[w_1, w_2, w_3,\dots w_n]$ and then summarizes the partial results in an *and*-wise manner such that y = $T_{i=1}^{n}$ $(w_i s x_i)$. Where, $T_{i=1}^{n}$ and s stands for t-norms (minimum) and t-conorms (maximum) fuzzy operators respectively. OR logic neuron on the other hand realizes an *and* logic aggregation for a set of inputs y = $[y_1, y_2,\ y_3,\dots y_n]$ with corresponding connections (weights) v = $[v_1, v_2, v_3,\dots v_n]$ and then summarizes the partial results in an *or*-wise manner such that z = $S_{i=1}^{n}$ $(v_i t y_i)$.

Previous research also suggested improving the approximation capability of fuzzy neural networks (i.e., using fuzzy operations) through the incorporation of an activation function such as the unipolar sigmoidal function to process AND and OR logic neurons (Dissanayake 2006).

Gradient-based learning is commonly used with FNN to provide the network with a supervised learning based on pairs of input-output data sets $\{x_n, z_k\}$. The learning is guided by a performance index Q whose values are minimized by adjusting the values of the connections (i.e., weights) associated with the FNN (Dissanayake 2006; Pedrycz and Gomide 2007; Pedrycz 2014). The adjustment is completed in an iterative process where, for *m* input-output data sets, a portion of the data set (e.g., 70%) is used for training and the remaining portion (e.g., 30%) is used for testing. The gradient-based learning scheme is presented in Eq. (4-9).

$$Connection\ (iter + 1) = Connection\ (iter) - \alpha \nabla_{connection(iter)} Q \tag{4-9}$$

Where:

α is a positive learning rate ranging from 0 to 1

$\nabla_{connection(iter)} Q$ is the gradient of Q determined with respect to a current connection iteration

$Connection\ (iter)$ is the current iteration

$Connection\ (iter + 1)$ is the successive iteration

It is important to note that the resulting values are retained by a constraint rule (Pedrycz and Gomide 2007) as described below:

$< Connection\ (iter) - \alpha \nabla_{connection(iter)} Q >$

Where:

<.> denotes the truncation operation such as <.a> = 1, if a>1.0; 0, if a<0; and a, otherwise.

The initial connection values (i.e., weights) are randomly initialized to avoid any potential bias. Once the network is trained a global error measure representing the network's performance can be calculated using Eq. (4-3).

4.2.3.3. Granular AND/OR Fuzzy Neural Networks for Modeling Construction Project Competencies and Their Relationship to Project Performance

Granular computing has recently emerged to construct and process information in real world problem such as decision-making and prediction models. Granular computing has shown several advancements in non-stationary fuzzy environments (i.e., with limited availability of data) that requires continuous updates and is subject to ongoing changes. The application of granular computing in FNNs improves transparency of the network, through the fuzzy connection weights, thus providing the ability to better trace the relationship between inputs and outputs (Pedrycz 2014). Advancing FNNs to granular FNNs rely on *"making the connections granular and admitting a certain formalism of information granularity"* (Pedrycz 2014, P142). This is achieved by fuzzifying FNNs connections (i.e., weights). The structure of the granular AND/OR FNNs, as the third processing unit of the fuzzy hybrid intelligent model, is displayed in Figure 4-6.

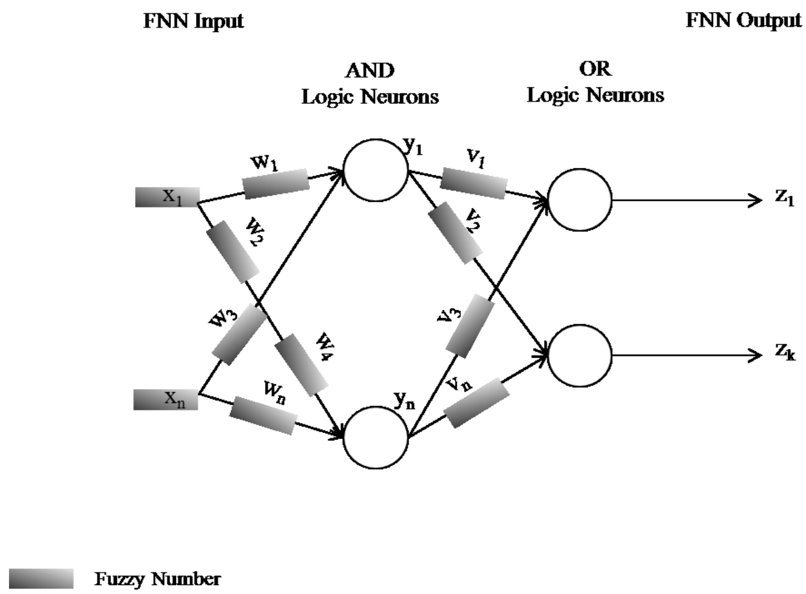


Figure 4-6 Example of a Granular AND/OR Fuzzy Neural Network (Omar and Fayek 2015)

The functional components of granular AND/OR FNNs belong to two main aggregation neurons namely; AND and OR logic neurons due to their common use (Pedrycz 2014). The AND logic neurons realizes, as described earlier, an *or* logic aggregation for a set of fuzzy inputs x = $[x_1, x_2, x_3, \ldots x_n]$ that represents the different project competencies (i.e., expressed by fuzzy factor groups) with corresponding fuzzy connections (weights) w = $[w_1, w_2, w_3, \ldots w_n]$ and then summarizes the partial results in an *and*-wise manner such that $y = T_{i=1}^{n}\ (w_i s x_i)$. The OR logic neurons, on the other hand, realizes an *and* logic aggregation for a set of inputs y = $[y_1, y_2, y_3, \ldots y_n]$ with corresponding fuzzy connections (weights) v = $[v_1, v_2, v_3, \ldots v_n]$ and then summarizes the partial results in an *or*-wise manner such that $z = S_{i=1}^{n}\ (v_i t y_i)$. Where, z is the network output representing the different project KPIs, $S_{i=1}^{n}$ and t stands for t-conorms (maximum) and t-norms (minimum) fuzzy logical operators respectively.

A gradient-based learning algorithm is associated with granular AND/OR FNNs to provide the networks with a supervised learning based on pairs of input-output (i.e., fuzzy factor groups and project KPIs) data sets $\{x_n, z_k\}$. The learning is guided by a performance index Q whose values are minimized by adjusting the values of the connections (i.e., weights) associated with the granular AND/OR FNNs (Pedrycz and Gomide 2007; Pedrycz 2014). The adjustment is completed in an iterative process where, for m input-output data sets, a portion of the data set is used for training and the remaining portion is used for testing. As the granular AND/OR FNNs are trained and tested using actual data sets, the relationship between the different project competencies (i.e., expressed by fuzzy factor groups) and project KPIs is identified through the connections (i.e., weights) of the granular AND/OR FNNs.

A gradient-based learning algorithm is used to improve the granular AND/OR FNNs structure (Pedrycz and Gomide 2007). Weak connections at the AND and OR logic neurons are masked (eliminated) as they are interpreted to be of minimal or no contribution (i.e., no connection strength) towards the network architecture.

The identification of project competencies, expressed by fuzzy factor groups, having the highest impact on project KPIs is realized by interpreting the granular AND/OR FNN through the interpretation of the connection weights. For the AND logic neuron, lower values of the connection imply higher relevance of the corresponding input (i.e., fuzzy factor groups) on the recipient AND neuron. For the OR logic neuron, higher values of the connection imply higher relevance of the corresponding input (i.e., AND logic neuron) on the recipient OR neuron, which is then deffuzzified to provide the final output (i.e., project KPIs). Different defuzzification methods, such as the smallest of maxima (SOM), middle of maxima (MOM), largest of maxima (LOM), and the centroid methods, are examined to identify the one that yields the most accurate results (Pedrycz and Gomide 2007) in terms of granular AND/OR FNNs global error. The centroid method provided the least global error as discussed later in chapter five of this thesis.

4.3. Evaluating Construction Project Competencies' Evaluation Criteria Effect on Project KPIs Using the Developed Fuzzy Hybrid Intelligent Model

The developed fuzzy hybrid intelligent model is further analyzed to determine the effect of lower hierarchical levels (i.e., project competencies' evaluation criteria) on the different project KPIs. This process is classified into two main phases namely; 1) identification phase and, 2) quantification phase. Figure 4-7 displays the analysis performed to determine which project competencies' evaluation criteria affect the different project KPIs and to quantify the effect, in terms of percentage of improvement, on the different project KPIs.

In the identification phase, fuzzy factor groups, representing the project competencies, are first identified from the granular AND/OR FNNs. Then, project competencies, associated with the fuzzy factor groups, and the prioritized evaluation criteria, within each project competency in a given fuzzy factor group, are identified from the factor analysis (i.e., second processing unit of the fuzzy hybrid intelligent model) and the new prioritized fuzzy aggregation respectively (i.e., first processing unit in the fuzzy hybrid model). In the quantification phase, the effect of the identified fuzzy factor groups on the different project KPIs is measured using the developed granular AND/OR FNNs. The effect of individual project competencies' prioritized evaluation criteria (i.e., one at a time) on project KPIs is performed using sensitivity analysis. Figure 4-10 illustrates the capacity of the fuzzy hybrid intelligent model (i.e., the three processing units) to identify project competencies at the lowest level (i.e., project competencies' evaluation criteria) that affect the different project KPIs. The developed fuzzy hybrid intelligent model also capture the nonlinear and dynamic relationship between project competencies' evaluation criteria and project KPIs.

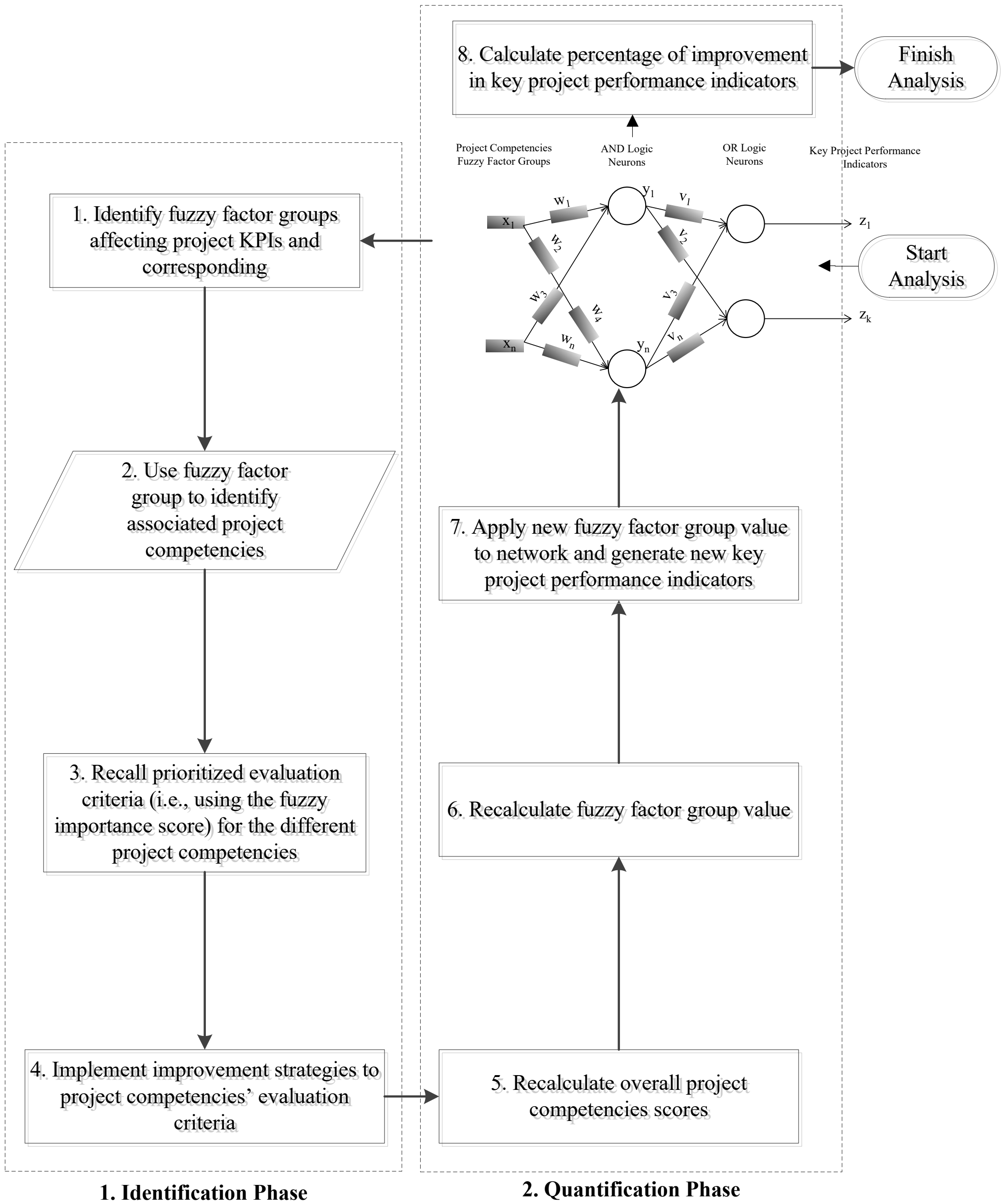


Figure 4-7 Identifying and Quantifying the Relationship between Project Competencies' Evaluation Criteria and Project KPIs

It is important to note that the prioritized relationship between the evaluation criteria of the different project competencies makes it necessary to consider the combined effect of evaluation criteria based on: 1) evaluation criteria importance and, 2) evaluation criteria satisfaction (i.e., maturity or agreement scores). Accordingly, the effect of project competencies' evaluation criteria on project KPIs will vary depending on: 1) the satisfaction scores (i.e., importance, maturity and agreement scores presented in chapter two of this thesis) associated with the prioritized project competencies' evaluation criteria and, 2) the overall fuzzy factor group value, based on the combined score of the different ranked project competencies (i.e., calculated using the fuzzy feature extraction technique described in this chapter) to calculate the fuzzy factor group value.

4.4. Concluding Remarks

This chapter presents a new fuzzy hybrid intelligent model for modeling project competencies and their relationship to project KPIs. The developed fuzzy hybrid intelligent model has the capacity to capture the multidimensional and subjective nature of project competencies' evaluation (i.e., through the application of fuzzy logic) and their relationship to project KPIs (through the application of granular AND/OR FNNs). The developed fuzzy hybrid intelligent model is capable of evaluating project competencies and quantifying the nonlinear relationship between project competencies and project KPIs as presented in the next chapter of this thesis.

The fuzzy hybrid intelligent model consists of three processing units. The first unit is an information fusion processing unit. This unit evaluates project competencies on the higher hierarchical level (i.e., project competency level) rather than the lower hierarchical levels (i.e., evaluation criteria of project competencies). Additionally, this processing unit reduces the number of variables considered for modeling (i.e., 41 project competencies rather than 248 project competencies' evaluation criteria). The second processing unit is the dimensionality reduction processing unit. A new fuzzy feature extraction technique is applied to perform an intermediate ranking, grouping and structuring of project competencies while preserving their fuzziness. The third processing unit is the granular AND/OR fuzzy neural networks (Pedrycz 2014). The granular AND/OR fuzzy neural networks are used to identify the relationship between project competencies, expressed by fuzzy factor groups, and project KPIs. Finally, the ability of the presented fuzzy hybrid intelligent model to determine the effect of lower hierarchical levels (i.e., project competencies' evaluation criteria) on the different project KPIs is presented. Chapter five presents an assessment of the fuzzy hybrid intelligent model using actual data collected from seven construction projects. Additionally, examination of the granular FNN performance against conventional ANNs and FNNs is performed.

4.5. References

Alroomi, A., Jeong, D. H. S., and Oberlender, G. D. (2011). "Analysis of cost-estimating competencies using criticality matrix and factor analysis." *J.Constr.Eng.Manage*., 138(11), 1270-1280.

Alvisi, S., & Franchini, M. (2011). Fuzzy neural networks for water level and discharge forecasting with uncertainty. *Environmental Modelling & Software*,*26*(4), 523-537.

Chen, S. H., (1984). “On the theory of operating, ranking, and estimating fuzzy numbers and its application”, Thesis for Doctor of Science, Tamkang University

Comon, P. (1994). Independent component analysis, a new concept?. *Signal processing*, *36*(3), 287-314.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation,10*(7).

Devijver, P. A., & Kittler, J. (1982). *Pattern recognition: A statistical approach* (Vol. 761). London: Prentice-Hall, Englewood Cliffs, NJ.

Dissanayake, M., Fayek, A. R., Russell, A. D., & Pedrycz, W. (2005). A hybrid neural network for predicting construction labour productivity. In*Proceedings of the International Conference on Computing in Civil Engineering, Cancun, Mex* (pp. 12-15).

Dissanayake, M (2006). “An integrated computational intelligence framework for construction performance diagnosis”, Thesis for Doctor of Science, University of Alberta.

DiStefano, C., Zhu, M., & Mindrila, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. Practical Assessment, Research & Evaluation, 14(20), 1-11.

Drew, P. J., & Monson, J. R. (2000). Artificial neural networks. *Surgery*, *127*(1), 3-11.

Dumais, Susan T. (2004). "Latent semantic analysis." *Annual review of information science and technology* (38.1): 188-230.

Fayek, A. Robinson. (2012). Advancing fuzzy hybrid techniques for competency modeling of construction organizations. *NSERC Discovery Grant Application* 2013-2017.

Field, A. (2005). Discovering statistics using SPSS , Sage, Thousand Oaks, CA.

Geng, X., Zhan, D. C., & Zhou, Z. H. (2005). Supervised nonlinear dimensionality reduction for visualization and classification. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, *35*(6), 1098-1107.

Ghiasi, M. M., Bahadori, A., & Zendehboudi, S. (2014). Estimation of triethylene glycol (TEG) purity in natural gas dehydration units using fuzzy neural network. *Journal of Natural Gas Science and Engineering*, *17*, 26-32.

Gupta, M. M. (1994). "Fuzzy Neural Networks: theory and applications." Proceedings of SPIE 1994, *The International Society for Optical Engineering*, 303-325

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, *2*(5), 359-366.

Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: theory and applications. *Neurocomputing*, *70*(1-3), 489-501.

Hyvärinen, A., Karhunen, J., & Oja, E. (2004). *Independent component analysis* (Vol. 46). John Wiley & Sons. NY.

Izenman, A. J. (2008). Linear discriminant analysis. In *Modern Multivariate Statistical Techniques* (pp. 237-280). Springer New York.

Jang, J. S. R. (1993). ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, *23*(3), 665-685.

Kasabov, N. (2001). Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, *31*(6), 902-918.

Kumar, A. C. (2009). Analysis of unsupervised dimensionality reduction techniques. *Computer science and information systems*, *6*(2), 217-227.

Leng, G., McGinnity, T. M., & Prasad, G. (2005). An approach for on-line extraction of fuzzy rules using a self-organising fuzzy neural network. *Fuzzy sets and systems*, *150*(2), 211-243.

Li, H., Chen, B., Zhou, Q., & Qian, W. (2009). Robust stability for uncertain delayed fuzzy Hopfield neural networks with Markovian jumping parameters. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*,*39*(1), 94-102.

Lin, D., Wang, X., Nian, F., & Zhang, Y. (2010). Dynamic fuzzy neural networks modeling and adaptive backstepping tracking control of uncertain chaotic systems. *Neurocomputing*, *73*(16), 2873-2881.

Mahabir, C., Hicks, F., & Fayek, A. R. (2006). Neuro-fuzzy river ice breakup forecasting system. *Cold regions science and technology*, *46*(2), 100-112.

Omar, M. and Fayek, A. Robinson. (2015). “Modeling and Evaluating Construction Project Competencies and Their Relationship to Project Performance.” Submitted for publication in *Journal of Automation in Construction*. Manuscript, 53 pages.

Pedrycz, W., and Gomide, F. (2007). *Fuzzy systems engineering: toward human-centric computing.* John Wiley & Sons.

Pedrycz, W. (2014). "Allocation of information granularity in optimization and decision-making models: towards building the foundations of granular computing." *Eur.J.Oper.Res.,* 232(1), 137-145.

Pinson, P., & Kariniotakis, G. N. (2003, June). Wind power forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment. In *Power Tech Conference Proceedings, 2003 IEEE Bologna* (Vol. 2, pp. 8-pp). IEEE.

Rencher, A. C. (2002). *Methods of multivariate analaysis.* John Wiley & Sons, New York.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. American Psychological Association.

Wu, S., & Er, M. J. (2000). Dynamic fuzzy neural networks-a novel approach to function approximation. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 30(2), 358-364.

Yu, W. D., & Skibniewski, M. J. (2009). Integrating neurofuzzy system with conceptual cost estimation to discover cost-related knowledge from residential construction projects. *Journal of Computing in Civil Engineering*, *24*(1), 35-44.

Zadeh, L. A. (1965). "Fuzzy sets." *Information and Control,* 8(3), 338-353.

CHAPTER 5. – Evaluating and Modeling Construction Project Competencies and Their Relationship to Project Performance: Model Development [1]

5.1. Introduction

The fuzzy hybrid intelligent model developed in the preceding chapter (i.e., chapter four) is applied, using data collected from seven construction projects, to examine its capacity to dynamically evaluate and quantify the effect of project competencies' evaluation criteria on the different project KPIs. A summary of the data collected from seven construction projects is first presented. Project competencies' evaluation criteria are then ranked based on the data collected from the seven construction projects as a prerequisite for performing the prioritized fuzzy aggregation. The prioritized fuzzy aggregation method, presented in chapter three of this thesis, is then applied to produce informative evaluation of the different project competencies on the higher hierarchical levels (i.e., project competency level) rather than the lower hierarchical levels (i.e., project competencies' evaluation criteria level) for the seven construction projects. The different project competencies are then analysed using factor analysis to calculate fuzzy factor groups for the granular AND/OR FNNs. The relationship between the effect of project competencies, expressed by fuzzy factor groups, and project KPIs is identified using the granular AND/OR FNNs. Finally, the developed fuzzy hybrid intelligent model is used to examine the effect of the different project competencies' evaluation criteria on project KPIs.

5.2. Data Summary

Several construction companies in Alberta, Canada were invited to participate in this study. Six companies expressed interest in the study. The six construction companies assigned seven

[1] Parts of this chapter have been submitted for publication in Automation in Construction. Omar, M. and Fayek, A. Robinson. (2015). "Modeling and Evaluating Construction Project Competencies and Their Relationship to Project Performance." Manuscript, 53 pages.

construction projects to have the study conducted at. Four of the projects provided by the companies were commercial projects and three were heavy industrial projects. Data collected from all seven construction projects participating in this study were used for analysis and fuzzy hybrid intelligent model development. Table 5-1 displays the key information for the seven construction projects.

Table 5-1 Key Information on Construction Projects Participating in Study

Project Number	Project Type	Project Budget (Million $ CAD)	Overall Project Percentage Complete at Time of Data Collection	Functional Competencies Surveys Collected	Behavioural Competencies Surveys Collected	Number of Project KPIs Collected
1	Commercial	32	25.00%	1	1. Supervisors:4 2. Self-evaluations:9	13
2	Commercial	50	58.00%	2	1. Supervisors:4 2. Self-evaluations:10	11
3	Commercial	68	25.00%	2	1. Supervisors:5 2. Self-evaluations: 37	12
4	Commercial	2.1	70.00%	1	1. Supervisors:2 2. Self-evaluations:7	10
5	Industrial	1,430	21.40%	5	1. Supervisors: 6 2. Self-evaluations: 14	27
6	Industrial	1,365	98.76%	5	1. Supervisors: 5 2. Self-evaluations: 12	28
7	Industrial	130	90.00%	2	1. Supervisors: 4 2. Self-evaluations:36	17
Total Number of Surveys Collected				18	1. Supervisors: 30 2. Self-evaluations:125	

A stratified random sampling approach was used at each construction project to identify the number of respondents to complete the functional and behavioural competencies surveys. A total of 18 functional competencies surveys and 155 behavioural competencies surveys were collected from the seven construction projects. Out of the 155 behavioural competencies surveys, 30 supervisors' behavioural competencies surveys were considered for analysis and 125 surveys were collected to ensure consistency between the supervisors' evaluations and their respective teams' self-evaluations using the Cronbach's reliability test as described earlier in chapter two of this thesis. None of the supervisors' surveys were excluded from the analysis (i.e., Cronbach's reliability test results ranged from 0.71 to 0.99). As for the project KPIs, 10 project KPIs were collected consistently from the seven construction projects. The fuzzy hybrid intelligent model structure –presented in chapter four- is used to identify project competencies at the lowest level (i.e., project competencies' evaluation criteria) that affect the different project KPIs as presented next.

5.3. Information Fusion Processing Unit: Application of the New Prioritized Fuzzy Aggregation Method

The steps for conducting the prioritized fuzzy aggregation (i.e., first processing unit) are presented in Figure 5-1.

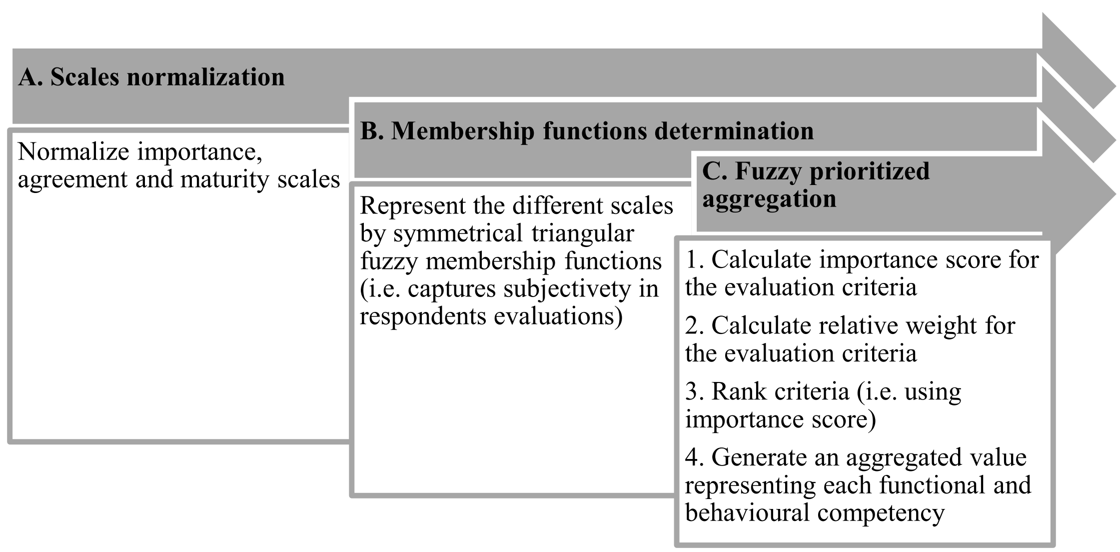


Figure 5-1 Prioritized Fuzzy Aggregation for Project Competencies (Omar and Fayek 2015a)

First, symmetrical triangular fuzzy numbers representing the different normalized importance, maturity and, agreement scales are developed (Pedrycz 1994; Omar and Fayek

2015b) as shown in Figures 5-2 to 5-4 respectively. As discussed earlier, the use of normalized measures is considered to avoid a situation where a given project competency evaluation criterion with a greater value dominates other evaluation criteria with smaller values.

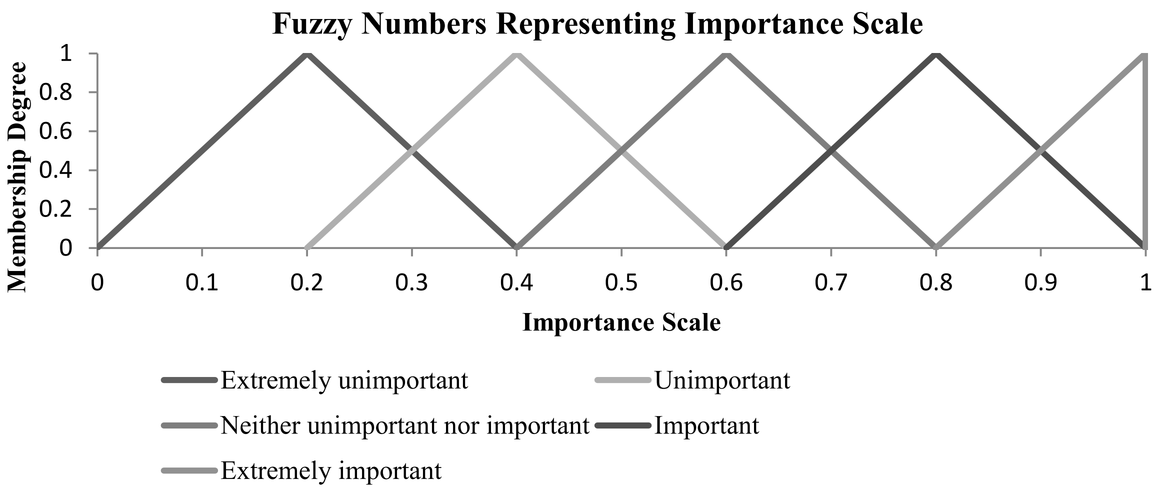


Figure 5-2 Fuzzy Numbers Representing Importance Scale

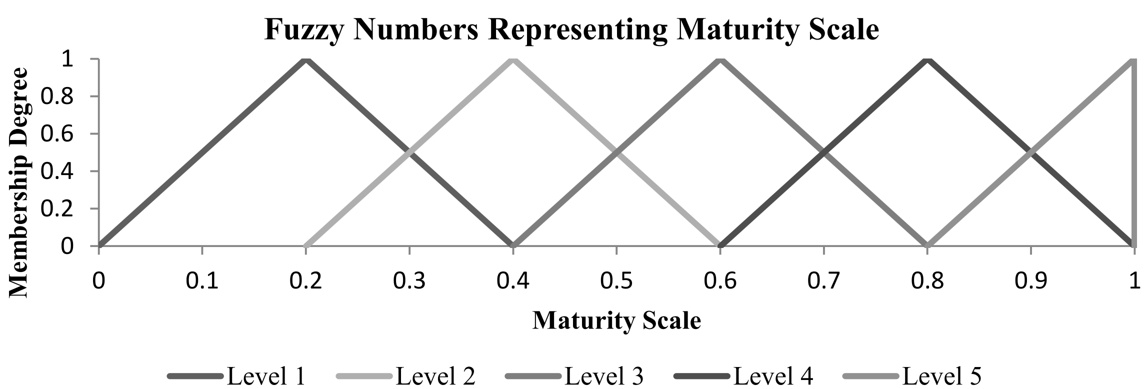


Figure 5-3 Fuzzy Numbers Representing Maturity Scale

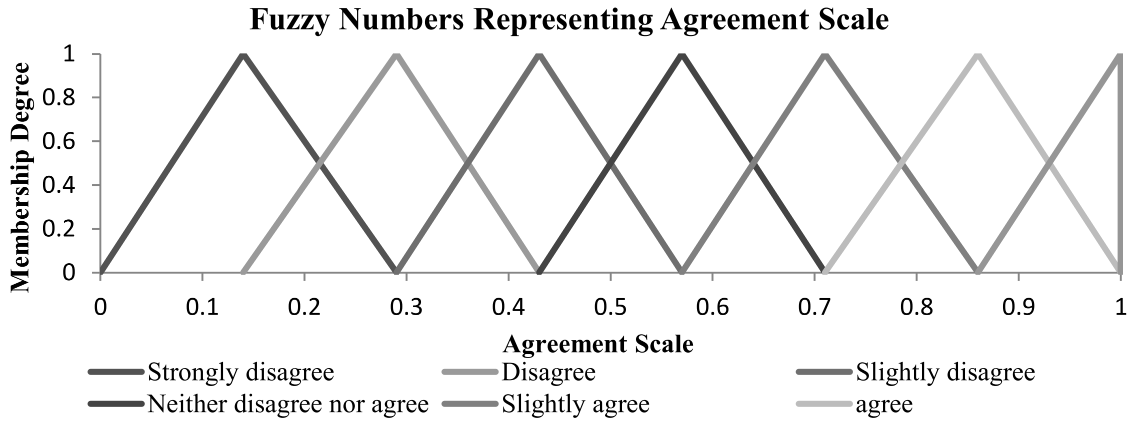


Figure 5-4 Fuzzy Numbers Representing Agreement Scale

Second, the importance score for each evaluation criteria is calculated. The calculation of the importance score is based on the total number of surveys (i.e., 18 functional competencies surveys to evaluate functional competencies' evaluation criteria and 30 supervisors' behavioural competencies surveys to evaluate behavioural competencies' evaluation criteria) collected from the seven construction projects. The determination of the importance score for each evaluation criteria enables proper ranking and relative weight calculation based on all survey respondents' evaluations as presented next.

