Risk-based Framework for Management of Construction Projects

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Abstract

Risk-based Framework for Management of Construction Projects

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Well-developed risk management tools provide critical support for successful delivery of construction projects. Considerable research has been conducted towards integration of risk management in front-end planning and in execution phases of this class of projects. The accuracy of these tools relies heavily on their respective assumptions and on the data used in their application. Consideration of risk in these tools utilizes two types of data: actual past records and estimated future data related to completion of projects under consideration. The literature reveals that most published work in this area utilized these data either in bidding phase or in one of individual project execution phases to minimize the negative impact of risk on project cost and duration at completion. However, there is a lack of a comprehensive framework that employs both types of data in different phases of construction projects. This prevents construction practitioners from implementing an efficient risk management program. In this research, a new risk-based framework is developed, addressing limitations of existing models for different management functions over project lifecycle. The developed framework employs past performance data of construction organizations and projects in the bidding phase for risk maturity evaluation, contingency estimation, markup estimation, planning and scheduling, and progress reporting. The framework has five developed models. The first introduces a decision support model for risk maturity evaluation of construction organizations to identify their strengths and weaknesses in risk management processes, employing the Analytic Network Process (ANP) and fuzzy set theory. It enables construction organizations to

assess and continuously improve their risk management capabilities. The second model introduces a new cost contingency estimation model considering correlations among project cost items, subjectively and objectively. It is also capable of modeling project cost contingency with and without the use of Monte Carlo simulation, which is deemed particularly useful when using subjective correlations. The third model introduces new pattern recognition techniques for estimating project markup. It utilizes Multiple Regression (MR), Artificial Neural Network (ANN) and Adaptive Nero-Fuzzy Inference System (ANFIS) techniques for that purpose, considering five factors: need for work, job uncertainty, job complexity, market condition, and owner capability. The fourth model introduces a newly developed multi-objective optimization model for scheduling of repetitive projects under uncertainty. The model considers the estimated cost contingency and the project markup in the total project cost and conducts, simultaneously, trade-offs between project duration, project cost, crew work interruptions, and interruption costs. It safeguards against assignment of unnecessary costly resources and provides a reliable project baseline. The fifth model presents a newly developed risk-based earned duration management model (RBEDM) that utilizes the generated project baseline in forecasting project duration at completion, considering critical activities only and their associated risk factors. It introduces a new risk adjustment factor (RAF_{cr}) that quantifies the impact of future uncertainties associated with critical activities in estimating project duration at completion. This unique aspect of the developed model addresses the main drawback of earned duration management (EDM) its reliance on past performance data only. It also assists project managers in estimating more accurate and realistic required time to project completion.

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To Canadian people, for their generosity, hospitality, and their warm welcome

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LIST OF ACRONYMS

AACE	Association for the Advancement of Cost Engineering
AAR	Ability to Analyse Risk
AD	Actual Duration
AI	Artificial Intelligence
AIR	Ability to Identify Risk
AIRR	Ability to Implement Risk Responses
AMR	Ability to Monitor Risk
ANFIS	Adaptive Nero-Fuzzy Inference System
ANN	Artificial Neural Network
ANP	Analytic Network Process
APR	Ability to Plan Risk
ARR	Ability to Plan Risk Responses
BC	Bid Coordinator
BCIS	Building Cost Information Service
BPD	Baseline Planned Duration
CCPM	Critical Chain Project Management

COA	Center of Area Method
DC	Direct Cost
DPI	Duration Performance Index
EC	Equipment Cost
ED	Earned Duration
EDAC	Estimated Project Duration at Completion
EDI	Earned Duration Index
EDM	Earned Duration Management
EPC	Engineering, Procurement, and Construction
ERM	Enterprise Risk Management
ERMMM	Fuzzy Enterprise Risk Management Maturity Model
ESM	Earned Schedule Management
EV	Earned Value
EV	Expected Value
EVM	Earned Value Management
FBMCS	Fuzzy-Based Monte Carlo Simulation
FCDM	Fuzzy Contingency Determination Model
FMCS	Fuzzy Monte Carlo Simulation

FNN	Fuzzy Neural Network
Fuzzy-FMEA	Fuzzy-Failure Mode and Effect Analysis
GA	Genetic Algorithm
GBELLMF	Generalized Bell-Shaped Membership Function
GRMM	Generic Risk Maturity Model
GRNN	General Regression Neural Networks
IC	Indirect Cost
IRM	Institute of Risk Management
ISO	International Organization for Standardization
LC	Labour Cost
LSM	linear Scheduling Method
MC	Material Cost
MCS	Monte Carlo Simulation
MDC	Mobilization and Demobilization Cost
MDT	Mobilization and Demobilization Time
MOF	Multi-Objective Function
MR	Multiple Regression
OPM3	Organizational Project Management Maturity Model

PD	Project Duration
PD	Project Director
PERT	Program Evaluation and Review Technique
PM	Project Manager
PMBOK	A Guide to the Project Management Body of Knowledge
PMI	Project Management Institute
PPM	Pre-construction Manager
PV	Planned Value
R^2	Coefficient of Determination
RA	Risk Analyst
RAF	Risk Adjustment Factor
RBEDM	Risk-Based Earned Duration Management Model
RFF	Activity Relaxation Free Float
RM	Risk Management
RMSE	Root Mean Squared Error
SD	Standard Deviation
SPI	Schedule Performance Index

TBRPI	Time-Based Risk Performance Indicator
TC	Project Total Cost
TCI	Total Cost of Interruptions
TDI	Total Duration of Interruptions
TED	Total Earned Duration
TIFN	Triangular Intuitionistic Fuzzy Number
TPD	Total Planned Duration
VP	Vice President

CHAPTER 1: INTRODUCTION

1.1. Overview

Risk management is a key driver in successful delivery of construction projects. According to the Project Management Institute (PMI 2017), risk management processes include: planning the risk management, identifying the risks, performing a qualitative risk analysis, performing a quantitative risk analysis, planning risk responses, implementing risk responses, and monitoring risks. The goal of risk management is to insure on-time and within budget delivery of the project. A survey conducted by Project Management Institute (PMI 2015) revealed that 83% of organizations that have high performance in project management practice risk management frequently. These organizations meet their goals 2.5 times faster and waste 13 times less money than those who do not practice risk management on a regular basis (PMI 2015). However, the majority of construction organizations are not fully aware of the added value of risk management and prefer to use their own traditional procedures (Liu et al. 2007, Deloitte 2012). A survey conducted by Deloitte Inc. in 2012 highlighted that nine out of ten construction practitioners are dissatisfied with their current approach to risk management. It is mainly due to lack of risk management culture in the organization level (Liu et al. 2007) as well as inadequate knowledge of risk management in selection and utilization of the right tools and techniques (Forbes et al. 2008). This results in an inefficient implementation of a risk management program which is the most common cause of project failure in the construction industry (Beckers et al. 2013). In the absence of the above, construction stakeholders develop their own company-based risk management procedures using a combination of the available tools and techniques which are project-based and can not be generalized at the organizational level.

1.2. Problem Statement

The available research in the literature mainly focused on five tools to minimize the negative impact of risk on project cost and duration including: risk maturity evaluation, contingency estimation, markup estimation, trade-off analysis, and earned value management (EVM) analysis. However, the literature reveals that there is a lack of a comprehensive framework that integrates the implementation of the above tools in different phases of construction projects based on their corresponding required data. Also, each of the above tools has its own limitations. The available risk maturity evaluation models do not consider the project personnel's authority level in the organization and their level of involvement in the risk management processes, providing misleading information where project personnel do not have enough knowledge and experience of risk management. The available contingency estimation models provided in the literature work based on either historical cost data captured from previous projects or experience and/or judgment of contractors. There is a need to develop a model allowing construction practitioners to estimate the required contingency budget based on either of those data, with or without computer simulation. The literature also reveals that most of the published work for markup estimation employed deterministic, probabilistic, or fuzzy set modelling, with less consideration of advance pattern recognition models that account for factors impacting markup estimation and their corresponding uncertainties. The literature also reveals that the available repetitive scheduling models provided in the literature perform trade-off analysis between either two objectives (project duration and cost) or three objectives (project duration, project cost, interruptions time) with no consideration of crew idle cost and mobilization and de-mobilization costs, imposing unnecessary costly resources on the project. The EVM-based methods provided in the literature do not account for the future uncertainties beyond the reporting date resulting in over or under estimation of project duration at completion.

1.3. Research Objectives

The aim of this research is to develop a comprehensive risk-based framework for management of construction projects. Accordingly, new tools are developed for that purpose focusing on risk maturity evaluation, contingency estimation, markup estimation, trade-off analysis, and earned value management (EVM) analysis. The below objectives have been generated to achieve the aim of this research:

1. Development of a new risk maturity evaluation model enabling construction organizations to identify their strengths and weaknesses in risk management processes. The developed model accounts for the project personnel's level of authority in the organization and their level of involvement in the risk management processes. It utilizes the data captured from project personnel who work at different levels of the organization including portfolio, program, and project levels.
2. Development of a new contingency estimation model enabling construction practitioners to estimate the required contingency budget based on the past cost data recorded from previous projects and/or the experience and/or judgment of contractors. The developed model also allows contingency estimation with or without computer simulation.
3. Development of new pattern recognition models for estimating project markup based on the past performance data recorded from similar projects. The introduced models account for influential factors in estimating project markup such as need for work, job uncertainty, job complexity, market condition, and owner capability. These introduced models are particularly useful in competitive bidding where bid price is a driving factor. They assist bidders in estimating the optimum markup that maximizes their expected value.

4. Development of a new trade-off analysis model that identifies optimum crew formations at unit execution level of repetitive projects that minimize project duration, project cost, crew work interruptions and interruption costs, simultaneously. The developed model accounts for the uncertainty associated with crew productivity rates and the quantities of work. It leads to establishment of a realistic project baseline which is the foundation of an accurate earned value management (EVM) analysis.
5. Development of a new risk-based earned duration management model that forecasts project duration at completion based on the past performance data of critical activities at the reporting date and the data associated with their future uncertainties beyond the reporting date. The model prevents project managers from over optimistic or pessimistic estimation of the required time for project completion.

1.4. Methodology Overview

Figure 1.1 shows the methodology to achieve the above objectives. It begins with defining the problem statement and objectives followed by an in-depth literature review in risk maturity evaluation for construction organizations, contingency estimation for construction projects, markup estimation for construction projects, trade-off analysis in scheduling of repetitive construction projects, and finally, EVM in construction projects. After identifying gaps and limitations in the current literature and in order to address the limitations and gaps, a new risk-based framework is developed consisting of five models entitled risk maturity evaluation model, contingency estimation model, markup estimation model, trade-off analysis model, and EVM analysis model. The input and output of each model is highlighted in Figure 1.1. Then, in order to assess the feasibility and applicability of the developed models, different case studies are examined. Eventually, the expected contribution and future works are presented in the conclusion.

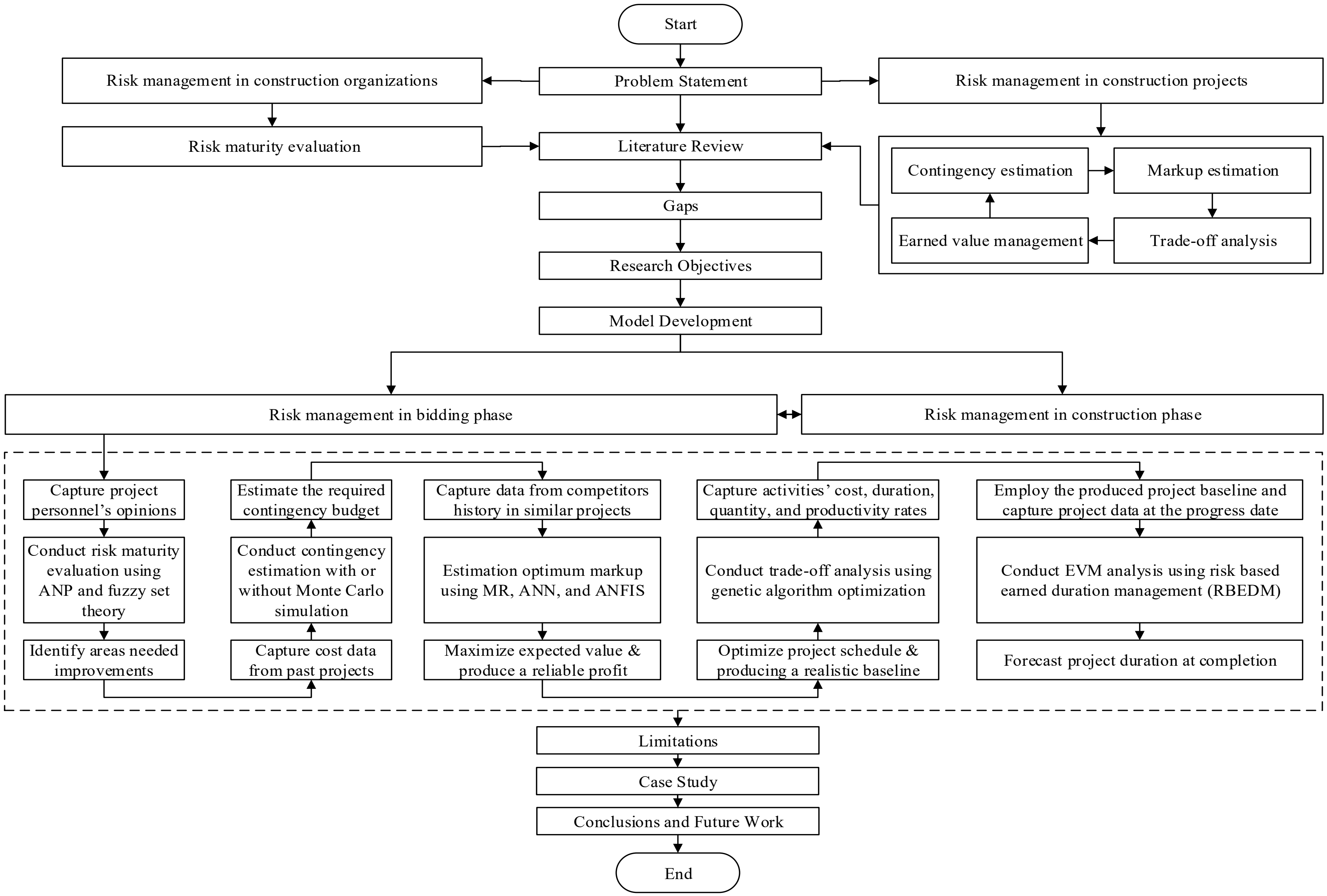


Figure 1.1: General research framework

1.5. Thesis Organization

This research is presented in five chapters. Chapter 2 presents a review of work done in previous years, focusing on risk maturity evaluation for construction organizations, contingency estimation for construction projects, markup estimation for construction projects, scheduling and trade-off analysis in repetitive construction projects, and EVM analysis in construction projects. The existing gaps in the literature are highlighted in this chapter. Chapter 3 presents an overview of the proposed methodologies. It begins by introducing a novel risk maturity evaluation model for construction organizations followed by introducing a new contingency estimation model for construction projects, introducing several pattern recognition techniques for construction projects, introducing a new trade-off analysis model that optimizes project schedule under uncertainty, and finally, introducing a new earned value management model that forecasts project duration at completion considering project uncertainties. The limitations of each model are highlighted at the end of this chapter. Chapter 4 presents five case studies, one for each of the developed models, to highlight the efficiency of the developed models over those models reported in the literature. Chapter 5 presents a summary of the developments accomplished in this research. It also highlights research contributions. And it finally concludes with proposed opportunities for future work.

CHAPTER 2: LITERATURE REVIEW

2.1. Overview

The present literature covers the current state of the art in the following domains:

- Risk management maturity evaluation for construction organizations
- Contingency estimation for construction projects
- Markup estimation for construction projects
- Optimized trade-off for scheduling of repetitive construction projects
- Earned value management analysis for construction projects

2.2. Risk Maturity Evaluation for Construction Organizations

This section is a marginally modified version of "A Fuzzy-Based Decision Support Model for Risk Maturity Evaluation of Construction Organizations" published in the journal of Algorithms (Roghabadi and Moselhi 2020a) and has been reproduced here.

Risk management in the construction industry has received considerable attention from researchers and industry professionals over the last four decades. The processes of risk management have been widely studied and documented in several international risk management standards and guidelines. Although each standard utilizes a different vocabulary to describe the processes, they mostly follow the same pattern. For instance, Table 2.1 shows the recent classification of risk management processes based on some major international standards including the Project Management Institute (PMI 2017), the International Organization for Standardization (ISO 2009), the Association for the Advancement of Cost Engineering International (AACEI 2013) and the Institute of Risk Management (IRM 2002). Through the examination of the processes presented in Table 2.1, one can map them into six processes: risk management planning, risk identification, risk analysis, risk response planning, risk responses implementation, and risk monitoring.

Table 2.1: General risk management processes

Risk Management Processes	Professional Organizations			
	PMI (2017)	ISO (2018)	AACE (2013)	IRM (2002)
Communication and consultation	-	✓	-	-
Scope, context and criteria	-	✓	-	-
Plan risk management	✓	-	✓	-
Organization’s strategic objectives	-	-	-	✓
Risk assessment (identification, analysis, evaluation)	-	✓	✓	✓
Identify risks	✓	-	-	-
Perform qualitative risk analysis	✓	-	-	-
Perform quantitative risk analysis	✓	-	-	-
Risk Reporting	-	-	-	✓
Decision	-	-	-	✓
Risk treatment	-	✓	✓	✓
Plan risk responses	✓	-	-	-
Implement risk responses	✓	-	-	-
Recording and reporting	-	✓	-	-
Residual risk reporting	-	-	-	✓
Monitor risks	✓	-	✓	✓
Monitoring and review	-	✓	-	-

Notes: ✓: considered, -: not considered

The literature reveals that considerable work has been carried out on risk identification, analysis, responses and monitoring, but far less on risk management planning and risk response implementation. Planning for risk management is the first process in a risk management program and it defines the scope of the risk management as well as the appropriate approaches, tools and responsibilities (PMI 2017, PMI 2009, ISO 2018, Jia et al. 2013). In order to increase the efficiency and effectiveness of this process, a risk maturity evaluation study should be conducted to identify the performance level of the organization in its risk management program. Risk maturity provides a measurable tool that shows the degree of formality and progress in the application of the risk management processes according to a set of attributes (Hoseini et al. 2019). It is an iterative process with a dynamic nature which must be carried out on a regular basis.

Over the last decade, several risk maturity models were developed for construction projects. The study conducted by Zou et al. (2010) is one of the earliest efforts, which introduced a new risk management maturity model measuring the risk maturity level of the construction organizations in accordance with the four aspects of project management, standardization, measurement, control and continuous improvement. However, considering these aspects does not reflect the risk maturity level of organizations in different processes of risk management. In order to address this limitation, Jia et al. (2013) developed a new risk maturity model measuring the risk maturity of organizations based on their level of maturity in the risk management processes as well as the organization management aspects. Their model, however, gave the same importance weight to individuals' responses, neglecting the individuals' level of authority in the organization and their level of involvement in the risk management processes. It also did not consider the uncertainty associated with the responses, neglecting the ambiguity, subjectivity and the imprecision involved in the responses provided by these individuals. In the same year, Zhao et al. (2013) introduced a new fuzzy enterprise risk management maturity model (ERMMM) enabling construction organizations to incorporate the uncertainty of the responses used in model development. However, no dependency was considered between the sixteen identified attributes which in turn reduced the accuracy of the results. One year later, Zhao et al. (2014) applied their earlier developed ERMMM model on the three case studies to investigate the influence of the firm size on the enterprise risk management (ERM) implementation. However, considering the dependency between the risk maturity attributes remained lacking. Recently, Alashwal et al. (2017) utilized the Organizational Project Management Maturity Model (OPM3) method introduced by the PMI (2008) to measure the risk maturity level of the organization and to consider its impact on the firm size and organizational learning. Hoseini et al. (2019) also developed a new generic risk maturity model (GRMM) to evaluate the performance of the construction organization in the application of the risk management program. However, their models focused on the theoretical aspects of the risk maturity evaluation without considering either the uncertainty resulting from individuals' judgments or the dependency between the identified attributes.

In summary, as shown in Table 2.2, none of the of the above cited models are capable of simultaneously: (a) modeling the interdependencies between the risk maturity attributes, (b) capturing the uncertainty associated with individuals' judgement, and (c) considering the importance weight of individuals' responses in calculating the weights associated with the risk maturity attributes.

Table 2.2: A summary of the risk maturity models for construction organizations

Source	Aspects		
	Modeling Interdependency	Capturing Uncertainty	Considering Individuals' Weight
Jia et al. (2013)	✓	-	-
Hoseini et al. (2019) & Zou et al. (2013)	-	-	-
Zhao et al. (2013) & Zhao et al. (2014)	-	✓	-
Alashwal et al. (2017) & Wibowo (2017)	-	-	-

Notes: ✓: considered, -: not considered

Unlike the models presented in the literature, this research presents a novel risk management maturity model which is capable of modeling the interdependencies among the identified risk maturity attributes considered in the model development, capturing the uncertainty associated with the input data provided by individuals who participate in the model development, and considering the relative importance of the responses used in calculating the weights associated with the risk maturity attributes.

2.3. Contingency Estimation for Construction Projects

This section is a marginally modified version of "Risk Quantification Using Fuzzy-Based Monte Carlo Simulation" published in the journal of Information Technology in Construction (ITcon) (Moselhi and Roghabadi 2020) and has been reproduced here.

Construction is a risky business and contingency is a vehicle for managing that risk (Hammad et al. 2016). Contingency is defined by the Association for the Advancement of Cost Engineering (AACE) as: "An amount added to an estimate to allow for items, conditions, or events for which the state, occurrence, or effect is uncertain and that experience will likely result, in aggregate, in additional costs. It is typically estimated using statistical analysis or judgment based on past asset or experience." (AACE 2010).

Contingency estimating methods were studied by Bakhshi and Touran (2014) and clustered in three groups: (1) deterministic, (2) probabilistic, and (3) modern methods. Table 2.3 shows a summary of them. Deterministic methods are the simplest methods in which cost contingency is estimated as a predetermined percentage of project cost based on past experience and historical data (Baccarini, 2005). However, these methods heavily rely on expert experience and can lead to errors or overestimation (Yeo 1990, Smith et al. 1999, Baccarini 2004, Olumide et al. 2010, Chou et al. 2013). Probabilistic methods include simulation and non-simulation methods. Monte Carlo

Simulation (MCS) is the commonly used probabilistic simulation method. The accuracy of MCS strongly relies on calculation of correction coefficients among cost items.

Table 2.3: A summary of contingency estimation methods for construction projects

Source	Method					
	Deterministic	MCS	Non-simulation	Regression	ANN	Fuzzy
Baccarini (2005)	✓	-	-	-	-	-
Yeo (1990)	✓	-	-	-	-	-
Smith et al. (1999)	✓	-	-	-	-	-
Baccarini (2004)	✓	-	-	-	-	-
Olumide et al. (2010)	✓	-	-	-	-	-
Chou et al. (2013)	✓	-	-	-	-	-
Touran and Wiser (1992)	-	✓	-	-	-	-
Touran and Suphot (1997)	-	✓	-	-	-	-
Touran (1993)	-	✓	-	-	-	-
Wall (1997)	-	✓	-	-	-	-
Yang (2005)	-	✓	-	-	-	-
Okmen et al. (2010)	-	✓	-	-	-	-
Firouzi et al. (2016)	-	✓	-	-	-	-
Moselhi (1997)	-	-	✓	-	-	-
Lam and Siwingwa (2017)	-	-	-	✓	-	-
Diab et al. (2017)	-	-	-	✓	-	-
Chen and Hartman (2000)	-	-	-	-	✓	-
Lhee et al. (2014)	-	-	-	-	✓	-
Leung et al., 2018	-	-	-	-	✓	-
Sadeghi et al. (2010)	-	-	-	-		✓
Idrus et al. (2011)	-	-	-	-		✓
Salah and Moselhi (2015)	-	-	-	-		✓
Elbarkouky et al. (2016)	-	-	-	-		✓
Jung et al. (2016)	-	-	-	-		✓

Notes: ✓: considered, -: not considered

The research conducted by Touran and Wiser (1992) is one of the earliest efforts in modeling the impact of correlation among cost items on the total cost variance of construction projects and hence on the estimated contingency. Touran and Suphot (1997) concluded that the use of rank correlations for generating correlated random variables outperforms those correlations established from traditional methods based on Pearson correlations. Moselhi (1997) presents a quantitative direct method for calculating total project cost variance considering correlations without the need for Monte Carlo simulation. To alleviate the difficulties associated with calculations of correlation coefficients, Touran (1993) introduced subjective correlations: high (with a correlation coefficient of larger than a predefined threshold), middle and weak. That method, however, did not consider the uncertainties associated with subjective correlation coefficients among cost items.

The second category of probabilistic methods is non-simulation methods which includes probability tree, expected value, first-order second-moment, program evaluation and review technique (PERT), analytical hierarchy process, optimism bias uplifts, and regression method (Diab et al., 2017). The last one is one of the traditional utilized methods in that category in which various independent variables (e.g location, size) are employed to predict the dependent variable (e,g. estimated final cost) (Baccarini, 2005). Lam and Siwingwa (2017) recently utilized the multiple regression method to predict the required contingency sum during the preconstruction phase of the project considering the risks associated with construction phases and clients. Diab et al. (2017) investigated the impact of risk drivers on contingency estimation from client and contractors points of view. They utilized a regression model to predict the required contingency budget in highway construction projects by rating the potential risk drivers based on their relative importance, cost impact, and schedule impact. However, the use of the regression method is recommended where there is a linear relationship between dependent and independent variables (Bakhshi and Touran, 2014) which is not the case in construction projects of a complex nature.

Therefore, modern methods such as Artificial Neural Networks (ANN) are employed to overcome the linearity assumption in estimating cost contingency (Leung et al. 2018). For instance, Chen and Hartman (2000) utilized a back propagation general regression neural networks (GRNN) model in order to estimate cost contingency at the front-end stage of the project development. Lhee et al. (2014) further proposed a two-step neural network-based method for optimal contingency estimation from an owner's perspective. Their proposed model accounted for modeling non-linearity between the predictor variables and the corresponding target solution. However, ANN-based contingency estimation methods are not capable of capturing the uncertainty associated with input data provided by individual experts and these methods require an extensive data collection for training and testing (Chen and Hartman 2000, Leung et al. 2018).

Fuzzy set theory is another type of modern methods which is capable of modeling subjectivity of input data, while providing an accurate result of cost contingency estimation. There are numerous publications on fuzzy-based contingency estimations methods. Sadeghi et al. (2010) proposed a Fuzzy Monte Carlo Simulation (FMCS) framework with the aim of dealing with fuzzy related imprecisions and ambiguities. Idrus et al. (2011) prioritized 14 risk factors impacting cost contingency utilizing the fuzzy expert system to account for contractors' subjective judgments. Salah and Moselhi (2015) developed a fuzzy-set based model for estimation, allocation, utilization and management of cost contingency. Elbarkouky et al. (2016) introduced a fuzzy contingency determination model (FCDM) for estimating project contingency. Their FCDM model provides a generalized approach to investigate the impact of different fuzzy arithmetic procedures on contingency determination. Jung et al. (2016) developed a Fuzzy-Failure Mode and Effect

Analysis (Fuzzy-FMEA) method for calculation of reserve construction expenses. However, these methods did not consider the impact of correlation coefficients in estimating project cost contingency.

In summary, all the methods cited above collectively or individually are incapable of simultaneously: (a) considering correlations among project cost items, either subjective or objective, (b) performing contingency estimation with or without using Monte Carlo simulation, (c) accounting for uncertainty associated with subjective correlation coefficients among cost items, (d) calculating the variance of total project cost regardless of the type of the marginal distributions of its cost items, and (e) assessing the impact of variability of the elements of the covariance matrix in estimating project cost contingency using a simple and user-friendly platform.

Unlike existing methods in the body of the literature, this research introduces a new contingency estimation model considering correlations among project cost items, either subjectively or objectively. The proposed method accounts for subjectivity of input data provided by individual experts and models the interdependency between cost items. It is also capable of modeling project cost contingency with and without computer simulation. This is deemed particularly useful when using subjective correlations.

2.4. Markup Estimation for Construction Projects

This section is a marginally modified version of "Three Models for Estimating Bid Markups" published in 2018 AACE® International Transactions (Roghabadi and Moselhi 2018) and has been reproduced here.

Bidding decisions, including estimation of optimum markup, remains crucial for contractors' success in the competitive bidding environment. In competitive construction bidding, project owners generally award the contract to the lowest qualified bidder where price is the driving factor and where financial, technical, management and safety issues are not present. Winning a bid and making profit are important for contractors to survive in the market and to achieve their targeted objectives (Puri and Tiwari 2014). Contractors competitively bidding on projects adjust their markups according to the level of competition to increase their chances of winning (Lo et al. 2007). Although different types of models have been developed to estimate optimum markup and to assist in bid/no bid decisions, many contractors are reluctant to use them due to their incapability to capture the complexity and uncertainty of construction projects (Drew and Skitmore 1997). When in a competitive bidding environment, estimating markup is a key component to winning or losing the bid. Therefore, determination of optimum markup is critical and has an undeniable role in winning a contract (Polat et al. 2016).

Moselhi and Hegazy (1993) clustered the markup estimation models in three groups: probabilistic models [e.g., Friedman (1956), Gates (1967), and Carr (1987)], decision analysis models such as the analytical hierarchy process [e.g., Seydel and Olson (1990)], and knowledge-based expert systems models such as Artificial Intelligence-based models (AI) [e.g., Tavakoli and Utomo (1989) and Ahmad and Minkarah (1988)]. All these models aim to maximize the expected profit and probability of winning while minimizing the bid price. However, the first two groups do not account for the influential factors that impact project markup (Moselhi and Hegazy 1993). They also do not account for the nonlinearity between the inferential factors (Liu and ling 2005). Therefore, the use of the third group is recommended where project markup is estimated using computer programing based on the pattern of previous data. Three main techniques are provided in the literature for that purpose: regression-based techniques, artificial neural network (ANN), and a combination of ANN and fuzzy set theory. ANN widely used for modeling construction problems such as forecasting construction productivity (Chao and Skibniewski 1994), estimating the deviation of cost from the planned value in reconstruction projects (Emsley et al. 2002), forecasting client satisfaction levels (Soetanto and Proverbs 2004), and estimating equipment productivity (Ok and Sinha 2006). The advantage of artificial neural networks is their ability to adapt learning using a data-driven model for training or initial experience (Moselhi et al. 1993). The model developed by Moselhi and Hegazy (1993) is one of the earliest applications of ANN for estimating project markup. Their proposed model considered the influential factors such as need for work, job uncertainty, job complexity, market condition, and owner capability in estimating project markup. Further efforts have been made in this area over the last two decades. Emsley et al. (2002) employed ANN technique for estimating project cost based on data collected from nearly 300 building projects. They compared the result of ANN with the linear regression technique concluding that ANN has higher ability in considering the nonlinearity between influential factors. Attalla and Hegazy (2003) employed statistical analysis and artificial neural networks for predicting cost deviation in reconstruction projects. The results indicated that the ANN model is more suitable where there are a large number of variables. However, the above ANN-based models do not account for the uncertainties involved in the process of markup estimation.

In order to address this limitation, Liu et al. (2005) constructed a fuzzy neural network (FNN) which combined fuzzy logic with ANN. The developed model captured the ambiguity of the contractors' judgment in providing input data. Through their proposed methodology, it is proven that the FNN is superior to the ANN model in providing a better accuracy for estimating project markup. However, the application of FNN is inefficient where there are many parameters influencing the model's output (Aliev et al.2015). Thus, the use of the Adaptive Neuro-Fuzzy

Interface System (ANFIS) is recommended which is a fast-learning model and combines the advantages of artificial neural network and fuzzy logic (Atef 2015, Azeez et al. 2013). Although fuzzy set theory has the capability of representing vague and imprecise knowledge, it does not come with learning algorithm and cannot learn or adapt by itself (Atef 2015, Azeez et al. 2013). Adaptive Neuro-Fuzzy Inference System applies knowledge of fuzzy logic design to the learning/training process. This results in a learning model which is able to completely bypass the repeated use of complex iterative processes (Jang 1993). Very limited studies have been conducted towards application of ANFIS for estimating project markup. This includes the model recently developed by Jumas et al. (2018). In that model, a conceptual cost estimation model is developed using ANFIS and multiple regression (MR) models. However, the developed model is adapted for cost estimation and does not account for factors influencing project markup and their dependencies.

Unlike the models cited above, in this research, an Adaptive Neuro-Fuzzy Interface System is introduced for estimating project markup. It considers 39 factors, recognized to impact the markups of estimates and 23 of which are clustered in into five independent categories: need for work, job uncertainty, job complexity, market condition, and owner capability. The introduced model considers the dependencies between these factors. The performance of the introduced ANFIS model is compared with ANN and MR and it is concluded that the ANFIS model outperforms both of the other two models in estimating markups under different project conditions.

2.5. Optimized Trade-off Analysis for Scheduling of Repetitive Construction Projects

This section is a marginally modified version of "Optimized Crew Selection for Scheduling of Repetitive Projects" published in the journal of Engineering, Construction and Architectural Management (Roghabadi and Moselhi 2020b) and has been reproduced here.

Repetitive projects are a unique class of construction projects which require timely movement of construction crews from one unit to the next. Repetitive projects are either linear or non-linear. They are distinguished based on having a linear geometric pattern. For example, highways, pipelines and railroad projects are characterized as linear projects, while skyscrapers and typical housing projects are considered as non-linear repetitive projects (Arditi and Albulak 1979).

Repetitive projects can also be classed as typical or non-typical (Vorster and Bafna 1992). The typical ones feature tasks where the similar amount of work with the same crew productivity rate is repeated for different units as shown in Figure 2.1.

However, generally, projects consist of non-typical units where different quantities of work and/or different crew productivity rates can be encountered in repeated units for each activity. This makes a repetitive schedule consisting of activities with different slopes (Bakry et al. 2014) as shown in Figure 2.1. The slope in that case is defined as the ratio of activity duration to its quantity of work.

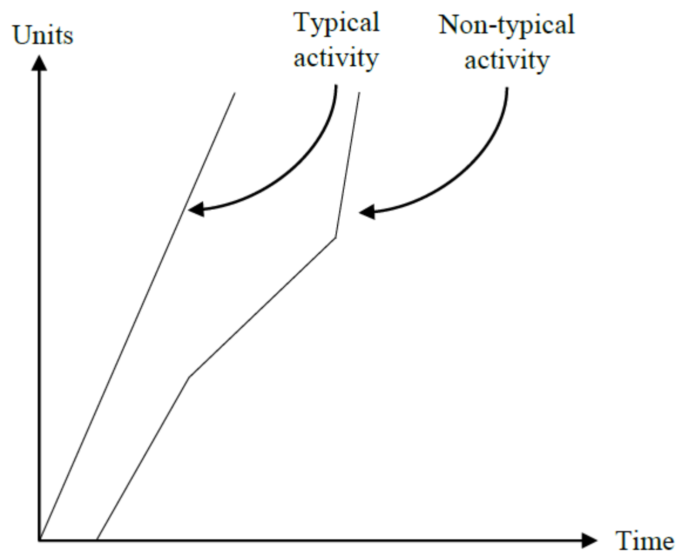


Figure 2.1: Typical and non-typical activities.

Scheduling of linear repetitive projects is unique due to the importance employed on sustaining crew work continuity. Maintaining the continuity of different crews in this class of projects allows for gaining from the learning curve effect, minimizing equipment idle time, reducing firing and hiring of labor and retaining skilled labor (Ashley 1980, Birrell 1980). Timely movement of crews from one location to the next is required to conserve crew work continuity and avoid crew idle time, called crew work continuity constraint (El-Rayes and Moselhi 1998). Therefore, maintaining crew work continuity or minimizing interruptions can pose a major concern in scheduling these projects (Vanhoucke 2006, Hyari and El-Rayes 2006).

A variety of scheduling models are proposed in the literature to consider work continuity constraint for repetitive projects. These are grouped in models that do not enable work interruptions and models that allow for work interruptions, while keeping that to a minimum as illustrated in Table 2.4.

Table 2.4: Scheduling models with and without crew work interruptions

Criteria	Authors
Without interruption	Selinger 1980, Perera 1983, Moselhi and El-Rayes 1993a, Moselhi and El-Rayes 1993b, Suhail and Neale 1994, Adeli and Karim 1997, Hegazy and Wassef 2001, Moselhi and Hassanein 2003, Hegazy et al. 2004, Huang and Sun 2006, Georgy 2008, Duffy et al. 2010, Lucko 2010, Ammar 2013, Damci et al. 2013, Bakry et al. 2014, Dolabi et al. 2014, Bakry et al. 2016, Zou et al. 2017.
With interruptions	El-Rayes and Moselhi 1998, Vanhoucke 2006, Hyari and El-Rayes 2006, Russell and Caselton 1988, El-Rayes and Moselhi 2001, El-Rayes 2001a, El-Rayes 2001b, Hegazy and Wassef 2001, Nassar 2011, Fan and Lin 2007, Liu and Wang 2007, Ipsilandis 2007, Hegazy and Kamarah 2008, Hyari et al. 2009, Long and Ohsato 2009, Fan et al. 2012, Agrama (2014), Altuwaim and El-Rayes 2018a, Altuwaim and El-Rayes 2018b, Salama and Moselhi 2019, Arabpour Roghabadi and Moselhi 2019.

Despite the seeming advantages of maintaining crew work continuity, its strict application may lead to longer overall project durations, while maximizing crew work continuity by allowing needed work interruptions can produce shorter project durations, accordingly minimizing indirect cost of these projects (Hyari and El-Rayes 2006). However, work interruptions result in idle crew time and, may lead to increased direct cost.

The main objective of optimization models to address crew work continuity constraint is to search for a set of feasible solutions to assist in achieving least project cost and/or project duration and/or crew work interruptions and /or interruption costs. These models can be based on single or multi-objective optimization.

Single-objective optimization models focused on (a) minimizing project duration (Russell and Caselton 1988, El-Rayes and Moselhi 2001, Liu and Wang 2007, Long and Ohsato 2009), (b) minimizing project cost (El-Rayes 2001b, Hegazy and Wassef 2001, Fan and Lin 2007, Liu and Wang 2007, Hegazy and Kamarah 2008, Long and Ohsato 2009, Huang et al. 2016), (c) minimizing work interruption (Ipsilandis 2007), (d) minimizing the summation of project duration and work interruptions (Nassar 2011), (e) minimizing total project cost in A+B type bidding (El-Rayes 2001a), (f) minimizing project duration and/or project cost (Bakry et al. 2016), and (g) minimizing interruption costs (Altuwaim and El-Rayes 2018a). However, all the above models considered deterministic values for crew productivity rates and quantities of work for calculating the duration of activities at unit execution level except the model developed by Bakry et al. (2016) which employed fuzzy set theory to represent the uncertainty associated with these two objectives. Their model, however, considers a strict application of crew work continuity and does not allow for interruptions. The model is also a single objective optimization model that considers either cost or duration during the optimization process, but not both.

Multi-objective optimization models focused on generating optimal trade-offs between (a) project duration and cost (Hyari et al. 2009), (b) project duration and work interruptions (Hyari and El-Rayes 2006), (c) project duration, total number of crews, and total work interruptions (Agrama 2014), (d) project duration, project cost, and resource fluctuation (Kim et al. 2015), and (e) project duration, project cost, and work interruptions (Salama and Moselhi 2019). The study conducted by Salama and Moselhi (2019) introduces a multi-objective optimization model accounting for uncertainty associated with amount of work and the production rate of crew for each activity employing fuzzy set theory. It, however, did not consider availability of crews at unit execution level and their respective acceleration or relaxation. This limitation leads to assigning more acceleration resources without a beneficial effect on project schedule, leading to increased project cost. In addition, their model considers an assigned user input interruption cost with no consideration of idle crew cost, demobilization and mobilization costs.

In summary, the aforementioned scheduling models are incapable of: (a) considering simultaneously trade-offs between project duration, project cost, crew work interruptions, and interruption costs, (b) identifying optimum crew formations at unit execution level accounting for crew availability, and (c) calculating the required crew productivity rate that minimizes crew work interruptions, without delaying successor activities and without impacting the optimized project duration.

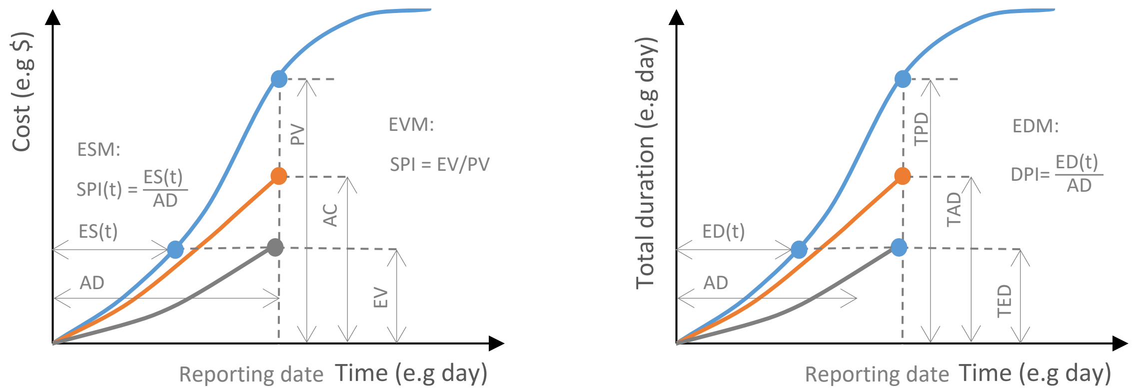
Unlike the models cited above, the developed model identifies optimum crew formations at the unit execution level, allowing activity acceleration and relaxation based on available crews. It also utilizes the introduced activity relaxation free float to calculate the required productivity rate at unit execution level that minimizes crew work interruptions without delaying successor activities and without impacting the optimized project duration.

2.6. Earned Value Management for Construction Projects

This section is a marginally modified version of "Forecasting Project Duration Using Risk-Based Earned Duration Management" under review in the International Journal of Construction Management (Roghabadi and Moselhi 2020c) and has been reproduced here.

Earned Value management (EVM) is a widely used managerial tool enabling project teams to estimate project cost and schedule status at reporting date and forecast its cost and time at completion. While its use for project cost is reported to be reasonably accurate, its use for schedule performance evaluation is inadequate and calls for further improvements (Paige 1963, Lipke 2003, Henderson 2003, Fleming and Koppelman 2004, Henderson 2004, Vandevoorde and Vanhoucke 2006, Lipke et al. 2009, Moselhi 2011, Khamooshi and Golafshani 2014). For example, in a scenario where at the reporting date non-critical activities with high cost are performed as planned but critical activities with low cost have delays, the schedule performance index calculated based on EVM is misleading. In that scenario, the high cost non-critical activities overshadow the delays experienced on the critical path.

In order to address this limitation, Lipke (2003) introduced the concept of Earned Schedule Management (ESM) as an extension to EVM. Unlike the traditional EVM, ESM uses the earned value of the project at the reporting date and converts it into its equivalent duration as shown in Figure 2.2 (a).



a). EVM & ESM graph b). EDM graph

Figure 2.2: Comparison between EVM, ESM, and EDM

Henderson (2003) and Vandevoorde and Vanhoucke (2006) compared the schedule performance evaluation of the project using ESM and EVM. They concluded that the schedule performance evaluation utilizing ESM leads to more accurate and reliable outcomes compared to EVM. Further work was carried out in this area over the last two decades. For example, Lipke et al. (2009) employed statistical prediction and testing methods to validate the reliability of ESM in estimating project duration at completion. They demonstrated that considering statistical confidence limits improves the accuracy of forecasting the final project duration. Elshaer (2013) improved the forecasting accuracy of ESM employing four sensitivity measures for project activities including:

criticality index, significance index, schedule sensitivity index, and cruciality index. His proposed model improved the schedule performance evaluation of the project by decreasing the false warning effects caused by the non-critical activities. Narbaev and Marco (2014) developed an earned schedule regression-based model to improve the accuracy of project cost estimation at completion using EVM. Their model employed a combined use of EVM and ESM to provide more reliable forecasts. Further, in the recent literature, Ballesteros-Pérez et al. (2019) introduced two new metrics, earned schedule minimum (ES_{min}) and earned schedule maximum (ES_{max}) which are calculated at the activity level, instead of project level. The two introduced metrics were reported to outperform the classical ESM metrics. However, the ESM-based models cited above all utilized the earned value of the project at the reporting date and converted it into its equivalent duration employing the primary cost-based data for schedule performance evaluation of the project. This conversion leads to a misleading evaluation of schedule performance, especially where critical activities have low cost and are behind schedule.

In an effort to introduce further improvements, Khamooshi and Golafshani (2014) proposed the concept of earned duration management (EDM) in which the schedule performance evaluation is a function of time-based data. Unlike EVM and ESM at reporting date (see Figure 2.2 (a)), EDM uses the earned duration as shown in Figure 2.2 (b). This unique capability of EDM eliminates the dependency of schedule performance evaluation on project cost data which subsequently leads to a more accurate and reliable evaluation of project schedule performance even in cases where on-time non-critical activities have high cost and delayed critical activities have low cost (Khamooshi and Golafshani 2014). Over the last six years, there have been numerous publications focusing on verification and improvement of EDM. For example, Vanhoucke et al. (2015) compared ESM with EDM, illustrating the strengths of EDM over ESM. Khamooshi and Abdi (2017) employed an exponential smoothing forecasting technique to improve the accuracy of forecasting project duration at completion using EDM. They concluded that the use of the earned duration index (EDI) of EDM is less erroneous than the schedule performance index ($SPI_{(t)}$) of ESM. Vanhoucke (2017) utilized earned duration (ED) from EDM and planned value (PV) from EVM to produce an EDM-based project-level earned value (EV_d) as an alternative to classical earned value (EV) for duration and cost performance evaluation of the project. Ghanbari et al. (2017a,b) developed models that utilized fuzzy set theory and fuzzy preference relations for project schedule performance evaluation using EDM. Most recently, Mortaji et al. (2018) developed an ex-ante control chart that indicates the duration variations of the project from its original bassline employing EDM. Andrade et al. (2019) improved the accuracy of EDM by introducing composite performance factors that combined the schedule performance and schedule adherence of the project as an indicator for forecasting project duration at completion. Votto et al. (2020) used EDM as a statistical project control method to monitor the performance of engineering, procurement, and construction (EPC) projects.

None of the above cited EDM-based models, however, distinguished between the progress made by critical activities and that made by non-critical activities at the reporting date, which leads to under estimation of the required time for project completion. Also, these models used only past performance data for forecasting project duration at completion with no consideration of future risks that might arise beyond the reporting date.

The accuracy of EDM strongly relies on consideration of critical activities and their associated risk factors. The study conducted by Moselhi (2011) is one of the earliest efforts that considered critical activities only in schedule performance evaluation of the project. The three cumulative curves of the traditional EVM were generated based on critical activities for calculating the schedule performance index (SPI) and for forecasting project duration beyond the reporting date. Wood (2018) also concluded that considering only critical activities using EDM prevents project managers from over optimistic estimation of the required time for project completion. His proposed model, however, utilized past performance data for schedule performance evaluation of the project and did not consider risk associated with the critical activities and their corresponding impact on estimated project duration at completion.

Risk management is a crucial driver of successful delivery of construction projects (Roghanian et al. 2018, Zafar et al. 2019, Moselhi and Roghabadi 2020, Roghabadi and Moselhi 2020a). Related risk management models reported in the literature are mostly in line with EVM which is by nature distinct from EDM (Pajares and Lopez-Paredes 2011, Diamantas et al. 2011, Tabriz et al 2013, Acebes et al. 2014, Kamyabniya and Bagherpour 2014, Khodakarami and Abdi 2014, Denas 2015, Acebes et al. 2015, Babar et al. 2017, Moradi et al. 2018, Khesal et al. 2019). These models cannot be directly applied to EDM and must be adapted to the unique aspect of the EDM. Very limited studies have been conducted towards integration of EDM with risk management (RM). This includes the model recently developed by Hamzeh et al. (2020). In that model a new time-based risk performance indicator (TBRPI) was introduced to consider the impact of project risk factors on project schedule performance employing triangular intuitionistic fuzzy numbers (TIFNs). However, the introduced TBRPI is calculated with no consideration of future uncertainties, which can lead to underestimation of the remaining time to project completion. It also utilized the progress made by critical and non-critical activities at the reporting date, and accordingly overshadowed experienced delays of critical activities.

The present research introduces a newly developed risk-based earned duration management model (RBEDM) at the micro level (activity level) that employs critical activities and their corresponding risk factors in monitoring and estimating project schedule performance.

Unlike the models cited above, the developed model employs critical activities for project schedule performance evaluation and utilizes a new risk adjustment factor (RAFcr). This allows for estimating project duration at completion considering the future uncertainties associated with critical activities. This unique feature of the developed model can assist project managers to have more accurate and realistic evaluation of the required time to project completion.

2.7. Findings of Literature Review

The following gaps were identified:

1) Lack of a comprehensive risk-based framework that employs past and future risk related data in management of different phases of construction projects.
2) Lack of studies that investigate the impact of individuals' level of authority in the organization and their level of involvements in risk management processes for risk maturity evaluation.
3) Lack of studies that allow construction practitioners to estimate project cost contingency considering correlations among project cost items, either subjectively or objectively, and perform the calculations with or without using Monte Carlo simulation.
4) Lack of studies that compare the accuracy of pattern recognition techniques for estimating project markup.
5) Lack of multi-objective optimization scheduling methods that account for crew idle cost and mobilization and demobilization costs in optimization process.

6) Lack of studies that forecast project duration at completion considering future uncertainties associated with critical activities.

CHAPTER 3: METHODOLOGY

3.1. Introduction

The proposed methodology consists of five models as shown in Figure 3.1. It includes risk maturity evaluation, contingency estimation, markup estimation, trade-off analysis, and earned value management (EVM) analysis. Each model is presented subsequently.

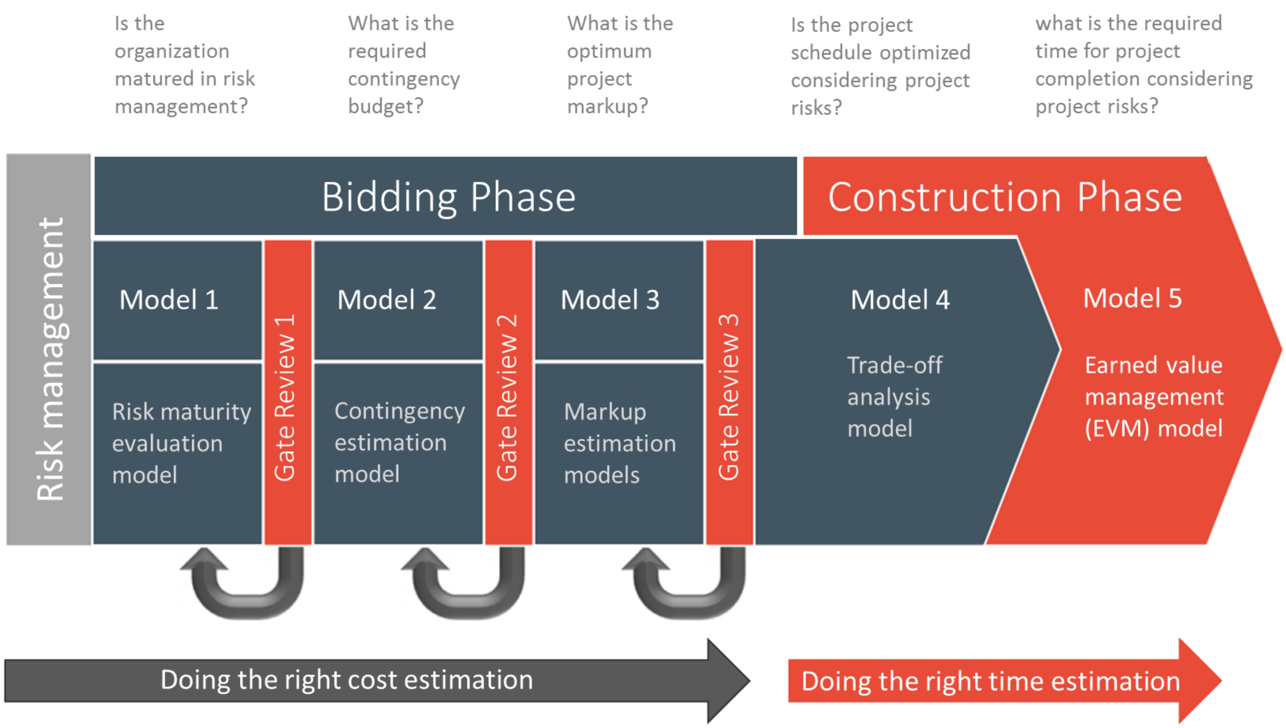


Figure 3.1: General framework of the proposed methodology

3.2. Risk Maturity Evaluation

This section is a marginally modified version of "A Fuzzy-Based Decision Support Model for Risk Maturity Evaluation of Construction Organizations" published in the journal of Algorithms (Roghabadi and Moselhi 2020a) and has been reproduced here.

The developed model is designed to measure the risk management maturity level of construction organizations. The framework of the developed model is shown in Figure 3.2.

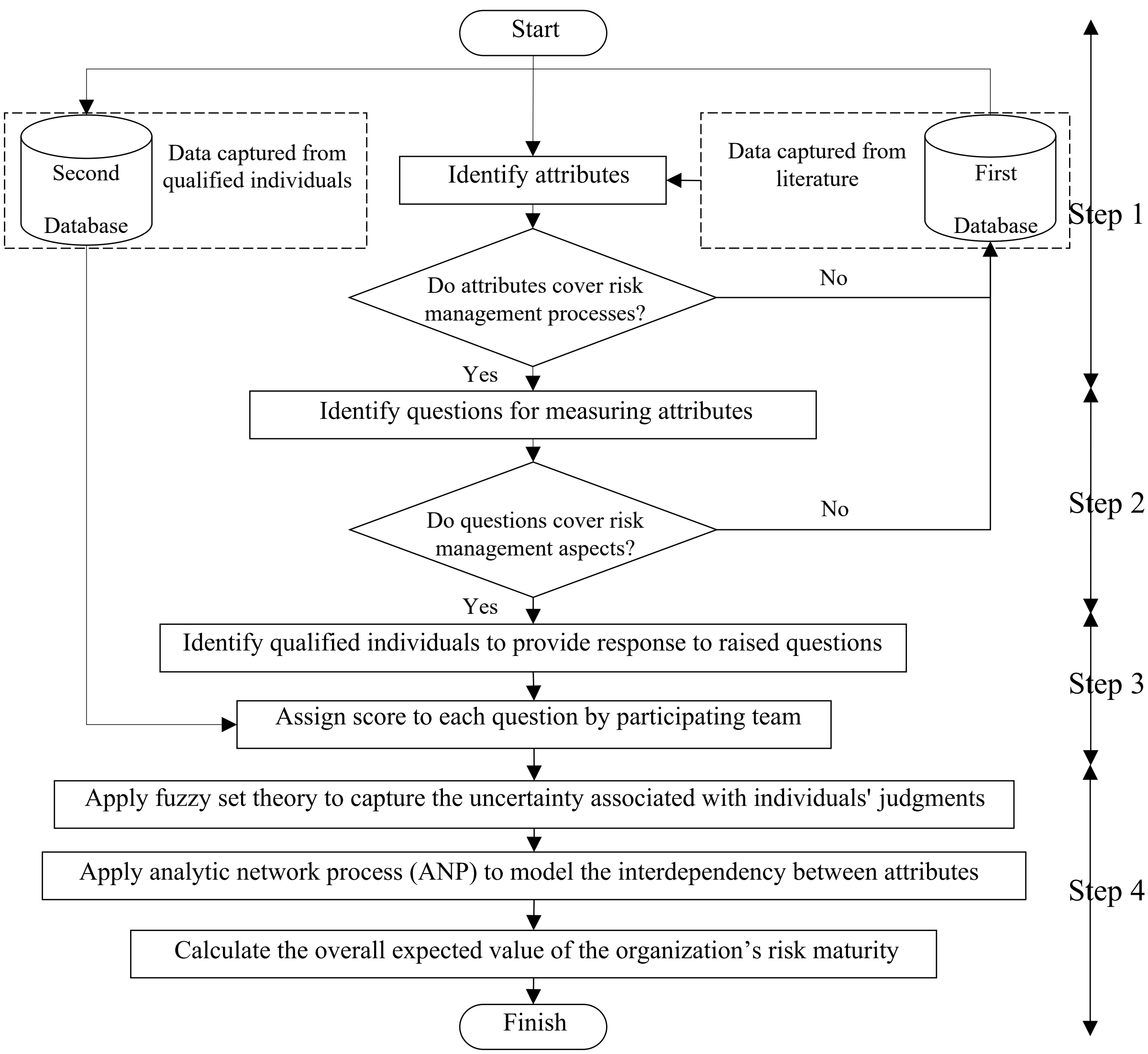


Figure 3.2: Framework of the developed risk maturity model

As shown in Figure 3.2, the developed model consists of four steps. In the first step, six attributes are identified. These attributes cover all the processes of risk management recently introduced by international risk management standards (PMI 2017, ISO 2018). In the second step, a set of questions for the evaluation of each risk maturity attribute are identified making use of different sources including standards, guidelines, academic articles and PhD theses. The questions are grouped and mapped into a questionnaire considering the feedback from members of the industrial partner. In this step, an effort is made to tailor these questions to suit the construction industry. In the third step, a list of qualified individuals who were expected to participate in risk maturity evaluation is established. The required input data for measuring the maturity level of each attribute is captured from the qualified individuals utilizing the designed questionnaire. Finally, in the fourth step which is data analysis and evaluation, the overall expected value of the organization's risk maturity is calculated. In this step the interdependency between the identified attributes along with the uncertainty associated with the collected input data is modeled utilizing an ANP and the fuzzy set theory respectively.

3.2.1. Identify attributes

Identifying attributes is the first step of risk management maturity evaluation. Existing risk maturity models utilize different sets of attributes covering different aspects of project management. As shown in Table 3.1, these attributes mainly cover four aspects of project management: standardization, measurement, control and continuous improvement as recommended by (PMI 2009).

However, according to the feedback received from the members of the industrial partner during the meeting sessions, it was found that it is more important for them to have a clear view of their capabilities and weaknesses in the risk management processes rather than project management aspects to enable them to identify areas of needed improvements in each process of risk management.