Considering, for example, the three evaluation criteria presented in Table 5-2, the fuzzy relative importance score *(FRIS)* for evaluation criterion "4.1.Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" is calculated, as described earlier in chapter three, as shown in Eq. (5-1).

Table 5-2 Examples of Evaluation Criteria for "Project Cost Management" Functional Competency

4. Project Cost Management
4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
4.7. A cash flow analysis is regularly carried out to monitor the financial status of the project.
4.8. Updated cash flow with changes to the cost baseline is regularly conducted.

$$FRIS_{4.1} = \frac{(0*(0.0\ 0.2,0.4))+(0*(0.2\ 0.4,0.6))+(2*(0.4\ 0.6,0.8))+(2*(0.6,0.8,1.0)+(14*(\ 0.8,1.0,1.0))}{(\ 0.8,1.0,1.0)*(0+0+2+2+14)} = (0.73, 0.93, 0.98) \quad (5\text{-}1)$$

Once the *FRIS* score is calculated for the different evaluation criteria, the fuzzy relative weight *(FRW)* for each evaluation criterion is calculated as shown in Eq. (5-2).

$$FRW_{4.1} = \frac{(0.73,0.93,0.98)}{(0.73,0.93,0.98)+(0.43,0.57,0.71)+(0.43,0.68,0.80)} = (0.29, 0.41, 0.62) \quad (5\text{-}2)$$

The *FRIS*s and *FRWs* for the "Project Cost Management" competency three evaluation criteria are listed in Table 5-3. Samples of the functional and behavioural competencies' evaluation criteria's *FRIS* and *FRW* are presented in Appendix 2.1 and 2.2 respectively.

Table 5-3 Sample Prioritized Fuzzy Aggregation *FRISs* and *FRWs*

Functional Competency/Evaluation Criteria	**Fuzzy Relative Importance Score ($FRIS$) (Based on all respondents)**	**Fuzzy Relative Weight (FRW) (Based on all respondents)**
4. Project Cost Management		
4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.73, 0.93, 0.98)	(0.28, 0.41, 0.62)
4.7. A cash flow analysis is regularly carried out to monitor the financial status of the project.	(0.43, 0.75, 0.87)	(0.16, 0.32, 0.51)
4.8. Updated cash flow with changes to the cost baseline is regularly conducted.	(0.43, 0.57, 0.71)	(0.14, 0.27, 0.47)

For the criteria listed in Table 5-3, the *FRISs* and maturity scores are considered as fuzzy coordinates. Fuzzy TOPSIS is then applied to determine the prioritized scoring operator (T_i) and calculate the adjusted *FRWs* to be used for the prioritized aggregation.

First, each criterion is measured against its fuzzy positive ideal solution (*FPIS)* and fuzzy negative ideal solution (*FNIS)*. The *FPIS* for the project cost management three evaluation criteria is A^{+} = [(0.73, 0.93, 0.98), (0.80, 1.00, 1.00)]. The *FNIS* for the for the project cost management three evaluation criteria is A^{-} = [(0.43, 0.57, 0.71), (0.00, 0.20, 0.40)].

For the "4.1.Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" criterion, the fuzzy coordinates representing *FRIS* and maturity score respectively are [(0.73, 0.93, 0.98), (0.40, 0.60, 0.80)]. The positive distance (d^{+}) and negative distance (d^{-}) are calculated following the normalized Euclidian method as presented in Eq. (5-3) and (5-4) respectively.

$$d_i{}^{+} = \sqrt{\frac{1}{3}\left[(0.73-0.73)^2+(0.93-0.93)^2+(0.98-0.98)^2\right]+\frac{1}{3}\left[(0.80-0.40)^2+(1.00-0.60)^2+(1.00-0.80)^2\right]} = 0.35. \quad (5\text{-}3)$$

$$d_i{}^{-} = \sqrt{\frac{1}{3}\left[(0.73-0.43)^2+(0.93-0.57)^2+(0.98-0.71)^2\right]+\frac{1}{3}\left[(0.40-0.00)^2+(0.60-0.20)^2+(0.80-0.20)^2\right]} = 0.57 \quad (5\text{-}4)$$

Next, a closeness coefficient (CC_1) is calculated for "4.1.Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" as shown in Eq. (5-5).

$$CC_{4.1} = \frac{0.57}{0.35+0.57} = 0.62 \quad (5\text{-}5)$$

The calculated CC_1 is then used to generate T for adjusting the prioritized criterion's FRW using Eq. (5-6).

$$T_{4.1} = 1 * 0.62 = 0.62 \tag{5-6}$$

For "4.1.Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams", $FRW_1{}'$ is calculated using Eq. (5-7).

$$FRW_{4.1}{}' = 0.62 \otimes (0.29, 0.41, 0.62) = (0.18, 0.25, 0.38) \tag{5-7}$$

The $FRWs'$ for the project cost management evaluation criteria are listed in Table 5-4.

Table 5-4 $FRWs'$ and T_i Values for Project Cost Management

Functional Competency/Evaluation Criteria	**Evaluation Criteria Prioritized Scoring Operator ($\boldsymbol{T_i}$)**	**Fuzzy Relative Weight ($\boldsymbol{FRW}$)**	**Adjusted Fuzzy Relative Weight ($\boldsymbol{FRW'}$)**
4. Project Cost Management			
4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	0.62	(0.29, 0.41, 0.62)	(0.18, 0.25, 0.38)
4.7. A cash flow analysis is regularly carried out to monitor the financial status of the project.	0.46	(0.14, 0.38, 0.56)	(0.06, 0.17, 0.26)
4.8. Updated cash flow with changes to the cost baseline is regularly conducted.	0.38	(0.08, 0.20, 0.36)	(0.00, 0.08, 0.14)

Finally, a Fuzzy Prioritized Weighted Average *(FPWA)* operator is used, as described in chapter three, to provide a collective value representing the project cost management functional competency using Eq. (5-8).

$$FPWA = \big((0.18, 0.25, 0.38) \otimes (0.40, 0.60,0.80)\big) \oplus \big((0.06, 0.17, 0.26) \otimes (0.60,0.80,1.00)\big) \oplus \big((0.00,0.08,0.14) \otimes (0.80,1.00,1.00)\big) = (0.11, 0.37\ 0.70) \quad (5\text{-}8)$$

The evaluation criteria for the different functional and behavioural competencies are aggregated similar to the example presented above to calculate project competencies' evaluations on the higher hierarchical levels (i.e., project competency level) rather than the lower hierarchical levels (i.e., project competencies' evaluation criteria level). These aggregated values are presented as a fuzzy number (i.e., as shown in Eq. (5-8)). The evaluation of each respondent is then defuzzified, using the centroid method, to generate crisp evaluations for the different project competencies to perform dimensionality reduction (i.e., factor analysis) as discussed next.

5.4. Dimensionality Reduction Processing Unit: Application of the New Fuzzy Feature Extraction Technique

Once the different project competencies per respondent are defuzzified, the correlation matrix, anti-image and Kaiser-Meyer-Olkin (KMO) tests are first conducted to examine the suitability of data for performing a factor analysis. SPSS 22 is used to perform the preliminary tests to evaluate the suitability of the collected functional and behavioural competencies data (i.e., respondents' surveys) to perform factor analysis (Alroomi et al. 2011).

5.4.1. Correlation Matrix for Project Competencies

The correlation matrix investigates the relationship between the different project competencies. First, Pearson correlation coefficients are used to measure the strength of the relationship between project competencies. The correlation coefficients can vary numerically between 0.0 and 1.0. The closer the correlation is to 1.0, the stronger the relationship between the two variables. A correlation of 0.0 indicates the absence of a relationship. If the correlation coefficient is 1.0, it indicates the presence of a perfect relationship between the two variables. The correlation coefficients' sign indicates the type of relationship. For any two project competencies, a positive correlation coefficient means that as one project competency increases, the second project competency increases, and conversely, as one project competency decreases, the second project competency decreases. In other words, the two project competencies move in the same direction when there is a positive correlation. A negative correlation means that as one project competency increase, the second project competency decreases and vice versa.

For the functional competencies, a correlation matrix is calculated using the 18 functional competencies surveys collected from the seven construction projects (i.e., See appendix 2.3). The matrix values ranges from 0.017 to 0.918. The positive correlation coefficients indicate that all functional competencies increase in the same direction.

For the behavioural competencies, a correlation matrix is calculated using the 30 behavioural competencies surveys collected from the seven construction projects (i.e., See appendix 2.4). The matrix values ranges from 0.094 to 0.835. The positive correlation coefficients indicate that all behavioural competencies increase in the same direction.

5.4.2. Anti-Image Matrix for Project Competencies

The anti-image correlation matrix provides a measure of the sample adequacy to perform factor analysis. The measure of the sample adequacy (MSA) assists in identifying project competencies that should be eliminated prior to performing factor analysis.

For the functional competencies, the anti-image correlation matrix shows that the measure of the sample adequacy (MSA) for all functional competencies ranges from 0.565–0.985 (≥ 0.5) (Field 2005), which indicates that none of the functional competencies needs to be eliminated and conducting factor analysis is appropriate (i.e., See appendix 2.5).

For the behavioural competencies, the anti-image correlation matrix shows that the measure of the sample adequacy (MSA) for all behavioral competencies ranges from 0.505–0.957 (≥ 0.5) (Field 2005), which indicates that none of the behavioural competencies needs to be eliminated and conducting factor analysis is appropriate (i.e., See appendix 2.6).

5.4.3. Kaiser-Meyer-Olkin Test for Project Competencies

The Kaiser-Meyer-Olkin (KMO) test is used to examine whether the correlation pattern between project competencies are suitable for factor analysis or not. KMO values greater than 0.6 are considered acceptable for performing factor analysis (Alroomi et al. 2011)

For the functional competencies, the result of the KMO test is 0.774 (≥0.6). The results indicate that the correlation pattern between functional competencies is suitable for conducting factor analysis.

For the behavioural competencies, the result of the KMO test is 0.643 (≥0.6). The results indicate that the correlation pattern between behavioural competencies is suitable for conducting factor analysis.

5.4.4. Factor Analysis for Project Competencies

Factor analysis is performed for the functional and behavioural competencies respectively. The varimax rotation is used to maximize high correlations and minimize low correlations between project competencies. The varimax rotation method is applied in order to enhance the interpretability of the factor analysis results (Field 2005; Alroomi et al. 2011). According to Kaiser's criteria, ranking the eigenvalues, after the varimax rotation, for each factor group from largest to smallest is first conducted, and then factor groups of eigenvalue greater than 1.0 are retained.

Factor analysis was first performed for the functional competencies. Four factor groups have eigenvalues greater than 1.0 for the functional competencies, which is the suggested number of factor groups to be retained. Table 5-5 lists the results of the factor analysis results for the functional competencies.

Table 5-5 Total Variance for Functional Competencies Factor Groups after Varimax Rotation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Varimax Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.575	59.880	59.880	12.575	59.880	59.880	6.423	30.586	30.586
2	2.071	9.862	69.742	2.071	9.862	69.742	5.835	27.785	58.371
3	1.862	8.868	78.609	1.862	8.868	78.609	2.868	13.659	72.030
4	1.416	6.744	85.353	1.416	6.744	85.3536	2.798	13.323	85.353
5	0.894	4.255	89.608						
6	0.725	3.452	93.060						
7	.438	2.048	95.143						
8	.297	1.416	96.560						
9	.210	.998	97.558						
10	.159	.758	98.316						
11	.119	.568	98.884						
12	.103	.490	99.375						
13	.058	.276	99.651						
14	.042	.198	99.849						
15	.022	.103	99.952						
16	.010	.048	100.000						
17	3.310E-16	1.576E-15	100.000						
18	2.903E-16	1.382E-15	100.000						
19	1.721E-16	8.195E-16	100.000						
20	6.022E-18	2.868E-17	100.000						
21	-3.377E-16	-1.608E-15	100.000						

The four functional competencies' factor groups explain 85.35% of the total variance in the data used for factor analysis. According to Rencher (2002), factor group loadings less than ±0.40 are removed because they are considered insignificant for factor group interpretation. The functional competencies within each factor group with factor loading values above the predefined cut-off value (i.e., ±0.40) are included in the computations of the project competencies' coefficients. The final factor groups and calculated functional competencies' coefficients are listed in Table 5-6.

Table 5-6 Functional Competencies Factor Groups and Coefficients

Factor Group	Factor Group	Rank	Project Competencies' Coefficients
Functional Competencies Factor Group 1 (x_1)	13.Project Stakeholders Management	1	0.097
	16.Project Innovation	2	0.095
	11.Project Quality Management	3	0.094
	12.Project Change Management	4	0.093
	18.Project Contract Administration	5	0.093
	19.Project Team Building	6	0.088
	20.Project Workforce Development	7	0.087
	14.Project Environmental Management	8	0.086
	8.Project Communication Management	9	0.080
	15.Project Commissioning and Startup	10	0.079
	17.Project Workface Planning	11	0.058
	9.Project Safety Management	12	0.051
Functional Competencies Factor Group 2 (x_2)	4.Project Cost Management	1	0.101
	2.Project Scope Management	2	0.099
	1.Project Integration Management	3	0.099
	6.Project Resource Management	4	0.092
	3.Project Time Management	5	0.086
	17.Project Workface Planning	6	0.082
	7.Project Risk Management	7	0.082
	14.Project Environmental Management	8	0.076
	9.Project Safety Management	9	0.072
	15.Project Commissioning and Startup	10	0.070
	11.Project Quality Management	11	0.065
	18.Project Contract Administration	12	0.053
Functional Competencies Factor Group 3 (x_3)	5.Project Engineering and Procurement Management	1	0.306
	20.Project Workforce Development	2	0.201
	7.Project Risk Management	3	0.180
	17.Project Workface Planning	4	0.174
Functional Competencies Factor Group 4 (x_4)	10.Project Human Resource Management	1	0.260
	21.Project Technology Integration	2	0.249
	6.Project Resource Management	3	0.165
	3.Project Time Management	4	0.160

Factor analysis was then performed for the behavioural competencies. Three factor groups have eigenvalues greater than 1.0 for the behavioural competencies, which is the suggested number of factor groups to be retained. These three behavioural competencies' factor groups explain 73.69% of the total variance in the data used for factor analysis. Table 5-7 lists the results of the factor analysis for the behavioural competencies.

Table 5-7 Total Variance for Behavioural Competencies Factor Groups after Varimax Rotation

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Varimax Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.011	60.057	60.057	12.011	60.057	60.057	6.467	32.333	32.333
2	1.535	7.673	67.730	1.535	7.673	67.730	5.466	27.331	59.664
3	1.193	5.964	73.694	1.193	5.964	73.694	2.806	14.030	73.694
4	.912	4.562	78.256						
5	.765	3.824	82.080						
6	.705	3.524	85.604						
7	.556	2.778	88.381						
8	.505	2.527	90.908						
9	.475	2.374	93.282						
10	.276	1.382	94.664						
11	.250	1.251	95.915						
12	.189	.943	96.858						
13	.144	.721	97.580						
14	.127	.634	98.214						
15	.119	.593	98.807						
16	.098	.492	99.299						
17	.058	.292	99.591						
18	.041	.206	99.797						
19	.027	.137	99.934						
20	.013	.066	100.000						

Similar to the functional competencies, behavioural competencies within each factor group with loading values above the predefined cut-off value (i.e., ±0.40) are included in the computations of the factor coefficients. The final factor groups and calculated behavioural competencies' coefficients are listed in Table 5-8.

Table 5-8 Behavioural Competencies Factor Groups and Coefficients

Factor Group	Factor Group	Rank	Project Competencies' Coefficients
Behavioural Competencies Factor Group 1 (x_5)	17.Interpersonal Skills	1	0.106
	10.Ethics	2	0.100
	11.Self-Control	3	0.091
	20.Initiative	4	0.078
	16.Building Trust	5	0.078
	13.Problem Solving	6	0.078
	18.Influence	7	0.077
	8.Motivation	8	0.076
	12.Reliability	9	0.072
	6.Teamwork	10	0.068
	14.Commitment	11	0.068
	1.Analytical Ability	12	0.059
	3.Assessment Ability	13	0.05
Behavioural Competencies Factor Group 2 (x_6)	19.Cultural Competence	1	0.117
	15.Adaptability	2	0.113
	9.Negotiation and Crisis Resolution	3	0.100
	7.Consultation	4	0.086
	16.Building Trust	5	0.086
	5.Leadership	6	0.073
	18.Influence	7	0.073
	6.Teamwork	8	0.073
	20.Initiative	9	0.072
	8.Motivation	10	0.072
	13.Problem Solving	11	0.068
	12.Reliability	12	0.066
Behavioural Competencies Factor Group 3 (x_7)	2.Training	1	0.348
	4.Decision Making	2	0.289
	1.Analytical Ability	3	0.200
	13.Problem Solving	4	0.163

5.4.5. Project Competencies Fuzzy Factor Groups Calculation

As described in chapter four of this thesis, once the different project competencies are clustered into factor groups and the factor coefficients for each factor group is calculated (i.e., See Table 5-6 and 5-8), the results are used with the results of the prioritized fuzzy aggregation, generated from the first processing unit, to generate fuzzy factor groups using Eq. (5-9).

$$Fuzzy\ Factor\ Group = \sum_{1}^{n}[\lambda * a_i{}^{l},\ \lambda * a_i{}^{m}, \lambda * a_i{}^{u}] \tag{5-9}$$

Where:

A_i is a fuzzy number (i.e., representing an overall evaluation of a project competency for a project) defined by a triplet ($a_i{}^{l}$, $a_i{}^{m}$, $a_i{}^{u}$).

λ is a crisp number representing the factor group coefficient for a given project competency (i.e., identified from factor groups' coefficients).

For example, functional competencies fuzzy factor group 2 (x_2) is calculated using Eq. (5-9) as shown in Table 5-9.

Table 5-9 Fuzzy Factor Group x_2 Value

Project Competency	Project Competency Coefficient	Project Competency Overall Prioritized Fuzzy Aggregated Maturity Score			Fuzzy Factor Group = Project Competency Coefficient * Project Competency Overall Prioritized Fuzzy Aggregated Maturity Score		
4.Project Cost Management	0.101	0.249	0.368	0.502	0.025	0.035	0.051
2.Project Scope Management	0.099	0.079	0.246	0.315	0.008	0.024	0.031
1.Project Integration Management	0.099	0.155	0.183	0.401	0.015	0.018	0.040
6.Project Resource Management	0.092	0.067	0.051	0.196	0.006	0.005	0.018
3.Project Time Management	0.086	0.157	0.293	0.364	0.014	0.025	0.031
17.Project Workface Planning	0.082	0.181	0.306	0.493	0.015	0.025	0.040
7.Project Risk Management	0.082	0.14	0.226	0.344	0.011	0.019	0.028
14.Project Environmental Management	0.076	0.210	0.334	0.502	0.016	0.025	0.038
9.Project Safety Management	0.072	0.154	0.202	0.284	0.011	0.015	0.020
15.Project Commissioning and Startup	0.070	0.277	0.434	0.649	0.019	0.030	0.045
11.Project Quality Management	0.065	0.133	0.209	0.305	0.009	0.014	0.020
18.Project Contract Administration	0.053	0.171	0.254	0.414	0.009	0.013	0.022
Fuzzy Factor Group x_2 value =					**0.158**	**0.248**	**0.385**

Once that the different fuzzy factor groups are calculated for each project, the project KPIs are normalized and tabulated for training and testing the granular AND/OR FNN as described next.

It is important to highlight that 10 project KPIs were consistently collected from the seven construction projects. The project KPIs related to quality, changes, satisfaction and productivity were not consistently collected through the seven projects and were not included in the development of the FNN. As for safety KPIs, data did not exhibit any sensitivity due to lack of variability in the safety KPIs values.

5.5. Granular Fuzzy Network Processing Unit: Application of the Granular AND/OR Fuzzy Neural Network

The generated fuzzy factor groups (i.e., See appendix 2.7) are used as inputs for the model (i.e., Granular AND/OR FNNs), where, a project is considered as one input data set and the collected KPIs for the same project are considered as the output data set. Six data sets (i.e., projects) are considered for training the granular AND/OR FNNs, and one data set (i.e., project) is considered for testing the granular AND/OR FNNs.

When constructing the granular AND/OR FNNs, it is important to consider that complex neural networks do not effectively apply learning algorithms to adjust the synaptic weights of the different layers. The synaptic weight adjustment problem can be avoided by modularizing these neural networks, thereby achieving modular/multiple neural networks which are simpler, smaller in size and, more reliable. The incorporation of *a priori* knowledge is a major advantage for constructing neural networks with multiple outputs (Azam 2000; Dragoni et al. 2009). *A Priori* knowledge allows a better configuration of the network in terms of inputs, hidden layers and outputs (Azam 2000). The configuration is dependent on the problem being modeled and the ability to utilize a priori knowledge to enhance the network functionality by modularizing it (Dragoni et al. 2009).

Following the rationale and justification described by Azam (2000) and Dragoni et al. (2009), it is advantageous to consider a number of modular networks to overcome the limitation of constructing a complex network (i.e., inability to retain knowledge gained by learning algorithms in high complex connections).

Two granular AND/OR FNNs are used to represent the different project KPIs based on the project KPIs measurements (e.g., cost and duration). The first granular AND/OR FNN network is the cost FNN. This FNN captures the different cost-related project KPIs involved in evaluating project performance based on monetary values. The second granular AND/OR FNN network is the schedule FNN. This FNN captures the different schedule-related project KPIs involved in evaluating project performance based on duration values (Rodrigues et al. 2009). Other project KPIs related to quality, changes, satisfaction and productivity were not consistently collected through the seven projects and were not included in the development of the FNNs. As for safety KPIs, the safety granular AND/OR FNN did not exhibit any sensitivity to safety indicators due to lack of variability in the safety indicator values.

The granular AND/OR FNNs structure in terms of the number of logic neurons and layers is adjusted using an iterative process as described by Pedrycz and Gomide (2007). First, a certain structure of the network is assumed based on a priori knowledge of the inputs (i.e., fuzzy factor groups representing functional and behavioural competencies) and outputs (i.e., project KPIs).

The final granular AND/OR FNNs' topology is as follows: fuzzy factor groups are denoted by *{x}*, where, x represents a fuzzy number represented by a triplet ($c_i{}^l$, $c_i{}^m$, $c_i{}^u$) which is the result of both; the prioritized fuzzy aggregation for a given project and the factor analysis discussed earlier in this chapter (i.e., fuzzy factor groups). The weights of the associated connections from the fuzzy factor groups *{x}* to the AND logic neurons are denoted by *{w}* and are randomly generated fuzzy numbers represented by triplets ($w_i{}^l$, $w_i{}^m$, $w_i{}^u$). The weights of the associated connections from the AND logic neurons are denoted by *{v}* and are are randomly generated fuzzy numbers represented by triplets ($v_i{}^l$, $v_i{}^m$, $v_i{}^u$). Finally, the output of the network from the OR logic neurons is defuzzified (i.e., using the centroid method presented in chapter four) and the resulting values {z} are the network outputs (i.e., project KPIs).

The granular AND/OR FNNs were trained using six data sets (i.e., projects), and were tested using one data set (i.e., project). The final network structure for the two FNNs (i.e., cost and schedule granular AND/OR FNNs) is shown in Figure 5-5 and 5-6 respectively. Project competencies, expressed by fuzzy factor groups, having the highest impact on project KPIs are identified from the two granular AND/OR FNNs through the interpretation of the connection weights. For the AND logic neurons, lower values of the connection indicate higher relevance of the corresponding input. For the OR logic neurons, higher values of the connection indicate higher relevance on the corresponding final output. The final connections weights resulting from the AND logic neurons in the cost and schedule granular AND/OR FNNs identify the fuzzy factor groups that affect the different cost and schedule project KPIs respectively.

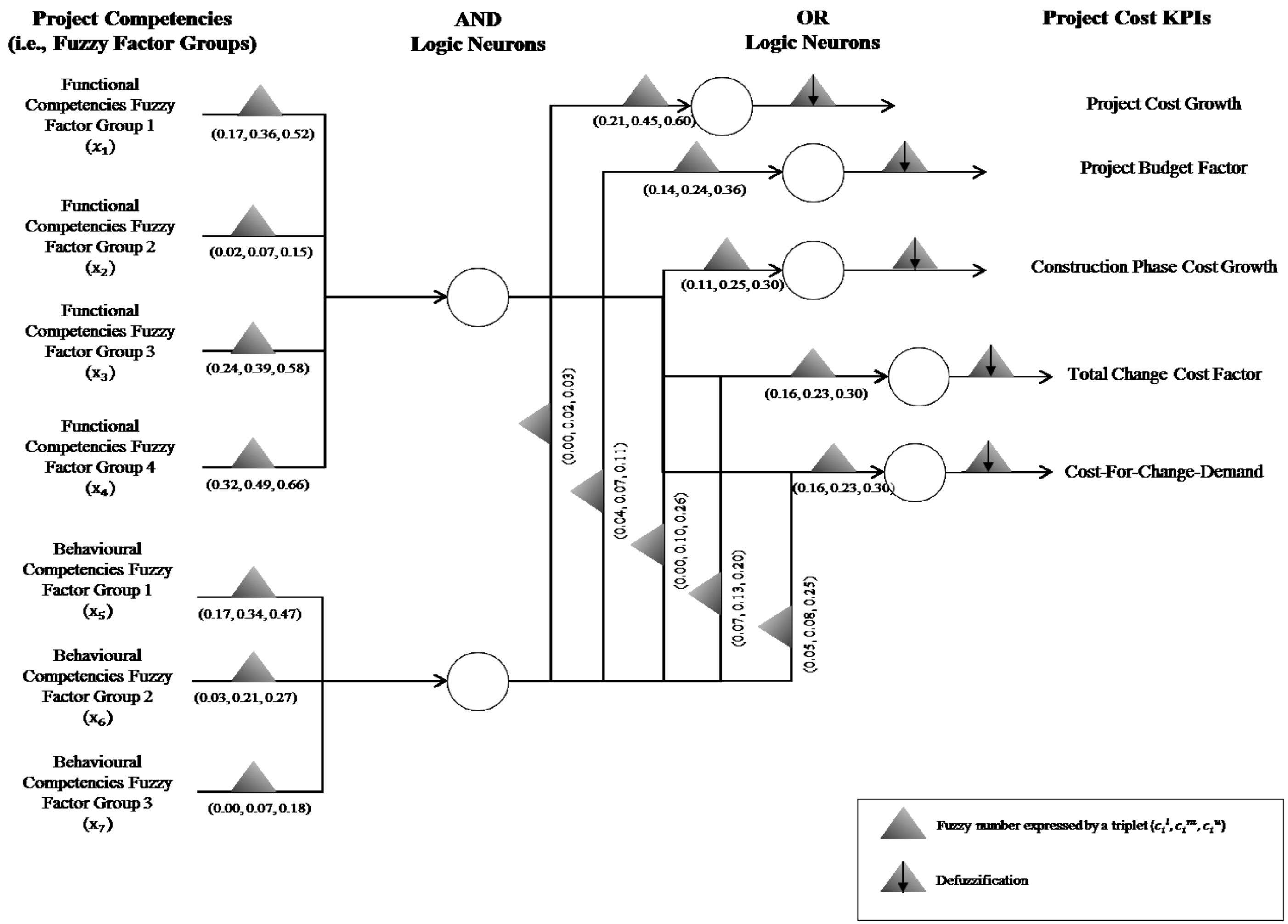


Figure 5-5 Cost AND/OR FNN

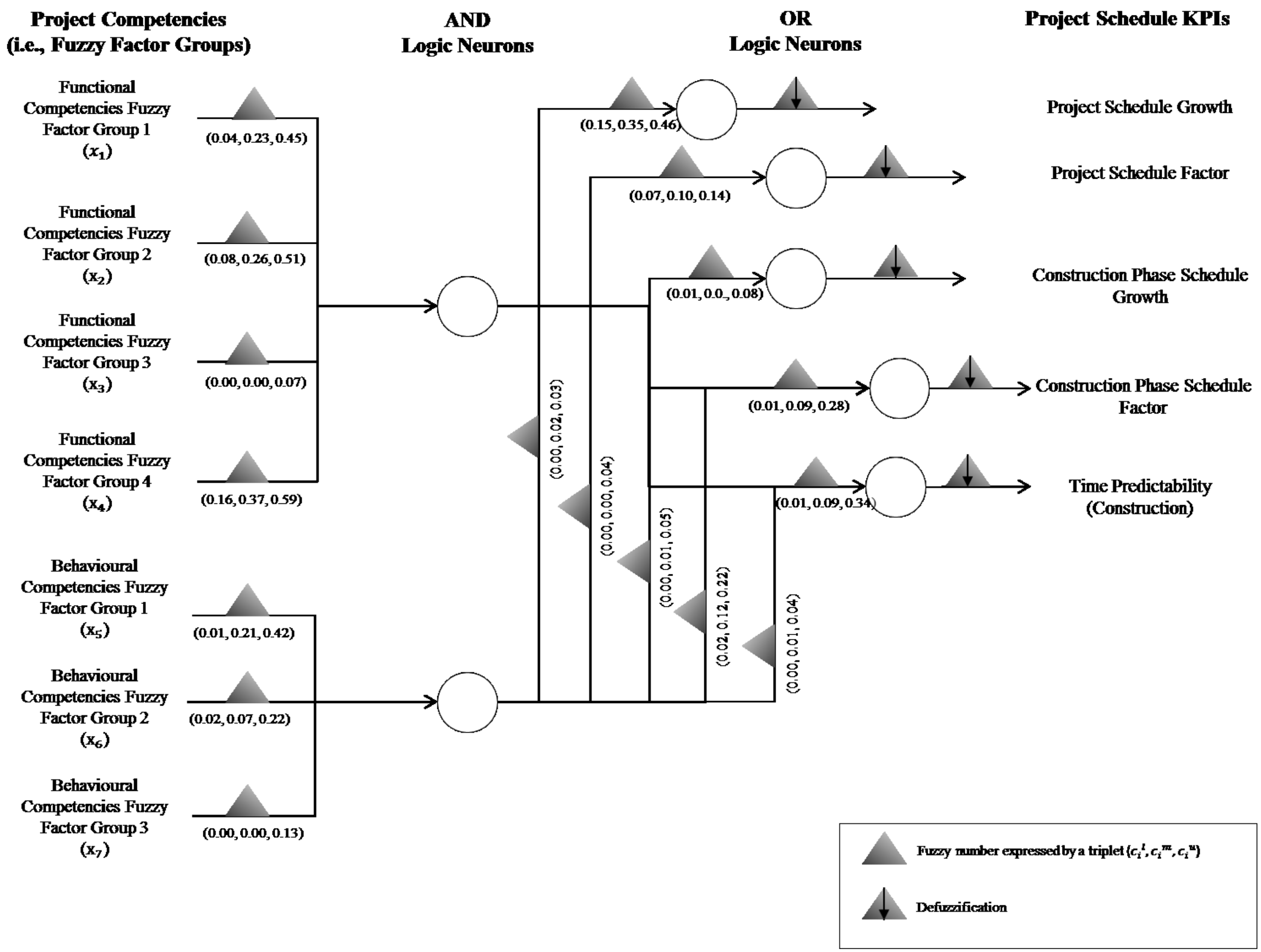


Figure 5-6 Schedule AND/OR FNN

Four different defuzzification methods, as described in chapter four, are examined to identify the one that yields the most accurate results. The smallest of maxima (SOM), middle of maxima (MOM), largest of maxima (LOM), and the centroid methods are used as defuzzification methods. The centroid method is identified as the one that provides the most accurate results (i.e., in terms of global error). The global error of the granular AND/OR FNNs using the SOM, MOM, and LOM ranged from 32.58% to 57.90%. The global error of the granular AND/OR FNNs using the centroid method ranged from 6.16% to 26.19%.

The performance of the network was evaluated using a global error measurement as described in chapter four, where, the network structure is revised by adjusting the number of logic neurons, connections and layers in order to minimize the global error of the network. This process is repeated until acceptable results are achieved (Pedrycz and Gomide 2007; Pedrycz 2014). The final two FNNs (i.e., cost and schedule FNNs) produced a global error for the different project KPIs ranging from 6.16% to 26.19% (Omar and Fayek 2015a).

A validation method is first applied to ensure the accuracy of the developed granular AND/OR FNNs. A leave-one out validation method is applied for validation. This validation method is based on developing an n number of granular AND/OR FNNs, where, n is the number of data sets (i.e., projects) available for training and testing the granular AND/OR FNNs. Each granular AND/OR FNN is repeatedly trained and tested by leaving out a single data set and then using the left-out data set to derive a prediction (Kohavi 1995).

5.5.1. Comparison between ANNs, Conventional FNNs and Granular AND/OR FNNs

The developed granular AND/OR FNNs are compared to: 1) traditional ANNs (Gupta 1994; Drew and Monson 2000) and, 2) conventional FNNs (i.e., as described in chapter four of this thesis) that incorporates fuzzy arithmetic instead of fuzzy operations (i.e., hereafter referred to as FNNs). A cost and schedule ANNs are developed. The cost and schedule ANNs considers crisp weights, crisp factor groups and, unipolar sigmoidal activation functions for generating networks outputs (i.e., project cost and schedule KPIs). Similar to ANNs, a cost and schedule FNNs are developed (Gupta 1994; Alvisi and Franchini 2011). The cost and schedule FNNs considers fuzzy weights, fuzzy factor groups, fuzzy arithmetic and, unipolar sigmoidal activation functions for generating networks outputs (i.e., project cost and schedule KPIs). The three types of networks were trained using six projects and tested using one project. The global error of the three types of networks (i.e., ANNs, FNNs and granular AND/OR FNNs) is presented in Figure 5-7.

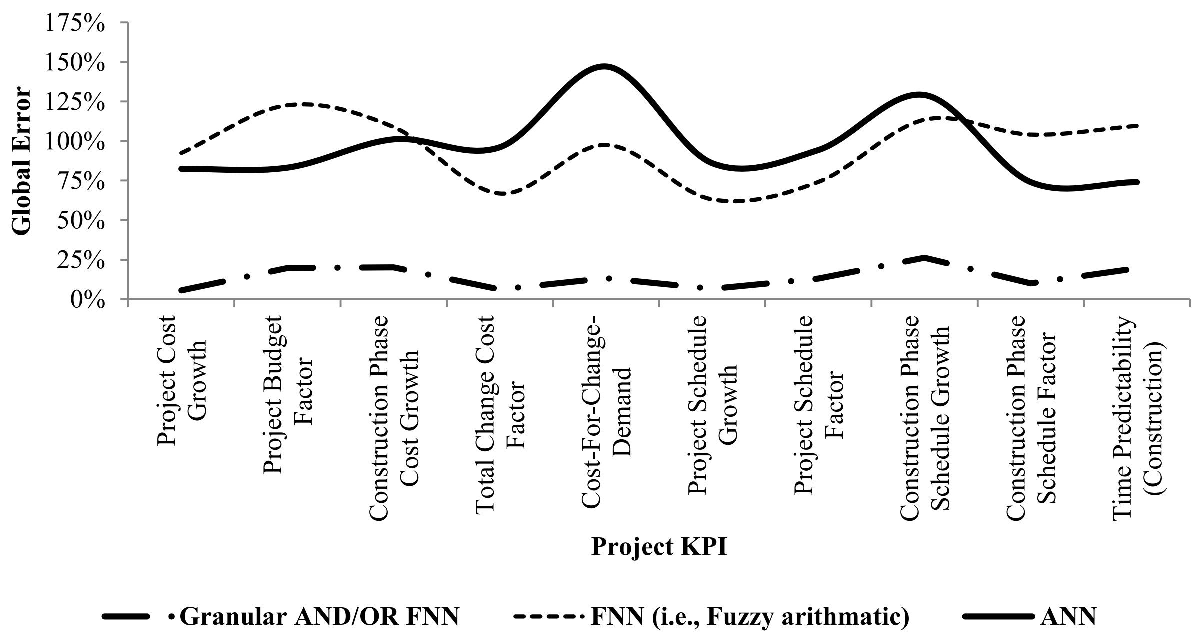


Figure 5-7 ANN, FNN and, Granular AND/OR FNN Global Error

The global error for the cost and schedule ANNs ranges from 74.10% to 147.15%. The global error for the cost and schedule FNNs (i.e., using fuzzy arithmetic) ranges from 66.81% to 122.58%. The global error for the cost and schedule granular AND/OR FNNs ranges from 6.16% to 26.19% (Omar and Fayek 2015a). This comparison illustrates the capacity of granular AND/OR FNNs to process information when limited data are available (Pedrycz 2014).

5.6. Fuzzy Hybrid Intelligent Model Findings and Results

First, fuzzy factor groups having the most significant effect (i.e., connection weights) on the different cost project KPIs are identified from the granular AND/OR FNNs (i.e., Granular fuzzy network processing unit of the fuzzy hybrid intelligent model) through the interpretation of the connection weights.

For the cost granular AND/OR FNN, project competencies, expressed by fuzzy factor groups having the most significant effect on project KPIs are identified as fuzzy factor groups x_2 "Functional Competencies Factor Group 2" and x_7 "Behavioural Competencies Factor Group 3" respectively. For the schedule granular AND/OR FNN, project competencies, expressed by fuzzy factor groups having the most significant effect on project KPIs are identified as fuzzy factor groups x_3 "Functional Competencies Factor Group 3" and x_7 "Behavioural Competencies Factor Group 3" respectively. A detailed list of ranked project competencies belonging to each factor group and the effect of each project competency on the fuzzy factor group is listed in Table 5-6 and 5-8.

Second, the developed cost and schedule granular AND/OR FNNs are further analyzed (i.e., using the information fusion and dimensionality reduction processing units of the fuzzy hybrid intelligent model) to determine the effect of project competencies' evaluation criteria on the different project KPIs. This process is classified into two main phases namely; 1) identification phase and, 2) quantification phase. Figure 5-8 displays the analysis performed to determine which project competencies' evaluation criteria affect the different project KPIs and to quantify the effect, in terms of percentage of improvement, on the different project KPIs.

In the identification phase, fuzzy factor groups, representing the project competencies, are first identified from the granular AND/OR FNN. Then, the project competencies, associated with the fuzzy factor groups, and the prioritized evaluation criteria, within each project competency in a given factor group, are identified from the factor analysis (i.e., project competencies' coefficients representing the contribution of each project competency to the fuzzy factor group listed in Table 5-6 and 5-8) and prioritized fuzzy aggregation respectively (i.e., project competencies' prioritized evaluation criteria representing the effect of each evaluation criterion on the project competency).

In the quantification phase, the effect of the identified fuzzy factor groups on the different project KPIs is measured using the developed granular AND/OR FNNs. The effect of individual project competencies' prioritized evaluation criteria (i.e., one at a time) on project KPIs is performed using sensitivity analysis.

Fuzzy Factor Group	Ranked Project Competency	Project Competency Coefficient
Functional Competencies Factor Group 2 (x_2)	Project Cost Management	0.101
	Project Integration Management	0.099
	Project Scope Management	0.099
	Project Resource Management	0.092
	Project Time Management	0.086
	Project Workface Planning	0.082
	Project Risk Management	0.082
	Project Environmental Management	0.076
	Project Safety Management	0.072
	Project Commissioning and Startup	0.07
	Project Quality Management	0.065
	Project Contract Administration	0.053

No.	Ranked Project Competencies & Evaluation Criteria
4	**Project Cost Management**
4.1	Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
4.7	A cash flow analysis is regularly carried out to monitor the financial status of the project.
4.8	Updated cash flow with changes to the cost baseline is regularly conducted.
…	…..
1	**Project Integration Management**
1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
…	…

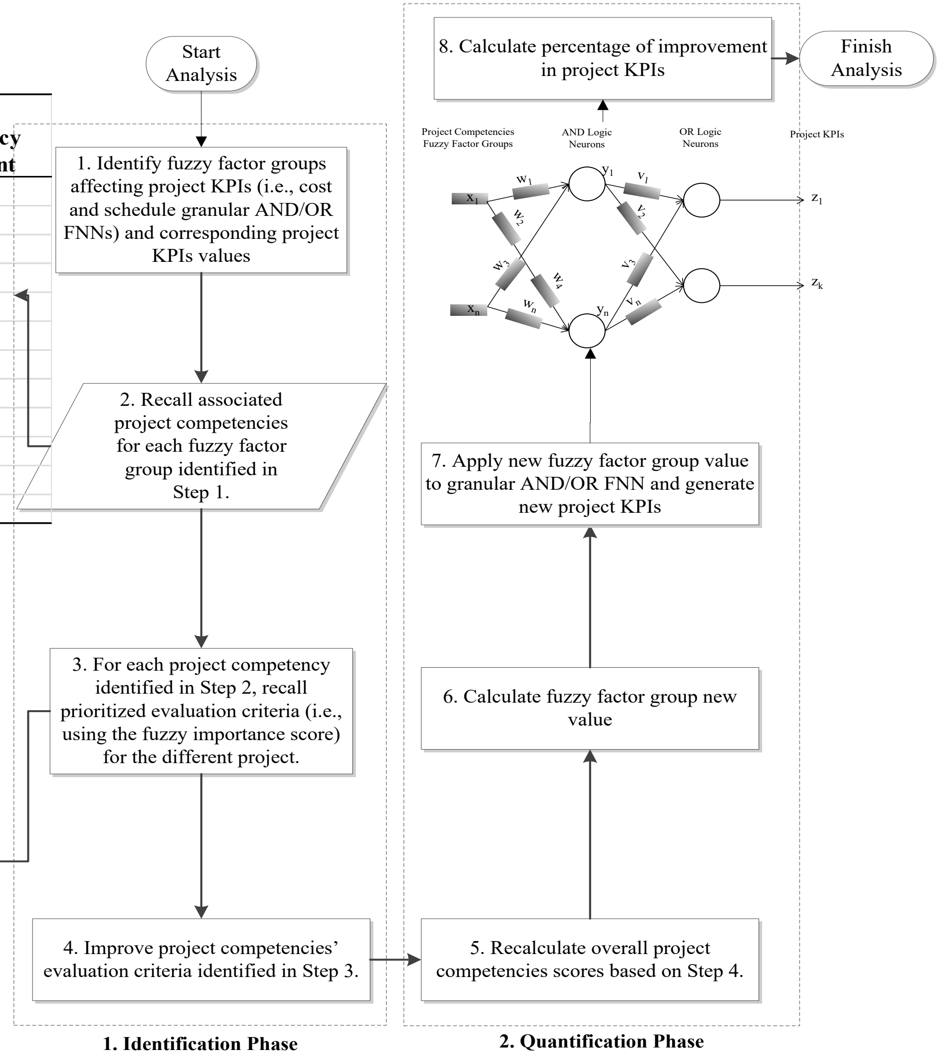


Figure 5-8 Identifying and Quantifying the Relationship between Project Competencies' Evaluation Criteria and Project KPIs

An example is discussed next to demonstrate the ability of the fuzzy hybrid intelligent model to: A) identify and, B) quantify the relationship between project competencies' evaluation criteria and project KPIs.

5.6.1. Identification of Project Competencies' Evaluation Criteria Affecting Project KPIs

The identification phase commences with identifying fuzzy factor groups affecting project KPIs from the granular AND/OR FNNs (as shown in Figures 5-5 and 5-6). The identified fuzzy factor groups are used with the factor analysis results to identify project competencies associated with a given fuzzy factor group (e.g., Fuzzy factor group x_2). For example, fuzzy factor group x_2 "Functional Competencies Factor Group 2" is identified from the cost granular AND/OR FNN to affect the different cost project KPIs. Table 5-8 lists project competencies, their ranking, and, associated project competencies' coefficients (i.e., representing the contribution of each ranked project competency on fuzzy factor group x_2) for fuzzy factor group x_2. For simplicity, the top three evaluation criteria affecting the top three project competency in fuzzy factor group x_2 are considered. It is important to mention that the identified top three evaluation criteria per project competency will influence both; their respective project competency and the fuzzy factor group x_2 (i.e., granular AND/OR FNN input).

As described earlier, a prioritized relationship exists between the evaluation criteria for a given project competency. A high maturity score of a lower priority evaluation criterion for a given project competency will not compensate for a low maturity score of a higher priority evaluation criterion for the same project competency. This prioritized relationship ensures that higher ranked evaluation criteria maturity score have greater impact on the overall evaluation (e.g., overall maturity score) of the project competency. For example, if "Project Cost Management" evaluation criterion "4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" is the highest ranked prioritized evaluation criterion. If this evaluation criterion is not fully satisfied by receiving the highest maturity score (e.g., maturity score = Level 5), then the next highest ranked prioritized evaluation criterion "4.7. A cash flow analysis is regularly carried out to monitor the financial status of the project" impact on "Project Cost Management" competency (e.g., overall maturity score) is reduced. This reduction will accordingly decrease the overall change in fuzzy factor group x_2 value. Moreover, If "Project Cost Management" highest ranked prioritized evaluation criterion "4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" receives the highest maturity score (e.g., maturity score = Level 5), then the next highest ranked prioritized evaluation criterion "4.7. A cash flow analysis is regularly carried out to monitor the financial status of the project." is considered as the highest ranked priority and its effect on fuzzy factor group x_2 value increases.

5.6.2. Quantification of Project Competencies' Evaluation Criteria Effect on Project KPIs

The quantification phase commences after identifying the prioritized evaluation criteria associated with the project competencies for fuzzy factor group x_2. The maturity score for the prioritized evaluation criteria is assessed to quantity the effect of its improvement on the different project cost KPIs. For example, if "Project Cost Management" competency evaluation criterion "4.1. Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams" is evaluated to measure the effect of its improvement on the different project cost KPIs.

Improvement to this evaluation criterion is applied using the maturity measure developed earlier in chapter two of this thesis. Assume the maturity score of a project competency evaluation criterion on the project is improved from maturity level 3 “A disciplined process exists for the practice across the different projects within the same organization” to maturity level 4 ”A quantitative process control is used across the organization to proactively manage the execution of the practice on the project.”. This improvement will change the overall maturity score for “Project Cost Management” competency, using the prioritized fuzzy aggregation results, from (0.249, 0.368, 0.502) as shown in Table 5-9, to (0.265, 0.455, 0.569) as shown in Table 5-10. Fuzzy factor group x_2 value was originally (0.158, 0.248, 0.385) according to “Project Cost Management” overall maturity score = (0.265, 0.368, 0.502). New fuzzy factor group x_2 is (0.160, 0.263, 0.393) according to improved “Project Cost Management” overall maturity score = (0.265, 0.455, 0.569) (i.e., as a result of improving the evaluation criterion from maturity level 3 to maturity level 4). Tables 5-9 and 5-10 display the original and new fuzzy factor group x_2 values based on original and improved “Project Cost Management” competency overall maturity score respectively.

Table 5-10 New Fuzzy Factor Group x_2 Value (i.e., after improving evaluation criterion 4.1)

Project Competency	Project Competency Coefficient	Project Competency Overall Prioritized Fuzzy Aggregated Maturity Score			Fuzzy Factor Group = Project Competency Coefficient * Project Competency Overall Prioritized Fuzzy Aggregated Maturity Score		
4.Project Cost Management	**0.101**	**0.265**	**0.455**	**0.569**	**0.027**	**0.046**	**0.057**
2.Project Scope Management	0.099	0.079	0.246	0.315	0.008	0.024	0.031
1.Project Integration Management	0.099	0.155	0.183	0.401	0.015	0.018	0.040
6.Project Resource Management	0.092	0.067	0.051	0.196	0.006	0.005	0.018
3.Project Time Management	0.086	0.157	0.293	0.364	0.014	0.025	0.031
17.Project Workface Planning	0.082	0.181	0.306	0.493	0.015	0.025	0.040
7.Project Risk Management	0.082	0.140	0.226	0.344	0.011	0.019	0.028
14.Project Environmental Management	0.076	0.210	0.334	0.502	0.016	0.025	0.038
9.Project Safety Management	0.072	0.154	0.202	0.284	0.011	0.015	0.020
15.Project Commissioning and Startup	0.070	0.277	0.434	0.649	0.019	0.030	0.045
11.Project Quality Management	0.065	0.133	0.209	0.305	0.009	0.014	0.020
18.Project Contract Administration	0.053	0.171	0.254	0.414	0.009	0.013	0.022
New fuzzy factor group x_2 value =					**0.160**	**0.263**	**0.393**

The new fuzzy factor group x_2 is then used as an input for the cost granular AND/OR FNN to measure the improvement in the cost project KPIs. A percentage of improvement is calculated based on the difference between the original cost project KPIs (i.e., value based on the original fuzzy factor group x_2 value = (0.158, 0.248, 0.385)) and the new cost project KPIs (i.e., value based on the new fuzzy factor group x_2 value = (0.160, 0.263, 0.393)). The improvement in the different cost KPIs ranges from 0.83% to 3.80%, as shown in Table 5-11. Table 5-11 displays the effect of improving the top three prioritized evaluation criteria (i.e., one evaluation criterion at a time) for “Project Cost Management”, “Project Integration Management” and, “Project Scope Management” on the different project cost KPIs. It is important to note that there are numerous scenarios of improvement based on the importance of an evaluation criterion and its original and improved maturity score respectively.

Table 5-11 Effect of Individual Evaluation Criteria Improvement on Cost Project KPIs

Ranked Project Competency	Prioritized Evaluation Criteria Number	Prioritized Evaluation Criteria Description	Factor Group (X_2) Overall Fuzzy Aggregated Value		Cost KPIs Percentage of Improvement $= \frac{(New\ cost\ KPI\ value - original\ cost\ KPI\ value)}{Original\ cost\ KPI\ value} * 100$				
			Original Fuzzy Factor Group (x_2) Value	**New Fuzzy Factor Group (x_2) Value**	**Project Cost Growth**	**Project Budget Factor**	**Construction Phase Cost Growth**	**Total Change Cost Factor**	**Cost-For-Change - Demand**
Project Cost management	4.1	Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.158, 0.248, 0.385)	(0.160, 0.263, 0.393)	3.80%	1.17%	2.19%	0.83%	0.83%
	4.7	A cash flow analysis is regularly carried out to monitor the financial status of the project.	(0.156, 0.248, 0.385)	(0.156, 0.248, 0.389)	1.14%	0.39%	0.44%	0.00%	0.00%
	4.8	Updated cash flow with changes to the cost baseline is regularly conducted.	(0.156, 0.248, 0.385)	(0.156, 0.248, 0.385)	0.00%	0.00%	0.00%	0.00%	0.00%
Project Integration Management	1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.156, 0.248, 0.385)	(0.160, 0.257, 0.387)	1.90%	1.17%	1.75%	0.00%	0.00%
	1.2	Kickoff meetings are initiated for the project at the planning stage.	(0.156, 0.248, 0.385)	(0.160, 0.257, 0.387)	1.90%	1.17%	1.75%	0.00%	0.00%

Ranked Project Competency	Prioritized Evaluation Criteria Number	Prioritized Evaluation Criteria Description	Factor Group (X_2) Overall Fuzzy Aggregated Value		Cost KPIs Percentage of Improvement $= \frac{(New\ cost\ KPI\ value - original\ cost\ KPI\ value)}{Original\ cost\ KPI\ value} * 100$				
			Original Fuzzy Factor Group (x_2) Value	New Fuzzy Factor Group (x_2) Value	Project Cost Growth	Project Budget Factor	Construction Phase Cost Growth	Total Change Cost Factor	Cost-For-Change - Demand
Project Scope Management	1.3	Key practices required for project planning and execution are identified at the planning stage.	(0.156, 0.248, 0.385)	(0.156, 0.248, 0.385)	0.00%	0.00%	0.00%	0.00%	0.00%
	2.6	Meetings are held during execution to verify scope and discuss any potential scope changes/creep.	(0.156, 0.248, 0.385)	(0.160, 0.260, 0.390)	3.04%	1.17%	2.19%	0.41%	0.42%
	2.1	Policies and procedures for project scope management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.156, 0.248, 0.385)	(0.163, 0.251, 0.386)	1.13%	0.39%	0.44%	0.42%	0.42%
	2.7	A scope control process is in place to identify scope changes/creep.	(0.156, 0.248, 0.385)	(0.156, 0.248, 0.385)	0.00%	0.00%	0.00%	0.00%	0.00%

It is important to note that the relationship between the different prioritized evaluation criteria for a given competency is not linear. This is due to the dynamic relationship that considers both the importance and maturity scores of the prioritized evaluation criteria (Omar and Fayek 2015b). Also, the relationship between the different project competencies, expressed by fuzzy factor groups, and the different project KPIs are not linear. Accordingly, the investigation of the effect of several evaluation criteria simultaneously on the different cost project KPIs is essential. Assume the nine evaluation criteria considered for analysis in Table 5-11 are improved simultaneously. The original fuzzy factor group x_2 value was (0.158, 0.248, 0.385). The new fuzzy factor group x_2 value, after improving the nine evaluation criteria simultaneously, is (0.241, 0.363, 0.527). The improvement in the different cost project KPIs as a result of improving the nine evaluation criteria (i.e., top three project competencies) simultaneously on the cost project KPIs ranges from 1.25% to 15.74% as displayed in Table 5-12.

Table 5-12 Effect of Combined Evaluation Criteria Improvement on Cost Project KPIs

Project Competency	Factor Group (X_2) Overall Fuzzy Aggregated Value		Cost KPIs Percentage of Improvement = $\frac{(New\ cost\ KPI\ value - original\ cost\ KPI\ value)}{Original\ cost\ KPI\ value} * 100$				
	Original Fuzzy Factor Group (x2) Value	New Fuzzy Factor Group (x2) Value	Project Cost Growth	Project Budget Factor	Construction Phase Cost Growth	Total Change Cost Factor	Cost-For-Change-Demand
Project Cost management Project Integration Management Project Scope Management	(0.156, 0.248, 0.385)	(0.241, 0.363, 0.527)	15.74%	1.17%	2.63%	1.25%	1.25%

The example above illustrated the ability of the developed fuzzy hybrid intelligent model to identify project competencies at the lowest level (i.e., project competencies' evaluation criteria) that affect the different project KPIs. The developed fuzzy hybrid intelligent model capture the nonlinear and dynamic relationship between project competencies' evaluation criteria and project KPIs. The prioritized relationship between the evaluation criteria for the different project competencies makes it necessary to consider the combined impact of evaluation criteria based on: 1) evaluation criteria importance and, 2) evaluation criteria maturity score. Accordingly, the effect of project competencies' evaluation criteria on project KPIs will vary depending on: 1) the maturity scores associated with the prioritized project competencies' evaluation criteria and, 2) the overall fuzzy factor group value, based on the combined score of the different ranked project competencies used to calculate the fuzzy factor group value.

5.7. Concluding Remarks

The application of the developed fuzzy hybrid intelligent model is presented in this chapter to measure and evaluate project competencies and project KPIs. Data collected from seven construction projects are first aggregated using prioritized fuzzy aggregation to measure the different construction project competencies. Project competencies' evaluation criteria are ranked based on the data collected from the seven projects. The prioritized fuzzy aggregation method, presented in chapter three of this thesis, is applied to produce informative evaluation of the different project competencies on the higher hierarchical level (i.e., project competency level) rather than the lower hierarchical levels (i.e., evaluation criteria of project competencies). The different project competencies are then analysed using factor analysis. The factor analysis results are used with the prioritized fuzzy aggregation results to calculate inputs (i.e., fuzzy factor groups) for a granular AND/OR FNN. Two granular AND/OR FNNs are developed (i.e., cost and schedule FNNs). The two granular AND/OR FNNs are trained and tested using the data collected from the seven construction projects to identify and quantify the relationship between the different project competencies and project key performance indicators. The presented fuzzy hybrid intelligent model is then used to determine the effect of project competencies lower hierarchical levels (i.e., project competencies' evaluation criteria) on the different project KPIs

The outcomes of the developed fuzzy hybrid intelligent model are used to improve the understanding of project competencies for construction organizations thus leading to improved performance for construction organizations and projects. Additionally, the outcomes of the developed fuzzy hybrid intelligent model contribute to the existing body of knowledge in project competencies and performance by establishing a systematic methodology for evaluating the impact of construction project competencies on project KPIs. The developed fuzzy hybrid intelligent model combines advanced modeling techniques through the joint application of prioritized fuzzy aggregation, factor analysis, and granular AND/OR FNNs to identify the relationship between the different project competencies and project KPIs. Chapter six presents a software tool developed for measuring and evaluating project competencies and project KPIs.

5.8. References

Alroomi, A., Jeong, D. H. S., and Oberlender, G. D. (2011). "Analysis of cost-estimating competencies using criticality matrix and factor analysis." *J.Constr.Eng.Manage*., 138(11), 1270-1280.

Alvisi, S., & Franchini, M. (2011). Fuzzy neural networks for water level and discharge forecasting with uncertainty. *Environmental Modelling & Software*,*26*(4), 523-537.

Azam, Farooq (2000). *Biologically inspired modular neural networks*. Diss. Virginia Polytechnic Institute and State University

Dragoni, A. F., Baldassarri, P., Vallesi, G., & Mazzieri, M. (2009, November). Multiple neural networks system for dynamic environments. In *Intelligent Systems Design and Applications, 2009. ISDA'09. Ninth International Conference on* (pp. 164-168). IEEE.

Drew, P. J., & Monson, J. R. (2000). Artificial neural networks. *Surgery*, *127*(1), 3-11.

Field, A. (2005). Discovering statistics using SPSS , Sage, Thousand Oaks, CA.

Gupta, M. M. (1994). “Fuzzy Neural Networks: theory and applications.” Proceedings of SPIE 1994, *The International Society for Optical Engineering*, 303-325

Kohavi, R. (1995). “A study of cross-validation and bootstrap for accuracy estimation and model selection”. *International Joint Conference on Artificial Intelligence.* 14(2), 1137-1145.

Omar, M. and Fayek, A. Robinson. (2015b). “A TOPSIS–based method for prioritized aggregation in fuzzy environments.” Submitted for publication in fuzzy sets and systems journal Manuscript, 18 pages

Pedrycz, W. (1994). Why triangular membership functions? *Fuzzy Sets and Systems* 64: 21–30.

Pedrycz, W., and Gomide, F. (2007). *Fuzzy systems engineering: toward human-centric computing.* John Wiley & Sons.

Pedrycz, W. (2014). "Allocation of information granularity in optimization and decision-making models: towards building the foundations of granular computing." *Eur.J.Oper.Res.,* 232(1), 137-145.

CHAPTER 6. – Organizational Competencies and Project Performance Tool (OCPPT©)[1]

6.1. Introduction

To enhance the practical benefits of the developed project competencies and project performance (i.e., project KPIs) evaluation methodology, presented in chapter two of this thesis, a software tool named Organizational Competencies and Project Performance Tool (OCPPT©), is developed. The OCPPT© has a user interface and a database (developed using Visual Basic.net© and SQL©, respectively) to enable the evaluation of project competencies (i.e., functional and behavioural competencies) and project KPIs. Additionally, the OCPPT© has the capacity to generate data required for calculating fuzzy factor groups, which are used as inputs for the granular AND/OR FNNs (i.e., third processing unit of the fuzzy hybrid intelligent model described in chapter four of this thesis). The granular AND/OR FNNs generate a set of predicted project KPIs. The predicted project KPIs are used to evaluate the effect of project competencies' improvement on project performance (i.e., percentages of improvement in project KPIs).

First, this chapter presents the OCPPT© structure and different components for storing and evaluating project competencies and project KPIs. The OCPPT© setup is used to define the different project competencies (i.e., functional and behavioural competencies' evaluation criteria) and project performance (project KPIs) libraries. The OCPPT© ability to evaluate the different project competencies and project KPIs is then demonstrated. Second, the OCPPT© ability to generate data required to calculate fuzzy factor groups for the granular AND/OR FNNs in order to predict project KPIs is described. Finally, an illustrative case study is considered to show the OCPPT© components and capabilities in evaluating project competencies and project

[1] Copyright (©) NSERC Industrial Research Chair in Strategic Construction Modeling and Delivery, University of Alberta.

KPIs. The illustrative case study is extended by a hypothetical example to present the OCPPT© capacity to predict project KPIs and evaluate the effect of project competencies' improvement on project KPIs (i.e., using the predicted project KPIs).

6.2. OCPPT© Development

The OCPPT© was created, using Visual Basic.net© and SQL©, to allow users (i.e., researchers and construction practitioners) to analyse and evaluate the different project competencies (i.e., functional and behavioural competencies) and project KPIs. The OCPPT©, as shown in Figure 6-1, consist of two principal components: (1) OCPPT© structure and (2) granular AND/OR FNNs. The OCPPT© structure consists of two units: (1) OCPPT© setup and (2) OCPPT© evaluation. Each unit (i.e., OCPPT© setup and evaluation units) has three sub-units namely: (1) organizational and projects' structures, (2) project competencies and, (3) project KPIs. A description of each of the components (i.e., OCPPT© and fuzzy hybrid intelligent model), units (i.e., OCPPT© setup and OCPPT© evaluation) and sub-units (i.e., organizational and projects' structures, project competencies, and project KPIs) is presented in Figure 6-1.

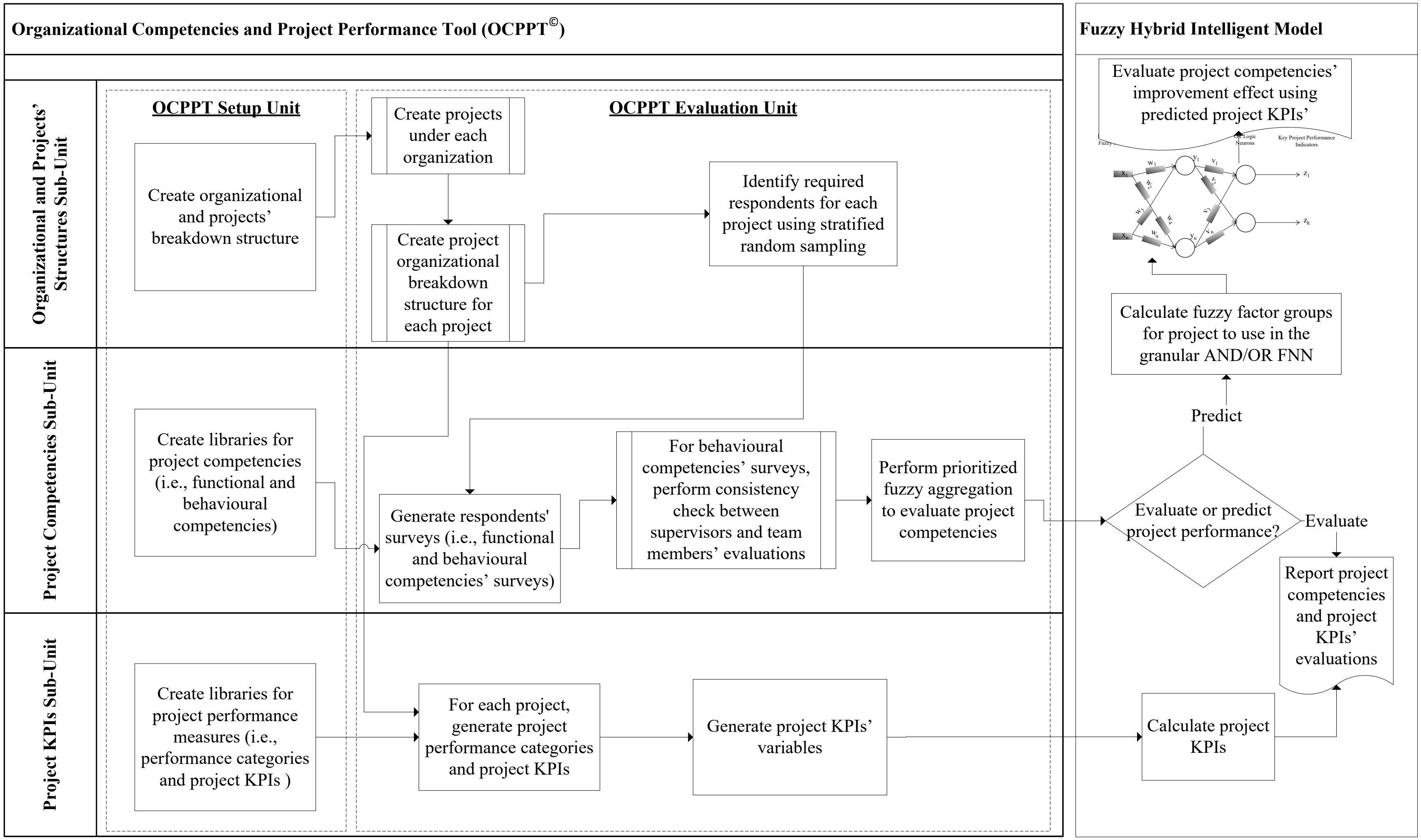


Figure 6-1 OCPPT© Structure, Components, Units, and Sub-Units

6.2.1. OCPPT© Setup Unit

As described earlier, the OCPPT© structure consists of two units: (1) OCPPT© setup and (2) OCPPT© evaluation units. Each of the units and their sub-units (i.e., organizational and projects' structures, project competencies, and project KPIs) are described next.

6.2.1.1 Organizational and Projects' Breakdown Structure Setup Sub-Unit

The organizational and projects' breakdown structure is first defined in the OCPPT©. Project information is entered, as shown in Figure 6-2, to provide information regarding project characteristics and progress. Examples of project information are: project name, contract type, project start date, project value and, required project respondents for completing the functional and behavioural competencies' surveys, respectively.