Table 3.1: Risk management aspects (PMI 2008)

Aspects	Attributes
Standardization	Development and application of standardized risk management process, Objective setting, Risk management planning.
Measurement	Risk identification, Risk analysis, Risk response.
Control	Risk management ownership, Iterative and dynamic enterprise risk management (ERM) process steps, Formalized key risk indicators, Integration of risk management into business processes, Risk monitoring, Risk review, Management capability in relation to risk, Risk management report, Project set risk management.
Continuous improvement	Risk management planning, Policy and strategy, Organization structure support, Commitment of the board and senior management, Risk appetite and tolerance, Risk-aware culture, Risk communication, Common risk language, Leveraging risks as opportunities, improvement of ERM framework, Organizational risk culture, Training programs, Top-management commitment, Personnel knowledge, Sufficient resources, Stakeholder management.

As such, in this study the attributes are defined to cover the risk management processes according to the recent classification of risk management processes suggested by the PMI (2017) and ISO (2018). Meanwhile, the defined questions are for measuring the maturity of the identified attributes, and they also cover the four aforementioned project management aspects. Therefore, out of the 30 attributes initially identified, 6 are considered: the ability to plan risk (APR), the ability to identify risk (AIR), the ability to analyze risk (AAR), the ability to plan risk responses (ARR), the ability to implement risk responses (AIRR) and finally the ability to monitor risk (AMR).

3.2.2. Identify questions

The current questions for evaluating the construction risk management maturity are captured from different sources (AACEI 2013, Jia et al. 2013, Zhao et al. 2013, Alashwal et al. 2017, PMI 2008). Collectively, this amounts to 249 questions which are utilized to measure the maturity level of different attributes. The questions that cover standardization and the continuous improvement aspects are clustered under the first attribute, while the rest, which cover the measurement and control aspects of project management, are utilized for the other attributes. Collaboratively with two senior members from the industrial partner, this large set of questions was reduced to the 35 questions listed in Table 3.2.

The criteria used in this process were the suitability to construction and the elimination of redundancy and repetition. It should be noted that the first attribute in that table covers two aspects of the organization project management including standardization and continuous improvement. Therefore, in evaluating the maturity level of that attribute, 10 questions are defined, unlike the other attributes which utilizes five questions each. The participating individuals were requested to assign a score for each question using a five-point scale. The answers received for these questions were used to calculate the risk maturity level of the organization. It must be pointed out that more questions could be used, but having fewer questions is an advantage, as pointed out by Zou et al. (2010). Also, it must be noted that these questions are subject to future modifications based on the new advancements in the area of risk management.

Table 3.2: Description of the questions

Attributes	Aspects	Questions
Ability to plan risk	Standardization	Q1: Does the organization describe the concept of risk maturity and its benefits?
		Q2: Does the organization define risk in terms of opportunities and threats?
		Q3: Does the organization describe the concepts of risk breakdown structure and the use of it in risk planning?
		Q4: Does the organization have a dedicated group for risk management with defined roles, responsibilities?
		Q5: Does the organization use standard documented procedures (e.g., PMBOK, ISO 31000) for risk management processes?
	Continuous improvement	Q6: Does the organization consider external risks from outside the company and internal risks from within the company?
		Q7: Do the organization teams use company-wide procedures, guidelines and methods for project risk planning?
		Q8: Does the organization regularly review the risk management guidelines and methods to ensure their effectiveness?
		Q9: Does the organization have a risk-aware culture communicated to staff at all levels in the organization?
		Q10: Are resources continuously invested in improving the risk management tools, techniques, and professional skills at organization?
Ability to identify risk	Measurement	Q1: Does the organization use the practices of brainstorming, checklists, root cause analysis, for risk identification?
		Q2: Does the organization apply the concepts of risk register?
		Q3: Does the organization compare actual risks against those initially identified and update its risk identification method accordingly?
		Q4: Does the organization define generic factors that give rise to risk?
		Q5: Does the organization define risk factors that depend on the project delivery method and its type of contract?
Ability to analyse risk	Measurement	Q1: Does the organization apply the recommended practices (e.g., PMBOK, ISO standards) for risk analysis?
		Q2: Does the organization apply a Monte Carlo simulation for contingency estimation?
		Q3: Does the organization model the uncertainty and subjectivity of input data which is used in risk analysis?
		Q4: Does the organization use qualitative and/or quantitative risk analysis tools?
		Q5: Does the organization consider correlation among cost items in contingency estimation?
Ability to plan risk responses	Measurement	Q1: Does the organization evaluate and select the best alternative from several risk response strategies using data analysis techniques?
		Q2: Does organization describe and prioritize risk treatment strategies for threats and for opportunities?
		Q3: Does the organization devise a set of company-based and a set of project-based risk response strategies?
		Q4: Does the organization update risk response strategies on a regular basis?
		Q5: Does the organization evaluate the effectiveness of the selected risk response strategies?
Ability to implement risk responses	Control	Q1: Does the organization assess residual risks?
		Q2: Do organization team members take risk ownership during project implementation?
		Q3: Are responsibilities for managing risks distributed and carried out by all team members?
		Q4: Do risk owners have sufficient authority to oversee risk-related action?
		Q5: Do the organization staff fully understand the authority and responsibility of risk owners at all levels of the company?
Ability to monitor risk	Control	Q1: Does the organization have standard project risk monitoring procedures and methods?
		Q2: Does the organization have standard procedures and methods for forecasting the performance of implemented risk responses?
		Q3: Does the organization check actual progress against risk treatment plan and do the necessary updating during the execution phase?
		Q4: Does the organization regularly update the standard monitoring methods?
		Q5: Does the organization use automated tools to track a risk performance index?

3.2.3. Identify qualified individuals

Identifying the right individuals with the specialized knowledge and experience of risk management ensures the accuracy and effectiveness of the risk maturity evaluation. According to the PMI (2017), experts who have adequate knowledge of organizational strategy, benefit management, technical knowledge of the industry and the focus area of the project, duration and budget estimation, and risk identification, are expected to participate in the risk management program. However, the required professional profiles of participants in these areas are not provided. In order to address this issue, the profiles of the individuals who participated in the risk maturity evaluation of construction organizations were gathered from the literature as shown in Table 3.3. As shown in that table, the research conducted by Wibowo (2017) did not provide information about the profiles of the qualified individuals.

Table 3.3: Individuals' profiles

Source	Individuals' Profiles						
	Risk Manager	Cost Manager	Contract/Bid Manager	Construction Manager	Developer Manager	Project Manager	Project Director
Hoseini et al. (2019)	✓	✓	✓	-	-	✓	✓
Zou et al. (2010)	✓	✓	-	✓	✓	✓	✓
Zhao et al. (2013)	✓	-	✓	✓	-	✓	-
Zhao et al. (2014)	-	-	-	-	-	✓	✓
Alashwal et al. (2017)	✓	-	-	-	-	✓	✓
Wibowo (2017)	-	-	-	-	-	-	-

Notes: ✓: Considered, - : not considered

The information captured in Table 3.3 was used in a process to identify the suitable participants in assessing the risk maturity level of the industrial partner's organization. In this process, a group of individuals are first identified and clustered into the three domains of organizational project management: portfolio management, program management, and project management (PMI 2008). Considering those three dimensions constitutes valuable reference points when an organization assesses its maturity and plans for possible improvement (PMI 2008). Typically, top decision makers form the strategy at the portfolio level and the middle managers have a role in implementing the agreed upon strategies at the program and project levels (Jugdev and Thomas 2002). The individuals who are expected to participate in the risk maturity evaluation of each attribute are then identified as shown in Table 3.4. The information captured by these individuals is utilized as the input data for the ANP and the fuzzy set theory to calculate the importance weight of each attribute as well as its degree of implementation.

Table 3.4 Individuals expected to be involved in measuring the risk maturity in construction organizations

Domain	Individuals	Attributes					
		APR	AIR	AAR	ARR	AIRR	AMR
Portfolio	Development manager	✓	✓	-	✓	-	-
Program	Project director	✓	✓	✓	✓	-	✓
	Risk manager	✓	✓	✓	✓	-	✓
	Tender manager	✓	✓	-	-	-	-
	Cost manager	✓	✓	✓	-	-	-
Project	Project manager	-	✓	✓	-	✓	✓
	Construction manager	-	✓	✓	-	✓	✓

Notes: ✓: Involved, - : not involved

3.2.4. Data analysis and evaluation

In this step, the data collected from the respondents are analyzed, making use of two methods: the ANP and the fuzzy set theory. Each is described subsequently.

3.2.4.1 Analytic Network Process (ANP)

ANP is an advanced multi-criteria decision-making method which considers the interdependencies between different factors throughout a relationship network (Jia et al. 2013). It determines the relative weights, which reflect the relative importance, of all the defined factors based on the data captured from the participants (Popic and Moselhi 2014). In this research, the Super Decisions software is employed for the computational processes (Super Decisions Tutorials 2020). Figure 3.3 shows a simple ANP network within two clusters, a criteria cluster (C_1) and an alternative cluster (C_2). The C_1 cluster includes the sub-decision factors and the C_2 cluster consists of key decision factors. The interdependency between the elements of these two clusters are shown with two-way arrows between them in Figure 3.3. In this study, the sub-decision factors are individuals' opinions and the key decision factors are the defined attributes APR, AIR, AAR, ARR, AIRR, and AMR.

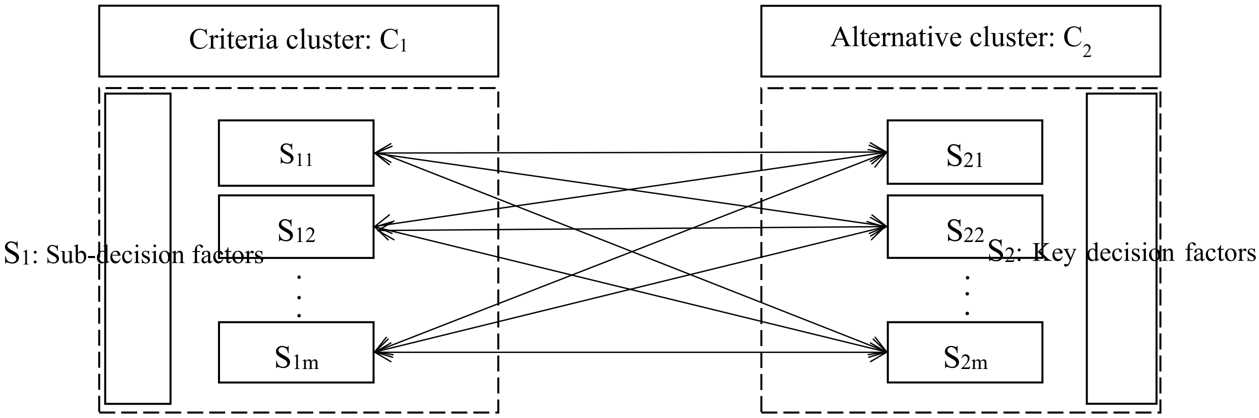


Figure 3.3: Analytic network process (ANP) model structure.

The goal is to prioritize the attributes based on their relative weights. This is done by comparing: (1) the attributes with respect to each individual's opinion, and (2) the individuals' opinions with respect to each attribute. The five-point scale method is utilized for scoring the relative importance (1 = very low, 2 = low, 3 = medium, 4 = high and 5 = very high). For instance, in comparing attribute one with respect to the first individual, if this individual is involved in the maturity evaluation of that particular attribute (as shown in Table 3.4), it gets a very high weight (5), otherwise its weight is considered as a function of its level of authority including high (individuals at portfolio level), medium (individuals at program level), low (individuals at project level). Subsequently, a comparison between the individuals' opinions with respect to each of the attributes is performed on a pairwise basis. For instance, in the first part of the questionnaire, the individuals are asked to score how much importance does an attribute have compared to another attribute concerning the goal. The assigned weights are utilized to construct the pairwise comparison matrices corresponding to each cluster. For all the pairwise comparisons, the inconsistency ratios are less than 10% as recommended by Saaty (2004). Subsequently, these matrices are used as inputs to form the unweighted supermatrix. Then, the weighted supermatrix is attained by normalizing the unweighted supermatrix. In other words, each column in the unweighted supermatrix is normalized based on the summation of its cells. Finally, the limited supermatrix is generated by raising the weighted supermatrix to considerable powers until convergence. The first column in the limited matrix shows the global weights. By normalizing that column and summing up the weights, the attributes are prioritized based on their relative weights.

Figure 3.4 shows the elements of the ANP supermatrix and sub-matrix (Saaty et al. 2005). Considering the clusters in the decision network, Figure 3.3, as C_p , p = 1, 2,…, m and given each cluster (np) elements, shown by (s_{p1},s_{p2},…, s_{pmn}), then Figure 3.4 (a) represents the decision network's supermatrix. W_{ij} of the network supermatrix is shown in Figure 3.4 (b) where W_{ij} shows the dependency of the elements in the ith cluster on the elements in the jth cluster. In case there is no dependency between the two elements of the ith and jth clusters, zero value is entered in the supermatrix. The result of the ANP will be used in the following section to calculate the overall expected value of the organization's risk maturity.

$$W = \begin{array}{cc} & \begin{array}{ccc} C_1 & C_2 & C_N \\ S_{11}\, S_{12} \cdots S_{1n2} & S_{21}\, S_{22} \cdots S_{2n2} & S_{N1}\, S_{N2} \cdots S_{NnN} \end{array} \\ \begin{array}{c} C_1 \; S_{11} \\ S_{12} \\ \cdots \\ S_{1n2} \\ S_{21} \\ C_2 \; S_{22} \\ \cdots \\ S_{2n2} \\ S_{N1} \\ S_{N2} \\ C_N \; \cdots \\ S_{NnN} \end{array} & \begin{pmatrix} W_{11} & W_{21} & \cdots & W_{1N} \\ W_{21} & W_{22} & \cdots & W_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ W_{N1} & W_{N2} & \cdots & W_{NN} \end{pmatrix} \end{array}$$

(a)

$$W_{ij} = \begin{pmatrix} W_{i1}^{(j_1)} & W_{i1}^{(j_1)} & \cdots & W_{i1}^{(j_{nj})} \\ W_{i2}^{(j_2)} & W_{i2}^{(j_2)} & \cdots & W_{i2}^{(j_{nj})} \\ \cdots & \cdots & & \cdots \\ W_{ini}^{(j_1)} & W_{inj}^{(j_2)} & \cdots & W_{inj}^{(j_{nj})} \end{pmatrix}$$

(b)

Figure 3.4: ANP entry-matrices: (**a**) the network supermatrix, (**b**) the network sub-matrix, (Saaty et al. 2005).

3.2.4.2 Fuzzy set theory

The fuzzy set theory is a frequently used method for managing construction risks (Islam et al. 2017, Hatefi et al. 2019, Moselhi and Roghabadi 2020). The fuzzy representation of linguistic terms can capture the vagueness and imprecision associated with the input data provided by the participants (Xia et al. 2011). In the second part of the questionnaire, the participants were asked to rate the degree of implementation corresponding to each risk maturity attribute. The input data collected from the qualified individuals was in a linguistic form, where values of 1 = very low, 2 = low, 3 = medium, 4 = high and 5 = very high. In order to transfer the linguistic term to a number, each linguistic value is represented with a fuzzy number as shown in Figure 3.5.

As shown in Figure 3.5, each fuzzy number has an overlap with its neighboring sets. It was pointed out by Cox (1998) that in most of the cases the overlap for triangle-to-triangle fuzzy regions varies between 25% and 50% of the fuzzy set base. In this study, the overlap is considered as 50% of fuzzy set base and the expected value of the organization's risk maturity can be calculated using Equations 3.1 to 3.5.

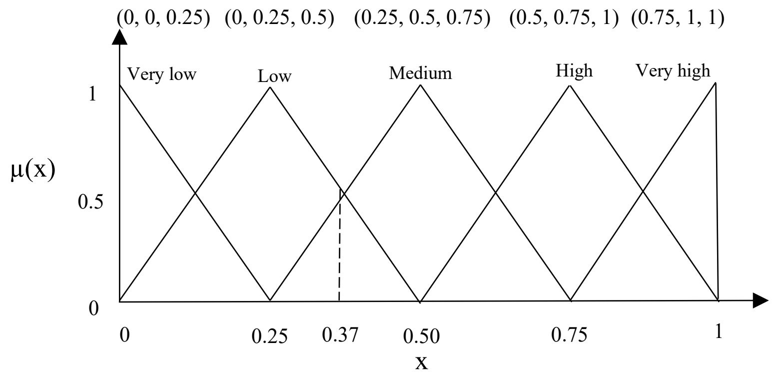


Figure 3.5: Membership functions of linguistic values (Zhao et al. 2013).

The fuzzy implementation level associated with attribute (i) can be calculated according to Equation 3.1 (Zhao et al. 2013):

$$F_i = (f_1, f_2, f_3) = {}^{1}/_{n} \times \sum_{p=1}^{n} F_{ip} \qquad Equation\ 3.1$$

Where F_i is the triangular fuzzy number of the attribute (i, f_{i1}, f_{i2} , f_{i3}), which are the lower bound, strongest membership degree, and upper bound of F_i , respectively, n is the number of questions associated with attribute (i), and F_{ip} is the triangular fuzzy number associated with pth question of attribute (i). F_{ip} is computed utilizing Equation 3.2:

$$\mathrm{F_{ip}} = {}^{1}/_{\mathrm{k}} \times \sum_{\mathrm{j=1}}^{\mathrm{k}} \mathrm{F_{i\,pj}} \qquad \text{Equation 3.2}$$

Where k is the number of individuals who assess the implementation level of each question, F_{ipj} is the triangular fuzzy number of pth question of attribute (i) collected from jth individual. The triangular fuzzy number of the overall risk maturity of the organization M can be computed according to the Equations 3.3 and 3.4:

$$\mathrm{M} = (\mathrm{m_1}, \mathrm{m_2}, \mathrm{m_3}) = \sum_{\mathrm{i=1}}^{6} (\mathrm{F_i} \times \mathrm{W_i}) \qquad \text{Equation 3.3}$$

Where (m_1), (m_2), (m_3) are the lower bound, the strongest membership degree, and the upper bound of M, respectively, W_i is the importance weight of the attribute (i) calculated by the ANP. The fuzzy number of the overall risk maturity is transferred to a crisp number employing the center of the area method, which is a commonly used method for defuzzification (Amaya et al. 2009). The expected value EV represents the defuzzified value of a fuzzy number according to Equation 3.4 (Salah 2012, Salah 2015).

$$\mathrm{EV} = \frac{(\mathrm{a} + 2\mathrm{b} + \mathrm{c})}{4} \qquad \text{Equation 3.4}$$

Where (a), (b), and (c) are triples of a triangular membership function. Therefore, in this study, the expected value of the organization risk maturity is calculated as Equation 3.5.

$$\mathrm{EV} = \frac{(\mathrm{m}_1 + 2\mathrm{m}_2 + \mathrm{m}_3)}{4} \qquad \text{Equation 3.5}$$

3.3. Contingency Estimation

This section is a marginally modified version of “Risk Quantification Using Fuzzy-Based Monte Carlo Simulation” published in the journal of Information Technology in Construction (ITcon) (Moselhi and Roghabadi 2020) and has been reproduced here.

The proposed method is designed to enable the use of an allocated range for each subjective correlation coefficient in estimating cost contingency with and without simulation. The framework of the developed method is illustrated in Figure 3.6. The method consists of five steps. The output of each step is used as an input to the following step automatically. In the first step, a qualitative variation range is assigned by the user for each subjective correlation coefficient. It must be noted that in this research the term user refers to either project managers or cost estimators who have enough knowledge and experience to assign that range. In the second step, based on the assigned qualitative variation ranges for the coefficients, three subjective correlation matrices are generated: optimistic, most likely, and pessimistic. Based on these three matrices, three covariance matrices are developed employing Equation 3.6 of Moselhi and Dimitrov (1993). Then, the sum of the covariance of each cost item with other cost items is calculated using Equation 3.7. In the third step, in the case of using simulation, the developed MCS in Microsoft Excel is applied to simulate the variation range of the sum of covariance of each cost item with other cost items. In the fourth step, Fuzzy set theory is applied in order to calculate the expected value of the sum of covariance of each cost item. In this step, the output of MCS is utilized to estimate the fuzzy number for cost items. The fuzzification and defuzzification processes are performed utilizing Equations 3.8, 3.9 and Equation 3.10

respectively. And finally, in the fifth step, the standard deviation of the project total cost is calculated based on Equation 3.14. The required steps for estimating cost contingency are depicted in Figure 3.7.

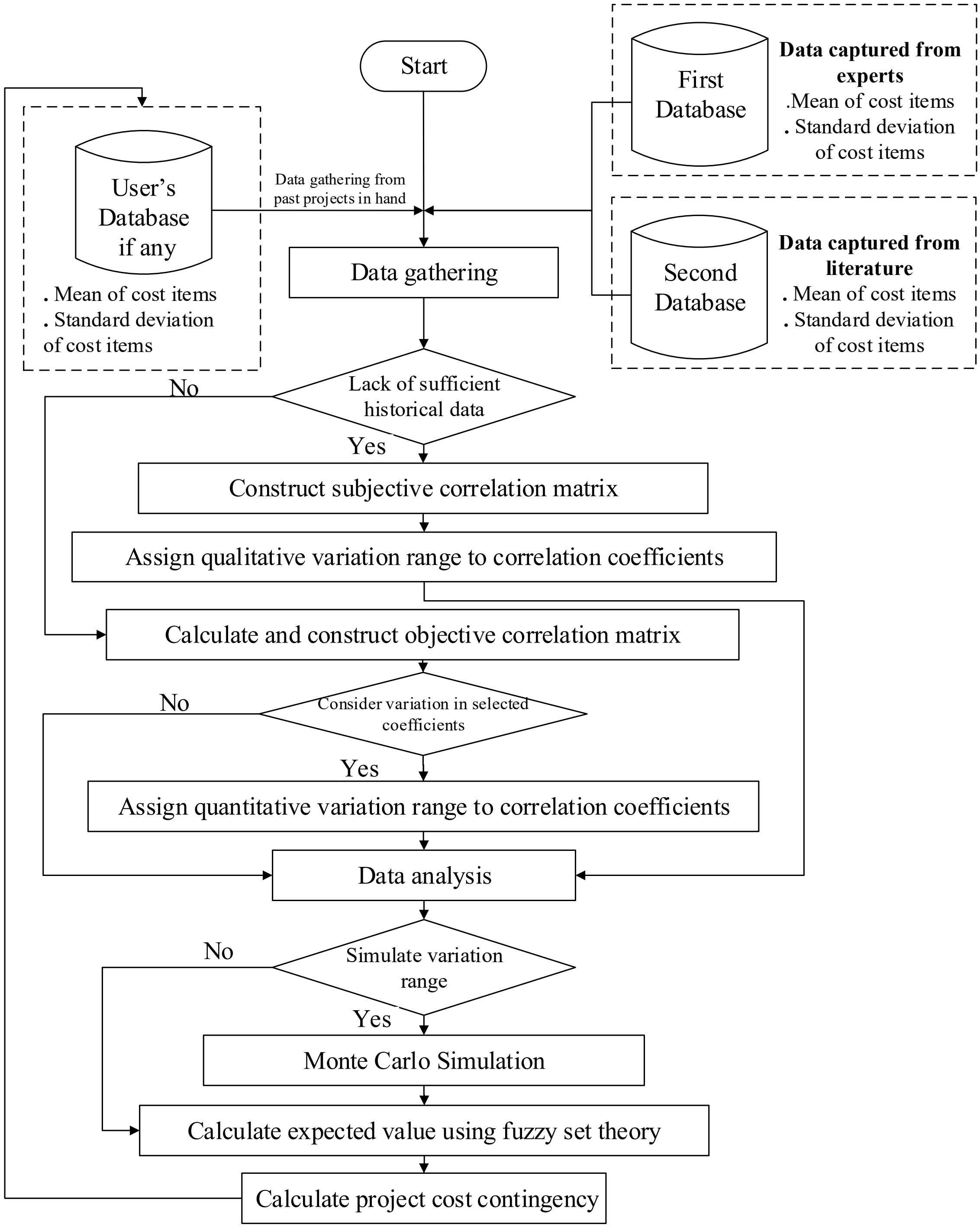


Figure 3.6: Framework of the contingency estimation model

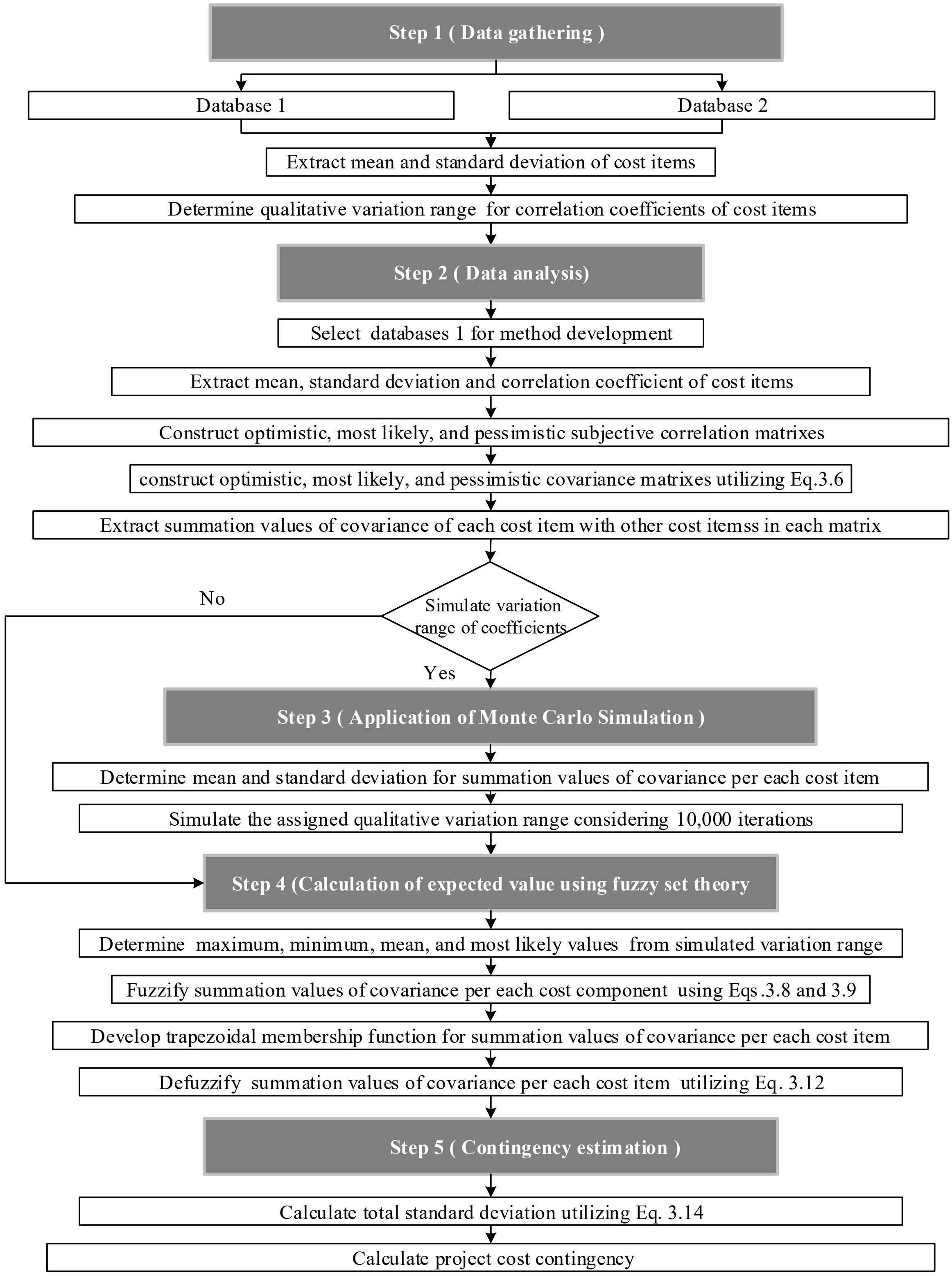


Figure 3.7: Overview of developed contingency estimation model

3.3.1. Data gathering

Two databases from the literature are used for the development of the proposed method and for its validation. The first database was reported in the work of Wall (1997). The data are based on the analysis of cost elements which were provided on-line by Building Cost Information Service (BCIS) of the Royal Institution of Chartered Surveyors in the UK. The data represents cost per square meter rates of 216 office buildings, having two or more storeys constructed between 1980 and 1994. The total mean and standard deviation of total unit cost are 543.8 (£/m^2) and 181.1 (£/m^2), respectively. The second database is drawn from the reported work of Touran (1993). This database represents various cost items of 1,014 low-rise office buildings consisting of two to four storeys. Each project cost is decomposed into 15 items. A sample of three correlated cost items which were used by Touran (1993) from a selected sub-set of 26 projects built between 1981 and 1983 is used in this research to enable a comparison. The mean and standard deviation of total unit cost are 16.6 (\$/ft^2) and 10.5 (\$/ft^2), respectively. The cost data of the two databases are presented in Table 3.5.

Table 3.5: Summary of actual cost data (Touran 1993, Wall 1997)

Database	Cost item	Number of projects	Mean	Standard deviation
Wall (1997)	Substructure (1)	216	47.2 (£/m^2)	30.9 (£/m^2)
	Superstructure (2)	215	263.6 (£/m^2)	82.4 (£/m^2)
	Internal finishes (3)	216	63.2 (£/m^2)	24.4 (£/m^2)
	Fittings (4)	202	9.7 (£/m^2)	14.2 (£/m^2)
	Services (5)	216	162 (£/m^2)	84.1 (£/m^2)
	Total (Building sub-total)	216	543.8 (£/m^2)	181.1 (£/m^2)
Touran (1993)	Electrical (1)	26	5.14 (\$/ft^2)	2.76 (\$/ft^2)
	Mechanical (2)	26	9.47 (\$/ft^2)	6.58 (\$/ft^2)
	Moisture protection (3)	26	1.81 (\$/ft^2)	2.12 (\$/ft^2))
	Total	26	16.16 (\$/ft^2)	10.50 (\$/ft^2)

3.3.1.1 Assigned range for correlation coefficient

Users, based on their experience, can assign a range for each correlation coefficient used for estimating cost contingency. For example, the user can assign a range from 0.0 to 0.30 for weak correlation and ranges from 0.30 to 0.60 and 0.60 to 1.0 for moderate and strong correlation, respectively.