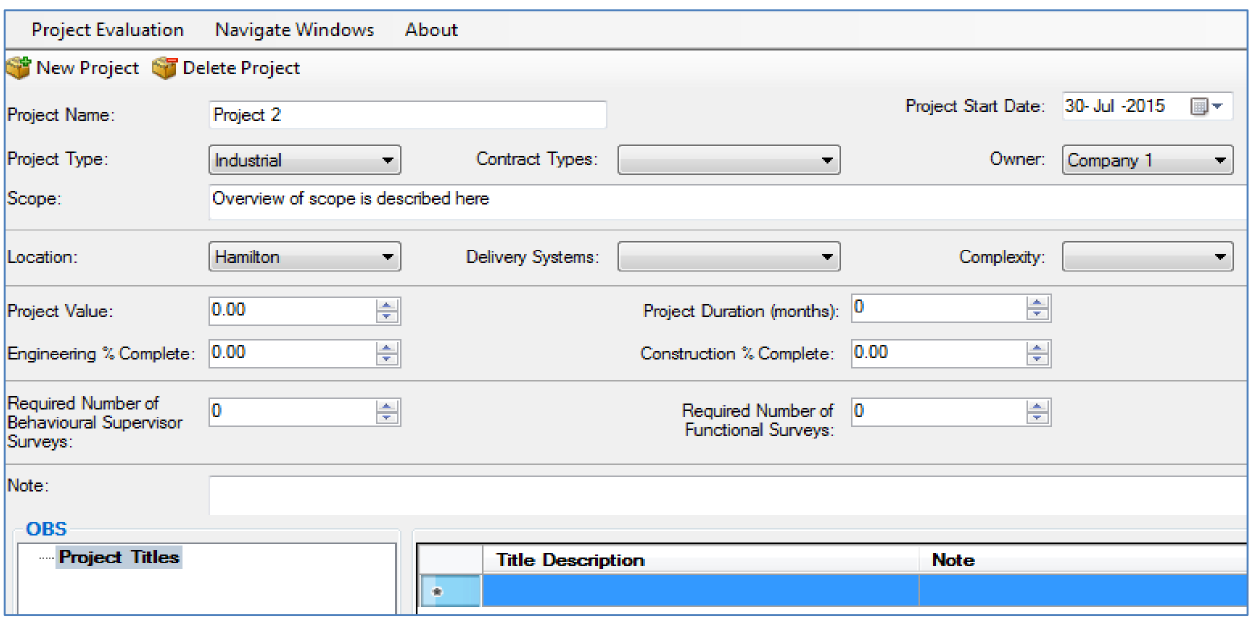


Figure 6-2 Project Information Setup

For organizational and projects' breakdown structure, the OCPPT© is capable of including several organizations (e.g., company A and company B) and projects within each organization. First, organizations are created. Then, projects, for each organization, are created for evaluation as presented in Figure 6-3.

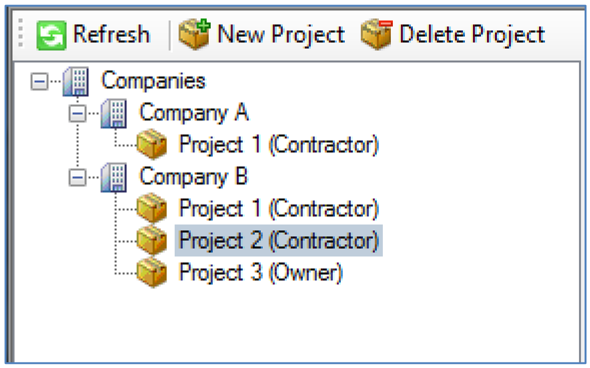


Figure 6-3 Sample Organizational and Projects' Breakdown Structure

6.2.1.2. Project Competencies' Setup Sub-Unit

After creating the organizational and projects' breakdown structure, the user defines the different project competencies to be evaluated. The OCPPT© has predefined libraries of project competencies (i.e., functional and behavioural competencies). The predefined libraries consist of project competencies' evaluation criteria identified in the course of this research (21 functional competencies that consist of 162 evaluation criteria and 20 behavioural competencies that consist of 86 evaluation criteria). The predefined libraries (i.e. functional and behavioural competencies) can be reconfigured to add, remove and, edit predefined project competencies to suit each company's needs. Figure 6-4 displays the predefined functional competencies' library and a sample evaluation criteria pertaining to one of the functional competencies (i.e., project time management).

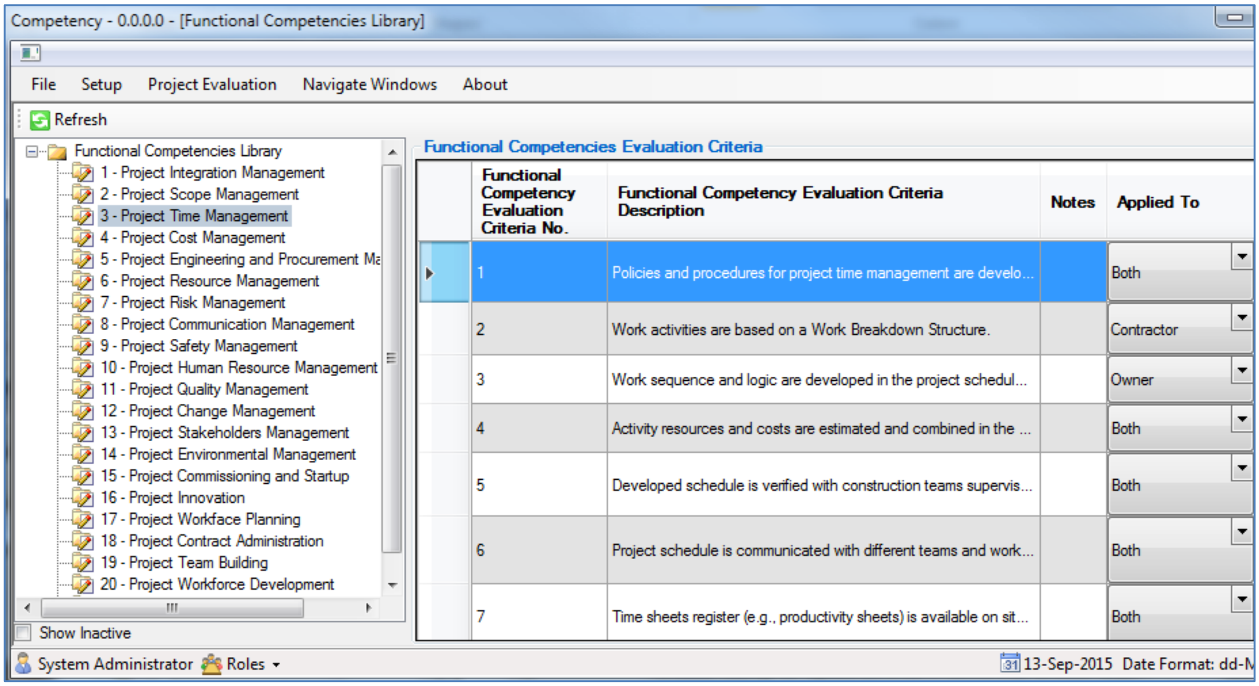


Figure 6-4 Functional Competencies Library and Sample Evaluation Criteria

6.2.1.3. Project KPIs' Setup Sub-Unit

As for project KPIs, the OCPPT© has a predefined library of project performance categories and project KPIs (i.e., seven performance categories that consist of 46 project KPIs). The predefined library can be reconfigured to add, remove and, edit predefined project KPIs to suit each company's needs. The predefined project performance categories and sample project KPIs library are shown in Figure 6-5. A sample Project KPI formula (i.e., Project Cost Growth) and variables created in the OCPPT© are shown in Figure 6-6.

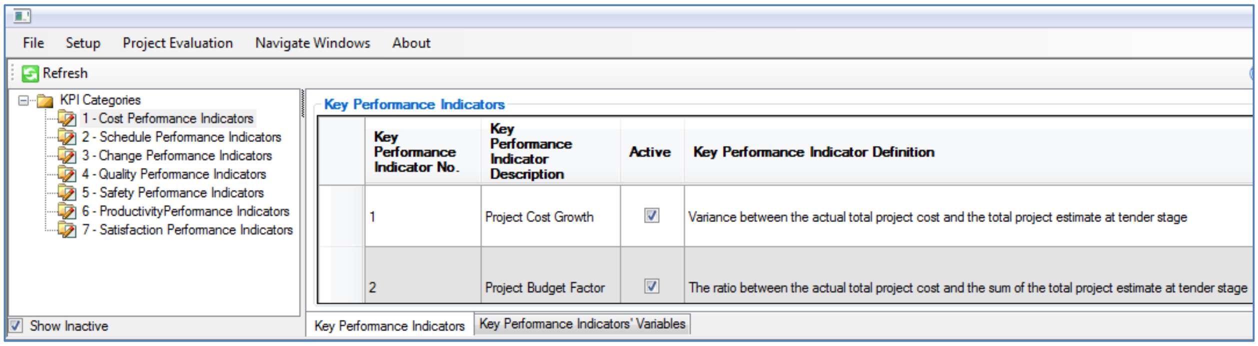


Figure 6-5 Project Performance Categories and Sample Project KPIs

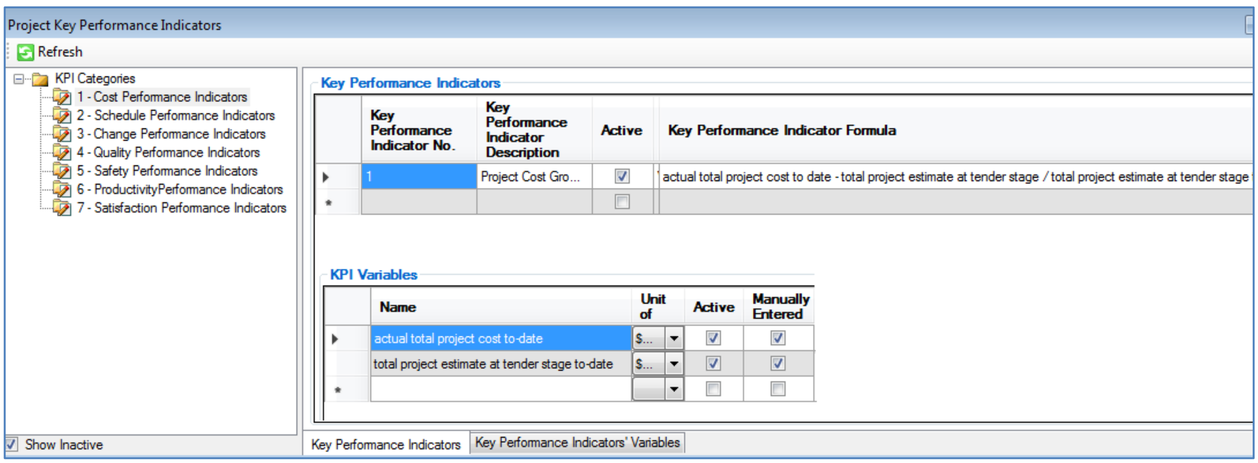


Figure 6-6 Project KPIs' Formulas and Variables

As displayed in Figure 6-6, Project Cost Growth KPI's (i.e., in the cost performance indicators category) variables are: (1) actual total project cost to-date and (2) total project estimate at tender stage to-date. The formula for calculating Project Cost Growth KPI (presented in chapter two of this thesis) is shown in Eq. 6-1:

$$Project\ Cost\ Growth = \frac{\text{actual total project cost to date} - \text{total project estimate at tender stage to date}}{\text{total project estimate at tender stage to date}} \tag{6-1}$$

Project competencies' respondents, as described in chapter two of this thesis, are identified using stratified random sampling of the different occupational clusters presented in the organizational breakdown structure of each project. Figure 6-7 display a sample project organizational breakdown structure.

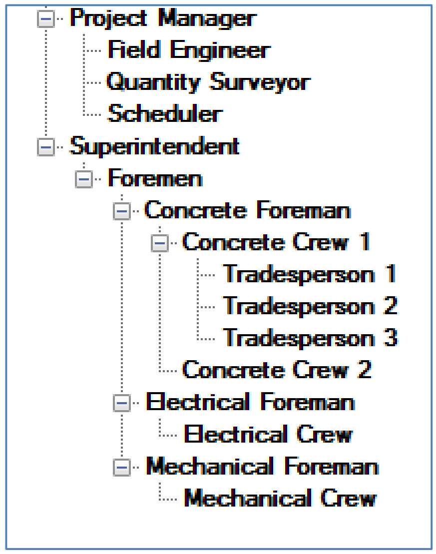


Figure 6-7 Sample Project Organizational Breakdown Structure

Stratified random sampling results (calculated manually based on the project organizational breakdown structure as shown in Figure 6-7) are entered by the user in the project setup as displayed in Figure 6-8.

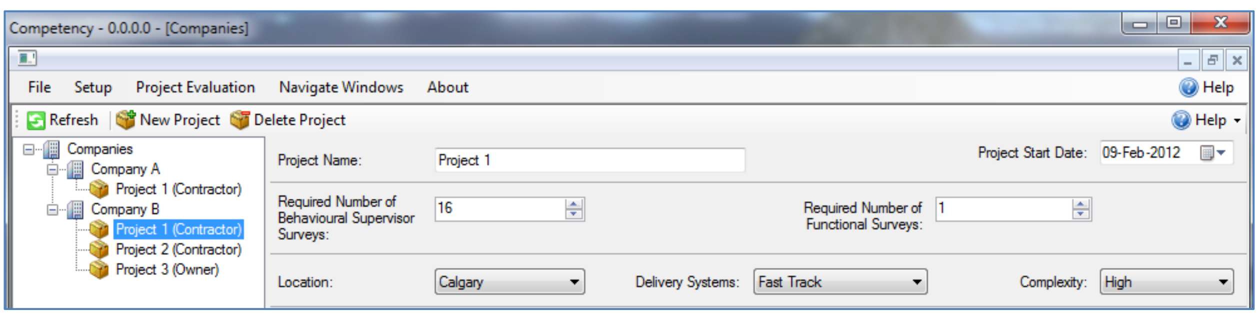


Figure 6-8 Project Competencies' Required Surveys

6.2.2. OCPPT© Evaluation Unit

The organization (i.e., company) and its projects, considered for evaluation and defined in the OCPPT© setup phase, are used for evaluation, as described next.

6.2.2.1 Organizational and Projects' Breakdown Structure Evaluation Sub-Unit

General information for the project is first entered. Then, the project organizational breakdown structure, based on the different project occupational clusters, is developed, as shown in Figure 6-7. The predefined libraries are used to generate the different project competencies required for evaluation, as described next.

6.2.2.2 Project Competencies' Evaluation Sub-Unit

The different functional and behavioural competencies are completed by the identified respondents for each project. A sample functional competency survey is entered in the OCPPT© as shown in Figure 6-9.

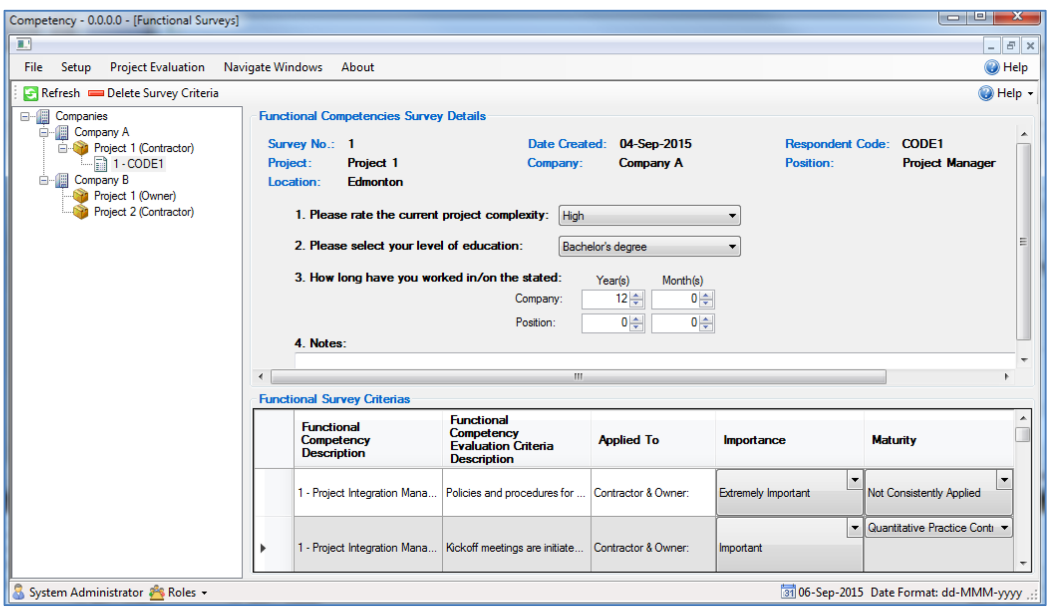
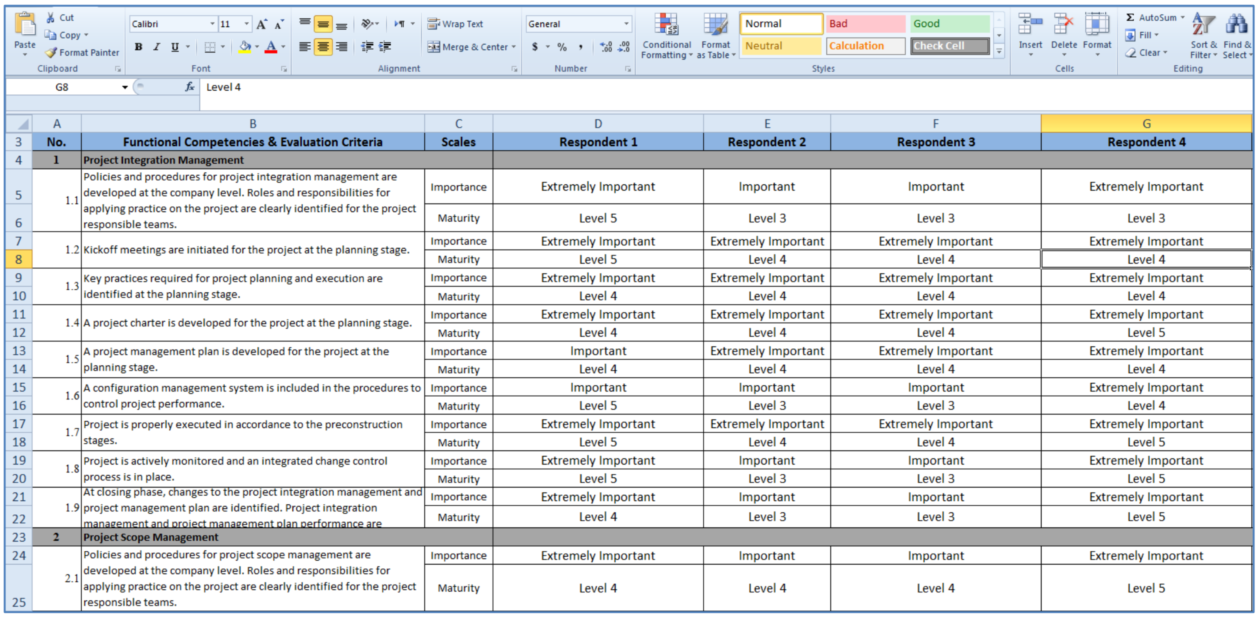


Figure 6-9 Sample Functional Competencies Survey

The entered functional and behavioural competencies' surveys are then exported to an Excel© template to perform the prioritized fuzzy aggregation described in chapter three of this thesis. Figure 6-10 display a sample export of functional competencies' surveys, for a given project, to the Excel© template associated with the OCPPT©.



No.	Functional Competencies & Evaluation Criteria	Scales	Respondent 1	Respondent 2	Respondent 3	Respondent 4
1	Project Integration Management					
1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	Importance	Extremely Important	Important	Important	Extremely Important
		Maturity	Level 5	Level 3	Level 3	Level 3
1.2	Kickoff meetings are initiated for the project at the planning stage.	Importance	Extremely Important	Extremely Important	Extremely Important	Extremely Important
		Maturity	Level 5	Level 4	Level 4	Level 4
1.3	Key practices required for project planning and execution are identified at the planning stage.	Importance	Extremely Important	Extremely Important	Extremely Important	Extremely Important
		Maturity	Level 4	Level 4	Level 4	Level 4
1.4	A project charter is developed for the project at the planning stage.	Importance	Extremely Important	Extremely Important	Extremely Important	Extremely Important
		Maturity	Level 4	Level 4	Level 4	Level 5
1.5	A project management plan is developed for the project at the planning stage.	Importance	Important	Extremely Important	Extremely Important	Extremely Important
		Maturity	Level 4	Level 4	Level 4	Level 4
1.6	A configuration management system is included in the procedures to control project performance.	Importance	Important	Important	Important	Extremely Important
		Maturity	Level 5	Level 3	Level 3	Level 4
1.7	Project is properly executed in accordance to the preconstruction stages.	Importance	Extremely Important	Extremely Important	Extremely Important	Extremely Important
		Maturity	Level 5	Level 4	Level 4	Level 5
1.8	Project is actively monitored and an integrated change control process is in place.	Importance	Extremely Important	Important	Important	Extremely Important
		Maturity	Level 5	Level 3	Level 3	Level 5
1.9	At closing phase, changes to the project integration management and project management plan are identified. Project integration management and project management plan performance are	Importance	Extremely Important	Important	Important	Extremely Important
		Maturity	Level 4	Level 3	Level 3	Level 5
2	Project Scope Management					
2.1	Policies and procedures for project scope management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	Importance	Extremely Important	Important	Important	Extremely Important
		Maturity	Level 4	Level 4	Level 4	Level 5

Figure 6-10 Sample Exported Functional Competencies' Surveys to the Excel© Template

A sample evaluation of a project's functional competencies, after performing the prioritized fuzzy aggregation using the Excel© template, is displayed in Table 6-1 and Figure 6-11 respectively.

Table 6-1 Sample Project Functional Competencies Overall Fuzzy and Crisp Evaluation (i.e., Prioritized Fuzzy Aggregation)

No.	Functional Competency	Project Overall Fuzzy Maturity Value			Project Overall Crisp Maturity Value
		a_i^{l}	a_i^{m}	a_i^{u}	
1	Project Integration Management	0.187	0.585	1.000	0.333
2	Project Scope Management	0.161	0.505	1.000	0.300
3	Project Time Management	0.184	0.594	1.000	0.333
4	Project Cost Management	0.223	0.682	1.000	0.360
5	Project Engineering and Procurement Management	0.067	0.211	0.466	0.279
6	Project Resource Management	0.137	0.363	1.000	0.240
7	Project Risk Management	0.195	0.611	1.000	0.338
8	Project Communication Management	0.155	0.496	1.000	0.300
9	Project Safety Management	0.238	0.668	1.000	0.347
10	Project Human Resource Management	0.114	0.429	1.000	0.279
11	Project Quality Management	0.206	0.640	1.000	0.350
12	Project Change Management	0.163	0.506	1.000	0.300
13	Project Stakeholders Management	0.225	0.518	1.000	0.301
14	Project Environmental Management	0.252	0.772	1.000	0.378
15	Project Commissioning and Startup	0.227	0.701	1.000	0.357
16	Project Innovation	0.089	0.331	0.823	0.269
17	Project Workface Planning	0.136	0.445	1.000	0.281
18	Project Contract Administration	0.184	0.562	1.000	0.308
19	Project Team Building	0.172	0.636	1.000	0.350
20	Project Workforce Development	0.122	0.473	1.000	0.297
21	Project Technology Integration	0.196	0.703	1.000	0.366

Figure 6-11 Sample Graphical Evaluation of Project Functional Competencies

6.2.2.3 Project KPIs Evaluation Sub-Unit

Project KPIs are calculated, using the predefined project categories and KPIs', as described earlier in this chapter. All project KPIs' variables are entered (e.g., by project controls manager). The variables' values are then exported to an Excel© template to calculate the different project KPIs. Figure 6-12 display sample KPIs' variables entered in the OCPPT© to calculate the project KPIs. Table 6-2 display a sample exported KPIs' variables.

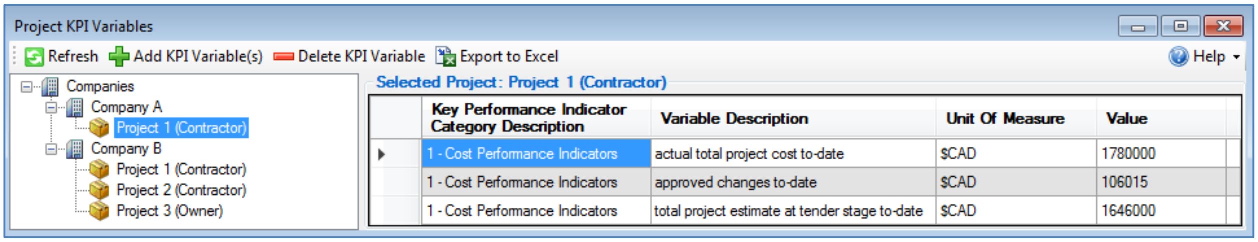


Figure 6-12 Sample Project KPIs' Variables

Table 6-2 Sample Exported Project KPIs' Variables

Cost Performance Category	Cost Performance Indicators	Value
1. Cost Performance Indicators	1. Actual total project cost to-date	**$1,780,000.00**
	2. Total project estimate at tender stage to-date	**$1,646,000.00**
	3. Approved changes to-date	**$106,015.00**

The calculated evaluations of project competencies and KPIs allow construction practitioners to measure and evaluate their project competencies. Furthermore, trends of improvement can be detected by performing periodic evaluations of project competencies and KPIs throughout the life cycle of the project.

6.2.3. Project Performance Prediction Using the OCPPT©

The OCPPT© is also capable of evaluating the effect of project competencies' improvement on project KPIs. This can be achieved by applying the fuzzy hybrid intelligent model, as shown in Figure 6-1. If, for example, a construction organization is investigating the effect of improving one or multiple project competencies on project KPIs, the OCPPT© can be used to generate data to perform this investigation. First, the evaluation of project competencies (i.e., functional and behavioural competencies) is carried out. Next, fuzzy factor groups are calculated using the OCPPT© evaluations of project competencies. The calculated fuzzy factor groups are then used as inputs for the granular AND/OR FNNs to predict project KPIs. An illustrative case study is described next to show the OCPPT© evaluative and predictive capabilities.

6.3. Illustrative Case Study

A sample commercial project is used to demonstrate the OCPPT© capabilities. In terms of project percentage completion at the time the surveys were conducted, the engineering works were 100% complete, construction works were 60% complete, and the overall engineering and construction works were 70% complete. The project team consisted of one project manager, one foreman, and one team (i.e., crew) consisting of three electrical tradespeople. The project manager completed the functional competencies survey. As for the behavioural competencies surveys, a total of five behavioural competencies surveys (i.e., one project manager, one foreman, and three available electrical tradespeople surveys) were collected and analysed to determine the different behavioural competencies of the team. Out of the five surveys, two were supervisors' behavioural competencies surveys (i.e., project manager and foreman) and three were team members' surveys (i.e., electrical tradespeople). Project KPIs data (i.e., provided by the project manager) relevant to project performance are used to derive project-specific KPIs to facilitate performance (i.e., project KPIs) evaluation for this particular project. Each of the setup and evaluation setups explained earlier in this chapter are applied in the illustrative case study, as described next.

6.3.1. Project Setup

First, the project's characteristics, general information, and project organizational breakdown structure are developed, as shown in Figure 6-13.

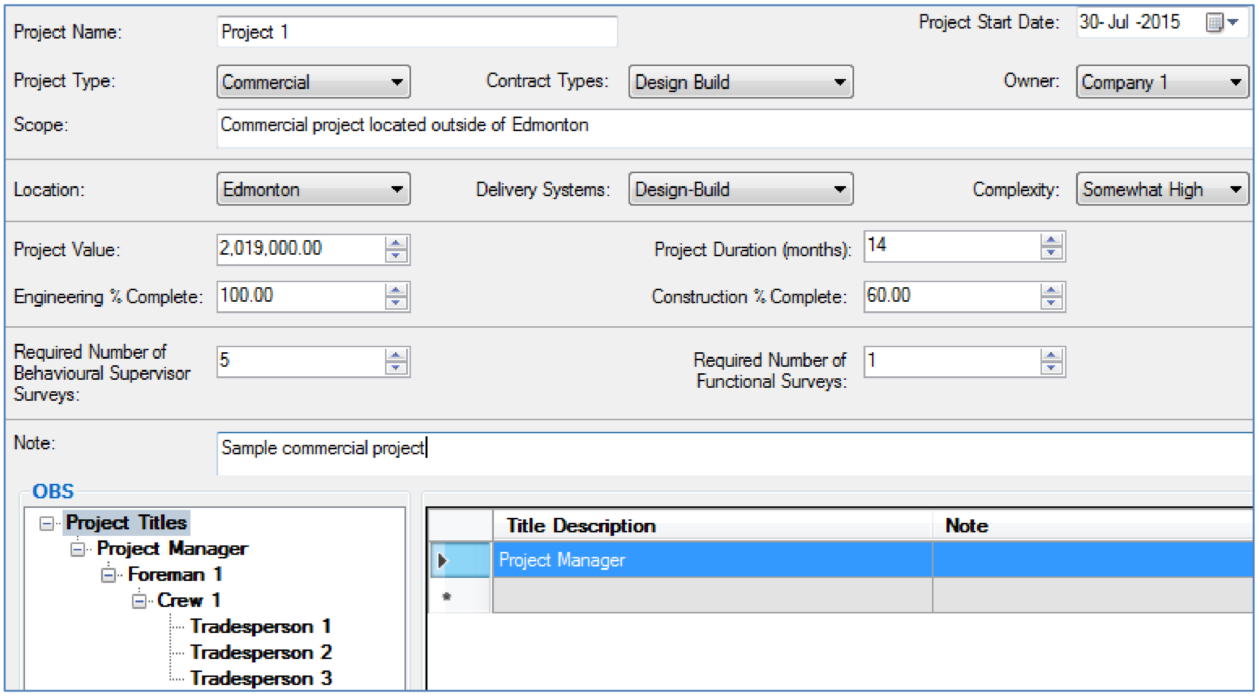


Figure 6-13 Project General Information and Breakdown Structure

Second, the predefined libraries for the project competencies (i.e., functional and behavioural competencies) and the project KPIs are used to generate the different project competencies surveys and project KPIs. For simplicity, only two project KPIs are considered in the evaluation of this illustrative case study.

6.3.2. Project Evaluation

The different project surveys (i.e., functional competencies survey for project manager and behavioural competencies surveys for project manager, foreman and, three electrical tradespeople) are generated in order to be completed by the identified project respondents' evaluating the project competencies. Project KPIs, similar to project competencies, are generated and completed by the project manager as described next.

The functional competencies' survey is designed to be completed by management staff who oversee the application of the different organizational practices on the project. Accordingly, in this project, the functional competencies' survey was completed by the project manager. Figure 6-14 displays the functional competencies' survey completed by the project manager.

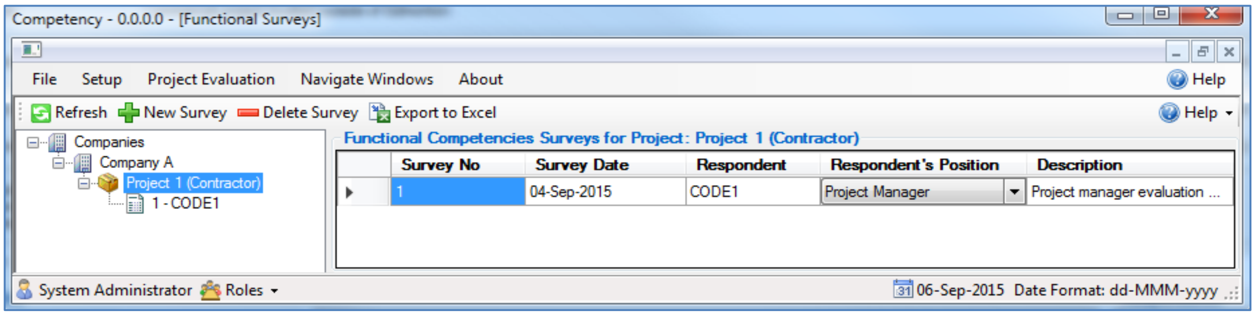


Figure 6-14 Functional Competencies' Survey Completed by Project Manager

For the behavioural competencies', supervisors (i.e., project manager and foreman) and team members (i.e., electrical tradespeople) surveys are completed to evaluate the project team's behavioural competencies. Figure 6-15 display the entered behavioural competencies' surveys (i.e., supervisors and team members).