3.3.2. Data analysis

The cost data gathered from database 1 are used for method development. The subjective correlation matrix of database 1 is shown in Table 3.6. In order to generate the subjective correlation matrix, all values between 0.0 - 0.3, 0.3 - 0.6, and 0.6 – 1.0 in the objective correlation matrix are replaced with 0.15, 0.45, and 0.8, respectively.

Table 3.6: Subjective correlation matrix

Cost item	1	2	3	4	5
1	1				
2	0.45	1			
3	0.15	0.45	1		
4	0.15	0.15	0.15	1	
5	0.15	0.45	0.8	0.45	1

Two more matrices, optimistic and pessimistic, are generated to cover the variation range of correlation coefficients. For example, the optimistic correlation matrix is produced by replacing all values between 0.0 - 0.3, 0.3 - 0.6, and 0.6 – 1.0 in subjective correlation matrix with 0.3, 0.6, and 0.9, respectively, while these values are replaced with 0.1, 0.3, and 0.6 for pessimistic correlation matrix. Based on the three produced correlation matrixes, three covariance matrixes are generated utilizing Equation 3.6 (Moselhi and Dimitrov 1993).

$$\mathrm{cov}\,(i,j) = \rho_{ij}\, sd_i\, sd_j \qquad \text{Equation 3.6}$$

Where cov (i,j) is the covariance between cost items (i) and (j), sd is the standard deviation of cost items, (ρ_{ij})is the correlation coefficient of cost items, and (i) and (j = 1,2 . . . n), with n the number of cost items. The most likely subjective covariance matrix of database 1 is shown in Table 3.7.

Table 3.7: Most likely subjective covariance matrix

Cost item	1	2	3	4	5
1	1				
2	1145.77	1			
3	113.09	904.75	1		
4	65.82	175.51	51.97	1	
5	389.80	3118.43	1641.63	537.40	1
∑covariance	1714.49	4198.69	1693.60	537.40	0

Then, the sum of covariance of each cost item i (i=1,2,3,…,n) with other cost items (j=1,2,3,…,n) is calculated in each covariance matrix utilizing Equation 3.7 as shown in Table 3.8.

$$S_i = \sum_{i=j=1}^{n} \rho_{ij}\, sd_i\, sd_j \qquad \text{Equation 3.7}$$

The mean and standard deviation of the calculated S_i (i=1, 2,…,n) are computed for each cost item enabling the generation a set of random data as shown in Table 3.8.

Table 3.8: Sum of covariance means and standard deviations for each cost item

Covariance matrix	Sum of covariance for each cost item				
	1	2	3	4	5
Most likely	1714.49	4198.69	1693.60	537.40	0
Pessimistic	1142.99	2799.13	1265.87	358.27	0
Optimistic	2665.13	5715.26	1950.78	716.53	0
Mean	1840.87	4237.69	1636.75	537.40	0
Standard deviation	627.80	1190.83	282.49	146.26	0

3.3.2.1. Application of Fuzzy-Based Monte Carlo Simulation

In this method, correlation between variables (i.e. between cost items) was long proven to be essential for accurate estimate of contingency (Touran and Wiser 1992). In this research, MCS is utilized to generate data from the means and standard deviations of the sum of covariance of cost items housed in Table 3.8. In other words, MCS is used to cover the variation range of the correlation coefficients between pairs of cost items using 10,000 iterations. This number of iterations is equal to that used by Wall (1997). The developed fuzzy-based MCS algorithm is shown in Figure 3.8.

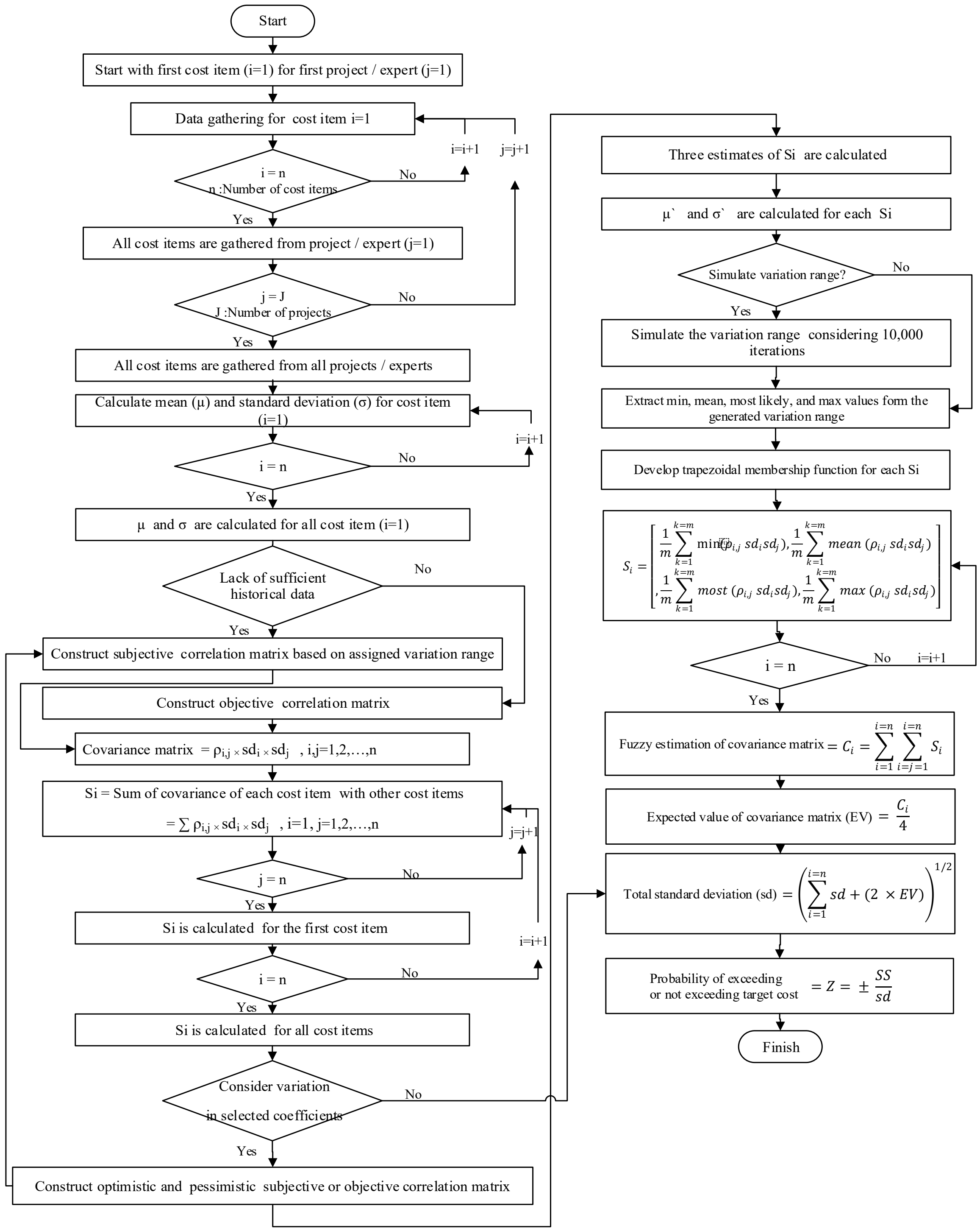


Figure 3.8: Fuzzy-based MCS algorithm for estimating contingency

3.3.2.2. Application of Fuzzy Set Theory

In this step, the output of MCS is used to generate fuzzy random variable, making use of two processes: fuzzification and defuzzification. Each is described subsequently.

3.3.2.2.1. Fuzzy estimation

The use of fuzzy number allows modeling imprecision and vagueness. In fuzzy estimation, the data gathering process, where items can be evaluated, uses one of the following fuzzy numbers:

- Crisp [a]: it represents that "a" is the item's definitive value.
- Uniform [a, b]: it represents that item's value is expressed by a range [a, b].
- Triangular [a, b, c]: it represents that the item's value is almost assumed to be equal to "b" but with a possibility to be within a minimum (a) and maximum (c) values.
- Trapezoidal [a, b, c, d]: it represents that the item's value has more possibility to be within the [b, c] range, but it cannot be less than "a" or greater than "d".

In this research, a trapezoidal membership function is developed for each cost item. Other membership functions can be used. The trapezoidal function of each cost item is calculated using Equation 3.8.

$$S_i = \left[\frac{1}{m}\sum_{k=1}^{k=m} \min(\rho_{i,j}\, sd_i sd_j), \frac{1}{m}\sum_{k=1}^{k=m} \mathrm{mean}(\rho_{i,j}\, sd_i sd_j), \frac{1}{m}\sum_{k=1}^{k=m} \mathrm{most}(\rho_{i,j}\, sd_i sd_j), \frac{1}{m}\sum_{k=1}^{k=m} \max(\rho_{i,j}\, sd_i sd_j)\right] \qquad \text{Equation 3.8}$$

Where S_i ($i = 1\ldots n_i$) is fuzzy estimation of the sum of covariance of each cost item with other cost items, m is the number of fuzzy estimation per each cost item, and min ($\rho_{ij}\ sd_i\ sd_j$), mean ($\rho_{ij}\ sd_i\ sd_j$), most likely ($\rho_{ij}\ sd_i\ sd_j$), and max ($\rho_{ij}\ sd_i\ sd_j$) are the minimum, mean, most likely, and maximum estimation of covariance of each cost item, respectively. The fuzzy number associated with the covariance of each cost item is shown in Table 3.9.

Table 3.9: Fuzzification and defuzzification of covariance matrix

Description	Fuzzy values of covariance per each cost item				Sum
	1	2	3	4	
a	-732.61	-502.546	612.6336	-11.7861	-634.309
b	1827.878	4235.609	1642.845	536.1128	8242.44
c	1840.868	4237.695	1636.752	537.399	8252.71
d	4615.386	9672.655	2666.02	1092.274	18046.33
EV			8476.79		

Note: a = Minimum, b= Mean, c = Most likely, d = Maximum

It should be noted that the fuzzy values associated with each cost item are extracted from the generated variation range of MCS 10,000 iterations. The total fuzzy estimation of covariance for project cost items is calculated using Equation 3.9.

$$C_i = \sum_{i=1}^{i=n} \sum_{i=j=1}^{i=n} S_i \qquad \text{Equation 3.9}$$

The last column in Table 3.9 is calculated using Equation 3.9.

3.3.2.2.2. Defuzzification

The commonly used method for defuzzification is the center of area method (COA) which can be expressed as (Amaya et al. 2009):

$$y^* = \frac{\int x\mu_i\,(x_i)}{\mu_i\,(x_i)} \qquad \text{Equation 3.10}$$

Where y*, μ, and x represent defuzzification value, membership function, and output variable. The expected value (EV) represents the defuzzified value of a fuzzy number according to Equation 3.11 (Salah 2012, Shaheen et al. 2007).

$$\text{Expected value (EV)} = \frac{(a + b + c + d)}{4} \qquad \text{Equation 3.11}$$

Where (a), (b), (c), and (d) are quadruples of a trapezoidal membership function. Therefore, in this study, the expected value is calculated as Equation 3.12.

$$EV = \frac{C_i = \sum_{i=1}^{i=n} \sum_{i=j=1}^{i=n} S_i}{4} \qquad \text{Equation 3.12}$$

Utilizing Equation 3.12, the expected value is calculated to be 8476.79, serving as the defuzzified value of the covariance matrix.

3.3.3. Contingency estimation

The standard deviation of the project cost is calculated using the method of Moselhi and Dimitrov (1993) as expressed by Equation 3.13 which considers correlation of cost items and avoids simulation.

$$sd_{total} = \left(\sum_{i=1}^{n} {sd_i}^2 + 2 \sum_{i=1}^{n} \sum_{i=j=1}^{n} \rho_{ij} sd_i \, sd_j \right)^{1/2} \qquad \text{Equation 3.13}$$

In this study, Equation 3.13 is adapted, where its second term is replaced by the expected value generated from the application of fuzzy set theory as shown in Equation 3.14. It should be noted that the second term addresses the covariances and their associated uncertainties calculated earlier (Table 3.8).

$$\text{Total standard deviation (sd)} = \left(\sum_{i=1}^{i=n} (sd_i)^2 + (2 \times \text{EV}) \right)^{1/2} \qquad \text{Equation 3.14}$$

By determining the mean or project target cost (TC) and its associated standard deviation, the probability of exceeding or not exceeding that target can be investigated by any specified sum (SS) (contingency) using Equation 3.15 and the appropriate probability table for normal distribution. Accordingly, one can develop a project cost curve similar to Figure 3.9 (Moselhi 1997).

$$Z = \pm \frac{SS}{sd} \qquad \text{Equation 3.15}$$

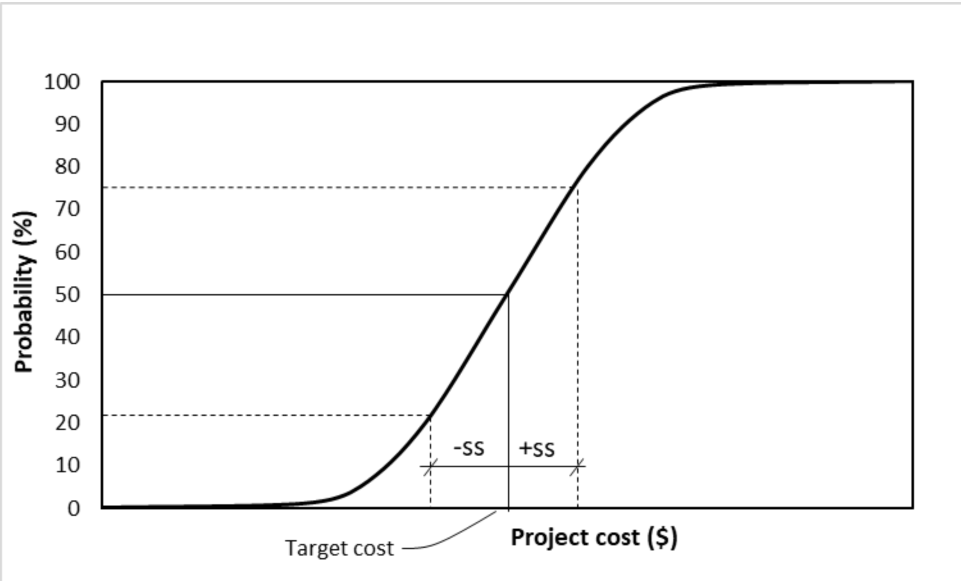


Figure 3.9: Project cost curve (Moselhi 1997)

A comparison between the results of the proposed model and those of Wall (1997) is shown in Table 3.10. Although the proposed model utilizes subjective correlation and is performed without simulation, it has almost equal accuracy to that of Wall which uses simulation, and objective correlation (2% vs 1.98%). The results also indicate maximum difference in error between the proposed method and the best results of Wall after experimenting with different probability distributions is 1.76% (2-.24%).

Table 3.10: Comparison of the results

Database	Method	Type of correlation	Standard deviation (£/m^2)	Difference from actual	Percentage of error
Wall (1997)	Actual	-	181.1	0.0	0.0
	Simulation (independent)	-	126.76	54.33	30.00
	Simulation (correlated-detailed)	Objective	177.51	3.58	1.98
	Simulation (lognormal distributions)	Objective	177.51	3.59	1.98
	Simulation (beta distributions)	Objective	180.67	0.43	0.24
	Proposed method with simulation	Subjective	180.46	0.63	0.35
	Proposed method without simulation	Subjective	177.47	3.63	2.00

3.4. Markup Estimation

This section is a marginally modified version of “Three Models for Estimating Bid Markups” published in 2018 AACE® International Transactions (Roghabadi and Moselhi 2018) and has been reproduced here.

This research is intended to compare the accuracy of the optimum markup estimated by three developed models using multiple regression (MR), artificial neural networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Thirty factors are identified from the literature, 23 of which have most effect on bid markup size (more than 90%) categorized into five categories as shown in Table 3.11. The input of the three models includes, need for work, job uncertainty, job complexity, market condition, and owner capability.

Those five input categories generally represent contractors' hypotheses in risk calculations and particularly in markup estimation (Hegazy 1993). Except for the need for work, each input category has a set of factors. For instance, market condition is a function of 5 factors: inflation rate, escalation rate, competition, economic condition, and resources. The assigned score for each factor is ranked from zero to five. For example, competition equal to five means there is large competition in bidding on this project. The total score values of the factors in each of the five categories are used as input in the three developed models. In the second step, in order to consider dependency and independency, the correlation between inputs and output have been obtained using SPSS-20. The independent variables are determined to be poorly correlated with dependent variables that affect the accuracy of the results. Finally, in the third step the performance of three different models is compared, based on several statistical indicators. Data used in this research comes from 72 contractors in the United States and Canada. This data accounts for quantitative as well as qualitative factors that affect bidding decisions (Hegazy 1993). The data captures bidding situations experienced by those contractors on past projects (Hegazy 1993). Table 3.11 depicts the elements of input and output data of each bid situation used in this study.

Table 3.11: Description of input and output data used in the developed models (Hegazy 1993)

Number	Category	Criterion	Value meaning
1	Need for work	Need for work	1: Low to 5: High
2	Job Uncertainty	Site conditions	1: Low to 5: High
		Owner attitude	1: Low to 5: High
		Location	1: Low to 5: High
		Safety hazard	1: Low to 5: High
		Inaccurate estimation	1: Low to 5: High
		Weather	1: Low to 5: High
3	Job Complexity	Technology needed	1: Low to 5: High
		Resources needed	1: Low to 5: High
		Job size	1: Low to 5: High
		Quality of design	1: Low to 5: High
		Stacking of trades	1: Low to 5: High
		Percentage of subcontracted	1: Low to 5: High
		Rigidity in specs	1: Low to 5: High
4	Market condition	Inflation rate	1: Low to 5: High
		Escalation rate	1: Low to 5: High
		Competition	1: Low to 5: High
		Economic condition	1: Low to 5: High
		Resources	1: Low to 5: High
5	Owner Capability	Similar experience	1: Low to 5: High
		Management and supervision	1: Low to 5: High
		Confidence in work force	1: Low to 5: High
		Financial capability	1: Low to 5: High
Description of Output Data			
Number	Group	Criterion	Value meaning
1	Markup	Markup	Real markup (%)

3.4.1. Multiple Regression (MR)

The main advantage of multiple linear regression is its ability to visually represent its results in a histogram or in normal probability plots. The equation, resulting from multiple regression, includes the independent variables with their corresponding coefficients which can be used to predict the output. Five independent input variables, including: need for work, job uncertainty, job complexity, market condition, owner capability, and one dependent (output) variable, real (actual) mark–up (%), make up the developed multiple analysis model.

In order to consider the dependency and interdependency between variables, the correlation between inputs and output is determined using the statistical package SPSS 20. After checking correlation, the following form of multiple regression equation is used (DeFries et al. 1985).

$$Y = b_0 + (b_1 \times X_1) + (b_2 \times X_2) + \ldots + (b_n \times X_n) \qquad \text{Equation 3.16}$$

Where Y is the dependent variable, b_0 is the constant of the regression equation. And (b_1 - b_n) are the regression coefficients. (X_1-X_n) are independent variables. By carrying out the MR method, the following equation is developed.

$$Markup=1.635-(0.182 \times X_1)+(0.903 \times X_2)+(0.131 \times X_3)+(0.406 \times X_4)+(0.148 \times X_5)$$

Equation 3.17

3.4.2. Artificial Neural Network (ANN)

Artificial neural networks attempt to mimic the generalization capabilities of the human brain. These neural networks learn from actual case projects (actual bid situations) by feeding the network the input values of the parameters in the actual project case and concurrently feeding it the actual value of its output. For example, a training case will have the complete set of inputs and associated output of a project bid situation. By repeating these training cases, the network will gain the knowledge and experience as with normal human beings and will be able to predict the output (i.e. estimated markup) given a new set of input data. In other words, the network learns by associating input values to the output value. Further details can be found in (Moselhi et al. 1991, Moselhi et al. 1993c). Neural network structure consists of an input and output layer, as well as one or more hidden layers as shown in Figure 3.10.

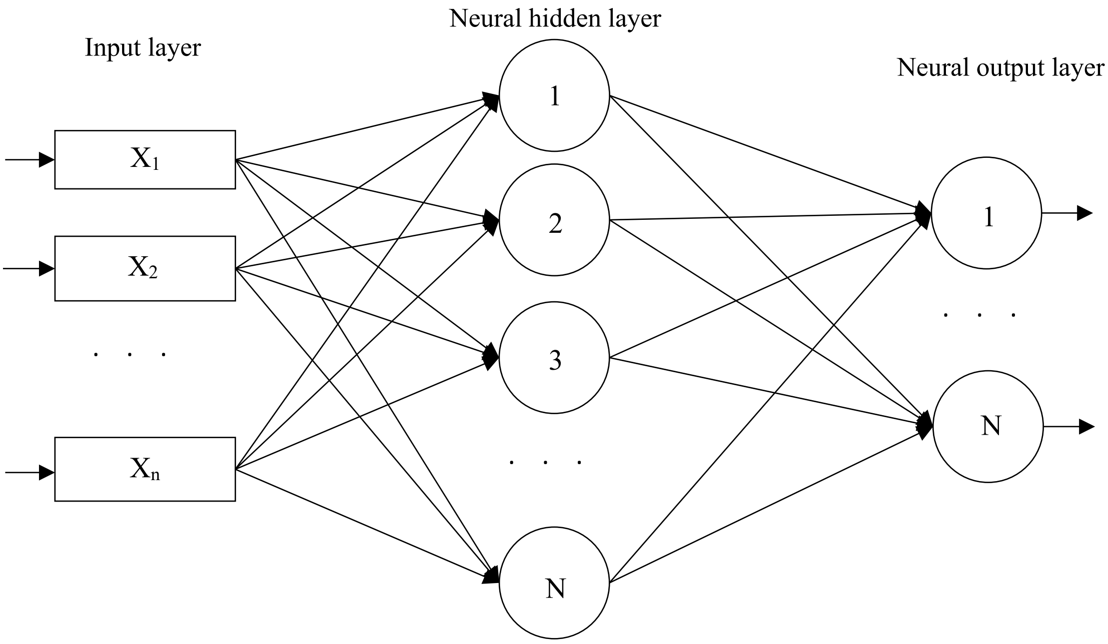


Figure 3.10: Sample architecture of ANN

Each layer consists of one or more artificial neurons, known as processing element, and referred to here as node. The role of neurons is to receive input, process it and transfer the resulting output to nodes in the next layer. The number of nodes depends on the problem being analyzed (Polat et al. 2016, Moselhi et al. 1991, Moselhi and Siqueira 1998).

The two main types of architecture of ANN are feed-forward and feed-back. The feed-forward approach has been used for complex pattern classification problems, while the feed-back type is recommended for combinatorial optimization problems. Feed-forward neural networks' type is used in this study for their recognized prediction and classification capabilities (Moselhi and Hegazy 1993, Moselhi et al. 1991, Reeves 1993). There are several types of training algorithms for these two types. Basically, the training algorithms use learning rules in order to modify weights during the training process to accurately map and correlate the input pattern to its associated output (Kişi 2007).

The ANN model is developed using "MATLAB 2017a". Since the object of this study is defined as a prediction (i.e. estimating) problem, the feed-forward type is selected for the architecture of the model. Actual data of 72 public projects are classified randomly into three categories including, 70%, 15% and 15% for training, validation and testing, respectively. The amount of training iteration is considered 1000 epochs. The numbers of neurons in the first and last layers are governed by the number of input and output parameters. This is not the case for the hidden layer(s). A trial and error process is used employing nine different hidden layers. Table 3.12 summarizes the performance of these trials.

Table 3.12: Performance indicators of ANN bid markup size estimation models

Indicator	Developed models								
Performance Indicator	ANN_2	ANN_3	ANN_4	ANN_5	ANN_6	ANN_7	ANN_8	ANN_9	ANN_{10}
No. of neurons	2	3	4	5	6	7	8	9	10
RMSE	20.10	10.63	19.25	11.00	9.63	17.45	6.92	14.73	19.63
R^2	0.033	0.01	0.13	0.42	0.29	0.13	0.43	0.21	0.29

Based on the results from ANN_8, it is identified to have the best performance (i.e. smallest RMSE and largest R^2 and is subsequently used in the analysis.

3.4.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Interface System is a fast learning model which combines the advantages of artificial neural network and fuzzy logic. Similar to ANN, ANFIS learns by mapping input values of input parameters to their associated output by processing the input through the set of nodes in each of the stages shown in Figure 3.11. Each node has its processing function with fixed or adjustable parameters on incoming signals. The formulas for the node functions may vary from node to node. The parameters of each node function are affected by fuzzy logic rules "if-then" to reduce the occurrence of errors at the output of the adaptive network in order to achieve a desired input-output mapping. These parameters are updated based on the training data (Jang 1993). A simple structure of ANFIS is shown in Figure 3.11.

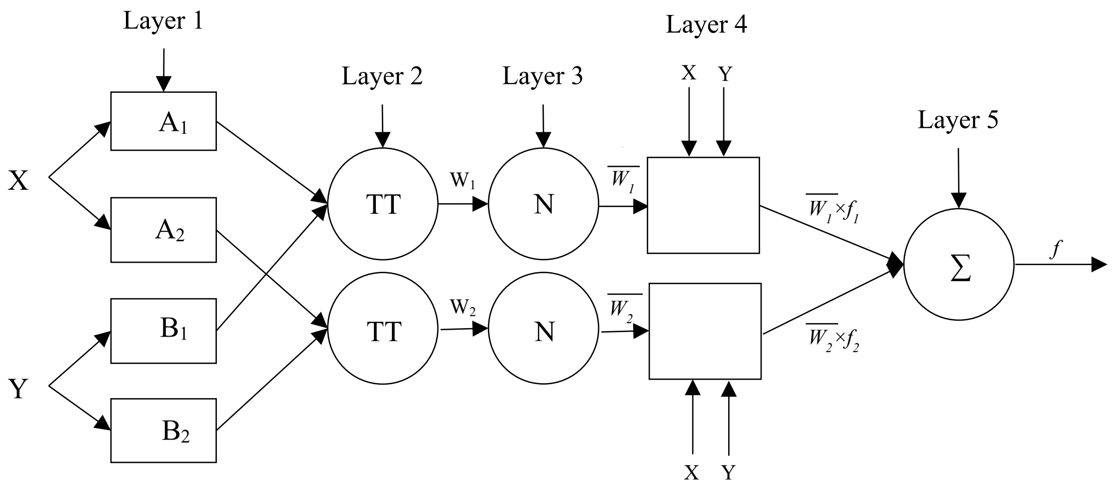


Figure 3.11: ANFIS structure

Figure 3.11 shows first, the fuzzification layer (the process of assigning membership function to fuzzy inputs which are derived from 'crisp' inputs values). Then the input is processed sequentially to the product layer, normalization layer, defuzzification layer (the process of producing a quantifiable result in Crisp value) and finally the total output layer. The functioning of each layer is described subsequently (Jang 1993).

A membership function has been assigned to each input, and then the fuzzy "if-then rule" is applied using Equation 3.18:

$$Rule\ I:\ IF\ x\ is\ A_i\ \ and\ y\ is\ B_i\ THEN\ \ f_i = p_i\,x + q_i\,y + r_i, \quad i = 1,2,\ldots,n \qquad Equation\ 3.18$$

Where n indicates the number of rules, (p_i), (q_i) and (r_i) define the parameters throughout the training process. The membership function (μ) related to each linguistic label (A_i and B_i) during the first learning sequence are calculated as the following:

$$O_i^1 = \mu_{Ai}(x), \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.19}$$

$$O_i^1 = \mu_{Bi}(y), \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.20}$$

Throughout the second layer, the calculated membership degrees which were demonstrated in Equations 3.19 and 3.20 are multiplied, utilizing Equation 3.21.

$$O_i^2 = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y), \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.21}$$

In the third layer, the calculation of the ratio of each weight to the total weights is illustrated as follows:

$$O_i^3 = \overline{W_i} = \frac{w_i}{\sum_{i=1}^{n} w_i} \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.22}$$

Within the fourth layer, which is the process of transfer, the fuzzy results transfer into a crisp output (defuzzification). The adaptive nodes are adjusted in order to reduce the amount of incurred error during the learning process. The relationship for these nodes is as below:

$$O_i^4 = \overline{w}_i f_i = \overline{w_i}(p_i\, x + q_i\, y + r_i) \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.23}$$

In the fifth layer, the summation of all incoming signals is executed to yield the output of the system.

$$O_i^5 = \sum_{i=1}^{n} \overline{w}_i\, f_i \qquad i = 1,2,\ldots,n \qquad \text{Equation 3.24}$$

The proposed ANFIS model is implemented using the fuzzy logic toolbox in MATLAB 2017a software, several alternative functions, such as triangular, trapezoidal, sigmoid, Gaussian, S-Shaped, generalized bell-shaped membership function (Gbellmf), are tested in order to choose the best type of membership function. Gbellmf function is selected in view of its minimum error. There are two functions for the output layer: constant and linear membership function. Both functions were tried and the constant function was chosen as it yielded the least errors. The characterizations of the developed ANFIS models are shown in Table 3.13.

Table 3.13: Different parameter types and their values used for training

ANFIS parameter type	ANFIS
MF type	Generalized bell-shaped membership function
Number of MFs	10
Output MF	Constant
Number of nodes	92
Number of linear parameters	192
Number of nonlinear parameters	30
Total number of parameters	222
Number of training data pairs	54
Number of checking data pairs	0
Number of fuzzy rules	32

3.5. Optimized Trade-off Analysis

This section is a marginally modified version of "Optimized Crew Selection for Scheduling of Repetitive Projects" published in the journal of Engineering, Construction and Architectural Management (Roghabadi and Moselhi 2020b) and has been reproduced here.

The developed model consists of four modules as shown in Figure 3.12, which also outlines the computational steps performed in the four modules. The first module models the uncertainties associated with the crew productivity rate and quantity of work in each activity using fuzzy set theory. The second module identifies the feasible boundaries for activity relaxation by generating an un-optimized schedule and a schedule that minimizes crew work interruptions accounting for crew availabilities. Project planners here are given the flexibility to utilize the introduced activity relaxation free float in order to calculate the required crew productivity rate at unit execution level that minimizes crew work interruptions without impacting optimized project duration. The third module computes the direct cost, indirect cost and interruption costs including idle crew cost as well as mobilization and demobilization costs. The fourth module identifies near optimum crew formation for each repetitive unit that leads to the optimal trade-off between project duration, project cost, crew work interruptions, and interruption costs, simultaneously. Genetic algorithm (GA) which is defined as one of the more effective techniques for providing a set of non-dominated solutions (Senouci and Eldin 2004) is utilized in this module. Finally, based on the outcome of the above modules, an optimized linear schedule is produced graphically.

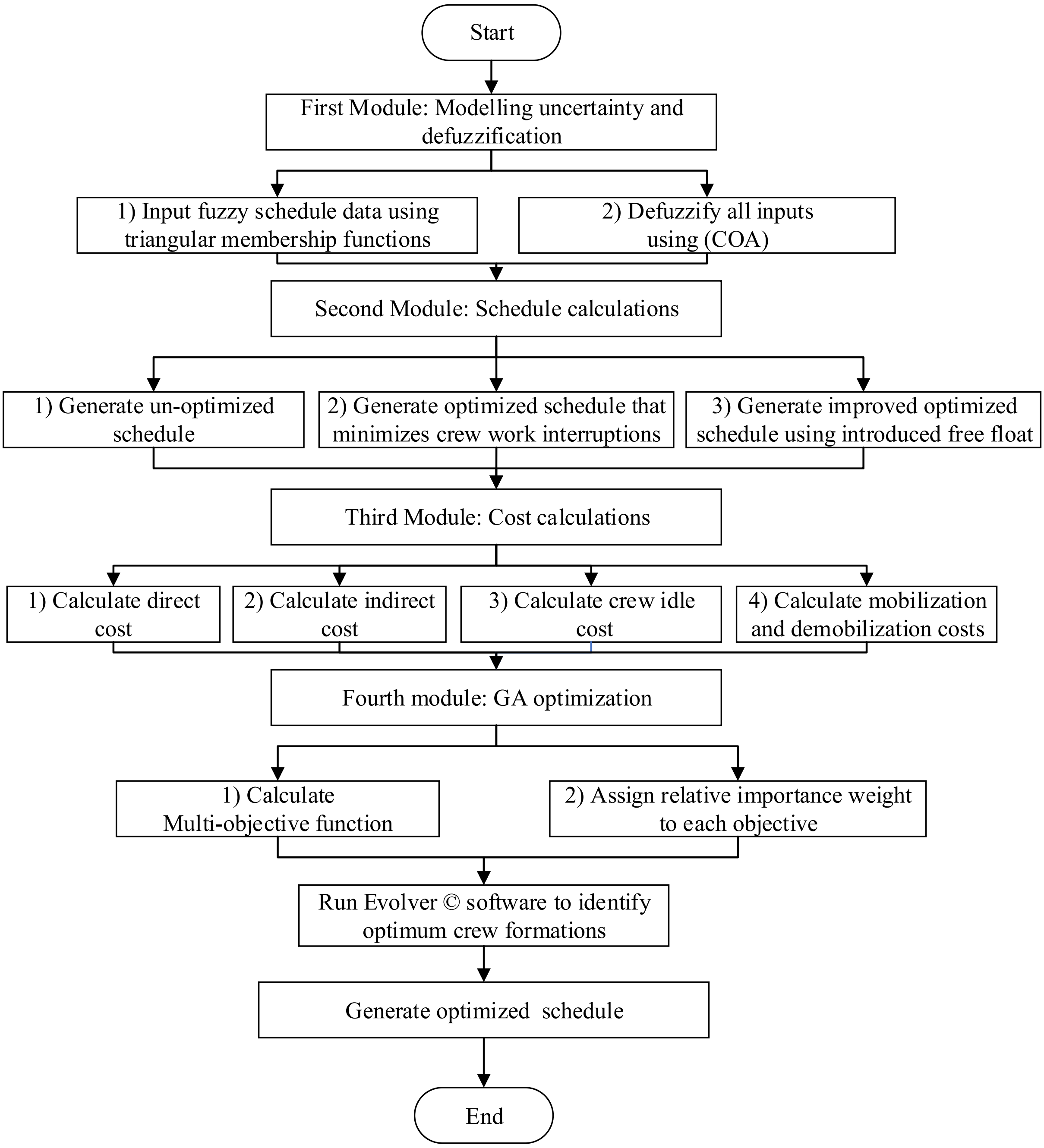


Figure 3.12 Framework of the optimized scheduling model

3.5.1. Modelling uncertainty and defuzzification

Fuzzy set theory is used to represent the subjectivity of the input data provided by members of project team (Moselhi and Roghabadi 2020). In this study, the model uses fuzzy sets to represent the uncertainty related to crew productivity rates and amounts of work in repetitive units. In this research, triangular fuzzy numbers are used to enable comparison with the result of Bakry et al. (2016), and Salama and Moselhi (2019). A triangular fuzzy number consists of three numbers (a), (b) and (c), in which each number is associated with its membership values of 0, 1 and 0, respectively. The value of (a), (b), and (c) demonstrates the pessimistic, most likely, and optimistic values of the original estimation respectively. After expressing crew productivity rates and quantities of work in each unit using fuzzy numbers, the centre of area (COA) method is used for defuzzification (Salah and Moselhi 2015) to transfer the fuzzy input to a crisp one. The expected value (EV) of a triangular fuzzy number is computed employing Equation 3.25 (Bakry et al. 2014, Shaheen et al. 2007).

$$\mathrm{EV} = \frac{\mathrm{a} + \mathrm{b} + \mathrm{c}}{3} \qquad \text{Equation 3.25}$$

3.5.2. Schedule calculations

The developed model utilizes the scheduling model of Salama et al. (2017) that integrates the linear scheduling method (LSM) and the critical chain project management (CCPM). The integration of these two methods allows for compliance with the work continuity constraint required by LSM and for CCPM aggressiveness in reducing project duration. The developed model allows not only for the use of interruptions in scheduling, but also for respecting no-interruption user-specified targeted constraints. In the developed model, schedule calculations are performed in three stages: un-optimized schedule, optimized schedule that minimizes crew work interruptions, and improved optimized schedule as described below.

3.4.2.1 Calculation of un-optimized schedule

In the first stage of the developed algorithm, the crisp (defuzzified) duration of each activity (i) which depends on uncertainty associated with its quantities and productivity rates are calculated using Equation 3.26. In this research the precedence among activities is considered as finish to start relationships, meaning that for each activity (i), the start date is calculated based on the maximum finish date of activities (i) in unit (j-1) and (i-1) in unit (j) according to Equation 3.27

$Dcr_{i,j} = Qcr_{i,j} \ / \ PRcr_{i,j}$ Equation 3.26

$SD_{i,j} = Max\ (FD_{i,j-1}, FD_{i-1,j})$ Equation 3.27

Where $Dcr_{i,j}$ represents the crisp duration of activity (i) in unit (j), $Qcr_{i,j}$ represents crisp quantity for activity (i) in unit (j), $PRcr_{i,j}$ represents crisp productivity rate for activity (i) in unit (j), $SD_{i,j}$ represents the start date of activity (i) in unit (j), $FD_{i,j-1}$ represents the finish date of activity (i) in unit (j-1), and $FD_{i-1,j}$, represents the finish date of activity (i-1) in unit (j).

It must be noted that for the first activity (i=1) in the first repetitive unit (j=1), its start date is equal to zero as shown in Figure 3.13.

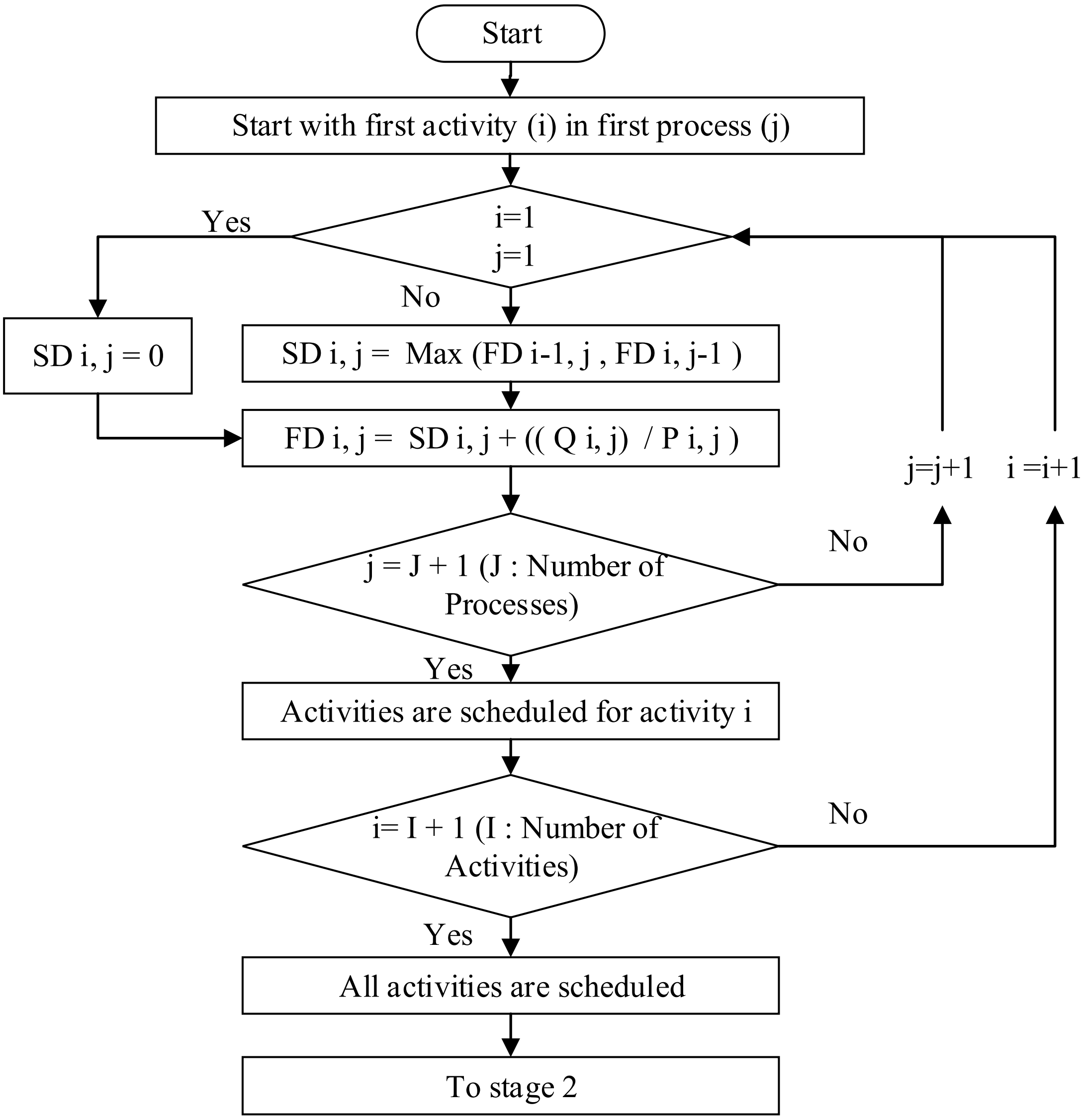


Figure 3.13: Flowchart of Stage 1 of the developed algorithm

Finally, the finish date of activity (i) in unit (j) is calculated by the sum of the start date of activity (i) in process (j) and its computed crisp duration according to Equation 3.28

$FD_{i,j} = SD_{i,\,j} + Dcr_{i,\,j}$ Equation 3.28

Where $FD_{i,j}$ represents the finish date of activity (i) in unit (j), and $SD_{i,j}$ represents the start date of activity (i) in unit (j).

As illustrated in Figure 3.13, the computations start from activity (i=1 to I) and from repetitive unit (j=1 to J). In this stage of the developed algorithm, an un-optimized project schedule is established that complies with project scheduling constraints of precedence relationship, crew availability, and crew work continuity.

3.4.2.2 Calculation of optimized schedule

Stage two of the developed algorithm shown in Figure 3.13 is set up in a spreadsheet. In this stage, the aim is to generate an optimized schedule that minimizes crew work interruptions without delaying the project duration using as late as possible scheduling of all activities. The total duration of interruptions (TDI) as well as the project duration are calculated using Equations 3.29 and 3.30 introduced by Salama and Moselhi (2019).

$$\mathrm{TDI} = \sum_{i=1,\, j=1}^{i=I,\, j=J} \mathrm{SD}_{i+1,\, j} - \mathrm{FD}_{i,j} \qquad \text{Equation 3.29}$$

$$\mathrm{PD} = \mathrm{FD}_{\text{last (i) in last (j)}} \qquad \text{Equation 3.30}$$

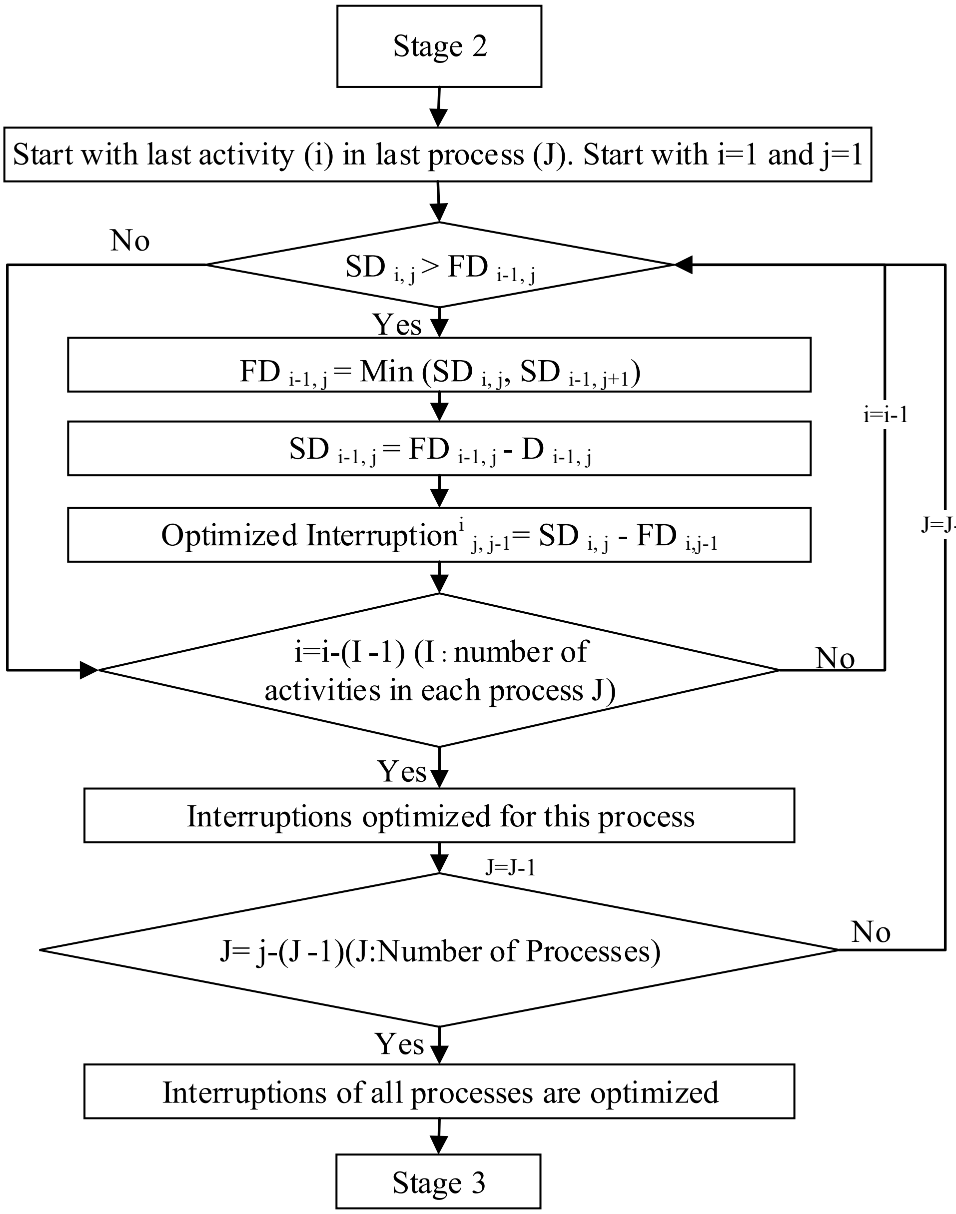


Figure 3.13: Flowchart of Stage 2 of the developed algorithm

3.4.2.3 Calculation of improved optimized schedule

In the third stage, the feasible boundaries for activity relaxation are identified as the difference between the un-optimized schedule and the schedule that minimizes crew work interruptions. In this stage, the developed algorithm is set up to calculate the required productivity rates at unit execution level utilizing the newly introduced activity relaxation free float for repetitive construction projects. That float is calculated using the number of days that an activity can be relaxed to minimize crew work interruption without delaying the early start of its successor activities and without impacting the optimized project duration. It must be noted that the relaxation here refers to assignment of a new crew with less productivity rate not minimizing the production of the available crew. The algorithm is designed to perform the calculation is shown in Figure 3.14. The activity relaxation free float (RFF) is calculated using Equations 3.31 to 3.32 for each activity (i) at each repetitive unit (j). Crew work interruption for each activity (i) at each repetitive unit (j=j+1) is calculated using Equation 3.33.

$RFF^{i}_{j} = \text{Min}(SD_{i+1,j}, SD_{i,j+1}) - \text{Max}(FD_{i,j,k}) \quad RFF_{i,j} \geq 0, \; k = K+1$ Equation 3.31

$RFF^{i}_{j} = 0 \quad j = J$ Equation 3.32

$RFF^{i}_{j} = \text{Interruption}^{i}_{j+1}$ Equation 3.33

Where RFF^{i}_{j} represents the activity relaxation free float of activity (i) at repetitive unit (j), $SD_{i+1,j}$ represents the start of activity (i+1) in unit (j), $SD_{i,j+1}$ represents the start of activity (i) in unit (j+1), $FD_{i,j,k}$ represents the finish of activity (i) in unit (j) based on crew number (k), K represents the number of available crews per each unit of each activity, $RFF^{i}_{j} = 0$ represents the activity relaxation free float of activity (i) at last repetitive unit (j=J), and $\text{Interruption}^{i}_{j+1}$ represents the crew work interruptions of activity (i) at repetitive unit (j=j+1).

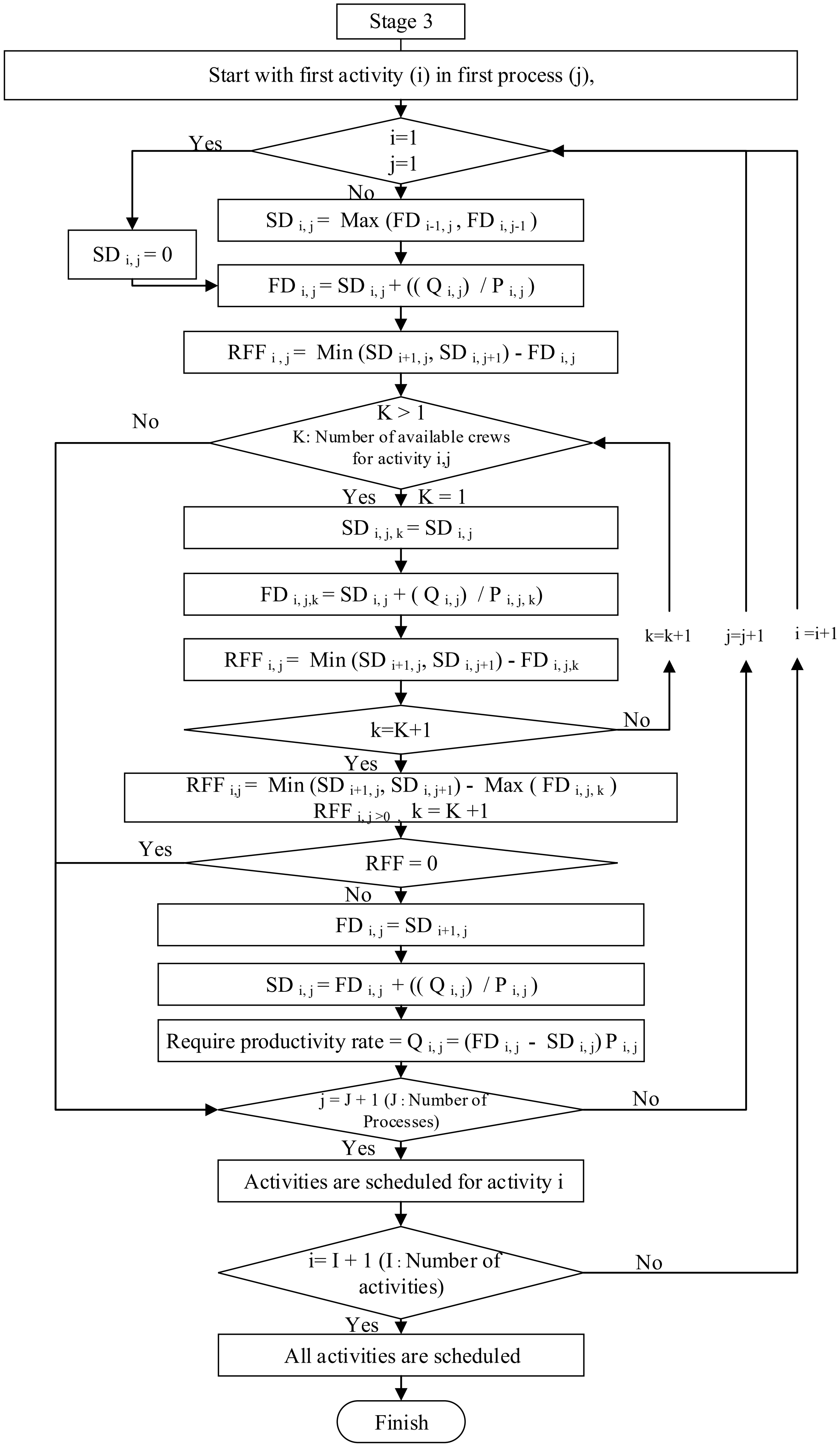

Stage 3
Start with first activity (i) in first process (j),
i=1
j=1
Yes
No
SD i, j = Max (FD i-1, j , FD i, j-1)
SD i, j = 0
FD i, j = SD i, j + ((Q i, j) / P i, j)
RFF i , j = Min (SD i+1, j, SD i, j+1) - FD i, j
K > 1
K: Number of available crews
for activity i,j
No
Yes
K = 1
SD i, j, k = SD i, j
FD i, j,k = SD i, j + (Q i, j) / P i, j, k)
RFF i, j = Min (SD i+1, j, SD i, j+1) - FD i, j,k
k=K+1
No
k=k+1
j=j+1
i =i+1
Yes
RFF i,j = Min (SD i+1, j, SD i, j+1) - Max (FD i, j, k)
RFF i, j >0 , k = K +1
RFF = 0
Yes
No
FD i, j = SD i+1, j
SD i, j = FD i, j + ((Q i, j) / P i, j)
Require productivity rate = Q i, j = (FD i, j - SD i, j) P i, j
j = J + 1 (J : Number of Processes)
No
Yes
Activities are scheduled for activity i
i= I + 1 (I : Number of activities)
No
Yes
All activities are scheduled
Finish

Figure 3.14: Flowchart of Stage 3 of the developed scheduling algorithm

The new activity relaxation free float addresses the limitations associated with the traditional floats. For example, Figure 3.15 shows a comparison between the introduced activity relaxation free float with the traditional free float and the one recently introduced by Altuwaim and El-Rayes (2018b).

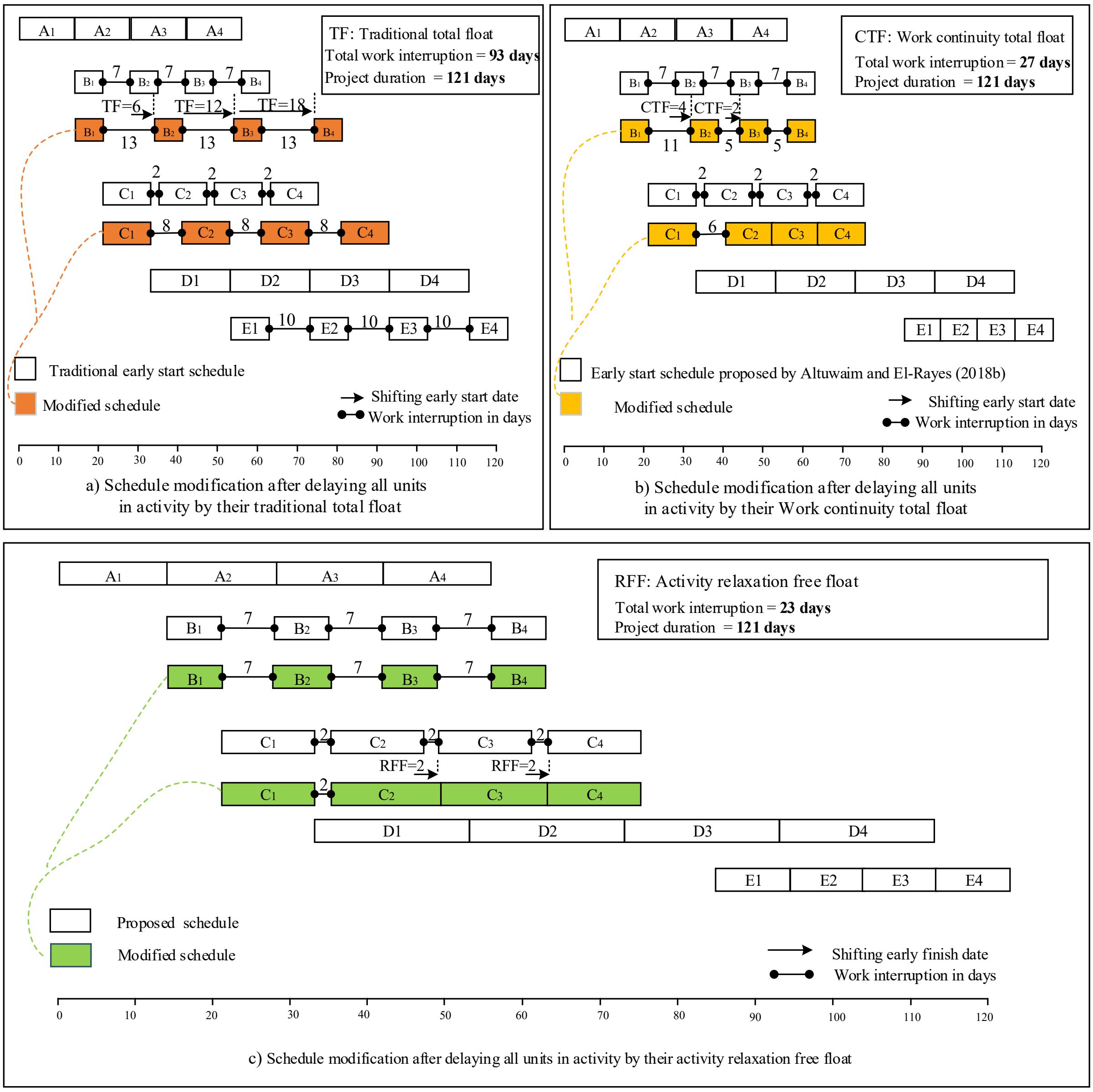


Figure 3.15 Comparison of different floats

As shown in that figure, delaying activities based on each of those floats does not extend project duration, but has a direct impact on project crew work interruptions. For instance, delaying the early start of activity B by its traditional total float (Figure 3.15 (a)) and the float introduced by Altuwaim and El-Rayes (2018b) (Figure 3.15 (b)) leads to 93 days and 27 days total work interruption for all construction crews respectively, while the total work interruption is minimized to 23 days utilizing the proposed activity relaxation free float (see Figure 3.15 (c)).

3.5.3. Cost calculations

In the third module, project total cost (TC) is calculated using Equation 3.34 by considering direct cost (DC), indirect cost (IC), and total cost of interruptions (TCI). The direct cost of the project which includes labour, equipment, and material costs is calculated using Equation 3.35. Labour, equipment, and material costs are calculated using Equations 3.36 to 3.38, respectively. As shown in Equations 3.36 and 3.37, labour and equipment costs are a function of activity duration, while material cost is a function of material quantity as shown in Equation 3.38. Indirect cost is calculated based on a daily rate specified by the user as shown in Equation 3.39.