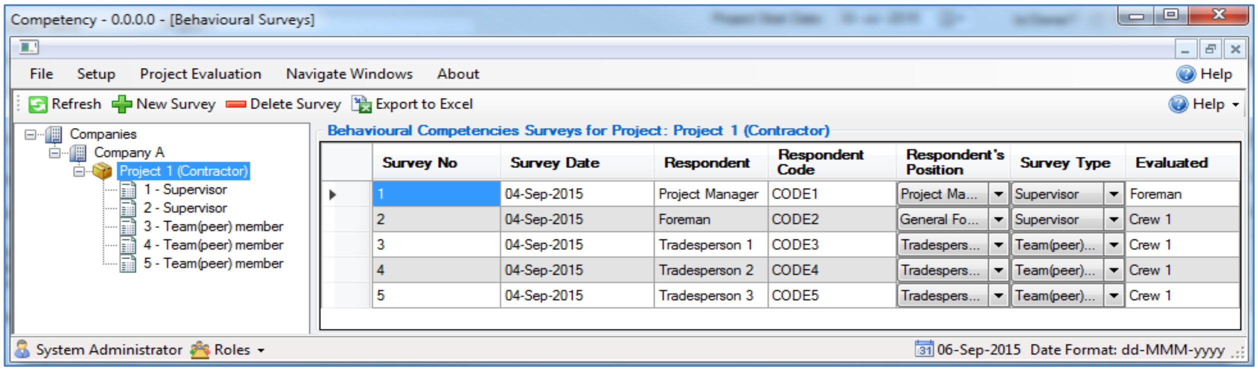


Figure 6-15 Behavioural Competencies Respondents' Surveys

The different behavioural competencies' evaluation criteria are assessed by the supervisors for their team as displayed in Figure 6-16. Also team members' evaluations are entered to perform self-evaluations of their own team as described next.

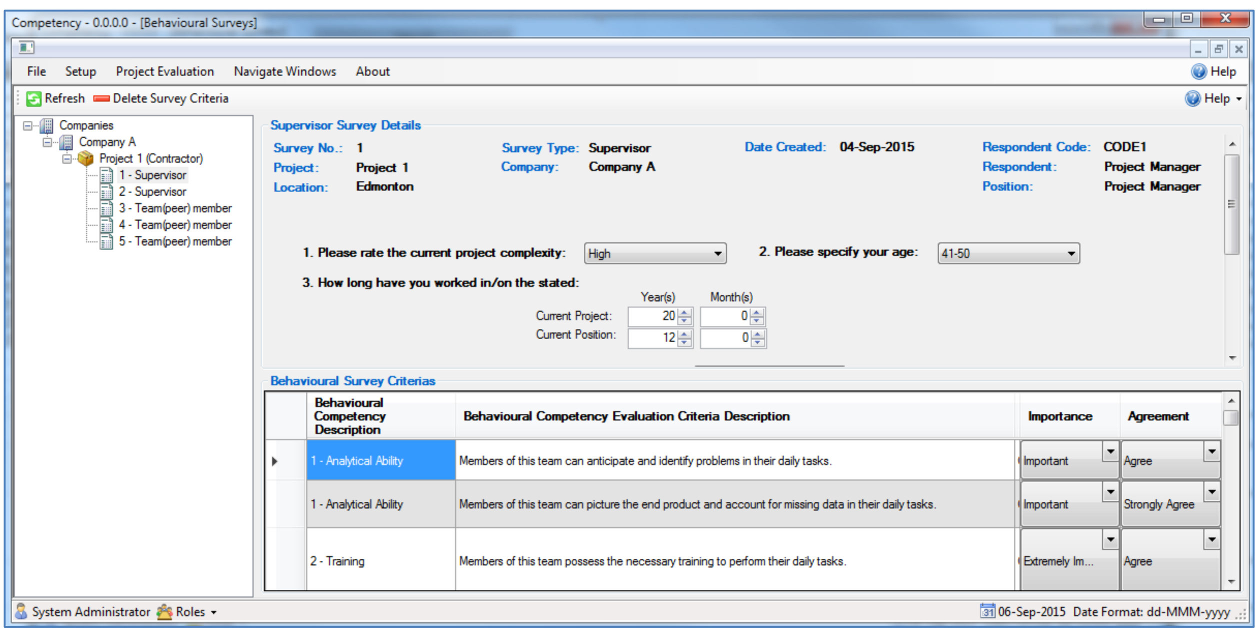


Figure 6-16 Sample Behavioural Competencies Supervisor Survey

After completing all behavioural competencies' surveys (i.e., supervisors and team members), a consistency check is performed (i.e., as explained in chapter two of this thesis) using Cronbach's alpha coefficient. Supervisors and team members' evaluations are exported to an Excel© template and a Cronbach's alpha coefficient is calculated using the supervisor evaluation (i.e., foreman) and the team members' self-evaluations (i.e., three electrical tradespeople) as displayed in Table 6-3.

Table 6-3 Cronbach's Alpha Coefficient for Crew Behavioural Competencies' Evaluation

Statistics for Respondents	Value
Number of evaluation criteria considered for consistency check	20
Mean for respondents	123
Standard deviation for respondents	7.528
Variance for respondents	56.667
Sum of evaluation criteria's variance	4.823
Cronbach's alpha coefficient	**0.963**

The Cronbach's alpha coefficient is used to analyse the consistency between the supervisor evaluations (i.e., completed by the foreman) and the crew self-evaluations (i.e., completed by each of the three electrical tradespeople). The Cronbach's alpha coefficient generated a value of 0.963. The foreman's consistency with the self-evaluation of the electrical tradespeople was considered of "excellent consistency" (George and Mallery 2003). Therefore, the supervisor evaluation (i.e., foreman evaluating the crew) was considered sufficiently representative to be used in the analysis. After ensuring the consistency of the evaluations, data (i.e., supervisors' evaluations of team's behavioural competencies) are exported to the Excel© template to perform the prioritized fuzzy aggregation. Radar diagrams are generated for the team's behavioural competencies' evaluation as presented in Figure 6-17.

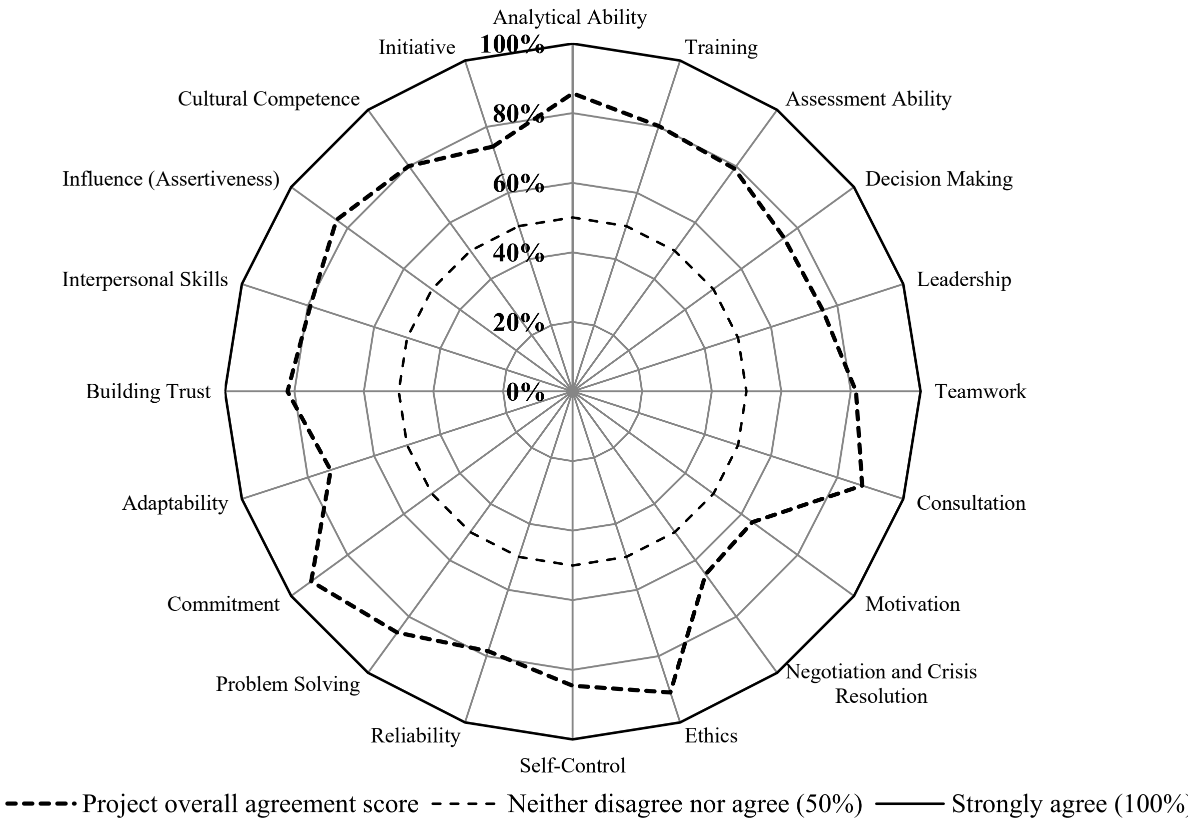


Figure 6-17 Project Behavioural Competencies Graphical Evaluation

For project KPIs' variables, data are collected at the same time project competencies' surveys are completed. A sample project KPIs' variables are displayed in Figure 6-12. A sample project KPIs' evaluation is listed in Table 6-4.

Table 6-4 Sample project KPIs' evaluations

KPI No.	KPI Name	KPI Definition	KPI Formula	KPI Value	KPI Threshold
1. Cost Performance Indicators					
1.1	Project Cost Growth	Variance between the actual total project cost and the total project estimate at tender stage, expressed as a ratio of the total project estimate at tender stage, and is expressed as a percentage	$\frac{\text{actual total project cost - total project estimate at tender stage}}{\text{total project estimate at tender stage}}$	7.53%	<0 Desirable Value =0 Planned Value >0 Undesirable Value
1.2	Project Budget Factor	The ratio between the actual total project cost to date and the sum of the total project estimate at tender stage and approved changes	$\frac{\text{actual total project cost}}{\text{total project estimate at tender stage + approved changes}}$	1.60%	<0 Desirable Value =0 Planned Value >0 Undesirable Value

Undesirable variances in the cost performance indicators category indicate that variances between planned and actual values occurred to date. A 7.53% increase in project cost growth and a 1.60% increase in project budget factor are encountered.

6.3.3. Project Performance Prediction

As described earlier, the OCPPT© is capable of generating data required for calculating fuzzy factor groups, which are used as inputs for the granular AND/OR FNNs to predict project KPIs. OCPPT© project performance (i.e., project KPIs) prediction capability is utilized when a construction organization is investigating the effect of project competencies (i.e., functional and behavioural competencies) improvements or lack thereof on project KPIs.

Assume, for the same illustrative case study, some of the functional competencies' overall maturity values are evaluated one more time after considering improvement strategies for their criteria. For example, the overall maturity value of project cost management, project scope management, project integration management, and project resource management functional competencies' evaluation criteria are hypothetically improved simultaneously during a periodic evaluation of project competencies. Accordingly, the new functional competencies' evaluations (i.e., maturity values) are calculated. Second, the new functional competencies' evaluations are used along with the dimensionality reduction (i.e., factor analysis) results, presented in chapter five (Table 5-6 and 5-8), to generate fuzzy factor groups. Table 6-5 presents the new calculated fuzzy factor groups representing the new evaluations of project competencies.

Table 6-5: Illustrative Case Study: Fuzzy Factor Groups

Fuzzy Factor Group	Factor Group (Ranked Project Competencies)	Fuzzy Factor Group Value
Functional Competencies Factor Group 1 (x_1)	13. Project Stakeholders Management 16. Project Innovation 11. Project Quality Management 12. Project Change Management 18. Project Contract Administration 19. Project Team Building 20. Project Workforce Development 14. Project Environmental Management 8. Project Communication Management 15. Project Commissioning and Startup 17. Project Workface Planning 9. Project Safety Management	(0.09, 0.38, 1.00)
Functional Competencies Factor Group 2 (x_2)	4. Project Cost Management 2. Project Scope Management 1. Project Integration Management 6. Project Resource Management 3. Project Time Management 17. Project Workface Planning 7. Project Risk Management 14. Project Environmental Management 9. Project Safety Management 15. Project Commissioning and Startup 11. Project Quality Management 18. Project Contract Administration	(0.09, 0.38, 0.98)
Functional Competencies Factor Group 3 (x_3)	5. Project Engineering and Procurement Management 20. Project Workforce Development 7. Project Risk Management 17. Project Workface Planning	(0.07, 0.31, 0.86)
Functional Competencies Factor Group 4 (x_4)	10. Project Human Resource Management 21. Project Technology Integration 6. Project Resource Management 3. Project Time Management	(0.12, 0.44, 0.83)

Fuzzy Factor Group	Factor Group (Ranked Project Competencies)	Fuzzy Factor Group Value
Behavioural Competencies Factor Group 1 (x_5)	17. Interpersonal Skills 10. Ethics 11. Self-Control 20. Initiative 16. Building Trust 13. Problem Solving 18. Influence 8. Motivation 12. Reliability 6. Teamwork 14. Commitment 1. Analytical Ability 3. Assessment Ability	(0.10, 0.42, 0.89)
Behavioural Competencies Factor Group 2 (x_6)	19. Cultural Competence 15. Adaptability 9. Negotiation and Crisis Resolution 7. Consultation 16. Building Trust 5. Leadership 18. Influence 6. Teamwork 20. Initiative 8. Motivation 13. Problem Solving 12. Reliability	(0.05, 0.28, 0.78)
Behavioural Competencies Factor Group 3 (x_7)	2. Training 4. Decision Making 1. Analytical Ability 13. Problem Solving	(0.01, 0.32, 0.81)

Next, the calculated fuzzy factor groups are used as inputs for the developed granular AND/OR FNN (i.e., cost FNN) as described earlier in chapter five of this thesis (Figure 5-5). Finally, the resulting predicted project KPIs are calculated, using the granular AND/OR FNN as shown in Table 6-6.

Table 6-6 Illustrative Case Study: Predicted Project KPIs

KPI No.	KPI Name	KPI Formula	Predicted KPI Value (i.e., Using the Granular AND/OR FNNs)	KPI Threshold
1.1	Project Cost Growth	$\frac{\text{actual total project cost - total project estimate at tender stage}}{\text{total project estimate at tender stage}}$	-5.79%	<0 Desirable Value =0 Planned Value >0 Undesirable Value
1.2	Project Budget Factor	$\frac{\text{actual total project cost}}{\text{total project estimate at tender stage + approved changes}}$	-4.34%	<0 Desirable Value =0 Planned Value >0 Undesirable Value

The predicted project KPIs show improvement in Project Cost Growth and Project Budget Factor respectively. This improvement is a result of improving project cost management, project scope management, project integration management, and project resource management functional competencies (i.e., compared to the project KPIs presented in Table 6-3). A 5.79% decrease in Project Cost Growth and a 4.34% decrease in Project Budget Factor are expected to occur as a result of the improvement of the abovementioned functional competencies.

6.4. Concluding Remarks

The OCPPT© is developed to evaluate project competencies and project KPIs. The OCPPT© is also applied for evaluating the effect of project competencies' improvement or lack thereof by providing predictions for project KPIs. First, the OCPPT© applications are presented in this chapter. Then an illustrative case study is presented to demonstrate the OCPPT© evaluative and predictive capabilities. The OCPPT© allows construction practitioners to evaluate their project competencies and project performance respectively at different points in the project life cycle. Furthermore, construction practitioners can identify the effect of improving project competencies on project KPIs, using the OCPPT© and the fuzzy hybrid intelligent model, to predict project KPIs after improving competencies.

6.5. Acknowledgments

The Organizational Competencies and Project Performance Tool (OCPPT©) is funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) Industrial Research Chair in Strategic Construction Modeling and Delivery and the NSERC Discovery Grant for Advancing Fuzzy Hybrid Techniques for Competency Modeling of Construction Organizations, both held by Dr. Aminah Robinson Fayek. The effort exercised by Maria Al-Hussein, Stephen Arychuck, and Ramandeep Dhatt in the course of developing the OCPPT© is gratefully recognized.

6.6. References

George, D., & Mallery, M. P. (2003). *Using SPSS for Windows Step by Step: A Simple Guide and Reference*. Allyn & Bacon: Boston, MA.

CHAPTER 7. – Conclusions and Recommendations

This chapter provides a review of the research work conducted in this thesis and summarizes its contributions. Limitations of the research work and recommendations for future research are also presented.

7.1. Research Summary

Construction organizations measure their performance against a set of predefined performance measures. These performance measures are governed by the ability of the organization to maintain some necessary sets of "competencies" that assist in the successful execution of its construction projects. These competencies in general are difficult to define and measure due to the multidimensional and subjective nature of their assessment. Therefore, the main motivation of this research was to introduce a methodology and a fuzzy hybrid intelligent model capable of evaluating project competencies, while considering project competencies' multidimensional and subjective nature, and their relationship to project performance for construction projects. In the course of this research, several state of the art techniques and models are developed, presented, and applied to evaluate and model project competencies and their relationship to project performance.

7.1.1. First Phase Summary

The first phase commenced with identifying previous research gaps in organizational competencies and project performance. A methodology was developed to identify and measure the different project competencies and performance measures. Measurements were developed to evaluate project competencies (i.e., functional and behavioural competencies) and project performance. Data sampling and collection tools were developed and applied to collect data from construction projects. Several data verification and validation methods (i.e., previous research review, questionnaires, one-on-one interviews, and interactive group workshops with highly experienced construction practitioners of varying level of expertise) were applied to verify and validate the findings of this phase (i.e., as described in chapter two of this thesis).

7.1.2. Second Phase Summary

A new prioritized aggregation method was developed, as presented in chapter three of this thesis, in crisp and fuzzy environments. The new prioritized aggregation method combines construction practitioners' evaluations of the different project competencies that were collected from construction projects. The new prioritized aggregation method provides an evaluation of the different project competencies, which are subjective in nature, while considering the prioritized relationship between project competencies' evaluation criteria. The new prioritized aggregation method also accounts for the dynamic relationship between individual project competencies' evaluation criteria importance and their level of satisfaction (i.e., maturity and agreement). The notion of satisfaction implies, in the new prioritized aggregation method, the degree to which an evaluation criterion is adjacent to its most favourable setting (i.e., importance, maturity, and agreement).

7.1.3. Third Phase Summary

A fuzzy hybrid intelligent model was developed, as described in chapter four of this thesis, to evaluate project competencies and identify their relationship to project performance (i.e., project KPIs). First, project competencies' evaluation criteria were combined using the new prioritized fuzzy aggregation method described in the preceding phase (i.e., second phase). Second, the results of the prioritized fuzzy aggregation method were defuzzified for the application of a dimensionality reduction technique (i.e., factor analysis). The dimensionality reduction technique identified a set of fewer factor groups that represented the different project competencies. Then, coefficients representing the contribution of each project competency towards its factor group were calculated. Third, the calculated coefficients were used jointly with the project competencies' prioritized fuzzy aggregation results to calculate fuzzy factor groups. Finally, the calculated fuzzy factor groups and project KPIs were used together in granular AND/OR fuzzy neural networks (i.e., cost and schedule FNNs) to identify and quantify the relationship between project competencies, expressed by fuzzy factor groups, and project KPIs. Chapter five presented a detailed analysis of seven construction projects. This analysis resulted in the identification of the relationship between project competencies' evaluation criteria and project KPIs. Additionally, the granular AND/OR fuzzy neural networks were used to evaluate the effect of project competencies' improvement on project KPIs.

7.1.4. Fourth Phase Summary

A software tool, named Organizational Competencies and Project Performance Tool (OCPPT©), was developed to create an executable, stand-alone system that is connected to a user interface to evaluate project competencies and project performance. The OCPPT© is capable of evaluating the effect of improving project competencies on project KPIs, using the fuzzy hybrid intelligent model, as described in chapter six of this thesis.

7.2. Research Contributions

The research presented in this thesis provides several contributions in: (1) organizational competencies and project performance evaluation and modeling, (2) prioritized aggregation in multi-criteria decision-making problems, (3) dimensionality reduction in fuzzy environments, and (4) fuzzy hybrid intelligent modeling. These research contributions are classified as academic and industrial contributions as follows:

7.2.1. Academic Research Contributions

The academic research contributions of this thesis are as follows:

1. *Development and application of a new prioritized aggregation method for multi-criteria decision-making (MCDM) problems*: A new prioritized aggregation method is developed for multi-criteria decision-making (MCDM) problems such as the evaluation of project competencies. The new prioritized aggregation method accounts for the dynamic interrelations between project competencies' evaluation criteria considered in the aggregation, and their satisfaction relative to the most favourable satisfaction that a given project competency's evaluation criterion can achieve. This dynamic relationship ensures that high satisfaction of a lower priority project competency's evaluation criterion do not compensate for low satisfaction of a higher priority project competency's evaluation criterion.
2. *Development and application of a dimensionality reduction technique suitable for fuzzy environments:* Project competencies are structured and grouped, using a dimensionality reduction technique (i.e., factor analysis). This structuring and grouping considers the correlation relationship between the different project competencies based on the higher hierarchical level (i.e., project competency level). The dynamic relationship between project

competencies' evaluation criteria is realized through the new prioritized fuzzy aggregation method described in the previous point.

3. *Development and application of a new fuzzy hybrid intelligent model for evaluating the relationship between project competencies and project performance:* Hybridization of fuzzy models is first explored, to overcome the existing limitations of learning in fuzzy logic-based models, as presented earlier in chapter four of this thesis. A fuzzy hybrid intelligent model is then developed to relate project competencies' evaluation criteria to project KPIs by learning from actual data. This fuzzy hybrid intelligent model integrates state of the art techniques such as the new prioritized fuzzy aggregation method (i.e., described in chapter three of this thesis), a dimensionality reduction technique suitable for fuzzy environments and, granular AND/OR FNNs (i.e., described in chapter four of this thesis). The developed fuzzy hybrid intelligent model identifies and quantifies the relationship between project competencies and project performance (i.e., project KPIs). Furthermore, the fuzzy hybrid intelligent model is capable of measuring the effect of project competencies' improvement on project performance (i.e., project KPIs).

7.2.2. Industrial Research Contributions

The industrial research contributions of this thesis are as follows:

1. *Deliver a methodology for measuring and evaluating project competencies and project performance*: Comprehensive hierarchies of project competencies and project KPIs are developed, thus allowing construction organizations to measure and evaluate their project competencies and project performance (i.e., project KPIs). Comprehensive lists of project competencies' evaluation criteria and measurement scales are developed for construction

organizations to measure and evaluate their projects' competencies. A comprehensive breakdown of performance measures (i.e., project KPIs) is also provided to construction organizations to better evaluate their projects' performance. Data sampling and collection tools are developed for construction organizations to measure their organizational functional competencies and teams' behavioural competencies on construction projects. Data collection tools are also developed to evaluate project performance (i.e., project KPIs) on construction projects.

2. *Deliver a model for evaluating project competencies' effect on project performance*: the developed fuzzy hybrid intelligent model, described in the academic contribution section, is capable of assisting construction organizations to evaluate the effect of project competencies' improvement on project performance (i.e., project KPIs) and predict, if needed, project KPIs based on current project competencies. The fuzzy hybrid intelligent model assists construction practitioners to formalize and improve the evaluation of project competencies and project performance.

3. *Deliver a software tool for evaluating project competencies and project performance:* A software tool (i.e., OCPPT©) is developed to facilitate the evaluation of project competencies and project performance of construction organizations and projects. The OCPPT© allows construction practitioners to evaluate their project competencies and project performance at different points of the project life cycle and to identify the effect of project competencies' improvement on project performance (i.e., project KPIs).

7.3. Limitations and Recommendations for Future Research

This research provides a basis for future research in project competencies and their relationship to project performance. A comprehensive methodology for evaluating project competencies and project performance is defined. A new prioritized aggregation method for MCDM problems is developed. A fuzzy hybrid intelligent model is developed to identify and quantify the relationship between project competencies' evaluation criteria and project performance (i.e., project KPIs). The fuzzy hybrid intelligent model is capable of evaluating the effect of improving project competencies on project KPIs. Despite the contributions presented in this research, the research has certain limitations and recommendations for future research that are categorized as: (1) research scope, (2) model improvement, (3) model validation.

7.3.1. Research Scope

1. This research considered a limited set of data (i.e., seven construction project) to identify and quantify the relationship between project competencies' evaluation criteria and project performance (i.e., project KPIs). This research, due to limited data availability, did not distinguish between the different construction stakeholders (e.g., owners and contractors), different construction contexts (e.g., industrial, commercial and, residential sectors), and different stages of project completion when evaluating project competencies and project KPIs. Future work should consider context-specific models (i.e., fuzzy hybrid intelligent models) that can account for varying project characteristics and information (e.g., different construction stakeholders and different stages of project completion) within a given context.
2. Capturing the changes in project competencies through the project lifecycle, and how they impact project KPIs will assist in building appropriate project competencies (i.e., functional and behavioural competencies) necessary during the different phases of the project life cycle. A sensitivity analysis will then determine the impact of project competencies on project KPIs at varying stages of the project life cycle.

3. Evaluating the same projects at varying stages of the projects' life cycle should be considered to validate the predicted project KPIs (i.e., using the developed fuzzy hybrid intelligent model).
4. This research considered the project as the only unit of measurement. Future work should consider expanding project competencies and performance assessment from the project level to the organizational level. Once enough data relevant to the different contexts and the organizational level are collected, critical competencies at the organizational and project levels (i.e., different contexts) can be identified. Ranking techniques, such as priority ranking and value tree-based ranking methods (Clémençon and Vayatis, 2009), and data mapping techniques, such as structural clustering (Huang et al., 2010), can be investigated to identify the relationship between organizational and project level competencies and performance.

7.3.2. Model Improvement

The state of the art techniques used in this research will be considered for further improvement in future work to enhance the practical benefits of the developed fuzzy hybrid intelligent model as follows:

1. The application of the new prioritized aggregation method, developed in the course of this research, did not consider decision makers' levels of expertise when evaluating multiple interrelated criteria (e.g., project competencies' evaluation criteria). Future work will extend the presented new prioritized aggregation method to include attributes related to the levels of expertise of decision makers such as knowledge, experience, relevance, and credibility. These attributes will be investigated using heuristic methods, such as the Analytical Hierarchy Process (AHP) and decision trees, and automated methods such as

genetic algorithms and neural networks to calculate a relative score that represents decision makers' levels of expertise. The calculated relative score will then be included while performing the prioritized aggregation. The inclusion of decision makers' levels of expertise, when performing prioritized aggregation in MCDM problems, will result in improved results and ultimately better decision-making for a wide range of engineering applications.

2. This research has considered triangular membership functions to represent the different linguistic terms (i.e., importance, maturity, and agreement). Different shapes of membership functions (e.g., trapezoidal and Gaussian) should be investigated to quantify their influence on the capturing the different project competencies' evaluation and subsequently on their effect on predicted project KPIs.

3. Advancing granular fuzzy neural networks to granular fuzzy spiking neural networks is suggested for future work. The concept of fuzzy spiking neural networks is yet to be investigated for modeling construction engineering-related problems. In the past decade, Spiking Neural Networks (SNNs) have been developed to account for a vital aspect that is not considered in traditional Artificial Neural Networks (ANNs), which is the time aspect. The inclusion of spikes (e.g., project percentage of completion) representing time will improve the identification of the relationship between inputs (e.g., project competencies) and outputs (e.g., project KPIs) as well as improving the learning of ANNs (Kasabov et al. 2013; Wang and Peng 2013; Kasabov 2014). Furthermore, the inclusion of project competencies' and project KPIs evaluations at varying stages of the project life cycle will better model, using SNNs, the effect of project competencies on project KPIs while considering the stage at which the project is currently at. As such, extending SNNs to

granular FNNs (Pedrycz 2014) is of great potential in solving complicated time-dependent construction engineering-related problems that are subjective in nature and encompass a certain degree of vagueness and imprecision.

4. Context adaptation was not considered in this research due to the limited data set considered for analysis. Context adaptation is a widely used concept in computing fields. Context adaptation approaches are used to adjust the membership functions of fuzzy hybrid intelligent models from one context to another. The adjustment of membership functions, using context adaptation, is carried out by means of optimization techniques such as ANNs and genetic algorithms. The results of the optimization produce adapted membership functions for the new context (i.e., new fuzzy hybrid intelligent model suitable for a new context). Investigating context adaptation, as a future research direction, will allow the reuse of existing fuzzy hybrid intelligent models and knowledge bases to new contexts and will save considerable effort required to collect data for developing new models. It will also improve the implementation of existing models by industry as the models can be adapted to suit specific construction industry contexts (e.g., industrial and commercial contexts). Context adaptation of fuzzy hybrid intelligent models first requires adequate analysis of the context upon which the original or base fuzzy hybrid intelligent model was developed, and the new context for which an adapted fuzzy hybrid intelligent model is required. Therefore, the context adaptation process will rely heavily on collecting data and capturing experts' knowledge in order to formulate the properties of the new context.

5. The developed Organizational Competencies and Project Performance Tool (OCPPT©) can be expanded to have built-in dimensionality reduction and granular AND/OR FNNs components to automate the different analyses presented in this thesis. The ultimate

objective of this software tool is to provide the construction industry with a standalone software tool with built-in capabilities to perform the different types of analyses and modeling presented earlier in this thesis.

7.3.3. Model Validation

The developed fuzzy hybrid intelligent model considered a limited number of available projects to perform the analysis (i.e., dimensionality reduction using factor analysis and granular AND/OR FNN training and testing) and derive results. It is recommended that future work consider collecting more data from different construction stakeholders (e.g., owners and contractors), different construction contexts (e.g., industrial, commercial and, residential sectors), and different stages of project completion to strengthen the reliability of the findings and results pertinent to this research. The data collected will assist in developing context-specific models (i.e., fuzzy hybrid intelligent models) that can account for varying project characteristics and information (e.g., different construction stakeholders and different stages of project completion) within a given context.

7.4. References

Clémençon, S., & Vayatis, N. (2009). Tree-based ranking methods. *Information Theory, IEEE Transactions on*, *55*(9), 4316-4336.

Huang, Y., Niu, B., Gao, Y., Fu, L., & Li, W. (2010). CD-HIT Suite: a web server for clustering and comparing biological sequences. *Bioinformatics*, *26*(5), 680-682. Kasabov, N. K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio-and spectro-temporal pattern recognition. *Neural Networks*, *41*, 188-201.

Kasabov, N. K. (2014). NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data. *Neural Networks*, *52*, 62-76.

Pedrycz, W. (2014). "Allocation of information granularity in optimization and decision-making models: towards building the foundations of granular computing." *Eur.J.Oper.Res.,* 232(1), 137-145.

Wang, J., & Peng, H. (2013). Adaptive fuzzy spiking neural P systems for fuzzy inference and learning. *International Journal of Computer Mathematics*,*90*(4), 857-868.

BIBLIOGRAPHY

AbouRizk, S. and Halpin, D. (1990). "Probabilistic simulation studies for repetitive construction processes." *Journal of Construction Engineering and Management*, 116(4), 575–594.

Albert P.C. Chan, Ada P.L. Chan, (2004) "Key performance indicators for measuring construction success." *Benchmarking: An International Journal*, 11(2), pp.203 – 221.

Alvisi, S., & Franchini, M. (2011). Fuzzy neural networks for water level and discharge forecasting with uncertainty. *Environmental Modelling & Software*,*26*(4), 523-537.

Ajzen, I. (1991). "The theory of planned behavior." *Organ.Behav.Hum.Decis.Process.,* 50(2), 179-211.

Alroomi, A., Jeong, D., Oberlender, G. (2011). "Analysis of cost-estimating competencies using criticality matrix and factor analysis." *Journal of Construction Engineering and Management*, 138(11), 1270–1280.

Azam, Farooq (2000). *Biologically inspired modular neural networks*. Diss. Virginia Polytechnic Institute and State University

Antonacopoulou, E. P. and FitzGerald, L. (1996). "Reframing competency in management development." *Human Resource Management Journal*, 6: 27–48.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American psychologist*, *37*(2), 122.

Bardossy, A., Duckstein, L., and Bogardi, I. (1993). Combination of fuzzy numbers representing expert opinions. *Fuzzy Sets and Systems* 57.2: 173–181.

Bassioni, H. A., Price, A. D., and Hassan, T. M. (2004). "Performance measurement in construction." *J.Manage.Eng.,* 20(2), 42-50.

Berberian SK. (1998). *Fundamentals of Real Analysis*. Springer: New York, New York, USA.

Bisdorff R, Meyer P, and Veneziano T. (2014). Elicitation of criteria weights maximising the stability of pairwise outranking statements. *Journal of Multi‐Criteria Decision Analysis* 21: 113–124.

Bourne, M. , Mills, J. , Wilcox, M. , Neely, A. , and Platts, K. (2000). “Designing, implementing and updating performance measurement systems.” *Int. J. Operat. Product. Manage.* , 20 (7), 754–771.9

Calvo T, Mayor G, and Mesiar R (eds). (2002). *Aggregation Operators: New Trends and Applications*. Springer: New York, New York, USA.

Carlsson, C., and Fullér, R. (1996). Fuzzy multiple criteria decision making: Recent developments. *Fuzzy Sets and Systems* 78.2: 139–153.

Caupin, G., Knöpfel, H., Morris, P., Motzel, E., Pannenbäcker, O. (2006). ICB-IPMA Competence Baseline, International Project Management Association, Netherlands.

Chan, A. P., & Chan, A. P. (2004). Key performance indicators for measuring construction success. *Benchmarking: an international journal*, 11(2), 203-221.

Chandler, A. (1977). The visible hand: the managerial revolution in American business. Cambridge. *Massachusetts.*

Chen S.H. (1984). On the theory of operating, ranking, and estimating fuzzy numbers and its application. Doctor of Science thesis, Tamkang University, Taipei University, Taiwan, 1984.

Chen LH and Xu ZS. (2014). A prioritized aggregation operator based on the OWA operator and prioritized measure. *Journal of Intelligent and Fuzzy Systems* 27: 1297–1307.

Chen L, Xu Z, and Yu X. (2014). Prioritized measure-guided aggregation operators. *Fuzzy Systems, IEEE Transactions on* 22: 1127–1138.

Chen SJ and Hwang CL . (1992). *Fuzzy Multiple Attribute Decision Making.* Springer-Verlag: New York, New York, USA.

Cheung, S. O., Suen, H. C., & Cheung, K. K. (2004). PPMS: a web-based construction project performance monitoring system. *Automation in construction*, *13*(3), 361-376.

Cholewa, W. (1985). Aggregation of fuzzy opinions—an axiomatic approach. *Fuzzy Sets and Systems* 17.3 (1985): 249–258.

Choo EU, Schoner B, and Wedley WC. (1999). Interpretation of criteria weights in multicriteria decision making. *Computers and Industrial Engineering* 37: 527–541.

Chu TC. (2002). Facility location selection using fuzzy TOPSIS under group decisions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 10: 687–701.

Clémençon, S., & Vayatis, N. (2009). Tree-based ranking methods. *Information Theory, IEEE Transactions on*, *55*(9), 4316-4336.

Comon, P. (1994). Independent component analysis, a new concept?. *Signal processing*, *36*(3), 287-314.

Construction Industry Institute (CII) (2005). “Core competency toolkit.” Research Summary 111-3, Construction Industry Institute, Austin, Texas, September, 2005.

Costa, D. B., Formoso, C. T., Kagioglou, M., Alarcón, L. F., & Caldas, C. H. (2006). Benchmarking initiatives in the construction industry: lessons learned and improvement opportunities. *Journal of Management in Engineering*, *22*(4), 158-167.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation,10*(7).

Cronbach, L. J. (1951). "Coefficient alpha and the internal structure of tests." *Psychometrika,* 16(3), 297-334.

Delgado, M., J. L. Verdegay, and M. A. Vila. (1993). On aggregation operations of linguistic labels. *International Journal of Intelligent Systems* 8.3: 351–370.

Detyniecki M. (2001). Fundamentals on aggregation operators. Manuscript based on PhD thesis, Berkeley Initiative in Soft Computing, Computer Science Division, University of California, Berkeley, California, USA. Available at: http://www.poleia.lip6.fr/~marcin/papers/Detynieck_AGOP_01.pdf (accessed June 16, 2014).

Devijver, P. A., & Kittler, J. (1982). *Pattern recognition: A statistical approach* (Vol. 761). London: Prentice-Hall, Englewood Cliffs, NJ.

Dissanayake, M., Fayek, A. R., Russell, A. D., & Pedrycz, W. (2005). A hybrid neural network for predicting construction labour productivity. In*Proceedings of the International Conference on Computing in Civil Engineering, Cancun, Mex* (pp. 12-15).

Dissanayake, M (2006). "An integrated computational intelligence framework for construction performance diagnosis", Thesis for Doctor of Science, University of Alberta.

DiStefano, C., Zhu, M., & Mindrila, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. Practical Assessment, Research & Evaluation, 14(20), 1-11.

Dragoni, A. F., Baldassarri, P., Vallesi, G., & Mazzieri, M. (2009, November). Multiple neural networks system for dynamic environments. In *Intelligent Systems Design and Applications, 2009. ISDA'09. Ninth International Conference on* (pp. 164-168). IEEE.

Drew, P. J., & Monson, J. R. (2000). Artificial neural networks. *Surgery*, *127*(1), 3-11.

Dubois D and Prade H. (2004). On the use of aggregation operations in information fusion processes. *Fuzzy Sets and Systems* 142: 143–161.

Dumais, Susan T. (2004). "Latent semantic analysis." *Annual review of information science and technology* (38.1): 188-230.

Eccles, R. (1991). "The performance measurement manifesto." Harvard Bus. Rev. 69 (1), 131–137.

Edgar, W. B., & Lockwood, C. A. (2008). Organizational competencies: clarifying the construct. *Journal of Business*, *22*, 21-32.

Emrouznejad A, and Marra M. (2014). Ordered weighted averaging operators 1988–2014: A citation-based literature survey. *International Journal of Intelligent Systems* 29: 994–1014.

Fayek, A. Robinson. (2012). Advancing Fuzzy Hybrid Techniques for Competency Modeling of Construction Organizations, Natural Sciences and Engineering Research Council of Canada Discovery Grant Proposal, University of Alberta, Edmonton, AB.

Field, A. (2005). Discovering statistics using SPSS , Sage, Thousand Oaks, CA.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wesley

Geng, X., Zhan, D. C., & Zhou, Z. H. (2005). Supervised nonlinear dimensionality reduction for visualization and classification. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, *35*(6), 1098-1107.

Ghiasi, M. M., Bahadori, A., & Zendehboudi, S. (2014). Estimation of triethylene glycol (TEG) purity in natural gas dehydration units using fuzzy neural network. *Journal of Natural Gas Science and Engineering*, *17*, 26-32.

George, D., & Mallery, M. P. (2003). *Using SPSS for Windows Step by Step: A simple Guide and Reference*. Allyn & Bacon: Boston, MA.

Grabisch M, Orlovski SA, and Yager RR. (1998). Fuzzy aggregation of numerical preferences. *Fuzzy Sets in Decision Analysis, Operations Research and Statistics*, R Słowiński (Ed). Springer: New York, New York, USA; 31–68.

Grzegorzewski, P. (2004). Distances between intuitionistic fuzzy sets and/or interval-valued fuzzy sets based on the Hausdorff metric. *Fuzzy Sets and Systems* 148.2 (2004): 319–328.

Gupta, M. M. (1994). “Fuzzy Neural Networks: theory and applications.” Proceedings of SPIE 1994, *The International Society for Optical Engineering*, 303-325

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational behavior and human performance*, *16*(2), 250-279.

Hater, J. J., & Bass, B. M. (1988). Superiors' evaluations and subordinates' perceptions of transformational and transactional leadership. *Journal of Applied psychology*, *73*(4), 695.

Hitt, M. A., and Ireland, R. D. (1986). "Relationships among corporate level distinctive competencies, diversification strategy, corporate structure and performance." *Journal of Management Studies,* 23(4), 401-416.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural networks*, *2*(5), 359-366.

Hsu, H. M., and Chen, C. T. (1996) Aggregation of fuzzy opinions under group decision making. *Fuzzy Sets and Systems* 79.3: 279–285.

Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: theory and applications. *Neurocomputing*, *70*(1-3), 489-501.

Huang, Y., Niu, B., Gao, Y., Fu, L., & Li, W. (2010). CD-HIT Suite: a web server for clustering and comparing biological sequences. *Bioinformatics*, *26*(5), 680-682.

Hung, W. L., and Yang, M. S. (2004). Similarity measures of intuitionistic fuzzy sets based on Hausdorff distance. *Pattern Recognition Letters*, 25.14: 1603–1611.

Hyvärinen, A., Karhunen, J., & Oja, E. (2004). *Independent component analysis* (Vol. 46). John Wiley & Sons. NY.

Isik, Z., Arditi, D., Dikmen, I., and Birgonul, M. T. (2009). "Impact of corporate strengths/weaknesses on project management competencies." *Int.J.Project Manage*., 27(6), 629-637.

Izenman, A. J. (2008). Linear discriminant analysis. In *Modern Multivariate Statistical Techniques* (pp. 237-280). Springer New York.

Jang, J. S. R. (1993). ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, *23*(3), 665-685.

Kagioglou, M., Cooper, R., & Aouad, G. (2001). Performance management in construction: a conceptual framework. *Construction management and economics*, *19*(1), 85-95.

Kaplan Robert S.; Norton David P. (2005): The balanced scorecard: Measures that drive performance. Boston, MA, ETATS-UNIS: Harvard Business School Publishing Corporation (Harvard business review, 83) (7).

Kasabov, N. (2001). Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, *31*(6), 902-918.

Kasabov, N. K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio-and spectro-temporal pattern recognition. *Neural Networks*, *41*, 188-201.

Kasabov, N. K. (2014). NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data. *Neural Networks*, *52*, 62-76.

Kohavi, R. (1995). "A study of cross-validation and bootstrap for accuracy estimation and model selection". *International Joint Conference on Artificial Intelligence.* 14(2), 1137-1145.

Kometa, S. T., Olomolaiye, P. O., and Harris, F. C. (1995). "An evaluation of clients' needs and responsibilities in the construction process." *Engineering, Construction and Architectural Management,* 2(1), 57-76.

Kululanga, G. K., Edum-Fotwe, F. T., McCaffer, R. (2001). "Measuring construction contractors' organizational learning." *Building Research and Information*, 29(1), 21–29.

Levenson, A. R., Van der Stede, Wim A, and Cohen, S. G. (2006). "Measuring the relationship between managerial competencies and performance." *Journal of Management,* 32(3), 360-380.

Kumar, A. C. (2009). Analysis of unsupervised dimensionality reduction techniques. *Computer science and information systems*, *6*(2), 217-227.

Jones DF and Mardle SJ. (2004). A distance-metric methodology for the derivation of weights from a pairwise comparison matrix. *Journal of the Operational Research Society* 55: 869–875. doi: 10.1057/palgrave.jors.2601745.

Lee, H. (1999). An optimal aggregation method for fuzzy opinions of group decision. *IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics* Vol. 3.

Letza, S. R. (1996). “The design and implementation of the balanced scorecard.” *Bus. Process Re-engineering Manage. J.*, 2 (3), 54–76.

Levenson, A. R., Van der Stede, Wim A, and Cohen, S. G. (2006). "Measuring the relationship between managerial competencies and performance." *Journal of Management,* 32(3), 360-380.

Li, D., and Yang, J. (2004). Fuzzy linear programming technique for multi attribute group decision making in fuzzy environments. *Information Sciences* 158 (2004): 263–275.

Lin, D., Wang, X., Nian, F., & Zhang, Y. (2010). Dynamic fuzzy neural networks modeling and adaptive backstepping tracking control of uncertain chaotic systems. *Neurocomputing*, *73*(16), 2873-2881.

Li, H., Chen, B., Zhou, Q., & Qian, W. (2009). Robust stability for uncertain delayed fuzzy Hopfield neural networks with Markovian jumping parameters. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*,*39*(1), 94-102.

Lootsma FA. (2000). Distributed multi-criteria decision making and the role of the participants in the process. *Journal of Multi-Criteria Decision Analysis*, 9(1–3): 45–55.

Markus, L., Thomas, H. C., and Allpress, K. (2005). “Confounded by competencies? An evaluation of the evolution and use of competency models.” *New Zealand Journal of Psychology*, 34(2), 117.

Marichal JL. (1998). Aggregation operators for multicriteria decision aid. PhD thesis, Institute of Mathematics, University of Liège, Belgium.

Milani AS, Shanian A, Madoliat R, and Nemes JA. (2005). The effect of normalization norms in multiple attribute decision making models: A case study in gear material selection. *Structural and Multidisciplinary Optimization* 29: 312–318.

Nagoor, G. A. and Mohamed Assarudeen, S. N. (2012). A New operation on triangular fuzzy number for solving fuzzy linear programming problem. *Applied Mathematical Sciences* 6.11: 525–532.

Narukawa Y. (2007). *Modeling Decisions: Information Fusion and Aggregation Operators*. Springer: New York, New York, USA.

Nasir, H., Haas, C. T., Rankin, J. H., Fayek, A. Robinson, Forgues, D., and Ruwanpura, J. (2012). "Development and implementation of a benchmarking and metrics program for construction performance and productivity improvement." *Canadian Journal of Civil Engineering, Special Issue on Construction Engineering and Management,* 39(9), 957-967.

Navarre, C. and Schaan, J.L. (1990). Design of project management systems from top management's perspective. *Project Management Journal*, Vol. 21 No. 2, pp. 19-27.

Navon, R. (2005). Automated project performance control of construction projects. *Automation in Construction*, *14*(4), 467-476.

Neely, A., Bourne, M., (2000). Why measurement initiatives fail", *Measuring Business Excellence*, Vol. 4 Iss: 4, pp.3 – 7

Norreklit, H. (2000). The balance on the balanced scorecard—A critical analysis of some of its assumptions." *Manage. Account. Res.*, 11 (1), 65–88

Nunnally JC (1978) *Psychometric Theory*, 3rd edition. McGraw-Hill, New York.

O'Hagan M. (1988). Aggregating template or rule antecedents in real-time expert systems with fuzzy set logic. In Proceedings of the 22nd Annual IEEE Asilomar Conference on Signals, Systems and Computers, October 31–November 2, Pacific Grove, California, USA; 681–689.

Omar, M. and Fayek, A. (2014) A Framework for identifying and measuring competencies and performance indicators for construction projects. *Construction Research Congress,* 2043-2052.

Omar, M. and Fayek, A. Robinson (2015a). "Modeling and evaluating construction project competencies and their relationship to project performance" Manuscript submitted to *Journal of Construction Engineering and Management*. August 15, 2015.

Omar, M. and Fayek, A. Robinson. (2015b). "A TOPSIS–based approach for prioritized aggregation in multiple-criteria decision-making problems." Accepted for publication in international journal of multi-criteria decision analysis. Manuscript, 20 pages.

Omar, M. and Fayek, A. Robinson. (2015c). “A TOPSIS–based method for prioritized aggregation in fuzzy environments.” Submitted for publication in fuzzy sets and systems journal Manuscript, 18 pages

Pedrycz, W. (1994). Why triangular membership functions? *Fuzzy Sets and Systems* 64: 21–30.

Pedrycz, W., and Gomide, F. (2007). *Fuzzy Systems Engineering: Toward Human-Centric Computing*. John Wiley and Sons, Toronto, 2007.

Pedrycz, W. (2014). "Allocation of information granularity in optimization and decision-making models: towards building the foundations of granular computing." *Eur.J.Oper.Res.,* 232(1), 137-145.

Pinson, P., & Kariniotakis, G. N. (2003, June). Wind power forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment. In *Power Tech Conference Proceedings, 2003 IEEE Bologna* (Vol. 2, pp. 8-pp). IEEE.

Pinto, M.B. and Pinto, J.K. (1991), Determinants of cross-functional cooperation in the project implementation process. *Project Management Journal*, Vol. 22 No. 2, pp. 13-20

Provost, L., & Leddick, S. (1993). How to take multiple measures to get a complete picture of organizational performance. *National Productivity Review*,12(4), 477-490.

Ralescu, Anca L., and Dan A. Ralescu. (1997). Extensions of fuzzy aggregation. *Fuzzy Sets and Systems* 86.3: 321–330.

Rankin, J., Fayek, A. Robinson., Meade, G., Haas, C., and Manseau, A. (2008). "Initial metrics and pilot program results for measuring the performance of the Canadian construction industry." *Canadian Journal of Civil Engineering,* 35(9), 894-907.

Razmak J and Aouni B. (2014). Decision Support System and Multi-Criteria Decision Aid: A state of the art and perspectives. *Journal of Multi-Criteria Decision Analysis* (pre-publication online version).

Rencher, A. C. (2002). *Methods of multivariate analaysis.* John Wiley & Sons, New York.

Sarshar, M., Haigh, R., Finnemore, M., Aouad, G., Barrett, P., Baldry, D., and Sexton, M. (2000). "SPICE: a business process diagnostics tool for construction projects." *Engineering Construction and Architectural Management,* 7(3), 241-250.

Shih HS, Shyur HJ, and Lee ES. (2007). An extension of TOPSIS for group decision making. *Mathematical and Computer Modelling* 45: 801–813.

Sparrow, P. (1995): “Organizational competencies: A valid approach for the future?” *International Journal of Selection and Assessment*, 3(3), 168–177.

Steuer RE. (1989). *Multiple Criteria Optimization: Theory, Computation, and Application*. Krieger: Malabar, Florida, USA.

Walsh, S. T., Linton, J. D. (2001). “The competence pyramid: A framework for identifying and analyzing firm and industry competence.” *Technology Analysis and Strategic Management.*, 13(2), 165–177.

Sanvido, V., Grobler, F., Parfitt, K., Guvenis, M. and Coyle, M. (1992) “Critical success factors for construction projects.” *Journal of Construction Engineering and Management*, 118(1), 94–111.

Spencer L.M & Spencer S.M. (1993). "Competence at work: Models for superior performance. New York: John Wiley & Sons, Inc.

Stuart, R. (1983). Problems of training design, Industrial & Commercial Training, August, 239-40.

Tanino, T. (1984). Fuzzy preference orderings in group decision making. *Fuzzy Sets and Systems* 12: 117–131.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. American Psychological Association.

Tong, R. M., and Bonissone P. P. (1980). A linguistic approach to decision making with fuzzy sets. *IEEE transactions on Systems, Man and Cybernetics* 10.11: 716–723.

Ulubeyli S and Kazaz A. 2009. A multiple criteria decision-making approach to the selection of concrete pumps. *Journal of Civil Engineering and Management* 15: 369–376.

The Alberta Report: COAA Major Projects Benchmarking Summary". Construction Industry Institute. (n.d.). Accessed August 1, 2015, from https://www.construction-institute.org/nextgen/publications/COAA/COAA_Alberta_Report.pdf

Walsh, Steven T., Linton, Jonathan D. (2001). The competence pyramid: A framework for identifying and analyzing firm and industry Competence. In *Technology Analysis & Strategic Management* 13 (2), pp. 165–177.

Wang, J., & Peng, H. (2013). Adaptive fuzzy spiking neural P systems for fuzzy inference and learning. *International Journal of Computer Mathematics*,*90*(4), 857-868.

Ward, P. T., Duray, R., Leong, G. K., & Sum, C. C. (1995). Business environment, operations strategy, and performance: an empirical study of Singapore manufacturers. *Journal of operations management*, *13*(2), 99-115.

Wei, G. (2009). Some geometric aggregation functions and their application to dynamic multiple attribute decision making in the intuitionistic fuzzy setting. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 17.2: 179–196.

Wei, G. (2010). Some induced geometric aggregation operators with intuitionistic fuzzy information and their application to group decision making. *Applied Soft Computing* 10.2: 423–431.

Wei C and Tang X. (2012). Generalized prioritized aggregation operators. *International Journal of Intelligent Systems* 27: 578–589.

Wei, G. (2012). Hesitant fuzzy prioritized operators and their application to multiple attribute decision making. *Knowledge-Based Systems* 31: 176–182.

Willis, C. J., and Rankin, J. H. (2010). "Measuring the Maturity of Guyana's Construction Industry Using the Construction Industry Macro Maturity Model (CIM3)." *Journal of Construction in Developing Countries,* 15(2), 87-116.

Willis, C. J., and Rankin, J. H. (2012). "The construction industry macro maturity model (CIM3): theoretical underpinnings." *International Journal of Productivity and Performance Management,* 61(4), 382-402.

Wood, R. E., Atkins, P. W., & Bright, J. E. (1999). Bonuses, goals, and instrumentality effects. *Journal of Applied Psychology*, *84*(5), 703.

Wu, S., & Er, M. J. (2000). Dynamic fuzzy neural networks-a novel approach to function approximation. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 30(2), 358-364.

Xu Z and Yager RR. (2006). Some geometric aggregation operators based on intuitionistic fuzzy sets. *International Journal of General Systems* 35: 417–433.

Yager RR. (1988). On ordered weighted averaging aggregation operators in multicriteria decision making. *Systems, Man and Cybernetics, IEEE Transactions on* 18*:* 183–190.

Yager RR. (1996). Quantifier guided aggregation using OWA operators. *International Journal of Intelligent Systems* 11: 49–73.

Yager RR. (2004). Modeling prioritized multicriteria decision making. *Systems, Man, and Cybernetics, IEEE Transactions on—Part B: Cybernetics* 34: 2396–2404.

Yager RR. (2008). Prioritized aggregation operators. *International Journal of Approximate Reasoning* 48: 263–274.

Yager RR. (2009). Prioritized OWA aggregation. *Fuzzy Optimization and Decision Making* 8: 245–262.

Yager, RR, Gumrah G, and Reformat MZ. (2011). Using a web personal evaluation tool PET for lexicographic multi-criteria service selection. *Knowledge-Based Systems* 24: 929–942.

Yager RR, Kacprzyk, J, and Beliakov G. (2011). *Recent developments in the ordered weighted averaging operators: Theory and practice* 265. Springer-Verlag: Berlin, Germany.

Yan, H. B., Huynh, V. N., Nakamori, Y., & Murai, T. (2011). On prioritized weighted aggregation in multi-criteria decision making. *Expert Systems with Applications*, *38*: 812-823.

Yoon K and Hwang CL. (1985). Manufacturing plant location analysis by multiple attribute decision making: Part I—Single-plant strategy. *International Journal of Production Research* 23: 345–359.

Yoon KP and Hwang CL (eds). (1995). *Multiple Attribute Decision Making: An Introduction*. Sage: London, UK.

Yu, D., Wu, Y., and Lu, T. (2012). Interval-valued intuitionistic fuzzy prioritized operators and their application in group decision making. *Knowledge-Based Systems* 30: 57–66.

Yu, D. (2012). Group decision making based on generalized intuitionistic fuzzy prioritized geometric operator. *International Journal of Intelligent Systems* 27.7: 635–661.

Yu, X., and Xu, Z. (2013). Prioritized intuitionistic fuzzy aggregation operators. *Information Fusion* 14.1: 108–116.

Yu, W. D., & Skibniewski, M. J. (2009). Integrating neurofuzzy system with conceptual cost estimation to discover cost-related knowledge from residential construction projects. *Journal of Computing in Civil Engineering*, *24*(1), 35-44.

Zhao XF, Lin R, and Wei GW. (2013). Fuzzy prioritized operators and their application to multiple attribute group decision making. *Applied Mathematical Modelling* 37: 4759–4770.

Zadeh, Lotfi A. (1965). "Fuzzy sets." *Information and control* 8.3: 338-353.

APPENDIX 1. Project Competencies and KPIs' Criteria and Data Collection Forms

1.1. Functional Competencies Evaluation Criteria

No.	Functional Competencies and Evaluation Criteria
1	***Project Integration Management***
1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
1.2	Kickoff meetings are initiated for the project at the planning stage.
1.3	Key practices required for project planning and execution are identified at the planning stage.
1.4	A project charter is developed for the project at the planning stage.
1.5	A project management plan is developed for the project at the planning stage.
1.6	A configuration management system is included in the procedures to control project performance.
1.7	Project is properly executed in accordance to the preconstruction stages.
1.8	Project is actively monitored and an integrated change control process is in place.
1.9	At closing phase, changes to the project integration management and project management plan are identified. Project integration management and project management plan performance are documented.
2	***Project Scope Management***
2.1	Policies and procedures for project scope management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
2.2	Project requirements and scope are identified in the kickoff meeting at the planning stage.
2.3	Constructability principles are considered during scope identification and development.
2.4	A scope verification process is considered in the planning stage.
2.5	A constructability champion is assigned during the planning stage to oversee the constructability review process among different stakeholders.
2.6	Meetings are held during execution to verify scope and discuss any potential scope changes/creep.
2.7	A scope control process is in place to identify scope changes/creep.

No.	Functional Competencies and Evaluation Criteria
2.8	At closing phase, changes to the project scope are identified and documented. Project scope management performance is documented.
3	***Project Time Management***
3.1	Policies and procedures for project time management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
3.2	Work activities are based on a Work Breakdown Structure.
3.3	Work sequence and logic are developed in the project schedule prior to work execution.
3.4	Activity resources and costs are estimated and combined in the project schedule prior to work execution.
3.5	Developed schedule is verified with construction teams supervising the project execution.
3.6	Project schedule is communicated with different teams and workers on the project. Logic is explained and is followed.
3.7	Time sheets register (e.g., productivity sheets) is available on site to record the amount of time spent undertaking a project activity or task.
3.8	Schedule updates are regularly performed.
3.9	Resource usage profiles generated from schedule are regularly monitored to maintain project work continuity.
3.10	Schedule meetings are regularly performed to communicate schedule delays/impact of changes.
3.11	Commercial or in-house scheduling software is used for developing project time schedule. Practice performance is also documented.
3.12	At closing stage, as-built schedule is documented, and a report is generated with all changes to the as-planned schedule activities and resources. Project time management performance is documented.
4	***Project Cost Management***
4.1	Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
4.2	Estimates are developed based on a clear project scope.
4.3	A detailed budget for the project (associated with detailed expenses, risk, contingency, overheads, and profit) is defined at the early stages of the project.
4.4	An integration of the project budget and schedule is performed to generate the cash flow.
4.5	Government and market cost indices are used in developing cost estimate in order to consider any cost fluctuations/inflations (e.g., increase in wages).
4.6	Different expense forms are available on site (e.g., document expense forms) to track different expenditures.

No.	Functional Competencies and Evaluation Criteria
4.7	A cash flow analysis is regularly carried out to monitor the financial status of the project.
4.8	Updated cash flow with changes to the cost baseline is regularly conducted.
4.9	Cost control meetings are held to communicate budget changes / impact on overall project budget.
4.10	All related project costs (e.g., invoices and payments) are submitted in a timely manner.
4.11	Commercial or in-house cost control software is used for project cost management.
4.12	At closing phase, a final project budget is documented and a report is generated with all changes to the cost baseline. Project cost management performance is documented.
5	***Project Engineering and Procurement Management***
5.1	Policies and procedures for project engineering and procurement management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
5.2	Engineering lists are developed for items to be procured based on project contract, design, and specifications.
5.3	An integrated system for procuring material and equipment is established prior to work execution.
5.4	Communication procedures with different parties (stakeholders and suppliers) are established prior to work execution.
5.5	An integrated procurement system is applied with vendors to allow for proper tracking and monitoring of procured items during the different stages (purchase order, fabrication, delivery, and on site storage).
5.6	Warranties and operation manuals for procured material/equipment are documented for proper installation/use on site.
5.7	Engineering and procurement development cycles are integrated during execution with construction activities to maintain work continuity.
5.8	Periodic review of engineering and procurement activities through adequate administration is done to eliminate any backlog/delays.
5.9	At closing phase, changes to the project engineering and procurement are identified and documented. Project engineering and procurement management performance is documented.
6	***Project Resource Management***
6.1	Policies and procedures for project resource management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
6.2	Required resources for project execution are identified at the planning stage.
6.3	Resource allocation and levelling techniques are applied at the planning stage to optimize required resources for continuous work execution.
6.4	Critical resources/long lead resources are identified and communicated with different responsible project teams.

No.	Functional Competencies and Evaluation Criteria
6.5	Resources are monitored and directed during work execution.
6.6	Resource monitoring and updates are regularly conducted during execution (e.g., resource usage sheets) and variance analysis is conducted on regular basis to ensure continuous work execution.
6.7	At closing phase, project resource usage against planned usage is analysed and associated implications are documented. Project resource management performance is documented.
7	***Project Risk Management***
7.1	Policies and procedures for project risk management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
7.2	A process of defining relevant risks to the project is in place.
7.3	A qualitative analysis for risks and contingencies are performed at the planning stage of the project.
7.4	A quantitative analysis for risks and contingencies are performed at the planning stage of the project.
7.5	A risk response plan is established in the planning stage of the project.
7.6	A risk register is communicated among different parties during execution of work in the project.
7.7	Mitigation strategies are communicated among different parties for possible occurring risks during work execution on the project.
7.8	Periodic risk meetings are conducted and risk registers are updated regularly with different parties' responses on project risks.
7.9	At closing phase, project risks and contingency are analysed against planned ones, and associated deviations are documented for lessons learned. Project risk management performance is documented.
8	***Project Communication Management***
8.1	Policies and procedures for project communication management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
8.2	Stakeholders are identified for future communication at the planning stage, and a communication plan is established.
8.3	Information among different parties on site is communicated as dictated in the communication plan.
8.4	All project-related reporting (e.g., periodic progress reports, drawing schedules, RFIs, non-conformance reports) are submitted in a timely manner to relevant stakeholders.
8.5	Communication results are reported and communicated among different stakeholders.
8.6	At closing phase, different project communications (e.g., documents, letters) with

No.	Functional Competencies and Evaluation Criteria
	stakeholders are documented. Project communication management performance is documented.
9	***Project Safety Management***
9.1	Policies and procedures for project safety management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
9.2	Safety preplanning meetings are held, and a safety plan is established for the project.
9.3	Safety meetings are conducted regularly on site for proper safety practices execution.
9.4	Safety toolbox meetings are conducted regularly on site.
9.5	Safety requirements (e.g., PPE, hazard assessment procedures, evacuation plans) are implemented and communicated among different workers on site.
9.6	Safety training sessions are conducted regularly on site.
9.7	Safety reporting (e.g., accidents, near miss accidents, hours lost as a result of safety related incidents, site closure resulting from safety incidents) is regularly conducted.
9.8	At closing phase, project safety management performance is documented.
10	***Project Human Resource Management***
10.1	Policies and procedures for project human resource management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
10.2	Human resources plan is developed at the planning stage.
10.3	Project teams are identified and assigned to project once the project is awarded.
10.4	A strategy is established for enhancing recruitment by hiring from non-traditional pools.
10.5	A hierarchical work environment is identified for different crew levels, where roles and responsibilities are clearly identified during work execution within the same crews (e.g., seniority of workers).
10.6	Regular meetings are held to discuss workers' problems and possible solutions during project execution.
10.7	Hiring and layoff procedures are clearly identified and followed in the project.
10.8	At closing phase, project human resource plan performance is documented.
11	***Project Quality Management***
11.1	Policies and procedures for project quality management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.

No.	Functional Competencies and Evaluation Criteria
11.2	A quality management plan is created for project at the planning stage.
11.3	An integrated Quality Management System is implemented for project.
11.4	Quality meetings are conducted with different stakeholders prior to execution of work.
11.5	External quality recruitment services (e.g., recruiting quality control and assurance services from outside the company) are considered at the planning stage to ensure proper quality practice implementation on the project.
11.6	Quality meetings are regularly conducted on site for quality control and assurance improvement.
11.7	Project quality control inspections are routinely conducted on site.
11.8	Quality reporting identifying areas of concern and mitigation strategies is conducted in timely manner.
11.9	Related quality issues are communicated among different key stakeholders with proper remedial actions.
11.10	At closing phase, project quality management performance is documented.
12	***Project Change Management***
12.1	Policies and procedures for project change management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
12.2	A change management plan is established at the planning stage. Meetings with key stakeholders to communicate change management plan are held.
12.3	Changes to scope are identified and communicated during work execution.
12.4	Regular meetings are held to control changes against original scope.
12.5	A change register is monitored, controlled, and communicated among different key stakeholders.
12.6	The process of quantifying the impact of changes is conducted immediately and communicated among different key stakeholders, and is integrated with the project schedule and budget.
12.7	At closing phase, changes for project are documented against original contractual requirements. Project change management performance is documented.
13	***Project Stakeholders Management***
13.1	Policies and procedures for project stakeholder management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
13.2	A stakeholder management and engagement plan is established at the planning stage.