Total interruption costs of the project are calculated in three steps as stated by Altuwaim and El-Rayes (2018a) to compute: (1) the movement cost for each construction crew, (2) crew idle cost of all activities from (i) to (I) at each of its repetitive units through the last repetitive unit (j = 1 to J), and (3) interruption costs of all activities from (i) to (I) at each repetitive unit. To do so, the following input data are required: (a) crew work interruption ($Inter^{i}_{j,j-1}$), (b) mobilization and demobilization cost (MDC_i), (c) mobilization and demobilization time MDT_i, (d) daily labour cost (LC_i), and (e) minimum work duration in a temporary location in that project ($T_{min,i}$).

Cost associated with movement of a crew from its original location to a temporary location on the project is calculated in the first step based on the movement time which represents a work interruption. As such, crew movement cost is considered only for those activities which have a crew work interruption. It should be noted that in order to calculate crew movement cost, first the model needs to evaluate whether there is enough time for mobilization and demobilization. The crew movement cost of activity (i) is calculated as shown in Equation 3.40.

In the second step which is designed to calculate crew idle cost, the cost associated with maintaining the construction crew onsite is considered based on its interruption duration. Idle crew cost is calculated using Equation 3.41 for all activities from (i=1 to I) at each of its repetitive units (j = 1 to J) through the last repetitive unit.

In the third step, the interruption costs for each activity (i) is computed according to the result of the first two aforementioned steps. A crew can move if its minimum working time in a temporary location plus its mobilization and demobilization times are less than its work interruption as shown in Equation 3.42. However, if the crew is not allowed to move due to the short period of its interruption, the interruption cost is set equal to idle cost as shown in Equation 3.41. Furthermore, this step is devised to determine the total cost of interruption as shown in Equation 3.43.

$TC = DC + IC + TCI$ Equation 3.34

$$DC = \sum_{i=1}^{I} \sum_{j=i}^{j=J} LC_{i,j} + EC_{i,j} + MC_{i,j}$$ Equation 3.35

$LC_{i,j} = (\text{Daily labour cost})_{i,j} \times D_{i,j}$ Equation 3.36

$EC_{i,j} = (\text{Daily equipment cost})_{i,j} \times D_{i,j}$ Equation 3.37

$MC_{i,j} = (\text{Unit material cost})_{i,j} \times Qcr_{i,j}$ Equation 3.38

$IC = \text{Daily indirect cost} \times \text{project duration}$ Equation 3.39

$CMC_i = MDC_i + [MDT_i \times LC_i]$ Equation 3.40

$ICC_{i,j} = Inter^{i}_{j,j-1} \times LC_{i,j} \qquad 1 \leq j \leq J$ Equation 3.41

If $(T_{min,i} + MDT_i \leq Inter^{i}_{j,j-1})$, then $IC_{i,j} = Min\,(CMC_i, ICC_{i,j})$ Equation 3.42

Otherwise, $IC_{i,j} = ICC_{i,j} \qquad 1 \leq j \leq J$

$$TCI = \sum_{i=1}^{i=I} \sum_{j=1}^{j=J} IC_{i,j}$$ Equation 3.43

Where TC represents the project total cost, DC represents direct cost for all activities from (i=1 to I) in unit (j=1 to J), IC represents the indirect cost, TCI represents the total cost of interruptions, $LC_{i,j}$ represents labour cost of activity (i) in unit (j), $EC_{i,j}$ represents the equipment cost of activity (i) in unit (j), $MC_{i,j}$ represents the material cost of activity (i) in unit (j), CMC_i represents the crew movement cost for activity (i), MDC_i represents the mobilization and demobilization cost for activity (i), MDT_i represents the mobilization and demobilization time for activity (i), $ICC_{i,j}$ represents the idle crew cost of activity (i) in unit (j), $T_{min,I}$ represents the minimum work duration in a temporary project, and $IC_{i,j}$ represents the interruption cost for all activities from (i=1 to I) in units (j=1 to J).

3.5.4. GA optimization

Genetic algorithms (GAs) are considered one of the more effective techniques for determining near optimal solutions (Senouci and Eldin 2004) in which an artificial survival-of-the-fittest strategy is programed and applied on genetic operators taken from nature to form a mechanism that is suitable for a variety of optimization problems (Hegazy 1999). Evolver Optimization, as a GA optimization software, is used due to its capability in solving complex optimization problems quickly (Palisade Corporation, 2015). In this research, the Evolver Optimization of Microsoft Excel is formulated into a spreadsheet tool to identify the optimum crew formations that minimize project duration, project cost, crew work interruptions, and interruption costs, simultaneously.

The procedure for application of Evolver © 7.5.2 optimization starts by generating an initial population of random solutions (crew formations) with a set of strings named chromosomes. Each crew formation is considered as one chromosome. Each chromosome includes different set of genes. In this study, each gene represents the selected crew for each unite of each repetitive activity. The fitness of each chromosome is measured targeted objective function, also called fitness function (Palisade Corporation 2015). Evolver © 7.5.2 continues to generate a new population by generating new off-springs and testing them against the fitness function in search for a near optimum solution. Evolver © 7.5.2 employs two types of genetic operators named mutation and crossover. The mutation operator injects random changes into the genes of offspring chromosomes from its initial state. The crossover operator determines the procedure for exchanging genes between two parents to produce new offspring (Palisade Corporation 2015). The model is set to utilize an automatic mode in Evolver © 7.5.2 to select optimization engine and its settings. This includes determination of string size, population size, crossover rate, and mutation rate. Evolver © 7.5.2 uses the order solving method to accomplish mutation by shifting the positions of some variables in the chromosome. The number of performed shifts is a function of the mutation rate setting (from 0 to 1) (Palisade Corporation 2015). Formulation of multi-objective function (i.e. the fitness function) and its components are described below.

3.4.4.1 Multi-objective function

The developed model utilizes a multi-objective function (MOF) in order to search for and identify a set of non-dominated solutions (crew formations) that simultaneously minimize four objectives including: project duration, project cost, crew work interruptions, and interruption costs. The developed MOF integrates the four objectives utilizing the weighted-sum method which convert a multi-objective optimization problem into single optimization to optimize one objective instead of many (Deb 2001). This conversion reduces the complexity of solving a multi objective problem (Awad and Khanna 2015) and allows satisfactory compromise solutions (Agrama 2014). Although this method has a straightforward implementation and is considered a computationally efficient approach for calculating the fitness function score in multi-objective GAs, it has difficulty in setting the proper weights to obtain the optimum solution (Konak et al. 2006).

In order to alleviate this issue, a reasonable approach is to consider a set of solutions to investigate whether the obtained solution is truly the optimum solution (Konak et al. 2006). That method was utilized in similar research such as that of Agrama (2014) and that of Salama and Moselhi (2019) to convert a three-objective optimization problem into single optimization.

In this method, each objective is multiplied by a corresponding weight assigned by decision makers to reflect its relative importance. However, the units of the objectives are different. To account for the different units of measurement for the individual objectives, the MOF is converted into a normalized fitness function as in (Salama and Moselhi, 2019) by dividing the optimized value of each objective by its un-optimized value as shown in Equation 3.44. In that equation, (PD), (TC), (TDI), and (TCI) represent optimized values of project duration, project total cost, total duration of interruptions, and total cost of interruptions, respectively. The un-optimized values of (PD), (TC), (TDI), and (TCI) are those of the base case estimate (i.e. original estimate) of the user and are referred to here as (PD*), (TC*), (TDI*), and (TCI*). The weights of project duration, project total cost, total duration of interruptions, and total cost of interruptions are shown as W_d, W_c, W_{id}, and W_{ic}, respectively.

$$MOF= [W_d \times (PD/PD^*)] +[W_c \times (TC/TC^*)] +[W_{id} \times (TDI/TDI^*)]+[W_{ic} \times (TCI/TCI^*)]$$

Equation 3.44

It must be noted that the weight of each objective must be equal to or more than zero, and the summation of all weights must be equal to one. Considering the importance weight gives a unique capability to the developed model to optimize each objective as a single optimization problem. In other words, by assigning 1 as a weight for the required objective and 0 for the rest, the multi-objective optimization problem converts into a single optimization problem. The weights are assigned based on the user's requirement. For example, the assigned weight of 1 for project duration means that this objective has more importance from the decision maker's perspective.

The proposed multi-objective function is formulated into a spreadsheet tool which utilizes Evolver © 7.5.2, as a GA optimization software as stated earlier. It must be noted that the assigned weights affect the solution. For example, if all of the weights are positive, as assumed in this study, then minimizing multi-objective function provides a sufficient condition for Pareto optimality (Marler and Arora, 2010).

3.6. Earned Value Management Analysis

This section is a marginally modified version of "Forecasting Project Duration Using Risk-Based Earned Duration Management" under review in the International Journal of Construction Management (Roghabadi and Moselhi 2020c) and has been reproduced here.

The developed model employs the past performance data of critical activities plus the data associated with their future uncertainties to monitor and estimate the schedule performance of the project at each reporting date as shown in Figure 3.16.

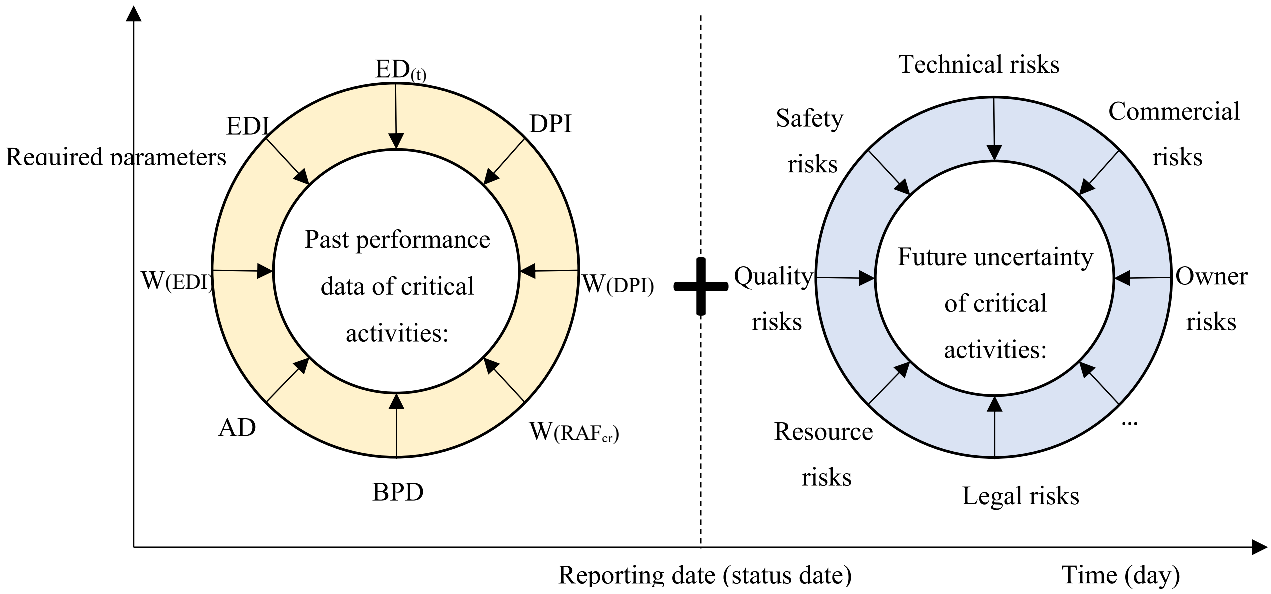


Figure 3.16: Required parameters for monitoring and estimating project schedule performance

It consists of four phases as shown in Figure 3.17. In the first phase the required input data for generating project Gantt chart are provided. In this phase the critical activities are identified at each reporting date. In the second phase, EDM parameters are calculated based on the past performance data of critical activities for the reporting date. In the third phase, risk factors associated with critical activities for the remaining period of the project are identified and quantified utilizing the newly introduced risk adjustment factor (RAF_{cr}). And finally, in the fourth phase, a new equation is introduced for estimating project duration at completion, considering critical activities and their associated risk factors.

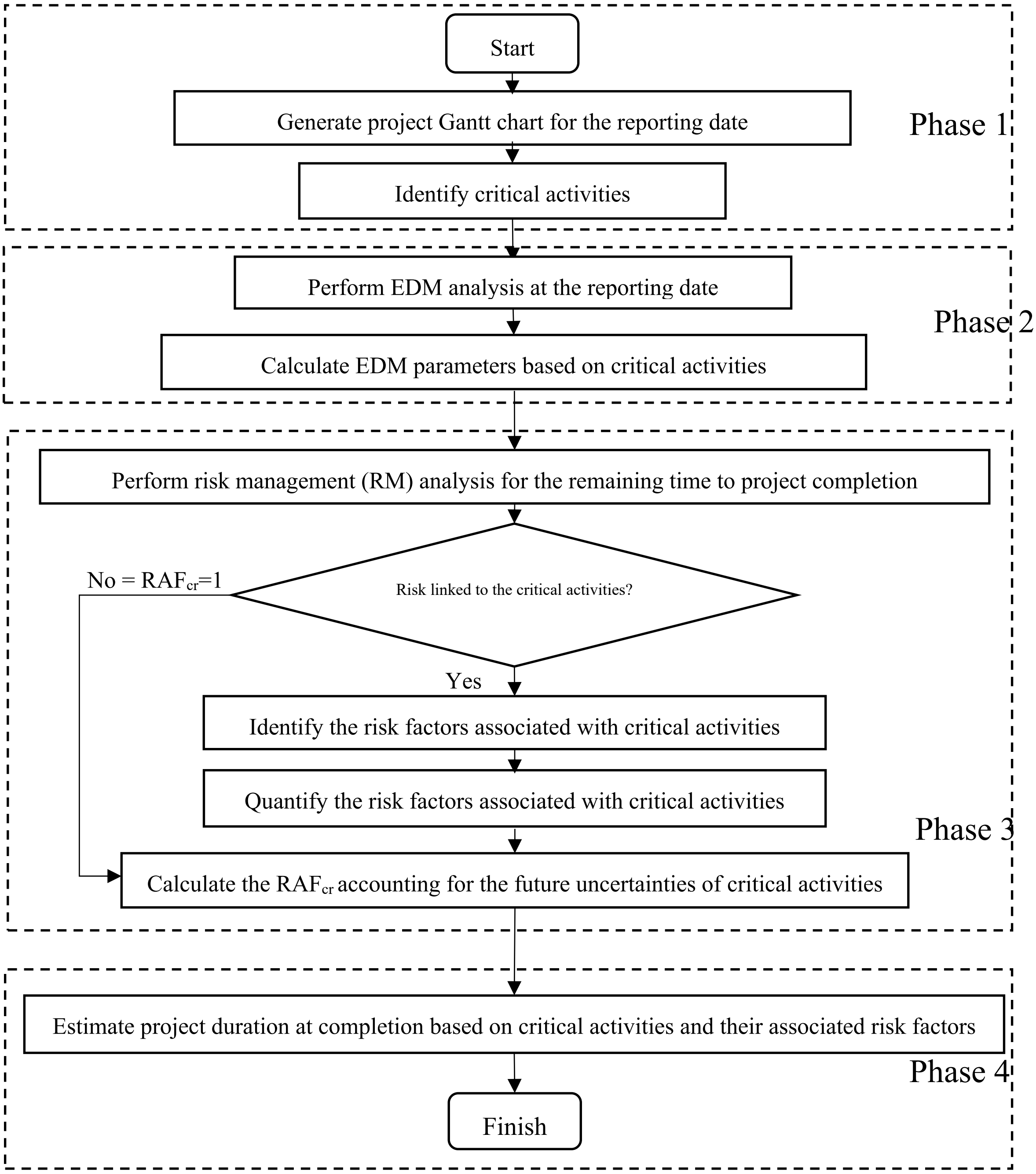


Figure 3.17: Framework of the developed risk-based EDM model

3.6.1. Input data

In the first phase the required input data for generating the project Gantt chart are provided including the precedence relationship between activities and the activities duration. Through the provided data, critical activities are identified at each reporting date.

3.6.2. Earned duration management (EDM) analysis

EDM is a member family of EVM that provides measurable indices to evaluate project schedule performance at each reporting date. As stated earlier, unlike the EVM that employs earned value (EV) of the project at reporting date to measure the schedule performance, in EDM, $ED_{(t)}$ is employed using Equation 3.45 (Khamooshi and Golafshani 2014).

$$ED_{(t)} = t + \left(\frac{TED_t - TPD_t}{TED_{t+1} - TPD_t}\right), \qquad TPD_t \leq TED_t \leq TED_{t+1} \qquad \text{Equation 3.45}$$

Where $ED_{(t)}$ is the earned duration of the project at the reporting date (t), TED_t is the total earned duration at the reporting date (t), TPD_t is the total planned duration at the reporting date (t). Figure 2.2 (b) shows a conceptual graph for calculating $ED_{(t)}$.

Based on $ED_{(t)}$ and the actual duration AD at the reporting date (t), the duration performance index of the project at the reporting date (t) is calculated using Equation 3.46.

$$DPI = \frac{ED_t}{AD} \qquad \text{Equation 3.46}$$

DPI represents the status of project schedule at the reporting date (t). Having a value of 1.0 indicates that the project schedule is performing as planned, while the values more or less than one indicate the project is ahead or behind schedule, respectively.

Another schedule performance index was introduced by Khamooshi and Golafshani (2014) called earned duration index EDI which shows the total earned duration TED of the project compared to the total planned duration TPD at the reporting date (t) as shown in Equation 3.47.

$$\mathrm{EDI} = \frac{\mathrm{TED}}{\mathrm{TPD}} \qquad \text{Equation 3.47}$$

The EDI less, equal, or more than one indicates that the project has achieved less, equal, or more progress in comparison with the work planned at the reporting date respectively.

Then, Equation 3.48 is utilized to estimate project duration at completion assuming the project maintains its current performance until the end of the project (Khamooshi and Golafshani 2014).

$$\mathrm{EDAC} = \frac{\mathrm{BPD}}{\mathrm{DPI}} \qquad \text{Equation 3.48}$$

Where EDAC is the estimated project duration at completion, and BPD is the baseline planned duration.

However, Equation 3.48 employs the past performance data for estimating project duration at completion with no consideration of project risk factors that might arise during project execution. In order to address this drawback, Hamzeh et al. (2020) recently proposed Equation 3.49 quantifying the project risk factors for each reporting date.

$$\widetilde{\mathrm{TBRPE}} = \sum_{\mathrm{l}=1}^{\mathrm{L}} \gamma_1 \times \widetilde{\mathrm{RPM}}_1 \qquad \text{Equation 3.49}$$

Where $\widetilde{\mathrm{TBRPE}}$ is the triangular intuitionistic fuzzy time-based risk performance indicator, $\widetilde{\mathrm{RPM}}$ is the triangular intuitionistic fuzzy number associated with each risk performance metric, (L) is the number of risk performance metrics, (γ) is the weight of risk performance matric (l).

Then, they employed the calculated $\widetilde{\mathrm{TBRPE}}$ for the reporting date and proposed Equation 3.50 for estimating the triangular intuitionistic fuzzy number of estimated project duration at completion$\mathrm{TI\widetilde{FED}AC}$.

$$\mathrm{TI\widetilde{FED}AC} = \mathrm{AD} + \frac{(\mathrm{BPD} - \mathrm{TI\widetilde{FED}_t})}{\left(\mathrm{W_1} \times \mathrm{TI\widetilde{FDP}I}\right) + \left(\mathrm{W_2} \times \mathrm{TI\widetilde{FED}I}\right) + (\mathrm{W_3} \times \widetilde{\mathrm{TBRP}}\mathrm{I})} \quad \text{Equation 3.50}$$

Where $\mathrm{TI\widetilde{FED}_t}$ is the triangular intuitionistic fuzzy number associated with the earned duration of the project at the reporting date of (t), $\mathrm{TI\widetilde{FDP}I}$ is the triangular intuitionistic fuzzy number associated with the duration performance index of the project at the reporting date of (t), $\mathrm{TI\widetilde{FED}I}$ is the triangular intuitionistic fuzzy number associated with the earned duration index of the project at the reporting date of (t), and (W_1), (W_2), (W_3) are the importance weights of performance indicators $\mathrm{TI\widetilde{FDP}I}$, $\mathrm{TI\widetilde{FED}I}$, and $\widetilde{\mathrm{TBRP}}\mathrm{I}$ respectively which are determined by project experts for each quarter of the project.

The $\widetilde{\mathrm{TBRPE}}$ in Equation 3.49 is calculated at the macro level based on the current performance of the project risk factors at the reporting date, neglecting future uncertainties in estimating project duration at completion. Also, the estimated project duration at completion is calculated based on the progress made by critical and non-critical activities at the reporting date, which, as stated earlier, can lead to an inaccurate estimate of project duration at completion. Consider a case where critical and no-critical activities executed in parallel and non-critical activities are advancing well, but critical activities are experiencing delays. This case can result in a DPI and EDI equal to almost 1.0 meaning that the schedule performance is on target while in reality it is behind the planned progress. In order to address the limitations highlighted above, the developed model introduces a new risk adjustment factor which accounts for the future uncertainties associated with critical activities. The developed model also introduces a set of new indices and equations for calculating project duration at completion utilizing only critical activities and their associated risk factors. This unique aspect of the developed model prevents project managers from over and under estimation of the required time for project completion. The computational process of the new RAFcr and EDAC is described in the following sections.

3.6.3. Risk adjustment factor

In the third phase of the developed model the known and unknown project risk factors associated with critical activities for the remaining time for project completion are identified employing the risk identification model proposed by Salah and Moselhi (2016). For instance, for each critical activity, experts identify known risk items using a combination of risk identification methods including documentation review, expert judgment, influence diagram, Delphi technique, and interviewing. The unknown risk factors also are identified based on previous experience, learned lessons databases, and root cause analyses. After identifying future risk factors that might happen during the project execution, the identified risk factors associated with each critical activity are quantified as shown in Figure 3.18.

As shown in that figure, the developed model utilizes the output of the risk identification model developed by Salah and Moselhi (2016). Then, the risk adjustment factor associated with the risk (j) critical activity (i) for the reaming time to project completion is calculated. Unlike

Hamzeh et al. (2020) that quantify the risk factors at the macro level with no consideration of the future uncertainties, in this research the risk factors are quantified at micro level based on the future uncertainties associated with critical activities according to Equation 3.51.

$$\mathrm{RAF_j} = \frac{1}{\mathrm{K}}\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{P_k} \times \mathrm{I_K} \qquad \text{Equation 3.51}$$

Where RAF_j is the risk adjustment factor associated with risk (j) of critical activity (i), P_k is the probability of occurrence for risk (j) of activity (i) assigned by expert (k), (I_k) is the magnitude of the potential impact of risk (j) of activity (i) assigned by expert k, and K refers to the number of experts. The probability of occurrence and the potential impact associated with each risk factor scored from 0 to 1 (0.1 = very low, 0.25 = low, 0.5 = medium, 0.75 = high and 1= very high).

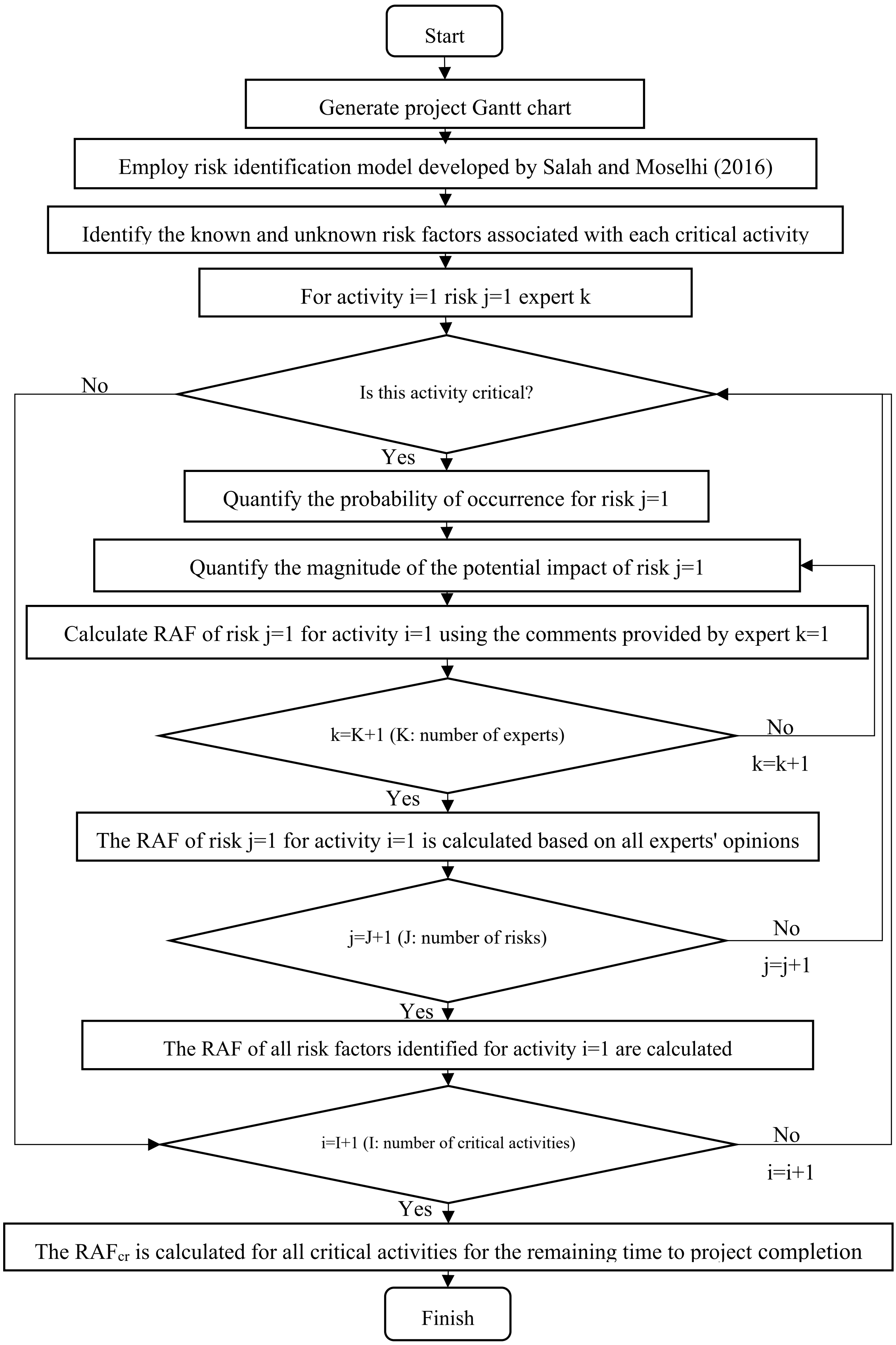


Figure 3.18: Flowchart of risk adjustment factor associated with critical activities

The risk adjustment factor of the critical activity (i) is calculated according to Equation 3.52 assuming no dependency between risk factors.

$$\mathrm{RAF_i} = \sum_{j=1}^{j} \mathrm{RAF_J} \qquad \text{Equation 3.52}$$

Where J refers to the number of risk factors associated with critical activity (i).

Finally, the total risk adjustment factor associated with critical activities RAF_{cr} for the remaining time to project completion is calculated using Equation 3.53.

$$\mathrm{RAF_{cr}} = \sum_{i=1}^{I} \mathrm{W_i} \times \mathrm{RAF_i} \qquad \text{Equation 3.53}$$

Where W_i is the importance weight of the critical activity (i), which is a function of its duration, and I refers to the number of critical activities. In that equation, W_i is calculated based on Equation 3.54.

$$\mathrm{W_i} = \frac{\mathrm{D_i}}{\mathrm{BPD}} \qquad \text{Equation 3.54}$$

Where D_i is the duration of the critical activity (i), and BDP is the baseline project duration which is calculated based on the sum of critical activities' duration at the reporting date.

Considering the importance weight of critical activities improves the reliability of project schedule performance indicators, especially where critical activities display a wide range of individual durations (Wood 2018).

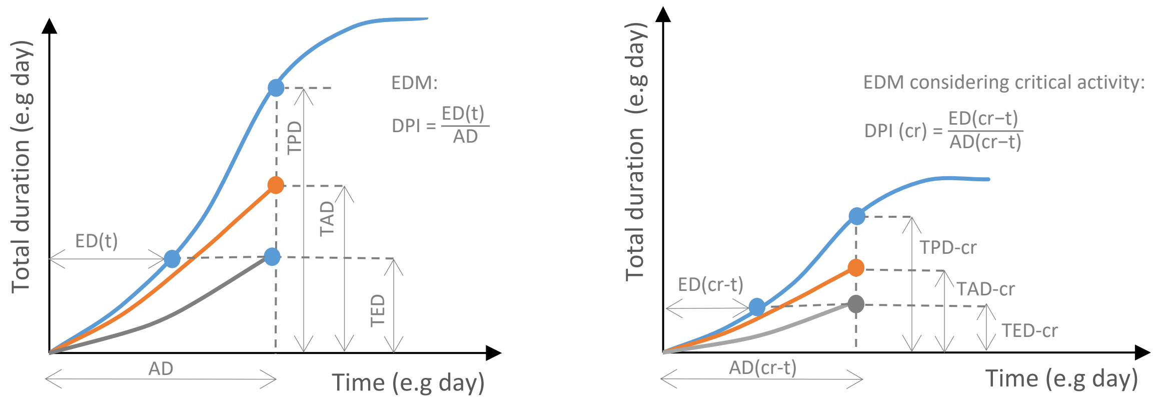
3.6.4. Realistic schedule performance evaluation

In this phase, new performance indicators are introduced in order to increase the reliability of schedule performance evolution. Unlike Equation 3.49 which considers critical and non-critical activities in calculating earned duration of the project at the reporting date, in this study the below equation is proposed that considers the earned duration of only critical activities in evaluating schedule performance at the reporting date.

$$\mathrm{ED}_{(cr-t)} = t + \left(\frac{\mathrm{TED}_{cr-t} - \mathrm{TPD}_{cr-t}}{\mathrm{TED}_{cr-t+1} - \mathrm{TPD}_{cr-t}}\right), \qquad \mathrm{TPD}_{cr-t} \leq \mathrm{TED}_{cr-t} \leq \mathrm{TED}_{cr-t+1}$$

Equation 3.55

Where $\mathrm{ED}_{(cr\text{-}t)}$ is the earned duration of the critical activities at the reporting date (t), $\mathrm{TED}_{cr\text{-}t}$ is the total earned duration of critical activities at the reporting date (t), $\mathrm{TPD}_{cr\text{-}t}$ is the total planned duration of critical activities at the reporting date (t). Figure 3.19 shows the difference between $\mathrm{ED}_{(t)}$ calculated by Equation 3.49 and the $\mathrm{ED}_{(cr\text{-}t)}$ calculated by the newly proposed Equation 3.55.



a) EDM graph considering all project activities

b). EDM graph considering only critical activities

Figure 3.19: Comparison between EDMs

As shown in that figure, the $\mathrm{TED}_{cr\text{-}t}$ is less than the TED_t. This scenario can happen when critical activities overlap with the non-critical activities. In other words, in this particular scenario, which is common in construction projects, the progress made by non-critical activities overshadows the delays of critical activities.

By dividing the $ED_{(cr-t)}$ to the actual duration AD at the reporting date (t), the duration performance index of the project at the reporting date (t) is calculated using Equation 3.56.

$$DPI_{cr} = \frac{ED_{cr-t}}{AD} \qquad \text{Equation 3.56}$$

The DPI_{cr} shows the status of project schedule in achieving the target completion date based on critical activities only. The DPI equal to one indicates that the project schedule is performing as planned, while the values more or less than one indicate the project is ahead and behind schedule respectively.

Another schedule performance indicator is introduced called earned duration index of critical activities EDI_{cr} which shows the total earned duration of the critical activities TED_{cr} compared to their total planned duration TPD_{cr} at the reporting date (t) as shown in Equation 3.57.

$$EDI_{cr} = \frac{TED_{cr-t}}{TPD_{cr-t}} \qquad \text{Equation 3.57}$$

The EDI_{cr} less, equal, and more than one indicates that the cumulative amount of work achieved by critical activities at the reporting date is less, equal, or more than the amount of their planned work at the reporting date respectively.

Then, the two introduced schedule performance indices (DPI_{cr}, EDI_{cr}) plus the new risk adjustment factor RAF_{cr} are employed to estimate project duration at completion using Equation 3.58.

$$EDAC = AD + \frac{(BPD - ED_{cr-t})}{(W_1 \times DPI_{cr-t}) + (W_2 \times EDI_{cr-t}) + (W_3 \times RAF_{cr})} \qquad \text{Equation 3.58}$$

Where (W_1), (W_2), (W_3) are the importance weights of performance indicators (DPI_{cr}), EDI_{cr}, and RAF_{cr} respectively which are determined by project experts for each quarter of the project.

3.7. Limitations of the Developed Models

The main limitations of the developed models are:

- The developed risk maturity evaluation model is limited to the use of trapezoidal membership function in representing the subjectivity associated with the individual responses. The model validation is also limited to the use of one case example.
- The developed contingency estimation model also is limited to the use of trapezoidal membership function as the fuzzy set theory applied on the subjective correlation matrix.
- The developed trade-off analysis model is limited to finish-to-start relationships among activities. It also does not incorporate the effects of crew learning curve and loss of productivity because of change in resource assignment in the optimization process.
- The developed Earned Value Management (EVM) model is validated utilizing a numerical example. More real case examples are required to demonstrate its estimating accuracy.

CHAPTER 4: CASE EXAMPLES

4.1. Introduction

This chapter presents five different case studies drawn from literature and an industrial partner which is a construction company based in Montreal, Quebec, Canada. The purpose of this chapter is to provide comparisons between the results of developed models in this research with those reported in the literature. The first case study is utilized to demonstrate the ability of the introduced risk maturity evaluation model for evaluating the risk performance of the industrial partner. The data captured from project personnel working in that organization are utilized for that purpose. The second case study, drawn from the literature, is presented to validate the performance of the introduced contingency estimation model over those reported in the literature. The third case study also drawn from the literature is presented to compare the results of the three introduced pattern recognition models for estimating project markup. The fourth case study is analysed to illustrate the capability of the developed scheduling model in identifying the optimum trade-off between project duration, project cost, crew work interruptions and interruption costs, simultaneously. This case example also was drawn from the literature. And, finally, the fifth case study presents a hypothetical example illustrating the strength of the developed risk-based earned duration management for forecasting project duration at completion over previous methodologies presented by other researchers. Each is described subsequently.

4.2. Case Example for Risk Maturity Evaluation

This section is a marginally modified version of "A Fuzzy-Based Decision Support Model for Risk Maturity Evaluation of Construction Organizations" published in the journal of Algorithms (Roghabadi and Moselhi 2020a) and has been reproduced here.

In order to demonstrate the applicability of the developed risk maturity model, the model is used to measure the risk maturity level of the industrial partner's organization. The partner has over 50 years of extensive experience working on civil and infrastructure projects in Canada and is known as one of the leading general contractors in the country.

Table 4.1: Qualified individuals in the industrial partner organization.

Source	Authority Level	Profile	Individual Involvement Level per Attribute					
			APR	AIR	AAR	ARR	AIRR	AMR
Industrial partner	Portfolio	Executive vice president	✓	✓	-	✓	-	-
		Vice president	✓	✓	-	✓	-	✓
		Stakeholders	✓	✓	-	✓	-	-
	Program	Construction project director	✓	✓	✓	✓	✓	✓
		Pre-construction project director	✓	✓	✓	✓	-	-
		Bid manager	✓	✓	-	-	-	-
		Insurance manager	-	✓	✓	-	-	✓
		Real estate manager	-	✓	-	-	-	-
		Financial risk analyzer	-	✓	✓	-	-	✓
	Project	Project planer	-	✓	-	-	-	✓
		Project manager	-	✓	✓	✓	✓	✓
		Project coordinator	-	✓	-	-	-	-
		Superintendent manager	-	✓	-	✓	-	✓
		Pre-construction manager	-	✓	✓	-	-	-

Notes: ✓: Involved, - : not involved

In November 2019, a pilot study was conducted with the Assistant Director of the Innovation Department to finalize the list of qualified individuals who were expected to participate in this maturity assessment study. Table 4.1 shows the final list of the chosen qualified individuals which are clustered based on their level of authority in the organization and their involvement level in the maturity evaluation of each attribute.

A questionnaire survey was distributed to the identified individuals through their internal email address. Out of the 20 distributed questionnaires, a total of 14 questionnaires were completed reflecting a 70% response rate. The questionnaire was answered by one vice president, five project directors, three project managers, three preconstruction project managers, one bid coordinator, and one risk analyst, as shown in Table 4.2. As shown in that table, one respondent had more than 30 years of experience, nine respondents had 10–20 years of experience and the remaining had 5–10 years of experience.

Table 4.2: Respondents' profiles.

ID	Profile	Years of Experience
VP	Vice president alternative (projects and infrastructure)	32
PD_1	Project director	10
PD_2	Regional director	13
PD_3	Director - preconstruction and methods	17
PD_4	Director - project support	16
PD_5	Project director	15
PM_1	Project manager	05
PM_2	Senior project manager	14
PM_3	Senior project manager	13
PPM_1	Pre-construction manager	15
PPM_2	Pre-construction manager	13
PPM_3	Pre-construction manager	15
BC	Bid coordinator	10
RA	Risk analyst – financial risk analyzer	09

The individuals were asked to assign a score, expressing the relative importance of each attribute in comparison to the other attributes as well as its degree of implementation. The five-point scale method was utilized for that purpose, making it convenient for individuals to judge (Zhao et al. 2013). However, in this study, this scaling method is modified to a nine-point scale following the scaling method provided in the Super Decisions software. This means the values of 1, 2, 3, 4, 5 are equivalent to 1, 3, 5, 7, 9 respectively. Figure 4.1 shows the weight associated with each individual's response for each attribute. These weights are utilized to form the pairwise comparison matrices.

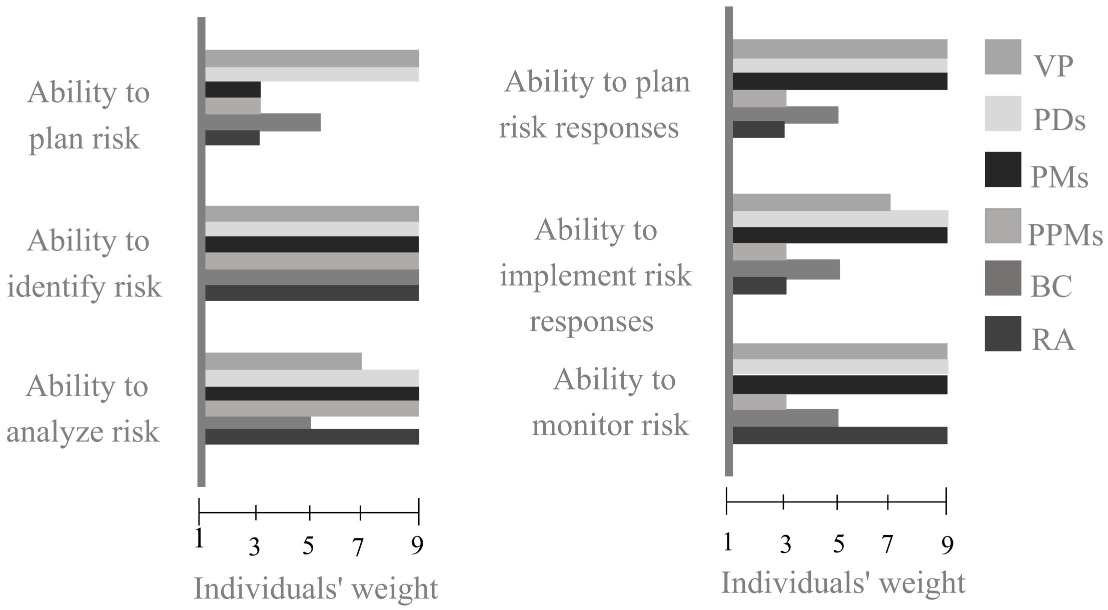


Figure 4.1: The individuals' responses weights per each attribute.

Table 4.3 shows the individuals' opinions pairwise comparison matrix with regard to the first attribute which is the ability to plan risk. For instance, as shown in the first row of that matrix, the response provided by the vice president (VP) of the company is equally as important as the responses provided by individuals PD_1 to PD_5 and BC. The reason behind that is that all these individuals are involved in the maturity evaluation of that attribute and they all have a weight of nine. However, it is strongly to very strongly more important than the responses provided by PM_1 to PM_3, PPM_1 to PPM_3 and RA. This is mainly because these individuals are not involved in the maturity evaluation of that attribute as shown in Table 4.1 and their level of authority in the organization is at a project level which is at low weight (3). The difference between the VP's response weight with the responses provided by the PM_1 to PM_3, PPM_1 to

PPM_3 and RA shows the importance of the VP's response over those of the others, which in this case is equal to six (6), as shown in the first row of Table 4.3.

Table 4.3: Ability to plan the risk sub-decision factors pairwise comparison.

Factors	VP	PD_1	PD_2	PD_3	PD_4	PD_5	PM_1	PM_2	PM_3	PPM_1	PPM_2	PPM_3	BC	RA
VP	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PD_1	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PD_2	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PD_3	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PD_4	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PD_5	1	1	1	1	1	1	6	6	6	6	6	6	1	6
PM_1	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
PM_2	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
PM_3	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
PPM_1	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
PPM_2	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
PPM_3	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1/6	1
BC	1	1	1	1	1	1	6	6	6	6	6	6	1	6
RA	1/6	1/6	1/6	1/6	1/6	1/6	1	1	1	1	1	1	1	1

The participants were then requested to perform the pairwise comparison of the importance of the six attributes as described earlier. For example, Table 4.4 shows the pairwise comparison between the attributes based on the response provided by the vice president (VP) of the company. Given the provided response, the ability to plan risk (APR) is as important as the ability to analyze risk (AAR) and the ability to monitor risk (AMR). However, it is equal to moderately less important than the ability to identify risk (AIR), the ability to plan risk responses (ARR), and the ability to implement risk responses. The same process is carried out for the other individual participants and their corresponding pairwise comparison matrices are generated.

The results of the pairwise comparison matrices are utilized to form the unweighted super matrix as shown in Table 4.5. The value of zero in that matrix is entered for the elements with no dependency. Accordingly, the weighted and limited super matrices are attained and the relative importance weight of each attribute is obtained as shown in Figure 4.2 As shown in that figure, the ability to plan risk responses is the most important attribute with the overall weight of 20%.

Table 4.4: Key decision factors pairwise comparison concerning the VP's opinion.

Factors	APR	AIR	AAR	ARR	AIRR	AMR
APR	1	1/2	1	1/2	1/2	1
AIR	2	1	2	1	1	2
AAR	1	1/2	1	1/2	1/2	1
ARR	2	1	2	1	1	2
AIRR	2	1	2	1	1	2
AMR	1	1/2	1	1/2	1	1

However, the least important attributes are identified as the ability to analyze risk as well as the ability to monitor risk with the overall weight of 13%. The remaining attributes including the ability to plan risk, the ability to identify risk and the ability to implement risk responses have almost the same importance with the overall weights of 17%, 19% and 18% respectively. These weights are multiplied to their corresponding degree of implementation score calculated based on Equations 3.1 to 3.5 and the overall expected value of the risk maturity level of the industrial partner's organization is calculated as shown in Table 4.6.

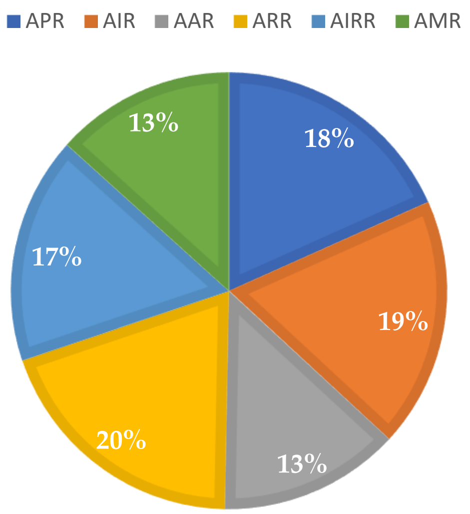


Figure 4.2: Attributes' importance.

Table 4.5: Unweighted super matrix.

Factors	APR	AIR	AAR	ARR	AIRR	AMR	VP	PD_1	PD_2	PD_3	PD_4	PD_5	PM_1	PM_2	PM_3	PPM_1	PPM_2	PPM_3	BC	RA
APR	0	0	0	0	0	0	0.111	0.096	0.111	0.363	0.307	0.154	0.153	0.166	0.200	0.166	0.166	0.210	0.166	0.143
AIR	0	0	0	0	0	0	0.222	0.096	0.222	0.182	0.154	0.154	0.307	0.166	0.200	0.166	0.166	0.0105	0.166	0.285
AAR	0	0	0	0	0	0	0.111	0.051	0.111	0.182	0.077	0.154	0.077	0.166	0.200	0.166	0.166	0.052	0.166	0.285
ARR	0	0	0	0	0	0	0.222	0.369	0.222	0.091	0.154	0.307	0.153	0.166	0.100	0.166	0.166	0.210	0.166	0.143
AIRR	0	0	0	0	0	0	0.222	0.193	0.222	0.091	0.154	0.154	0.153	0.166	0.200	0.166	0.166	0.210	0.166	0.071
AMR	0	0	0	0	0	0	0.111	0.193	0.111	0.091	0.154	0.077	0.153	0.166	0.100	0.166	0.166	0.210	0.166	0.071
VP	0.122	0.071	0.039	0.100	0.058	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PD1	0.122	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PD2	0.122	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PD3	0.122	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PD4	0.122	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PD5	0.122	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PM_1	0.020	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PM_2	0.020	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PM_3	0.020	0.071	0.078	0.100	0.104	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PPM_1	0.020	0.071	0.078	0.016	0.024	0.015	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PPM_2	0.020	0.071	0.078	0.016	0.024	0.015	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PPM_3	0.020	0.071	0.078	0.016	0.024	0.015	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BC	0.122	0.071	0.019	0.027	0.020	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RA	0.020	0.071	0.078	0.016	0.017	0.093	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4.6: Risk maturity score of industrial partner's organization.

Attributes	Attributes' Importance		Degree of Implementation		Attributes' Maturity Score
	Weights (ANP)	Rank	Fuzzy Number	Crisp Number	
APR	18.33	3	(0.075, 0.408, 0.655)	0.379	6.95
AID	18.55	2	(0.107, 0.453, 0.696)	0.419	7.77
AAR	13.42	5	(0.071, 0.282, 0.528)	0.294	3.94
ARR	19.54	1	(0.064, 0.396, 0.639)	0.366	7.15
AIRR	16.83	4	(0.092, 0.471, 0.703)	0.422	7.10
AMR	13.33	6	(0.05, 0.335, 0.582)	0.322	4.29
Industrial partner risk maturity score					37.2

The organization risk maturity score falls into the regions of low and medium as shown in Figure 3.5. As that figure shows, the low has a higher membership value than the medium when the X value is 0.372. Thus, the risk maturity level of the industrial partner is low. The maturity study reveals areas that need further improvement. For example, it is found that the risk performance of the industrial partner on risk analysis is lower than other areas with the degree of implementation equal to 29.4% as shown in Figure 4.3, indicating a call for more improvements in this area.

The model validation is conducted through using the feedback received from the individuals who participated in this study. A call for a meeting was made by the Assistant Director of the Innovation Department, inviting the individuals shown in Table 4.2 to review the final results. The comments received confirmed the applicability and validity of the developed model. It revealed that the risk maturity level of the industrial partner is at low level and its ability to analyze risk is the lowest attribute.

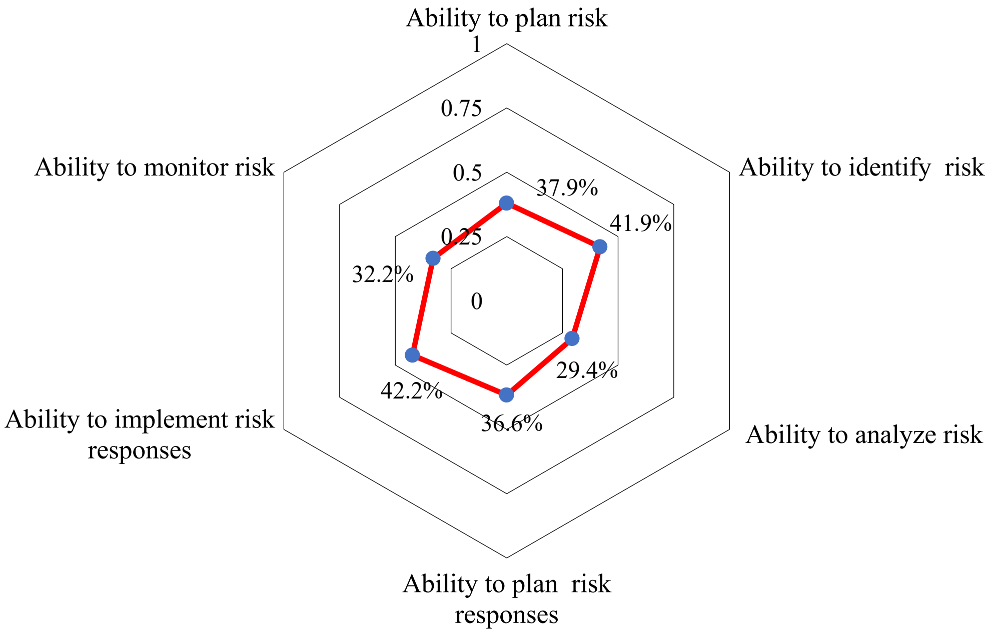


Figure 4.3 Degree of implementation for each attribute.

4.3. Case Example for Contingency Estimation

This section is a marginally modified version of "Risk Quantification Using Fuzzy-Based Monte Carlo Simulation" published in the journal of Information Technology in Construction (ITcon) (Moselhi and Roghabadi 2020) and has been reproduced here.

The cost data captured from Touran (1993) (second database) are utilized to validate the proposed method. Table 4.7 summarizes the cost data of the three sample cost items including electrical systems, mechanical systems, and moisture protection (the cost of roofing, insulation, and waterproofing) as reported by Touran (1993).

Table 4.7: Summary of actual cost data

Database	Cost item	Number of projects	Mean ($/ft^2)	Standard deviation ($/ft^2)
Touran (1993)	Electrical (1)	26	5.14	2.76
	Mechanical (2)	26	9.47	6.58
	Moisture protection (3)	26	1.81	2.12
	Total	26	16.6	10.5

The subjective correlation matrix of cost items is shown in Table 4.8.

Table 4.8: Most likely Subjective correlation matrix (Touran 1993)

Cost item	1	2	3
1	1		
2	0.8	1	
3	0.45	0.8	1

Based on the assumed variation range, the optimistic and pessimistic correlation matrices are generated and the application of the developed method yielded the results summarized in Table 4.9. The results indicated that the developed method outperforms those of Touran (1993) in estimating the standard deviation of project cost (1 % vs 0.01% error). It is interesting to note that same performance is experienced even in the application of the proposed method without simulation.

Table 4.9: Comparison of the results

Database	Method	Type of correlation	Standard deviation ($\$/ft^2$)	Difference from actual	Percentage of error
Touran (1993)	Actual	-	10.50	0.00	0.0
	Simulation (lognormal distribution)	Subjective	10.60	0.10	1
	Proposed method with simulation	Subjective	10.51	0.01	0.01
	Proposed method without simulation	Subjective	10.51	0.01	0.01

4.4. Case Example for Markup Estimation

This section is a marginally modified version of "Three Models for Estimating Bid Markups" published in 2018 AACE® International Transactions (Roghabadi and Moselhi 2018) and has been reproduced here.

The case study used by Hegazy (1993) is utilized for model validation. In that study, the data were collected from 72 contractors in Canada and the USA. This data accounts for quantitative as well as qualitative factors that affect bidding decisions. The data captured bidding situations experienced by those contractors on past projects. To facilitate the modeling process, thirty factors, recognized to impact the mark-ups of estimates and 23 of which are clustered in into five independent categories: need for work, job uncertainty, job complexity, market condition, and owner capability. The ANN and ANFIS models are developed using "MATLAB 2017a" and the results obtained by these methods are compared to their respective performance against the actual estimated markups by the contractors. Table 4.10 presents an abbreviated list of the actual input data and the associated bid markup percentage for each of the 72 projects and the estimated percent markup by the developed MR, ANN and ANFIS models.

Table 4.10: Actual data and the predicted data by MR, ANN and ANFIS

Project No.	INPUTS					Output	Predicted Markup		
	MF1	MF2	MF3	MF4	MF5	MF6 (Actual Markup)%	MR	ANFIS	NN_8
2	4	2.50	2.43	1.8	4.25		4.84	5.00	4.67
3	4	4.00	3.14	2.2	3.25		6.30	6.00	9.52
4	3	2.83	3.86	2.8	2.75		5.70	6.00	6.44
5	4	2.17	2.29	3.6	4.75		5.33	5.00	5.20
.	.	.	.	.	.		.	.	.
.	.	.	.	.	.		.	.	.
70	5	1.33	3.00	3	5		4.28	2.00	2.64
71	5	2.67	3.43	3	4.5		5.47	4.00	5.94
72	3	4.33	4.00	3.2	4		7.42	11.00	5.96

The accuracy of each model is accounted for by using the following two statistical indicators: root mean squared error (RMSE) and coefficient of determination (R^2).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y-\hat{y})^2} \qquad \text{Equation 4.1}$$

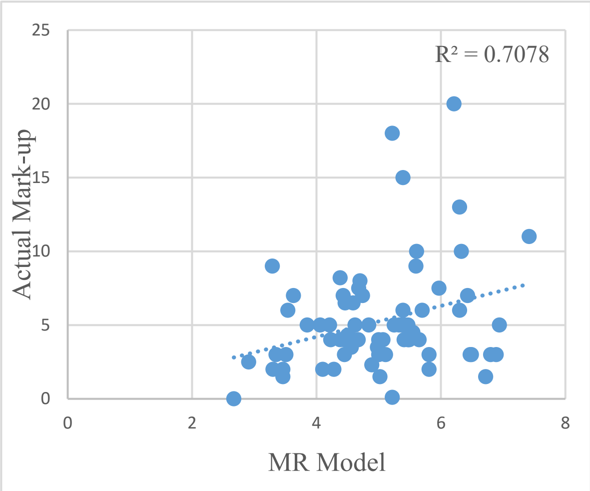
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y-\hat{y})^2}{\sum_{i=1}^{n}(y-y_{ave})^2} \qquad \text{Equation 4.2}$$

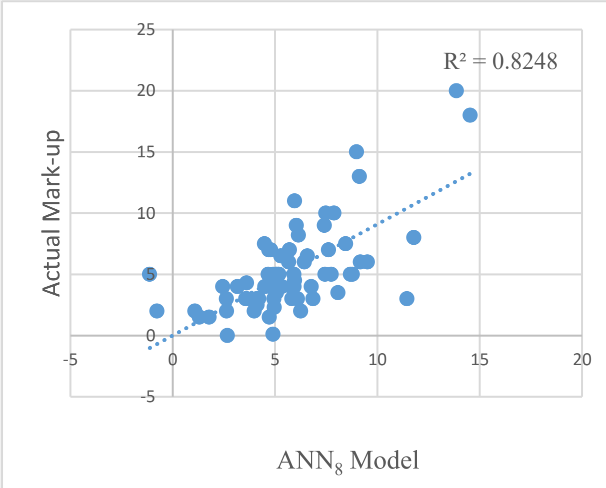
In the formula above, y and ŷ are the measured and predicted values, respectively, and N is the number of samples. The higher the R^2 value the better the model performance. For instance, $R^2 = 1$ means that the measured output has been estimated perfectly. $R^2= 0$ means that the model performs poorly. In addition, the lower the RMSE, the better the performance of the model.

Table 4.11: Comparison of errors in proposed models

Method	RMSE (%)	R^2 (%)
MR	11.98	7.44
ANFIS	4.58	64.98
ANN_8	7.48	44.51

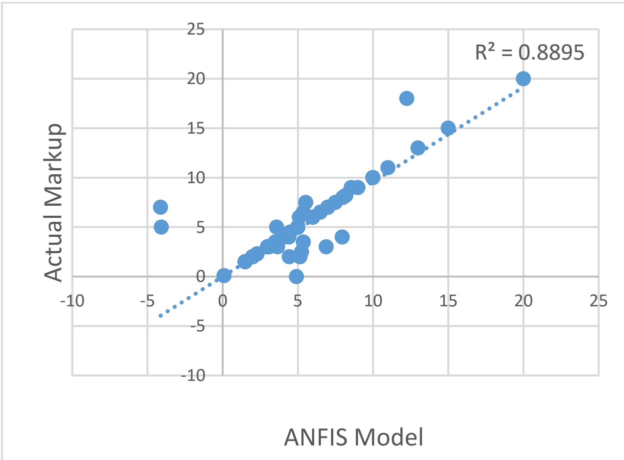
The analysis results shown in Table 4.11 indicates that the ANFIS model's predictions are more accurate than ANN_8 and MR indicating a coefficient correlation above 64%. Figure 4.4 shows visual comparison of coefficient of determination of proposed methods. As is observable, the ANFIS model's predictions have better performance compared with other models.





a) Performance of MR (Created by Excel)

b) Performance of ANN_8 (Created by Excel)



c) Performance of ANFIS model in predicting Markup (Created by Excel)

Figure 4.4: Comparison of coefficient of determination of proposed methods

4.5. Case Example for Trade-off Analysis

This section is a marginally modified version of "Optimized Crew Selection for Scheduling of Repetitive Projects" published in the journal of Engineering, Construction and Architectural Management (Roghabadi and Moselhi 2020b) and has been reproduced here.

A concrete bridge case study was adopted from the literature. The case study was analysed by several researchers (Selinger 1980, Russell and Caselton 1988, El-Rayes 1997, El-Rayes and Moselhi 2001, Long and Ohsato 2009, Bakry et al. 2016, Huang et al. 2016, Salama and Moselhi 2019). The project was separated into four major units and each unit included five repetitive activities as follows: excavation, foundations, columns, beams, and slabs Figure 4.5.