No.	Functional Competencies and Evaluation Criteria
13.3	Meetings with stakeholders are held to analyse and document relevant information regarding their interests, involvement, interdependencies, influence, and potential impact on project success.
13.4	Regular meetings with different stakeholders are conducted during project execution.
13.5	At closing phase, project stakeholder management performance is evaluated and documented.
14	***Project Environmental Management***
14.1	Policies and procedures for project environmental management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
14.2	Clear understanding of environmental goals and investments is communicated with the different stakeholders at the planning stage.
14.3	Environmental impact assessment is conducted at the planning stage.
14.4	Ecological benefits and community input are considered in the design development and estimate analysis at the planning stage.
14.5	Permits and approvals are identified at the planning stage, and are obtained in a timely manner to avoid any work execution delays.
14.6	At closing phase, project environmental management performance is evaluated and documented.
15	***Project Commissioning and Startup***
15.1	Policies and procedures for project commissioning and startup are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
15.2	A commissioning and startup plan is established and communicated with different key stakeholders.
15.3	A construction checklist with required rectification actions is communicated among different key stakeholders to finalize the execution of work (e.g., snag list).
15.4	Regular meetings concerning commissioning and startup are held to discuss pending items.
15.5	System and operation manuals are discussed with the key stakeholders/clients to properly operate and maintain the facility if appropriate.
15.6	A resolution strategy/flowchart is developed for pending issues during commissioning and startup.
15.7	At closing phase, project commissioning and startup phase performance is evaluated and documented.
16	***Project Innovation***
16.1	Policies and procedures for project innovation are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
16.2	Work ideas at the project level are generalized and are communicated to the company.

No.	Functional Competencies and Evaluation Criteria
16.3	Development and production of new technologies is adopted at the company level and is applied on the project.
16.4	Subsequent application of innovation is applied to solving problems and enhancing existing practices and processes on the project.
16.5	At closing phase, the application of innovation strategies in improving project performance is documented.
17	***Project Workface Planning***
17.1	Policies and procedures for project workface planning are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
17.2	A workface planning sponsor/champion is assigned to the project.
17.3	Workface planning requirements are communicated to different team members.
17.4	A review process of the workface planning execution plan for the project is in place.
17.5	Field installation work packages are identified and applied on the project.
17.6	Integration and coordination of field installation takes place for the different work packages during execution.
17.7	At closing phase, project workface planning performance is evaluated and documented.
18	***Project Contract Administration***
18.1	Policies and procedures for project contract administration are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
18.2	A designated contract administrator is identified at the planning stage for the project.
18.3	A contract review process is identified to ensure conformance of procurement, engineering, design, and work execution to contract requirements for the project.
18.4	A contract administrator is responsible for communication with different key stakeholders and vendors in the project.
18.5	Variances in schedule, budget, safety, and quality are communicated with the contract administrator.
18.6	A contract administrator ensures adherence of project change management practices with contract documents.
18.7	At closing phase, project contract administration performance is evaluated according to compliance with the contract requirements. Any occurring contractual deviations are documented.
19	***Project Team Building***
19.1	Policies and procedures for project team building are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.

No.	Functional Competencies and Evaluation Criteria
19.2	Meetings are held with different teams for project scope briefing at the planning stage to ensure teams are aligned during execution of work.
19.3	Different key stakeholders are involved in the team building process.
19.4	A formal process for team alignment with different project participants is applied.
19.5	During execution, periodic team evaluation is conducted.
19.6	At closing phase, project team building performance is evaluated and documented.
20	***Project Workforce Development***
20.1	Policies and procedures for project workforce development are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
20.2	A workforce improvement strategy and plan is established at the planning stage.
20.3	Workshops and training sessions are conducted for workers regularly on the project.
20.4	Workforce development and improvement meetings are held to discuss possible improvements to current workforce on the project.
20.5	At closing phase, workforce development performance is evaluated and documented.
21	***Project Technology Integration***
21.1	Policies and procedures for project technology integration are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.
21.2	Proper investment is allocated for research and development at the company level.
21.3	Proactive participation in the development of industry standards and best practices exists by sharing project execution experience.
21.4	Advanced technologies (for communication, on-site equipment, systems, and design) are considered for this project.
21.5	Implementation and communication of used technology in project is clear for the different processes on the project.
21.6	Standardized operating procedures are available on site for different technologies used. Clear instructions are given to workers on how to apply these technologies on the project.
21.7	Regular meetings are held to discuss applied technologies and their impact on work execution on the project.
21.8	At closing phase, the application of new technologies is analysed and its performance is documented for the project.

1.2. Behavioural Competencies Evaluation Criteria

No.	Behavioural Competencies and Evaluation Criteria
1	***Analytical Ability***
1.1	Members of this team can anticipate and identify problems in their daily tasks.
1.2	Members of this team can picture the end product and account for missing data in their daily tasks.
2	***Training***
2.1	Members of this team possess the necessary training to perform their daily tasks.
2.2	Members of this team have performed similar tasks to their current tasks.
3	***Assessment Ability***
3.1	Members of this team are capable of breaking down problems into components and recognizing interrelationships in order to solve them in their daily tasks.
3.2	Members of this team have the ability to properly estimate the potential impact of existing problems in their daily tasks.
3.3	Members of this team have the ability to properly estimate the magnitude of existing problems in their daily tasks.
4	***Decision Making***
4.1	Members of this team make sound, well-informed, and objective decisions in their daily tasks.
4.2	Members of this team compare data, information, and input from a variety of sources to draw conclusions before applying them in their daily tasks.
4.3	Members of this team take actions that are consistent with available facts, constraints, and probable consequences in their daily tasks.
4.4	Members of this team consider costs, benefits, and risks when making decisions related to their daily tasks.
4.5	Members of this team guide their team members toward making effective decisions in their daily tasks.
4.6	Members of this team collaborate before making important decisions.
5	***Leadership***
5.1	Members of this team find resources, training, and tools to support their team members' needs in executing their daily tasks.
5.2	Members of this team guide their team members in accomplishing their daily work objectives.
5.3	Members of this team reward and recognize their team members, both formally and informally, in ways that motivate them during the execution of their daily tasks.
5.4	Members of this team set high performance expectations for their team members in their daily tasks.
5.5	Members of this team hold their team members accountable for achieving results in their

No.	Behavioural Competencies and Evaluation Criteria
	daily tasks.
5.6	Members of this team encourage a work culture of continuous learning, information sharing, and professional development.
5.7	Members of this team accept their assigned responsibilities, and take action within the scope of their position and responsibility in their daily tasks.
6	***Teamwork***
6.1	Members of this team participate as active and contributing members to achieve their team's daily goals.
6.2	Members of this team work cooperatively with other teams on their daily tasks.
6.3	Members of this team share information as appropriate to other teams.
6.4	Members of this team share credit for team accomplishments.
6.5	Members of this team value the input and know-how of other team members.
6.6	Members of this team recognize their team members for their achievements and support.
6.7	Members of this team ask for help from other team members, when needed.
6.8	Members of this team offer help to other team members, when needed.
6.9	Members of this team try to build trust and respect among fellow team members.
6.10	Members of this team behave professionally and supportively when working with individuals from a variety of ethnic, social, and educational backgrounds.
6.11	Members of this team take actions that demonstrate consideration for the feelings and needs of others.
7	***Consultation***
7.1	Members of this team possess a high level of effectiveness in consulting their own team members with problems they encounter in their daily tasks.
7.2	Members of this team consult members of other teams working on site when they encounter a problem.
8	***Motivation***
8.1	Members of this team have a high level of motivation.
8.2	Members of this team are capable of properly recognizing rewards.
8.3	Members of this team have a high level of interest in work assigned to them.
9	***Negotiation and Crisis Resolution***

No.	Behavioural Competencies and Evaluation Criteria
9.1	Members of this team have the ability to develop several solution scenarios to resolve a conflict.
9.2	Members of this team have a high level of flexibility when resolving an existing conflict.
9.3	Members of this team are able to identify common interests during conflicts thus facilitating resolution.
9.4	Members of this team conduct a structured approach in negotiation (co-operative, competitive, principled) to solve an existing conflict.
10	***Ethics***
10.1	Members of this team conform to any legal or regulatory framework enforced by the company.
10.2	Members of this team have the ability to detect possible unethical situations arising or unethical proposals being made during their daily tasks.
10.3	Members of this team report ethical violations to their supervisor(s).
10.4	Members of this team act with integrity, tell the truth, and admit to mistakes.
10.5	Members of this team have the ability to properly communicate ethics among others.
11	***Self-Control***
11.1	Members of this team have good working behaviour with others.
11.2	Members of this team have the ability to identify actions to reduce stress in themselves and others while executing their daily tasks.
12	***Reliability***
12.1	Members of this team have the ability to deliver work within agreed-upon quality requirements.
12.2	Members of this team have the ability to deliver work within agreed-upon time periods.
12.3	Members of this team are willing to learn and use new technologies for their work tasks.
13	***Problem Solving***
13.1	Members of this team can recognize situations where there is a problem to be solved.
13.2	Members of this team can determine members who can contribute to finding a creative solution to an existing problem.
13.3	Members of this team can determine the feasibility of possible solutions and determine the most suitable solution.
14	***Commitment***
14.1	Members of this team comply to the organizational values and goals during execution of work.

No.	Behavioural Competencies and Evaluation Criteria
15	***Adaptability***
15.1	Members of this team adapt well to changes in assignments and priorities in their daily tasks.
15.2	Members of this team adapt to work methods in response to new information, changing conditions, or unexpected obstacles in their daily tasks.
15.3	Members of this team approach change positively and adjust behaviours in different situations encountered.
15.4	Members of this team talk positively about change and demonstrate willingness to try new ways of doing things.
15.5	Members of this team facilitate the implementation and acceptance of change within the workplace.
15.6	Members of this team encourage others to seek opportunities for different and innovative approaches to addressing problems and opportunities.
16	***Building Trust***
16.1	Members of this team interact with others in a way that gives them confidence.
16.2	Members of this team keep confidences and commitments in different situations.
16.3	Members of this team admit and hold themselves accountable for mistakes resulting from their actions/inactions.
17	***Interpersonal Skills***
17.1	Members of this team demonstrate good written, oral, and listening skills.
17.2	Members of this team are pleasant and friendly and build rapport with co-workers.
17.3	Members of this team treat others with respect.
17.4	Members of this team communicate openly and honestly.
17.5	Members of this team use diplomacy and tact to diffuse tense situations.
17.6	Members of this team express facts and thoughts in a clear and organized way.
17.7	Members of this team promote cooperation, trust, and exchange of ideas.
17.8	Members of this team make an extra effort to put others at ease.
17.9	Members of this team establish an environment of open interpersonal communication
17.10	Members of this team build a constructive relationship within the project.

No.	Behavioural Competencies and Evaluation Criteria
18	***Influence (Assertiveness)***
18.1	Members of this team use appropriate interpersonal skills and techniques to gain acceptance for ideas or solutions.
18.2	Members of this team use influencing strategies to gain agreement on their opinions and suggestions.
18.3	Members of this team seek to persuade rather than impose company-related regulations and rules.
18.4	Members of this team have the ability to state their views persuasively.
19	***Cultural Competence***
19.1	Members of this team support work achievement regardless of diversity in identities and backgrounds.
19.2	Members of this team respect and relate well to people from varied backgrounds and are sensitive to cultural differences among their team members.
19.3	Members of this team see diversity as an opportunity for increasing knowledge about cultures.
19.4	Members of this team behave professionally when working with individuals of different ethnic, social, and educational backgrounds.
20	***Initiative***
20.1	Members of this team take action within the scope of their work responsibility without being asked or required to do so.
20.2	Members of this team achieve goals beyond job requirements.
20.3	Members of this team show the ability to plan, schedule, and direct work for themselves and others.
20.4	Members of this team set challenging yet achievable goals for themselves and others.
20.5	Members of this team take prompt action to accomplish objectives.

1.3. Project Performance Categories and Project Key Performance Indicators (KPIs)

Cost Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
1.1	Project Cost Growth	Variance between the actual total project cost and the total project estimate at tender stage, expressed as a ratio of the total project estimate at tender stage	$\frac{\text{actual total project cost} - \text{total project estimate at tender stage}}{\text{total project estimate at tender stage}}$
1.2	Project Budget Factor	The ratio between the actual total project cost and the sum of the total project estimate at tender stage and approved changes	$\frac{\text{actual total project cost}}{\text{total project estimate at tender stage + approved changes}}$
1.3	Project Indirect Cost Growth	The ratio between the actual construction phase indirect cost and the actual total project cost	$\frac{\text{actual construction phase indirect cost}}{\text{actual total project cost}}$
1.4	Construction Phase Cost Growth	The ratio between the actual construction phase cost and the actual total project cost	$\frac{\text{actual construction phase cost}}{\text{actual total project cost}}$
1.5	Project Start-Up Cost Growth	The ratio between the actual start-up phase cost and the actual total project	$\frac{\text{actual start-up phase cost}}{\text{actual total project cost}}$
1.6	Cost Predictability (Design)	The variance between the actual design phase cost at begin procurement and the estimated design phase cost expressed as a percentage of the actual design phase cost	(actual design phase cost − estimated design phase cost) ÷ actual design phase cost × 100
1.7	Cost Predictability (Construction)	The variance between the actual construction phase cost and the estimated construction phase cost, expressed as a percentage of the actual construction phase cost	(actual construction phase cost − estimated construction phase cost) ÷ actual construction phase cost × 100
1.8	Percentage Net Variation Over Final Cost	The ratio between the net value of cost variations within the same work scope and the total project estimate at tender stage, expressed as a percentage	net value of variations ÷ total project estimate at tender stage × 100
1.9	Cost per Unit at Tender	Average cost for the product at tender (e.g., cost per m^2 of floor space)	$\frac{\text{product estimate at tender stage}}{\text{unit of measurement}}$

KPI No.	KPI Name	KPI Definition	KPI Formula
1.10	Cost For Defects Warranty	The contractor's cost taken to rectify all defects, expressed as a percentage of the actual construction phase cost	construction cost of rectifying all defects ÷ actual construction phase cost × 100
1.11	Cost in Use	The annual operation and maintenance cost expressed as a percentage of the actual design and construction phases cost	annual operation and maintenance cost ÷ actual design and construction phases cost × 100

Schedule Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
2.1	Project Schedule Growth	The variance between the actual total project duration and the project duration at tender stage, expressed as a ratio of the project duration at tender stage	$\frac{\text{actual total project duration} - \text{project duration at tender stage}}{\text{project duration at tender stage}}$
2.2	Project Schedule Factor	The ratio between the actual total project duration and the sum of the project duration at tender stage and approved changes to duration	$\frac{\text{actual total project duration}}{\text{project duration at tender stage} + \text{approved changes to duration}}$
2.3	Construction Phase Schedule Growth	The variance between the actual construction phase duration and the construction phase duration at tender stage, expressed as a ratio of the construction phase duration at tender stage	$\frac{\text{actual construction phase duration} - \text{construction phase duration at tender stage}}{\text{estimated construction phase duration at tender stage}}$
2.4	Construction Phase Schedule Factor	The ratio between the actual construction phase duration and the actual total project duration at available for use	$\frac{\text{actual construction phase duration}}{\text{actual total project duration}}$
2.5	Time Predictability (Design)	The variance between the actual design phase duration and the estimated design phase duration at tender stage, expressed as a percentage of the actual design duration	(actual design phase duration − estimated design phase duration at tender stage) ÷ actual design phase duration × 100
2.6	Time Predictability (Construction)	The variance between the actual construction phase duration and the estimated construction phase duration at tender stage, expressed as a percentage of the actual construction phase duration	(actual construction phase duration − estimated construction phase duration at tender stage) ÷ actual construction phase duration × 100
2.7	Time Predictability (Design and Construction)	The variance between the actual design and construction phases duration and the estimated design and construction phases duration at tender stage, expressed as a percentage of the actual design and construction phases duration	(actual design and construction phases duration − estimated design and construction phases duration at tender stage) ÷ actual design and construction phases duration × 100

KPI No.	KPI Name	KPI Definition	KPI Formula
2.8	Time Variance	The ratio between the increase or decrease in the actual total project duration, discounting the effect of Extension Of Time (EOT) granted by the client and the original contract period	$\frac{\text{increase / decrease in actual total project duration} - \text{EOT}}{\text{original contract period}}$
2.9	Time per Unit at Tender	The average product duration at tender stage per unit of measurement (e.g., months per m^2 of floor space)	$\frac{\text{construction duration at tender stage}}{\text{unit of measurement}}$

Change Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
3.1	Total Change Cost Factor	The ratio between the total cost of scope changes (contractor and client) and the actual total project cost	$\frac{\text{total cost of scope changes}}{\text{actual total project cost}}$
3.2	Cost-For-Change-Demand	The change, attributable to client approved change orders originating from client, between the actual construction phase cost and the estimated construction phase cost	approved change orders cost originating from client ÷ total project cost × 100
3.3	Cost-For-Change-Supply	The change, attributable to client approved change orders originating from the contractor, between the actual construction phase cost and the estimated construction phase cost	approved change orders originating from contractor ÷ total project cost × 100
3.4	Time-For-Defects-Warranty	The contractors' time taken to rectify all defects in the maintenance period, expressed in weeks	time taken to rectify all defects by the contractor, expressed in weeks
3.5	Time-For-Change-Demand	The ratio between the approved client-initiated change orders and the actual total project duration	approved client-initiated change orders ÷ actual total project duration × 100
3.6	Time-For-Change-Supply	The ratio between the approved contractor-initiated change orders, and the actual total project duration, expressed as a percentage	approved contractor-initiated change orders ÷ actual total project duration × 100

Quality Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
4.1	Total Field Rework Cost Factor	The ratio between the total direct cost of field rework, and the actual construction phase cost	$\frac{\text{total direct cost of field rework}}{\text{actual construction phase cost}}$
4.2	Total Field Rework Time Factor	The ratio between total duration of field rework, and the actual total project duration	$\frac{\text{total duration of field rework}}{\text{actual total project duration}}$
4.3	Construction Field Rework Index	The ratio between the sum of direct and indirect cost of field rework and the actual total construction phase cost	$\frac{\text{total direct and indirect cost for field rework}}{\text{actual total construction phase cost}}$
4.4	Quality Issues-Available for Use	The level of client satisfaction with the product at the time the product is considered available for use based on the number of open (outstanding) non-conformances when product was available for use	Rating of performance from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied
4.5	Quality Issues-Warranty	The level of client satisfaction with the product at the end of defects liability period based on the number of open (outstanding) non-conformances at end of warranty	Rating of performance from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied

Safety Performance Indicators

KPI No.	KPI Name	**KPI Definition**	**KPI Formula**
5.1	Lost Time Rate	The ratio between the time lost to incidents in hours measured over 100,000 hours of work	$\frac{\text{amount of lost time to incidents, in hours}}{\text{100,000 hours of work}}$
5.2	Lost Time Frequency	The ratio between the total number of lost time cases reported and the total site work-hours at end of construction phase	$\frac{\text{total number of lost time cases reported}}{\text{total site work-hours at end of construction phase}}$
5.3	Reported Incidents Rate	The number of reported incidents measured over 100,000 hours of work during construction	$\frac{\text{number of reported incidents}}{\text{100,000 hours worked}}$
5.4	First Aid Frequency Rate (per 200,000 hours)	The ratio between the number of reported first aid cases measured over 200,000 hours of work, and is expressed as a percentage	$\frac{\text{number of reported first aid cases}}{\text{200,000 hours worked}}$
5.5	Near miss incident Frequency Rate (per 200,000 hours)	The ratio between the number of reported first aid cases measured over 200,000 hours of work, and is expressed as a percentage	$\frac{\text{number of reported near miss incidents cases}}{\text{200,000 hours worked}}$

Productivity Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
6.1	Engineering Productivity Factor	The ratio between actual engineering hours per issued for construction quantity	$\frac{\text{actual engineering hours}}{\text{issued for construction quantity}}$
6.2	Construction Productivity Factor (Physical Work)	The actual direct work hours required to install a unit quantity	$\frac{\text{actual direct work hours}}{\text{actual installed quantity}}$
6.3	Construction Productivity Factor (Cost)	The ratio between the total installed work cost and the total actual man-hours	$\frac{\text{total installed cost}}{\text{total actual man-hours worked}}$
6.4	Productivity Estimate Accuracy (Productivity Index)	The ratio between estimated productivity rate and the actual productivity rate for the entire project	$\frac{\text{estimated productivity rate}}{\text{actual productivity rate}}$
6.5	Project Absenteeism Rate	The ratio between the amount of man-hours lost due to unplanned absenteeism and the total actual man-hours worked	$\frac{\text{man-hours lost due to unplanned absenteeism}}{\text{total actual man-hours worked}}$
6.6	Project Employee Turnover	The ratio between the total number of workers who left (e.g., laid off or resigned) by the end of the project and the average total number of workers on site	$\frac{\text{total number of workers who left the project}}{\text{average total number of workers}}$

Satisfaction Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula
7.1	Satisfaction (Owner/ Contractor)	Contractor/Owner overall satisfaction with the Owner/Contractor	Rating of satisfaction from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied
7.2	Satisfaction (Design Team)	Owner/Contractor overall satisfaction with the design team	Rating of satisfaction from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied
7.3	Satisfaction (Subcontractors)	Owner/Contractor overall satisfaction with the subcontractors	Rating of satisfaction from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied
7.4	Satisfaction (Suppliers)	Owner/Contractor overall satisfaction with the suppliers	Rating of satisfaction from 1 to 7 with 1 being extremely dissatisfied and 7 being extremely satisfied

1.4. Sample Functional Competencies' Survey

STUDY ON CONSTRUCTION PROJECTS' FUNCTIONAL COMPETENCIES FOR PROJECT PERFORMANCE IMPROVEMENT IN ALBERTA

Interview Survey

Dear Participant,

The University of Alberta under the Natural Sciences and Engineering Research Council of Canada (NSERC), Industrial Research Chair in Strategic Construction Modeling and Delivery would like to thank you for agreeing to participate in this survey. This study is intended to improve sourcing functional competencies, and identifying critical functional competencies in the construction industry in Alberta that affects construction projects performance.

Background:
Construction projects tend to rely on functional competencies to ensure successful execution of work. For example, the ability to maintain effective management practices among different projects of a construction company will enhance projects performance. However, quantification of competencies has been limited to the investigation of competencies in terms of training and formal education of individuals in the construction industry, thereby ignoring other qualities such as standards, management practices, and production related skills that might better assess relevant competencies and ensure better project performance. An interpretation of why and to what extent project performance has improved as a result of these functional competencies is yet to be investigated.

This study aims to establish key conclusions on functional competencies affecting performance on the project level. Also, recommendations will be made on how to improve project performance by improving functional competencies.

Your participation in this survey is purely voluntary. You do not have to participate, and there are no consequences if you do not. All answers will remain confidential, and only the aggregated results will be made public in the form of reports and publications.

Your participation will be limited to completing the survey, which will take approximately *thirty to sixty minutes* to complete.

This survey consists of two main sections. The first section is designed to collect general information about the organization you work for and your position in this organization. The second section includes a list of predefined functional competencies from collected literature review and experts' focus groups meetings conducted in the area of construction projects functional competencies.

SECTION 1: GENERAL INFORMATION

1.1. Please select the industry of your organization: (please specify **ALL** that applies)

□ New Home Building and Renovation - building, remodelling or renovating houses and apartment buildings

□ Civil Engineering Construction engineering projects - highways, dams, water and sewer lines, power and communication lines, and bridges

□ Institutional and Commercial Construction - building commercial and institutional buildings and structures such as stadiums, schools, hospitals, grain elevators and indoor swimming pools

□ Heavy Industrial Construction - building industrial facilities such as cement, automotive, chemical or power plants, refineries and oil-sands installations

□ Other (please specify): ______________________

1.2. Please select your organization type in this project: (please specify **ALL** that applies)

□ Consultant and/or project management services

□ Main Contractor

□ Sub/Speciality Contractor

□ Other (please specify): ______________________

1. 3. Please indicate the name of your current employer (Company you work for):

____

1. 4. Approximately, how long have you been employed by your current employer?

________ Year(s) ________Month(s)

1.5. Please select your current occupation:

□ Senior Management	□ Project Management	□ Human Resources
□ Field Operations	□ Technical Office	□ Other (please specify): _____________

1. 6. Approximately, how long have you worked in the stated occupation?

________ Year(s) ________Month(s)

1.7. Please specify your highest educational degree: (please specify **ALL** that applies)

□ Professional designation/degree

□ Master's degree or above

□ Bachelor's degree

□ Some university credit (no degree)

□ College Diploma

□ Some college credit (no degree)

□ Technical, vocational, or trade school

□ Other (please specify): ___________

1.8. Please select the industry that this project belongs to:

□ New Home Building and Renovation - building, remodelling or renovating houses and apartment buildings

□ Civil Engineering Construction engineering projects - highways, dams, water and sewer lines, power and communication lines, and bridges

□ Institutional and Commercial Construction - building commercial and institutional buildings and structures such as stadiums, schools, hospitals, grain elevators and indoor swimming pools

□ Heavy Industrial Construction - building industrial facilities such as cement, automotive, chemical or power plants, refineries and oil-sands installations

□ Other (please specify): ______________________

1.9. Please specify the project delivery system for this project from those listed below:

□ Traditional Design-Bid-Build

□ CM at Risk

□ Design-Build

□ Parallel Prime

□ Other (please specify): ____________

1.10. Please specify the project contract type from the listed below:

□ Unit Rate

□ Lump Sum

□ Cost Plus

□ Other (please specify): ____________

SECTION 2: PROJECT MANAGEMENT AND ENGINEERING COMPETENCIES

This section of the survey recognizes project management and engineering competencies. Projects management and engineering competencies are the organization's knowledge- and production-related skills implemented on a construction project. These knowledge- and production-related skills stem from the organization to assist in the application of different project-related practices required for successful accomplishment of tasks on a construction project. Two measurement scales are provided to measure each competency as follows:

1. **Importance Measurement:** is to measure how an evaluation criterion - related to a given practice - is important to the overall performance of a specific construction project practice **(irrespective of its existence in this project),** and can vary within five levels as shown below:

Scale value	**Scale description**
1	Criterion is extremely unimportant for the practice
2	Criterion is unimportant for the practice
3	Criterion is neither unimportant or important for the practice
4	Criterion is important for the practice
5	Criterion is extremely important for the practice

2. **Maturity Measurement:** is a measurement of the extent of existence of a construction project criterion pertaining to a given practice (**with respect to this project)**, and can vary within five levels (in addition to NA – Not Applicable) as shown below:

Scale value	**Scale description**
Not Applicable	Use of the practice is non-existent on this project
Level 1	Use of the practice is not consistently applied on this project
Level 2	A disciplined process exists for the practice on this project
Level 3	A disciplined process exists for the practice across the different projects within the same organization
Level 4	Quantitative process control is used across the organization to proactively manage the execution of the practice on this project
Level 5	Continuous process improvement is used across the organization to optimise the practice on this project

Please provide your evaluation for the different criteria - pertaining to each practice - by providing a value for each of the measurement scales (Importance and Maturity measurements) as identified above.

1) Project Integration Management

No.	Evaluation Criteria	Importance					Maturity					
		Extremely Unimportant	*Unimportant*	*Neither Unimportant or Important*	*Important*	*Extremely Important*	*Not Applicable*	*Level 1 (Not Consistently Applied)*	*Level 2 (Disciplined Practice for Project)*	*Level 3 (Disciplined Practice Across All Project)*	*Level 4 (Quantitative Practice Control)*	*Level 5 (Continuous Process Improvement)*
1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams	1	2	3	4	5	0	1	2	3	4	5
1.2	Kickoff meetings are initiated for the project at the planning stage.	1	2	3	4	5	0	1	2	3	4	5
1.3	Key practices required for project planning and execution are identified at the planning stage	1	2	3	4	5	0	1	2	3	4	5
1.4	A project charter is developed for the project at the planning stage	1	2	3	4	5	0	1	2	3	4	5
1.5	A project management plan is developed for the project at the planning stage	1	2	3	4	5	0	1	2	3	4	5
1.6	A configuration management system is included in the procedures to control project performance	1	2	3	4	5	0	1	2	3	4	5
1.7	Project is properly executed in accordance to the preconstruction stages	1	2	3	4	5	0	1	2	3	4	5
1.8	Project is actively monitored and an integrated change control process is in place	1	2	3	4	5	0	1	2	3	4	5
1.9	At closing phase, changes to the project integration management and project management plan are identified. Project integration management and project management plan performance are documented.	1	2	3	4	5	0	1	2	3	4	5
1.10												
1.11												

1.5. Sample Behavioural Competencies' Supervisor Survey

STUDY ON CONSTRUCTION PROJECTS' BEHAVIOURAL COMPETENCIES FOR PROJECT PERFORMANCE IMPROVEMENT IN ALBERTA

Supervisor Interview Survey

Dear Participant,

The University of Alberta under the Natural Sciences and Engineering Research Council of Canada (NSERC), and the Industrial Research Chair in Strategic Construction Modeling and Delivery would like to thank you for agreeing to participate in this survey. This study is intended to improve sourcing of behavioural competencies, and identifying critical behavioural competencies in the construction industry in Alberta that affect construction project performance.

Background:

Construction projects tend to rely on the behavioural competencies of its employees to ensure successful execution of work. For example, communication skills of teams are vital for better project performance. However, quantification of competencies has been limited to the investigation of competencies in terms of training and formal education of individuals in the construction industry, thereby ignoring the need to comprehensively investigate other qualities such as skills, knowledge, and personal attributes of team members that might better assess behavioural competencies and ensure better project performance. An interpretation of why and to what extent project performance has improved as a result of these behavioural competencies is yet to be investigated.

This study aims to establish key conclusions on teams' behavioural competencies affecting performance on the project level. Also, recommendations will be made on how to improve project performance by improving behavioural competencies.

Your participation in this survey is purely voluntary. You do not have to participate, and there are no consequences if you do not. All answers will remain confidential, and only the aggregated results will be made public in the form of reports and publications.

Your participation will be limited to completing this survey (for a number of teams under your supervision), which will take approximately *twenty minutes or less* to complete for each of your teams considered for this study.

This survey consists of two main sections. The first section is designed to collect general information about the project and yourself. The second section includes a list of predefined behavioural competencies collected from past literature review and experts' focus groups meetings conducted in the area of construction project competencies.

SECTION 1: GENERAL INFORMATION

1.1. Please select the industry that the current project belongs to:

□ New Home Building and Renovation - building, remodeling or renovating houses and apartment buildings

□ Civil Engineering Construction Engineering Projects - highways, dams, water and sewer lines, power and communication lines, and bridges

□ Institutional and Commercial Construction - building commercial and institutional buildings and structures such as stadiums, schools, hospitals, grain elevators and indoor swimming pools

□ Heavy Industrial Construction - building industrial facilities such as cement, automotive, chemical or power plants, refineries and oil-sands installations

□ Other (please specify): ______________________

1.2. Please indicate the current project name:

____

1.3. Please indicate the current project location:

____

1.4. Please rate the current project complexity:

□ Low

□ Somewhat Low

□ Average

□ Somewhat High

□ High

1. 5. How long have you been employed in the current project?

________ Year(s) _________ Month(s)

1.6. Please select your position:

□ Senior Management	□ Project Manager	□ Technical Coordinator
□ Contracts Administrator	□ Project Control	□ Field Engineer
□ Superintendent	□ General Foreman/Foreman	□ Tradesperson
□ Labourer	□ Other (please specify):	______________________

1.7. How long have you been employed by your current employer in the stated position?

________ Year(s) _________ Month(s)

1.8. Are you currently a member of a construction labour group?

□ Yes □ No

If you answered "Yes", please indicate which one:

□ Building Trades □ CLAC □ Merit

□ Other (please specify): ________________________

1.9. Please specify your age:

□ Under 20 □ 20 - 30 □ 31 - 40 □ 41 - 50 □ 51 - 60 □ Over 60

1.10. How long have you supervised the team you are evaluating?

________ Year(s) ________Month(s)

1.11. How many crew members are in the team you are evaluating?

____

SECTION 2: PROJECT BEHAVIOURAL COMPETENCIES

This section of the survey identifies your team's behavioural competencies. Behavioural competencies are a mixture of knowledge, skills, abilities, motivation, beliefs, values, and interests" that are attained by individuals in your team and influences the performance of the work duties. An "Importance Scale" is given to determine how important a given criteria related to a behavioural competency is **regardless of this project**, and an "Agreement Scale" is given to determine the extent to which you agree/disagree to the presence of a given criteria related to a behavioural competency within your team **on this project**. Blank rows are left intentionally to add additional criteria that you feel are critical in the assessment of the different behavioural competencies of your team.

No.	**Evaluation Criteria**	**Importance**					**Agreement**						
		Extremely Unimportant	*Unimportant*	*Neither Unimportant nor Important*	*Important*	*Extremely Important*	*Strongly Disagree*	*Disagre e*	*Slightly Disagree*	*Neither Disagree Nor Agree*	*Slightly Agree*	*Agr ee*	*Strong ly Agree*
1	**Analytical Ability**												
1.1	Members of this team can anticipate and identify problems in their daily tasks	1	2	3	4	5	1	2	3	4	5	6	7
1.2	Members of this team can picture the end product and account for missing data in their daily tasks	1	2	3	4	5	1	2	3	4	5	6	7
1.3		1	2	3	4	5	1	2	3	4	5	6	7
1.4		1	2	3	4	5	1	2	3	4	5	6	7
2	**Training**												
2.1	Members of this team possess the necessary training to perform their daily tasks	1	2	3	4	5	1	2	3	4	5	6	7
2.2	Members of this team have performed similar tasks to their current tasks	1	2	3	4	5	1	2	3	4	5	6	7
2.3		1	2	3	4	5	1	2	3	4	5	6	7
2.4		1	2	3	4	5	1	2	3	4	5	6	7

1.6. Sample Behavioural Competencies' Team Member Survey

STUDY ON CONSTRUCTION PROJECTS' BEHAVIOURAL COMPETENCIES FOR PROJECT PERFORMANCE IMPROVEMENT IN ALBERTA

Team member Interview Survey

Dear Participant,

The University of Alberta under the Natural Sciences and Engineering Research Council of Canada (NSERC), and the Industrial Research Chair in Strategic Construction Modeling and Delivery would like to thank you for agreeing to participate in this survey. This study is intended to improve sourcing of behavioural competencies, and identifying critical behavioural competencies in the construction industry in Alberta that affect construction project performance.

Background:

Construction projects tend to rely on the behavioural competencies of its employees to ensure successful execution of work. For example, communication skills of teams are vital for better project performance. However, quantification of competencies has been limited to the investigation of competencies in terms of training and formal education of individuals in the construction industry, thereby ignoring the need to comprehensively investigate other qualities such as skills, knowledge, and personal attributes of team members that might better assess behavioural competencies and ensure better project performance. An interpretation of why and to what extent project performance has improved as a result of these behavioural competencies is yet to be investigated.

This study aims to establish key conclusions on teams' behavioural competencies affecting performance on the project level. Also, recommendations will be made on how to improve project performance by improving behavioural competencies.

Your participation in this survey is purely voluntary. You do not have to participate, and there are no consequences if you do not. All answers will remain confidential, and only the aggregated results will be made public in the form of reports and publications.

Your participation will be limited to completing this survey, which will take approximately *ten minutes or less* to complete. Please consider your team as a whole when completing the survey.

This survey consists of two main sections. The first section is designed to collect general information about the project and yourself. The second section includes a list of predefined behavioural competencies collected from past literature review and experts' focus group meetings conducted in the area of construction project competencies.

SECTION 1: GENERAL INFORMATION

1.1. Please rate the current project complexity:

□ Low □ Somewhat High

□ Somewhat Low □ High

□ Average

1. 2. How long have you been employed in the current project?

________ Year(s) _________ Month(s)

1.3. Please select your position:

□ Senior Management □ Project Manager □ Technical Coordinator

□ Contracts Administrator □ Project Control □ Field Engineer

□ Superintendent □ General Foreman/Foreman □ Tradesperson

□ Labourer □ Other (please specify): ______________________

1.4. How long have you been employed by your current employer in the stated position?

________ Year(s) _________ Month(s)

1.5. Are you currently a member of a construction labour group?

□ Yes □ No

If you answered "Yes", please indicate which one:

□ Building Trades □ CLAC □ Merit

□ Other (please specify): ________________________

1.6. Please specify your age:

□ Under 20 □ 20 - 30 □ 31 - 40 □ 41 - 50 □ 51 - 60 □ Over 60

1.7. How long have you worked with the team you are evaluating?

________ Year(s) ________Month(s)

1.8. Please rate how familiar you are with your team's daily duties

□ Not at all familiar

□ Slightly familiar

□ Somewhat familiar

□ Moderately familiar

□ Extremely familiar

1.9. In relation to the _____ teams you have worked with in your current position, how would you evaluate the overall performance of this team?

□ Inadequate

□ Marginal (lower 50%)

□ Average (top 50%)

□ Good (top 25%)

□ Superior (top 15%)

□ Outstanding (top 5%)

SECTION 2: PROJECT BEHAVIOURAL COMPETENCIES

This section of the survey identifies your team's behavioural competencies. Behavioural competencies are a mixture of knowledge, skills, abilities, motivation, beliefs, values, and interests that are attained by individuals in your team and influence the performance of the work duties. An "Agreement Scale" is given to determine the extent to which you agree/disagree to the presence of a given criteria related to a behavioural competency within your team **on this project.**

No.	Evaluation Criteria	Agreement						
		Strongly Disagree	*Disagree*	*Slightly Disagree*	*Neither Disagree Nor Agree*	*Slightly Agree*	*Agree*	*Strongly Agree*
1	**Analytical Ability**							
1.1	Members of this team can anticipate and identify problems in their daily tasks	1	2	3	4	5	6	7
2	**Training**							
2.1	Members of this team possess the necessary training to perform their daily tasks	1	2	3	4	5	6	7
3	**Assessment Ability**							
3.1	Members of this team are capable of breaking down problems into components and recognizing interrelationships in order to solve them in their daily tasks	1	2	3	4	5	6	7
4	**Decision Making**							
4.1	Members of this team make sound, well-informed, and objective decisions in their daily tasks	1	2	3	4	5	6	7
5	**Leadership**							
5.1	Members of this team find resources, training, and tools to support their team members' needs in executing their daily tasks	1	2	3	4	5	6	7
6	**Teamwork**							
6.1	Members of this team participate as active and contributing members to achieve their team's daily goals	1	2	3	4	5	6	7
7	**Consultation**							
7.1	Members of this team possess a high level of effectiveness in consulting their own team members with problems they encounter in their daily tasks	1	2	3	4	5	6	7
8	**Motivation**							
8.1	Members of this team have a high level of motivation	1	2	3	4	5	6	7

1.7. Sample KPIs' Survey

STUDY ON CONSTRUCTION PROJECTS' PERFORMANCE MEASUREMENT IN ALBERTA

Interview Survey

The University of Alberta, under the Natural Sciences and Engineering Research Council of Canada (NSERC) Industrial Research Chair in Strategic Construction Modeling and Delivery, would like to thank you for agreeing to participate in this survey. This survey is intended to identify common Key Performance Indicators (KPIs) used in construction projects in Alberta.

Your participation will be limited to completing the survey, which will take approximately *Twenty minutes or less* to complete.

KPIs in this survey are divided into seven main categories and forty six performance indicators. You are kindly requested to evaluate each KPI based on its use for construction projects. Figure 1 below provides a timeline for the project life cycle that is considered in some of the KPI definitions listed in the survey.

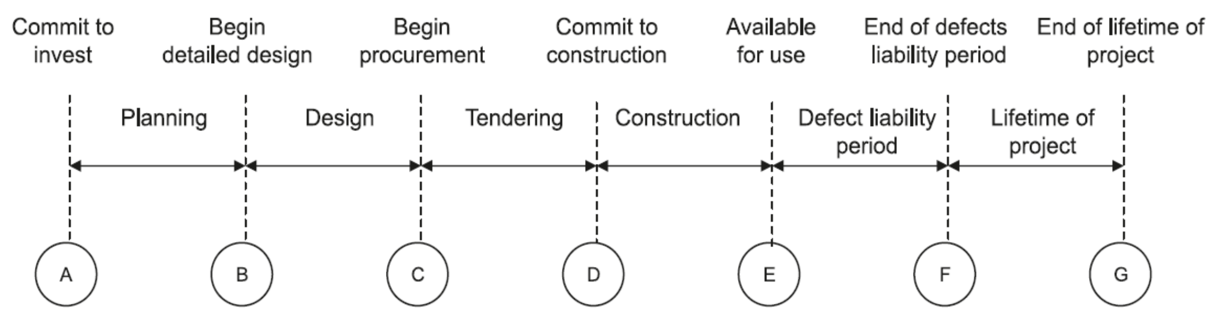


Figure 1: Project Life Cycle (Rankin et al. 2008)

Please complete the survey by assigning an appropriate scale value on how often you apply the predetermined KPIs –based on your organization's practices -. Blank rows are intentionally left in each category for adding additional KPIs that are not stated in this survey and are considered by your organization for measuring construction projects performance.

1) Cost Performance Indicators

KPI No.	KPI Name	KPI Definition	KPI Formula	KPI Never Used	KPI Rarely Used	KPI Sometimes Used	KPI Often Used	KPI Always Used
1.1	Project Cost Growth	The variance between the actual total project cost at end of defects liability period (point F) and the total project estimate at tender stage, expressed as a ratio of the total project estimate at tender stage	((actual total project cost- total project estimate at tender stage)/ total project estimate at tender stage)	1	2	3	4	5
1.2	Project Budget Factor	The ratio between the actual total project cost at end of defects liability period (point F) and the sum of the total project estimate at tender stage and approved changes	(actual total project cost/(total project estimate at tender stage + approved changes))	1	2	3	4	5
1.3	Project Indirect Cost Growth	The ratio between the actual construction phase indirect cost and the actual total project cost at available for use (point E)	actual construction phase indirect cost/actual total project cost	1	2	3	4	5
1.4	Construction Phase Cost Growth	The ratio between the actual construction phase cost (point E) and the actual total project cost at end of defects liability period (point F)	actual construction phase cost/actual total project cost	1	2	3	4	5
1.5	Project Start-Up Cost Growth	The ratio between the actual start-up phase cost and the actual total project cost at end of defects liability period (point F)	actual start-up phase cost/actual total project cost	1	2	3	4	5
1.6	Cost Predictability (Design)	The variance between the actual design phase cost at begin procurement (point C) and the estimated design phase cost at commit to invest (point A), expressed as a percentage of the actual design phase cost at begin procurement (point C)	((actual design phase cost- estimated design phase cost)/actual design phase cost) x 100	1	2	3	4	5
1.7				1	2	3	4	5

APPENDIX 2. Modeling Project Competencies' and Their Relationship to Project KPIs: Analysis and Results

2.1.Sample *FRIS* and *FRW* for the Functional Competencies' Evaluation Criteria

No.	Functional Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
1	***Project Integration Management***		
1.1	Policies and procedures for project integration management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.5583, 0.900, 1.00)	(0.066, 0.114, 0.203)
1.2	Kickoff meetings are initiated for the project at the planning stage.	(0.583, 0.900, 1.00)	(0.066, 0.114, 0.203)
1.3	Key practices required for project planning and execution are identified at the planning stage.	(0.561, 0.900, 1.00)	(0.063, 0.114, 0.203)
1.8	Project is actively monitored and an integrated change control process is in place.	(0.556, 0.900, 1.00)	(0.063, 0.114, 0.203)
1.4	A project charter is developed for the project at the planning stage.	(0.550, 0.878, 0.983)	(0.062, 0.111, 0.2)
1.5	A project management plan is developed for the project at the planning stage.	(0.550, 0.878, 0.983)	(0.062, 0.111, 0.2)
1.7	Project is properly executed in accordance to the preconstruction stages.	(0.544, 0.856, 0.967)	(0.062, 0.108, 0.197)
1.9	At closing phase, changes to the project integration management and project management plan are identified. Project integration management and project management plan performance are documented.	(0.511, 0.856, 0.967)	(0.058, 0.108, 0.197)
1.6	A configuration management system is included in the procedures to control project performance.	(0.494, 0.833, 0.95)	(0.056, 0.105, 0.193)
2	***Project Scope Management***		
2.6	Meetings are held during execution to verify scope and discuss any potential scope changes/creep.	(0.567, 0.900, 1.00)	(0.074, 0.133, 0.238)
2.1	Policies and procedures for project scope	(0.556, 0.900, 1.000)	(0.072, 0.133, 0.238)

No.	Functional Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
	management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.		
2.7	A scope control process is in place to identify scope changes/creep.	(0.55, 0.878, 0.983)	(0.072, 0.132, 0.234)
2.8	At closing phase, changes to the project scope are identified and documented. Project scope management performance is documented.	(0.522, 0.856, 0.967)	(0.068, 0.126, 0.230)
2.2	Project requirements and scope are identified in the kickoff meeting at the planning stage.	(0.539, 0.833, 0.950)	(0.07, 0.123, 0.226)
2.4	A scope verification process is considered in the planning stage.	(0.494, 0.811, 0.933)	(0.064, 0.120, 0.222)
2.3	Constructability principles are considered during scope identification and development.	(0.506, 0.811, 0.933)	(0.066, 0.120, 0.222)
2.5	A constructability champion is assigned during the planning stage to oversee the constructability review process among different stakeholders.	(0.472, 0.789, 0.917)	(0.061, 0.116, 0.218)
3	***Project Time Management***		
3.3	Work sequence and logic are developed in the project schedule prior to work execution.	(0.556, 0.900, 1.000)	(0.048, 0.089, 0.163)
3.1	Schedule meetings are regularly performed to communicate schedule delays/impact of changes.	(0.55, 0.900, 1.000)	(0.048, 0.089, 0.163)
3.8	Schedule updates are regularly performed.	(0.55, 0.878, 0.983)	(0.048, 0.086, 0.16)
3.5	Developed schedule is verified with construction teams supervising the project execution.	(0.528, 0.867, 0.978)	(0.046, 0.085, 0.159)
3.2	Work activities are based on a Work Breakdown Structure.	(0.511, 0.856, 0.967)	(0.044, 0.084, 0.158)
3.12	At closing stage, as-built schedule is documented, and a report is generated with all changes to the as-planned schedule activities and resources. Project time management performance is documented.	(0.506, 0.856, 0.967)	(0.044, 0.084, 0.158)
3.9	Resource usage profiles generated from	(0.511, 0.844, 0.961)	(0.044, 0.083, 0.157)

No.	Functional Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
	schedule are regularly monitored to maintain project work continuity.		
3.11	Commercial or in-house scheduling software is used for developing project time schedule. Practice performance is also documented.	(0.500, 0.833, 0.950)	(0.043, 0.082, 0.155)
3.6	Project schedule is communicated with different teams and workers on the project. Logic is explained and is followed.	(0.489, 0.822, 0.944)	(0.042, 0.081, 0.154)
3.4	Activity resources and costs are estimated and combined in the project schedule prior to work execution.	(0.483, 0.811, 0.933)	(0.042, 0.080, 0.152)
3.7	Time sheets register (e.g., productivity sheets) is available on site to record the amount of time spent undertaking a project activity or task.	(0.483, 0.800, 0.917)	(0.042, 0.079, 0.149)
3.1	Policies and procedures for project time management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.467, 0.789, 0.917)	(0.041, 0.078, 0.149)
4	***Project Cost Management***		
4.1	Policies and procedures for project cost management are developed at the company level. Roles and responsibilities for applying practice on the project are clearly identified for the project responsible teams.	(0.556, 0.900, 1.000)	(0.048, 0.087, 0.156)
4.7	A cash flow analysis is regularly carried out to monitor the financial status of the project.	(0.550, 0.900, 1.000)	(0.047, 0.087, 0.156)
4.8	Updated cash flow with changes to the cost baseline is regularly conducted.	(0.544, 0.900, 1.000)	(0.047, 0.087, 0.156)
4.11	Commercial or in-house cost control software is used for project cost management.	(0.544, 0.900, 1.000)	(0.047, 0.087, 0.156)
4.12	At closing phase, a final project budget is documented and a report is generated with all changes to the cost baseline. Project cost management performance is documented.	(0.561, 0.900, 1.000)	(0.048, 0.087, 0.156)
4.4	An integration of the project budget and schedule is performed to generate the cash flow.	(0.539, 0.878, 0.983)	(0.046, 0.084, 0.153)

No.	Functional Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
4.1	All related project costs (e.g., invoices and payments) are submitted in a timely manner.	(0.561, 0.878, 0.983)	(0.048, 0.084, 0.153)
4.2	Estimates are developed based on a clear project scope.	(0.533, 0.856, 0.967)	(0.046, 0.082, 0.151)
4.3	A detailed budget for the project (associated with detailed expenses, risk, contingency, overheads, and profit) is defined at the early stages of the project.	(0.544, 0.856, 0.967)	(0.047, 0.082, 0.151)
4.9	Cost control meetings are held to communicate budget changes / impact on overall project budget.	(0.528, 0.856, 0.967)	(0.045, 0.082, 0.151)
4.5	Government and market cost indices are used in developing cost estimate in order to consider any cost fluctuations/inflations (e.g., increase in wages).	(0.517, 0.833, 0.950)	(0.044, 0.080, 0.148)
4.6	Different expense forms are available on site (e.g., document expense forms) to track different expenditures.	(0.444, 0.733, 0.878)	(0.038, 0.071, 0.137)

2.2. Sample *FRIS* and *FRW* for the Behavioural Competencies' Evaluation Criteria

No.	Behavioural Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
1	***Analytical Ability***		
1.1	Members of this team can anticipate and identify problems in their daily tasks	(0.513,0.873, 0.980)	(0.263,0.503, 0.963)
1.2	Members of this team can picture the end product and account for missing data in their daily tasks	(0.503,0.860, 0.970)	(0.258,0.496, 0.954)
2	***Training***		
2.1	Members of this team possess the necessary training to perform their daily tasks	(0.526,0.873, 0.980)	(0.274,0.515, 1.104)
2.2	Members of this team have performed similar tasks to their current tasks	(0.476,0.820, 0.940)	(0.248,0.484, 1.000)
3	***Assessment Ability***		
3.1	Members of this team are capable of breaking down problems into components and recognizing interrelationships in order to solve them in their daily tasks	(0.513,0.873, 0.980)	(0.177,0.340, 0.646)
3.2	Members of this team have the ability to properly estimate the potential impact of existing problems in their daily tasks	(0.503,0.846, 0.960)	(0.173,0.329, 0.632)
3.3	Members of this team have the ability to properly estimate the magnitude of existing problems in their daily tasks	(0.500,0.846, 0.960)	(0.1724,0.329, 0.632)
4	***Decision Making***		
4.5	Members of this team guide their team members toward making effective decisions in their daily tasks	(0.530,0.886, 0.990)	(0.090,0.171, 0.318)
4.1	Members of this team make sound, well-informed, and objective decisions in their daily tasks	(0.540,0.873, 0.980)	(0.092,0.168, 0.315)
4.3	Members of this team take actions that are consistent with available facts, constraints, and probable consequences in their daily tasks	(0.540,0.873, 0.980)	(0.088,0.168, 0.315)
4.6	Members of this team collaborate before making important decisions	(0.533,0.873, 0.980)	(0.091,0.168, 0.315)
4.4	Members of this team consider costs, benefits, and risks when making decisions related to	(0.506,0.84, 0.956)	(0.086,0.162, 0.307)

No.	Behavioural Competencies and Evaluation Criteria	Ordered Fuzzy Relative Importance Score	Fuzzy Relative Weight
	their daily tasks		
4.2	Members of this team compare data, information, and input from a variety of sources to draw conclusions before applying them in their daily tasks	(0.480,0.833, 0.950)	(0.082,0.160, 0.305)

2.3.Functional Competencies: Correlation Matrix

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	**1.000**																				
2	.594	**1.000**																			
3	.378	.718	**1.000**																		
4	.577	.785	.823	**1.000**																	
5	.193	.469	.506	.575	**1.000**																
6	.347	.815	.904	.847	.581	**1.000**															
7	.549	.690	.674	.761	.627	.620	**1.000**														
8	.294	.492	.667	.717	.329	.576	.615	**1.000**													
9	.805	.725	.603	.794	.366	.655	.610	.551	**1.000**												
10	.138	.283	.493	.429	.079	.511	.069	.528	.264	**1.000**											
11	.569	.637	.611	.803	.355	.573	.675	.858	.751	.456	**1.000**										
12	.583	.541	.465	.710	.648	.435	.684	.674	.730	.023	.817	**1.000**									
13	.429	.513	.518	.703	.481	.462	.636	.815	.567	.313	.918	.827	**1.000**								
14	.613	.667	.610	.842	.436	.536	.762	.714	.724	.233	.905	.831	.841	**1.000**							
15	.566	.661	.619	.812	.495	.540	.783	.738	.655	.233	.896	.798	.888	.899	**1.000**						
16	.281	.544	.242	.345	.140	.237	.291	.518	.506	.050	.616	.628	.555	.563	.486	**1.000**					
17	.445	.689	.840	.849	.623	.752	.898	.802	.605	.358	.802	.720	.783	.806	.827	.358	**1.000**				
18	.547	.540	.581	.745	.586	.481	.771	.738	.679	.192	.889	.919	.901	.879	.889	.566	.848	**1.000**			
19	.430	.585	.459	.472	.257	.365	.657	.651	.484	.168	.689	.628	.578	.700	.549	.682	.657	.645	**1.000**		
20	.154	.229	.307	.324	.597	.219	.523	.582	.231	.017	.576	.720	.750	.556	.537	.441	.617	.722	.593	**1.000**	
21	.141	.286	.442	.291	.385	.460	.099	.550	.087	.548	.346	.268	.459	.133	.276	.340	.380	.312	.147	.481	**1.0**

Legend:

No.	Functional Competency	No.	Functional Competency
1	Project Integration Management	12	Project Change Management
2	Project Scope Management	13	Project Stakeholders Management
3	Project Time Management	14	Project Environmental Management
4	Project Cost Management	15	Project Commissioning and Startup
5	Project Engineering and Procurement Management	16	Project Innovation
6	Project Resource Management	17	Project Workface Planning
7	Project Risk Management	18	Project Contract Administration
8	Project Communication Management	19	Project Team Building
9	Project Safety Management	20	Project Workforce Development
10	Project Human Resource Management	21	Project Technology Integration
11	Project Quality Management		

2.4.Behavioural Competencies: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	**1.000**																			
2	.315	**1.000**																		
3	.558	.268	**1.000**																	
4	.434	.541	.548	**1.000**																
5	.286	.295	.451	.471	**1.000**															
6	.543	.384	.572	.614	.669	**1.000**														
7	.453	.241	.498	.457	.491	.599	**1.000**													
8	.570	.331	.620	.561	.631	.773	.651	**1.000**												
9	.443	.364	.612	.452	.548	.720	.627	.640	**1.000**											
10	.451	.299	.408	.395	.392	.700	.518	.637	.441	**1.000**										
11	.557	.316	.520	.487	.493	.773	.523	.715	.637	.823	**1.000**									
12	.539	.436	.495	.624	.517	.837	.628	.713	.689	.789	.813	**1.000**								
13	.611	.421	.692	.593	.649	.809	.680	.788	.774	.711	.835	.780	1.000							
14	.578	.389	.555	.329	.357	.598	.546	.785	.490	.598	.552	.592	.662	**1.000**						
15	.216	.096	.531	.363	.449	.595	.597	.639	.691	.401	.600	.609	.632	.503	**1.000**					
16	.465	.234	.664	.474	.716	.821	.654	.893	.646	.679	.747	.728	.805	.719	.725	**1.000**				
17	.460	.232	.523	.420	.461	.583	.331	.679	.228	.729	.724	.605	.685	.588	.382	.704	**1.000**			
18	.456	.250	.594	.552	.549	.782	.690	.732	.692	.696	.805	.767	.795	.583	.643	.777	.607	**1.000**		
19	.219	.132	.327	.313	.447	.540	.502	.495	.565	.222	.422	.529	.432	.483	.729	.603	.094	.428	**1.000**	
20	.457	.299	.499	.586	.624	.759	.772	.778	.655	.705	.814	.781	.853	.543	.617	.801	.629	.855	.429	**1.0**

Legend:

No.	Behavioural Competency	No.	Behavioural Competency
1	Analytical Ability	11	Self-Control
2	Training	12	Reliability
3	Assessment Ability	13	Problem Solving
4	Decision Making	14	Commitment
5	Leadership	15	Adaptability
6	Teamwork	16	Building Trust
7	Consultation	17	Interpersonal Skills
8	Motivation	18	Influence
9	Negotiation and Crisis Resolution	19	Cultural Competence
10	Ethics	20	Initiative

2.5.Functional Competencies: Anti-image Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	**0.667**[a]																				
2	0.568	**0.720**[a]																			
3	0.400	0.719	**0.846**[a]																		
4	0.600	0.813	0.840	**0.929**[a]																	
5	0.183	0.447	0.545	0.551	**0.872**[a]																
6	0.385	0.742	0.898	0.863	0.569	**0.975**[a]															
7	0.556	0.681	0.647	0.779	0.667	0.642	**0.800**[a]														
8	0.342	0.565	0.639	0.691	0.368	0.590	0.549	**0.848**[a]													
9	0.699	0.718	0.616	0.789	0.313	0.610	0.681	0.548	**0.803**[a]												
10	0.077	0.340	0.509	0.417	-0.061	0.536	0.089	0.528	0.264	**0.744**[a]											
11	0.580	0.676	0.635	0.789	0.345	0.568	0.679	0.857	0.747	0.428	**0.985**[a]										
12	0.534	0.578	0.493	0.677	0.575	0.420	0.757	0.670	0.642	0.050	0.821	**0.899**[a]									
13	0.411	0.550	0.549	0.670	0.484	0.471	0.654	0.816	0.575	0.295	0.885	0.834	**0.894**[a]								
14	0.650	0.690	0.595	0.787	0.448	0.539	0.759	0.717	0.775	0.219	0.897	0.853	0.813	**0.900**[a]							
15	0.568	0.669	0.624	0.777	0.513	0.578	0.748	0.726	0.713	0.243	0.859	0.825	0.807	0.852	**0.826**[a]						
16	0.340	0.332	0.263	0.393	0.158	0.186	0.381	0.536	0.417	0.180	0.636	0.564	0.601	0.575	0.540	**0.565**[a]					
17	0.470	0.722	0.783	0.856	0.681	0.777	0.788	0.753	0.669	0.340	0.802	0.771	0.784	0.788	0.805	0.446	**0.896**[a]				
18	0.528	0.624	0.573	0.736	0.579	0.506	0.768	0.751	0.667	0.165	0.878	0.902	0.878	0.876	0.857	0.585	0.825	**0.924**[a]			
19	0.449	0.479	0.412	0.557	0.313	0.349	0.544	0.600	0.549	0.187	0.722	0.676	0.679	0.694	0.660	0.490	0.595	0.698	**0.560**[a]		
20	0.105	0.254	0.295	0.359	0.590	0.208	0.500	0.599	0.222	0.012	0.583	0.719	0.752	0.553	0.591	0.455	0.604	0.731	0.503	**0.873**[a]	
21	-0.168	0.203	0.451	0.314	0.318	0.448	0.171	0.575	0.039	0.521	0.375	0.220	0.456	0.196	0.284	0.202	0.449	0.317	0.213	0.460	**0.713**[a]

(a) Measures of Sampling Adequacy (MSA)

Legend:

No.	Functional Competency	No.	Functional Competency
1	Project Integration Management	12	Project Change Management
2	Project Scope Management	13	Project Stakeholders Management
3	Project Time Management	14	Project Environmental Management
4	Project Cost Management	15	Project Commissioning and Startup
5	Project Engineering and Procurement Management	16	Project Innovation
6	Project Resource Management	17	Project Workface Planning
7	Project Risk Management	18	Project Contract Administration
8	Project Communication Management	19	Project Team Building
9	Project Safety Management	20	Project Workforce Development
10	Project Human Resource Management	21	Project Technology Integration
11	Project Quality Management		

2.6.Behavioural Competencies: Anti-image Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	**.713[a]**																			
2	.310	**.531[a]**																		
3	-.185	.183	**.820[a]**																	
4	-.122	-.548	-.539	**.685[a]**																
5	-.026	-.251	.119	.075	**.845[a]**															
6	-.112	.036	.192	-.212	-.112	**.957[a]**														
7	-.390	-.192	-.227	.246	-.010	.064	**.809[a]**													
8	-.016	.314	.347	-.551	-.167	.026	-.196	**.820[a]**												
9	.215	-.049	-.356	.270	-.220	-.088	.033	-.216	**.772[a]**											
10	.492	.339	.127	-.198	-.088	-.048	-.443	.309	.296	**.687[a]**										
11	-.534	-.411	-.059	.376	.308	-.029	.508	-.329	-.303	-.722	**.700[a]**									
12	-.388	-.282	.153	-.073	.219	-.221	.119	-.040	-.521	-.616	.403	**.796[a]**								
13	-.205	-.028	-.050	-.155	-.173	-.129	-.047	.260	-.558	-.130	-.029	.301	**.900[a]**							
14	-.382	-.582	-.145	.515	.446	.037	.194	-.617	-.088	-.535	.636	.310	-.183	**.655[a]**						
15	.349	.132	-.018	-.017	.318	.122	-.244	-.088	-.284	.152	-.065	-.030	-.053	.107	**.900[a]**					
16	-.092	-.186	-.456	.480	-.154	-.317	.245	-.552	-.062	-.449	.414	.298	.116	.294	-.099	**.805[a]**				
17	.262	.218	-.169	-.080	-.319	.085	.049	.045	.759	.356	-.531	-.557	-.402	-.404	-.255	-.378	**.681[a]**			
18	.242	.349	-.034	-.303	-.115	-.192	-.234	.329	-.128	.234	-.401	-.110	.248	-.436	-.053	-.170	.089	**.876[a]**		
19	.309	.408	.185	-.391	-.351	.006	-.290	.435	.341	.633	-.686	-.537	-.041	-.684	-.327	-.565	.659	.352	**.505[a]**	
20	.310	.199	.365	-.280	-.031	.199	-.564	.006	.212	.370	-.442	-.313	-.419	-.079	.127	-.418	.249	-.189	.344	**.829[a]**

(a) Measures of Sampling Adequacy (MSA)

Legend:

No.	Behavioural Competency	No.	Behavioural Competency
1	Analytical Ability	11	Self-Control
2	Training	12	Reliability
3	Assessment Ability	13	Problem Solving
4	Decision Making	14	Commitment
5	Leadership	15	Adaptability
6	Teamwork	16	Building Trust
7	Consultation	17	Interpersonal Skills
8	Motivation	18	Influence
9	Negotiation and Crisis Resolution	19	Cultural Competence
10	Ethics	20	Initiative

2.7.Projects' Fuzzy Factor Groups and Projects' KPIs

Fuzzy Factor Groups for the Seven Construction Projects

	Functional Competencies Fuzzy Factor Group 1 (x_1)			Functional Competencies Fuzzy Factor Group 2 (x_2)			Functional Competencies Fuzzy Factor Group 3 (x_3)			Functional Competencies Fuzzy Factor Group 4 (x_4)			Behavioural Competencies Fuzzy Factor Group 1 (x_5)			Behavioural Competencies Fuzzy Factor Group 2 (x_6)			Behavioural Competencies Fuzzy Factor Group 3 (x_7)		
Project 1	0.08	0.29	0.65	0.14	0.30	0.42	0.00	0.12	0.41	0.20	0.62	0.74	0.40	0.90	1.00	0.08	0.15	0.15	0.09	0.24	0.59
Project 2	0.12	0.44	0.85	0.25	0.72	0.80	0.14	0.40	0.73	0.00	0.00	0.03	0.24	0.59	0.84	0.15	0.37	0.38	0.16	0.40	0.72
Project 3	0.06	0.31	0.88	0.12	0.15	0.28	0.10	0.13	0.22	0.00	0.26	0.94	0.11	0.30	0.90	0.03	0.10	0.30	0.16	0.28	0.40
Project 4	0.07	0.30	0.63	0.14	0.24	0.37	0.03	0.15	0.31	0.11	0.51	0.85	0.14	0.35	0.92	0.27	0.68	0.81	0.21	0.32	0.50
Project 5	0.20	0.63	0.78	0.14	0.25	0.24	0.12	0.15	0.40	0.04	0.23	0.44	0.00	0.08	0.13	0.11	0.28	0.52	0.24	0.59	1.00
Project 6	0.02	0.21	0.71	0.00	0.05	0.46	0.05	0.17	0.46	0.13	0.39	0.66	0.20	0.51	0.98	0.00	0.08	0.16	0.04	0.11	0.21
Project 7	0.11	0.48	0.75	0.25	0.38	0.48	0.03	0.38	0.41	0.10	0.40	0.70	0.28	0.74	1.00	0.01	0.20	0.43	0.14	0.36	0.50

Normalized Project KPIs for the Seven Construction Projects

	Project Cost Growth	Project Budget Factor	Construction Phase Cost Growth	Total Change Cost Factor	Cost-For-Change-Demand	Project Schedule Growth	Project Schedule Factor	Construction Phase Schedule Growth	Construction Phase Schedule Factor	Time Predictability (Construction)
Project 1	0.21	1.00	0.31	1.00	0.02	0.04	0.05	0.05	0.00	0.05
Project 2	0.02	0.07	0.02	0.05	0.14	0.01	1.00	0.13	1.00	1.00
Project 3	1.00	0.02	0.10	0.00	0.08	0.00	0.16	0.01	0.09	0.01
Project 4	0.00	0.00	0.00	0.25	0.00	0.18	0.21	0.18	0.21	0.21
Project 5	0.10	0.00	0.10	0.38	0.09	0.16	0.00	0.00	0.23	0.12
Project 6	0.00	0.02	1.00	0.22	1.00	1.00	0.42	0.01	0.24	0.00
Project 7	0.08	0.01	0.08	0.43	0.00	0.22	0.11	1.00	0.11	0.10