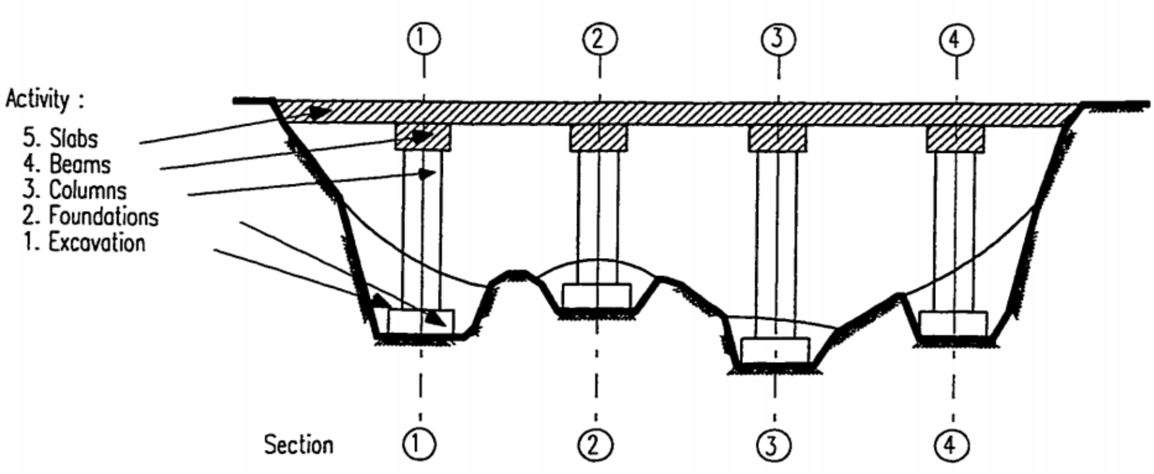


Figure 4.5: Three Span RC Bridge (Selinger, 1980)

Each activity is performed by availability of a set of crews. The activities are non-typical, which means that for each activity, work quantities and crews' productivity rates vary from one unit to another. Each crew in the set has its own productivity and cost. Table 4.12 shows the set of available crews for each activity in each unit. Selection of these crews forms a unique crew formation for the project. Each crew formation leads to a different project duration and cost. In expressing uncertainties associated with the input data related to these crews and activities, the same triangular fuzzy numbers used by Bakry et al. (2016) were utilized here to enable a comparison as illustrated in Table 4.12.

Table 4.12: Input of quantities for activities (Bakry et al., 2016)

Activity	Quantities (m^3)				Output of Available Crew (m^3/day)			
	Unit 1	Unit 2	Unit 3	Unit 4	Crew No.	a	b	c
Excavation	1,147	1,434	994	1,529	1	82.6	91.8	105.5
Foundations	1,032	1,077	943	896	1	85.3	89.8	103.2
					2	61	71.8	82.6
					3	43.1	53.9	67.3
Columns	94 104 130	82 86 103	103 129 155	95 100 125	1	5.7	-	-
					2	6.9	-	-
					3	8	-	-
Beams	85	92	101	80	1	9.9	-	-
					2	8.5	-	-
					3	7.1	-	-
					4	5.7	-	-
Slabs	0	138	114	145	1	7.9	8.7	10.5
					2	7	7.8	9.7

The fuzzy numbers in Table 4.12 represent the uncertainty associated with the quantity of columns and the productivity rate of excavation, foundations and slabs. Project indirect cost was considered $1,000 per day as included in the analysis of Bakry et al. (2016). Also, it is assumed that the contingency budget and the project markup are considered in the total project cost enabling comparison. The results of Bakry et al. (2016) and Salama and Moselhi (2019) were used for comparison. They represented uncertainty utilizing fuzzy inputs for this example.

The developed model was run ten times to indicate the impact of changing weights' values of project duration on the optimized project schedule. This is done by assignment of a different set of weights for project duration, project cost, crew work interruptions, and interruption costs to determine the optimum crew formation at unit execution level that leads in the least MOF as shown in Table 4.13 As shown in that table, each set of allocated weights was run three times to ensure the stability of the optimum solution as considered by Agrama (2014).

The first and the second runs optimized project duration without and with interruptions, respectively. These two runs indicate the capability of the developed model in considering interruptions where needed. They also show that the developed model is capable of converting a multi-objective optimization model into a single optimization model by assigning 1 as a weight for the required objective and 0 for the rest. In the third and the fourth runs the minimum importance weight of 0.1 was assigned for project cost and crew work interruptions, respectively, indicating the impact of each objective on the optimized schedule. The unique aspects of the developed model were highlighted in the fifth, sixth, and seventh runs. In other words, runs five and six were designed to show how relaxing activities at unit execution level within their activity relaxation free float leads to minimizing project cost, crew work interruptions, and interruption costs with no impact on the optimized project duration. The seventh run was designed to illustrate the relative importance of interruption costs, as a new objective, during the optimization process. This run was also utilized along with the eighth and ninth runs to investigate whether considering equal weights for project cost, crew work interruptions, and interruption costs lead to achievement of the same set of optimal solutions for the three runs of each set of allocated weights. And finally, the last run was designed to optimize project cost considering no interruption for the purpose of verification.

Table 4.13: Effect of changing weights' values of project duration on optimized schedule

Scenario								Optimized objectives				
Runs	Allow interruption	Allow relaxation	W_d	W_c	W_{id}	W_{ic}	No.	PD (Days)	TC ($)	TDI (Days)	TCI ($)	MOF
							1		1,511,321			
1	No	No	1	0	0	0	2	114.8	1,515,164	0	0	0.92933
							3		1,515,187			
							1		1,516,270	15.4	14,041	
2	Yes	No	1	0	0	0	2	105.5	1,509,820	19.6	15,941	0.85413
							3		1,516,270	15.4	14.041	
							1					
3	Yes	No	0.9	0.1	0	0	2	120.9	1,508,404	20.8	17,278	0.8673
							3					
							1		1,511,569		10,463	
4	Yes	No	0.9	0	0.1	0	2	109.1	1,509,231	7.19	9,025	0.82606
							3		1,510,304		9.501	
							1					
5	Yes	No	0.8	0.1	0.1	0	2	111.5	1,502,413	3.4	4,793	0.83501
							3					
							1					
6	Yes	Yes	0.8	0.1	0.1	0	2	109.6	1,502,979	6.9	7,222	0.83878
							3					
							1					
7	Yes	No	0.7	0.1	0.1	0.1	2	116.0	1,500,914	0	0	0.75591
							3					
							1	118.4	1,495,104	0	0	0.57889
8	Yes	No	0.4	0.2	0.2	0.2	2	118.4	1,495,104	0	0	0.57889
							3	116.0	1,500,914	0	0	0.57224
							1					
9	Yes	No	0.1	0.3	0.3	0.3	2	119.1	1,491,702	0	0	0.38889
							3					
							1					
10	No	No	0	1	0	0	2	141.11	1,463,835	0	0	0.95662
							3					

However, the results of the first, fifth, sixth, seventh, and tenth runs are utilized to compare the performance of the developed model with those of other models reported in the literature as shown in Table 4.14.

Table 4.14: Comparison of the results

Runs	Weights of MOF				Allow relaxation	Criteria	Developed Model	Salama and Moselhi (2019)	Bakry et al. (2016)
	W_d	W_c	W_{id}	W_{ic}					
1	1	0	0	0	No	TC	114.8	115.8	128
						PD	1,511,321	1,506,009	1,511,657
						TDI	0	0	0
						TCI	0	0	0
5	0.8	0.1	0.1	0	No	TD	111.5	109.6	-
						PC	1,502,413	1,505,960	-
						TDI	3.42	8.3	-
						TCI	4,793	8,300	-
6	0.8	0.1	0.1	0	Yes	TD	109.6	109.6	-
						PC	1,502,979	1,505,960	-
						TDI	6.9	8.3	-
						TCI	7,222	8,300	-
7	0.7	0.1	0.1	0.1	No	TD	116.06	-	-
						PC	1,500,914	-	-
						TDI	0	-	-
						TCI	0	-	-
10	0	1	0	0	No	TD	141.11	141.11	-
						TC	1,463,835	1,463,835	-
						TDI	0	0	-
						TCI	0	0	-

Notes: PD, optimized value of project duration (days), TC, optimized value of project total cost ($), TDI, optimized value of total duration of interruptions (days), TCI, optimized value of interruption costs ($).

As shown in that table, in the first run, the developed model provided an improvement of 0.9% and 10.3% in minimizing project duration from 115.8 in Salama's case and 128 in Bakry's case to 114.8 days, respectively. The reason behind that is that the developed model considers crews at the unit execution level allowing activity acceleration and relaxation. This particular aspect of the developed model leads to spending acceleration resources for right activities in right repetitive units. For instance, as shown in Table 4.15, based on the model of Salama and Moselhi (2019), the optimum crew formation for all the units of the foundation is crew number 2 with productivity rate equal to 71.81 (m^3/day), while based on the described procedure for the application of the developed model, units 1, 3 and 4 for the foundation should be accelerated using crew number 1 which has a productivity rate of 92.76 (m^3/day) as shown in Figure 4.6.

Table 4.15: Optimizing project duration with no interruption

Method	Weights of MOF			Optimum crew formation per each unit of each activity																				Project time (Days)
				Excavation				Foundations				Columns				Beams				Slabs				
	W_d	W_c	W_i	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	
Bakry et al. (2016)	1	0	0	1	1	1	1	2	2	2	2	3	3	3	3	3	3	3	3	-	2	2	2	128
Salama and Moselhi (2019)	1	0	0	1	1	1	1	2	2	2	2	3	3	3	3	3	3	3	3	-	1	1	1	115.8
Developed model	1	0	0	1	1	1	1	1	2	1	1	3	3	3	3	3	3	3	2	-	1	1	1	114.8

This acceleration leads to a one day reduction on the final project duration in comparison to the result of Salama and Moselhi (2019) that allows for benefiting from bonus payments and avoiding delay penalties. The limited improvement of project duration (one day) is attributed mainly to the scope and size of the illustrative example. Its impact on large scale repetitive construction projects having more repetitive units and activities can be much larger.

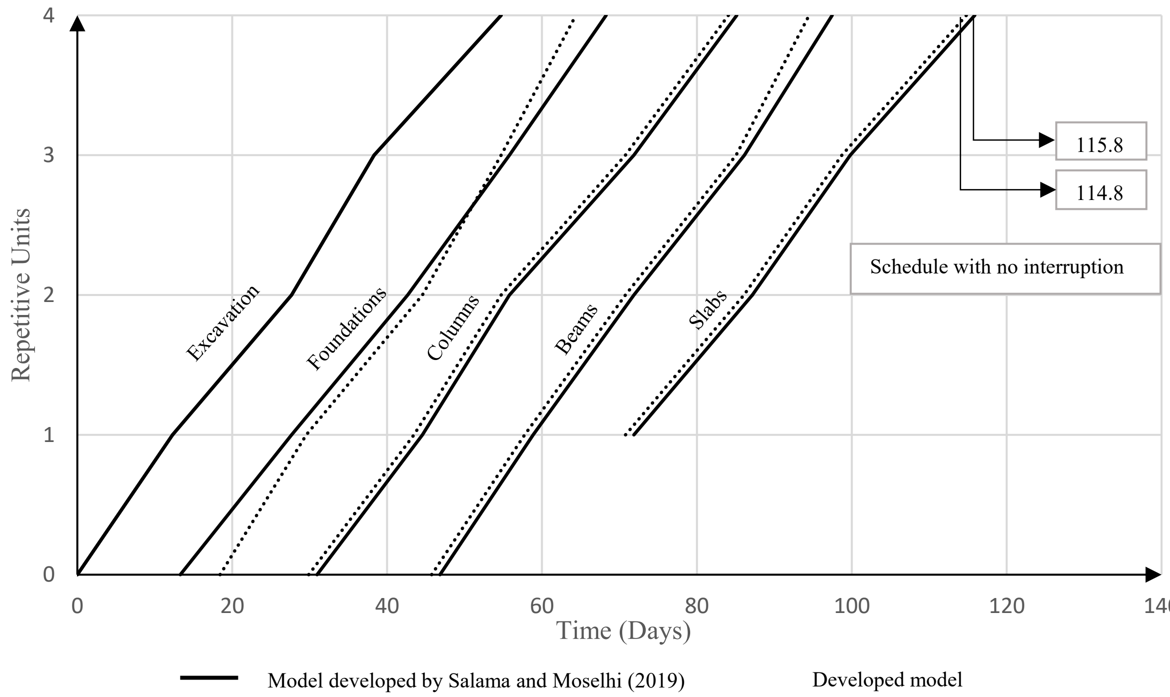


Figure 4.6: Comparison of optimized schedule generated by Salama and Moselhi (2019) and developed model

In the fifth run, the model was assigned importance weights of 0.1, 0.8, and 0.1 for project cost, project duration, and crew work interruptions, respectively, to enable a comparison with the result of Salama and Moselhi (2019). The results of this run are shown in Table 4.14. As shown in that table, the developed model provides an improvement of 0.2%, 58.8%, 42.3% in minimizing project cost, crew work interruptions, and interruption costs, respectively. It, however, increased project duration 1.7% which resulted in assignment of more acceleration resources to units 1 and 3 of foundation as shown in Figure 4.7.

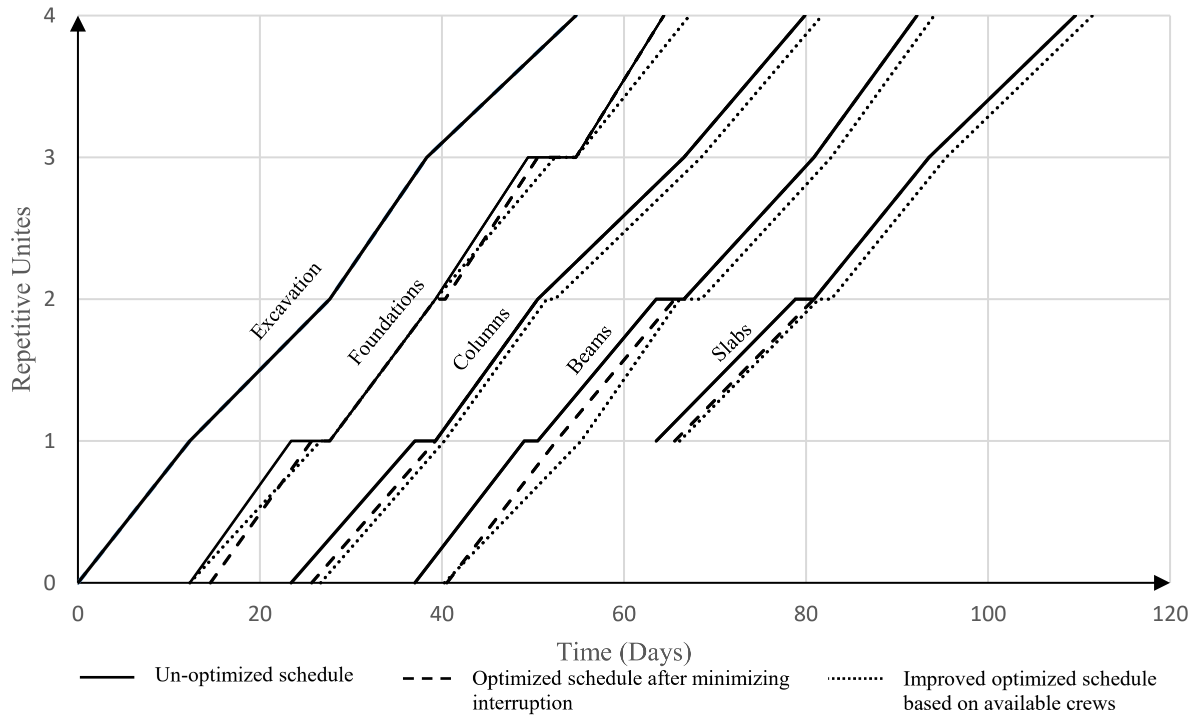


Figure 4.7 Comparison of crew work interruption (run two)

Therefore, the sixth run is designed to prevent the assignment of unnecessary acceleration resources for unit 1 and 3 of foundation by relaxing their production rates within their activity relaxation free float. The developed model is run assuming the same weights used in the fifth run to enable a comparison as shown in Table 4.16.

Table 4.16: Comparison with results of Salama and Moselhi (2019) for optimizing total interruptions

Method	Optimum crew formation per each unit of each activity																				Total Interruption (days)	Project duration (days)
	Excavation				Foundations				Columns				Beams				Slabs					
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4		
Salama and Moselhi (2019)	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	-	1	1	1	8.73	109.6
Developed model-available crews	1	1	1	1	2	1	2	2	3	3	3	3	4	2	3	3	-	1	1	1	3.42	111.48
Developed model-required crews	1	1	1	1	1*	1	2*	2	3	3	3	3	3	3	3	3	-	1	1	1	6.89	109.6

The feasible boundaries for activity relaxation in units 1 and 3 of foundation are identified as the difference between the un-optimized schedule and the optimized schedule that minimized crew work interruptions as shown in Figure 4.8.

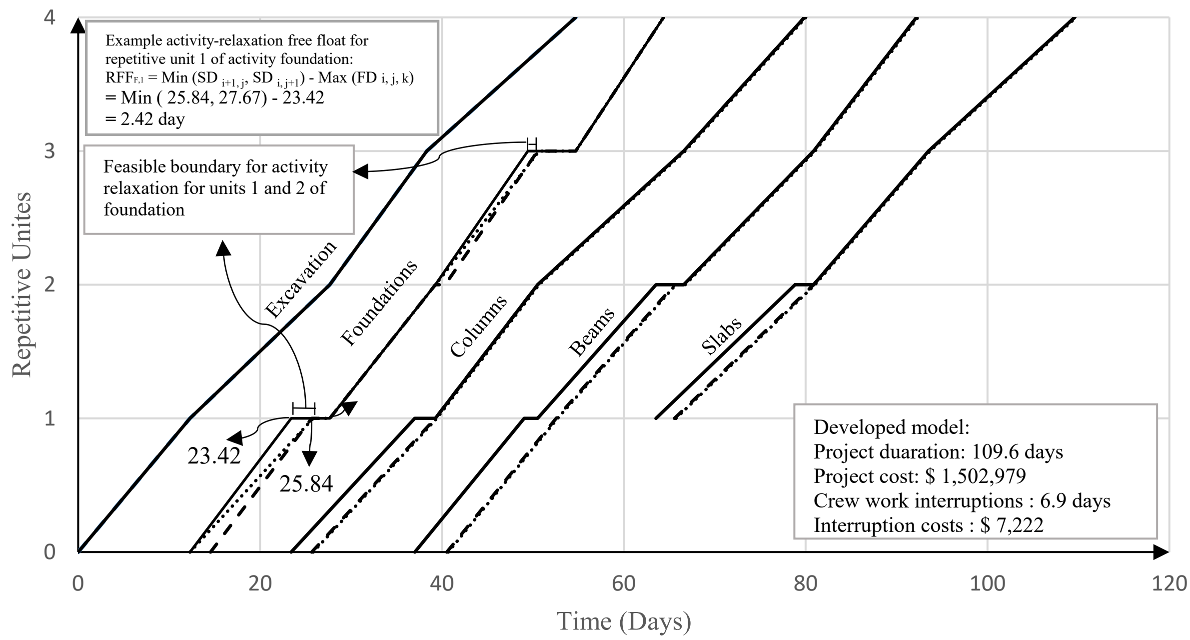


Figure 4.8 Comparison of crew work interruption (run three)

The required crew productivity rate for units 1 and 3 of foundation are calculated as 76.21 (m^3/day) and 82.79 (m^3/day), respectively after applying the third stage of the developed algorithm. As stated earlier, idle cost and mobilization and demobilization costs are considered in order to calculate interruption costs. The input data for interruption costs calculation are summarized in Table 4.17.

In this example, $T_{min,i}$ was assumed to be equal to one day for all construction crews. By comparing the result of this run with that of Salama and Moselhi (2019), it is noticed that by relaxing unit 1 and 3 of foundation within their activity relaxation free float, the project cost, crew work interruptions and interruption costs are improved 0.2%, 16.86%, and 12.98%, respectively with no impact on the optimized project duration as indicated in Table 4.14.

Table 4.17: Interruption costs data for the sixth run

Activity	Repetitive section	Quantities (m^3)	Optimum Crew	Crew Output(m^3/day)	Duration (day)	LC_i (\$/day)	MDC_i (\$)	MDT_i (day)
Excavation	1	1147	1	93.28	12.29	566	700	1
	2	1434	1	93.28	15.37	566	700	1
	3	994	1	93.28	10.65	566	700	1
	4	1529	1	93.28	16.39	566	700	1
Foundation	1	1032	1*	76.21	13.54	3,027	400	0.5
	2	1077	1	92.76	11.61	3,804	400	0.5
	3	943	2*	82.79	11.39	3,289	400	0.5
	4	896	2	92.76	9.66	3,804	400	0.5
Columns	1	109.2	3	8.03	13.59	3,000	400	0.5
	2	90.3	3	8.03	11.24	3,000	400	0.5
	3	129	3	8.03	16.04	3,000	400	0.5
	4	106.67	3	8.03	13.28	3,000	400	0.5
Beams	1	85	3	7.07	12.02	2,544	700	0.5
	2	92	3	7.07	13.01	2,544	700	0.5
	3	101	3	7.07	14.28	2,544	700	0.5
	4	80	3	7.07	11.31	2,544	700	0.5
Slabs	1	0	-	-	-	-	400	0.5
	2	138	1	9.02	15.3	2,230	400	0.5
	3	114	1	9.02	12.64	2,230	400	0.5
	4	145	1	9.02	16.07	2,230	400	0.5

In the seventh run, the model was assigned the minimum importance weight of 0.1 for the total interruption costs as well as importance weights of 0.7, 0.1, and 0.1 for project duration, project cost, and crew work interruptions, respectively as shown in Table 4.14.

By comparing the result of the sixth and the seventh run, it is noticed that by assigning the minimum importance weight of 0.1 for interruption costs, the project cost, crew work interruptions and interruption costs are improved by 0.14%, 100%, and 100%, respectively. However, project duration is increased 5.9% because of the small weight assigned to this objective in this run compared to the sixth run.

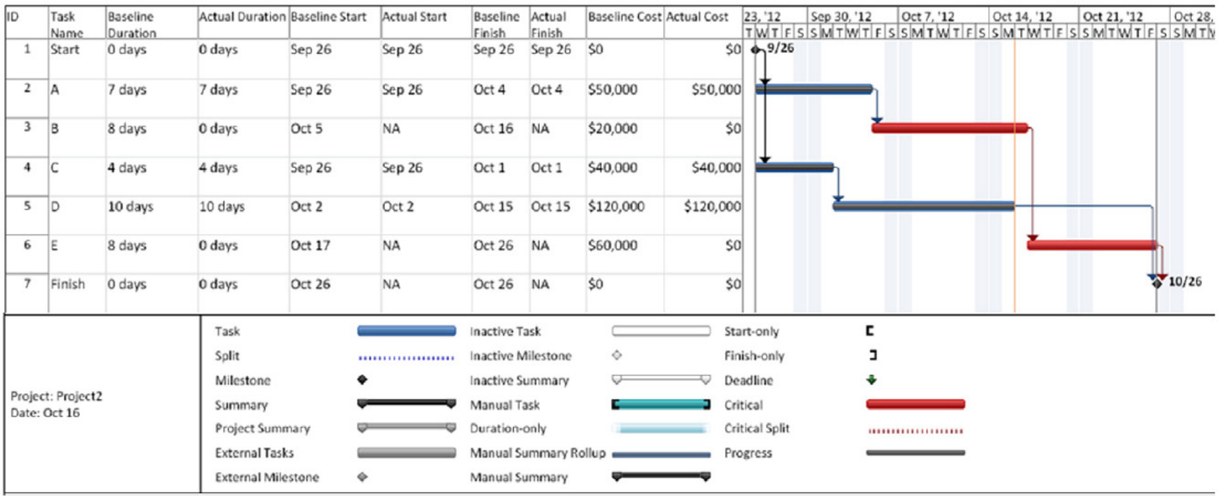
The logic of the developed model is verified in the last run. As shown in the Table 4.14, the output of the developed model for the tenth run is exactly the same as that of Salama and Moselhi (2019).

The generated outputs of the different runs show the capability of the developed model in providing optimal solutions which consider simultaneously the trade-off between four objectives including project duration, project cost, crew work interruptions, and interruption costs. For instance, the developed model produced the same set of optimal solutions for the three runs of the third, fifth, sixth, seventh, ninth, and tenth runs as shown in Table 4.13. However, different optimal solutions are achieved for the remaining runs. In addition, it is found that considering equal weights for project cost, crew work interruptions, and interruption costs while assigning reduced weights to project duration does not guarantee the achievement of the same set of optimal solutions as shown in run eight, Table 4.13

4.6. Case Example for Earned Value Management

This section is a marginally modified version of "Forecasting Project Duration Using Risk-Based Earned Duration Management" under review in the International Journal of Construction Management (Roghabadi and Moselhi 2020c) and has been reproduced here.

The numerical example of Khamooshi and Golafshani (2014) is used here to demonstrate the limitation of the existing models in monitoring and estimating project schedule performance. The Microsoft Project report of the case example is shown in Figure 4.9.



ID	Task Name	Baseline Duration	Actual Duration	Baseline Start	Actual Start	Baseline Finish	Actual Finish	Baseline Cost	Actual Cost
1	Start	0 days	0 days	Sep 26	Sep 26	Sep 26	Sep 26	$0	$0
2	A	7 days	7 days	Sep 26	Sep 26	Oct 4	Oct 4	$50,000	$50,000
3	B	8 days	0 days	Oct 5	NA	Oct 16	NA	$20,000	$0
4	C	4 days	4 days	Sep 26	Sep 26	Oct 1	Oct 1	$40,000	$40,000
5	D	10 days	10 days	Oct 2	Oct 2	Oct 15	Oct 15	$120,000	$120,000
6	E	8 days	0 days	Oct 17	NA	Oct 26	NA	$60,000	$0
7	Finish	0 days	0 days	Oct 26	NA	Oct 26	NA	$0	$0

Figure 4.9: Microsoft Project report of the numerical example (Khamooshi and Golafshani 2014)

As shown in that figure, the project consists of five activities (A, B, C, D, E), A, B and E are critical and C and D are non-critical. The project baseline duration is 23 days and the latest progress period is at day 14. In this example, it is assumed that the project baseline duration is optimized based on the available resources enabling comparison with the models provided in the literature.

The example is also used to enable a comparison with other methods. It is assumed that all the activities (critical and non-critical) are on time and on budget except critical activity B which has not yet started. Table 4.18 shows the EVM and EDM data of the case example at the end of the reporting period.

Table 4.18: EVM and EDM data

EVM parameters (cost-based data)				EDM parameters (time-based data)			
Working day	EV	PV	AC	Working day	TED	TPD	TAD
1	17,143	17,143	17,143	1	2	2	2
2	34,286	34,286	34,286	2	4	4	4
3	51,429	51,429	51,429	3	6	6	6
4	68,571	68,571	68,571	4	8	8	8
5	87,714	87,714	87,714	5	10	10	10
6	106,857	106,857	106,857	6	12	12	12
7	126,000	126,000	126,000	7	14	14	14
8	138,000	140,500	138,000	8	15	16	15
9	150,000	155,500	150,000	9	16	18	16
10	162,000	169,500	162,000	10	17	20	17
11	174,000	184,500	174,000	11	18	22	18
12	186,000	198,500	186,000	12	19	24	19
13	198,000	213,000	198,000	13	20	26	20
14	210,000	227,500	210,000	14	21	28	21

Note: EV (earned value), PV (planned value), AC (actual cost), TED (total earn duration), TPD (total plan duration), TAD (total actual duration),

Accordingly, the performance indicators of the project at the end of the reporting date are calculated separately based on EVM, ESM, and EDM as shown in Table 4.19.

Table 4.19: EVM, ESM and EDM performance indicators

EVM performance indicators (cost-based data)		ESM performance indicators (cost-based data)		EDM performance indicators (time-based data)	
Performance indicators	Value ($)	Performance indicators	Value (days)	Performance indicators	Value (days)
EV(t=14)	210,000	ES(t=14)	12.8	BPD	23
PV(t=14)	227,500	AD(t=14)	14	AD(t=14)	14
SPI	0.92	SPI (t)	0.91	TPD(t=14)	28
-	-	-	-	TED(t=14)	21
-	-	-	-	ED(t=14)	10.5
-	-	-	-	DPI(t=14)	0.75
-	-	-	-	EDI(t=14)	0.75

Note: EV (earned value), PV (planned value), AC (actual cost), TED (total earn duration), TPD (total plan duration), TAD (total actual duration),

As shown in Table 4.19, it is evident that the schedule performance evaluation based on EVM and ESM provide misleading schedule performance indicators with the values of 0.92 and 0.91, respectively. Therefore, EDM with the DPI equal to 0.75 is considered as a more reliable index for performance evaluation of project schedule at the reporting date. However, the DPI equal to 0.75 still does not fully represent the correct status of the schedule performance. In other words, considering non-critical activity D which performed as planned and has overlap with critical activity B overshadows the delay of critical activity B. In order to address this limitation DPI-cr and EDI-cr are calculated considering critical activities only based on the described procedures of the developed model as shown in Table 4.20.

Table 4.20: EDM based on critical activities

EDM-cr performance indicators	
Performance indicators	Value (days)
BPD	23
AD-$cr_{(t=14)}$	14
TPD-$cr_{(t=14)}$	14
TED-$cr_{(t=14)}$	7
ED-$cr_{(t=14)}$	7
DPI-$cr_{(t=14)}$	0.5
EDI-$cr_{(t=14)}$	0.5

As shown in Table 4.20, considering critical activities provides a more accurate and realistic performance of the project schedule. Based on the information provided in that table, it is obvious that the project is 50% behind schedule at the reporting date, which is equivalent to the delay of critical activity B in that day. In order to calculate the estimated project duration at completion, the described procedures of the developed model are employed. First, the RAF_{cr} for the remaining time to project completion is calculated. Table 4.21 shows the risk adjustment factor associated with each critical activity.

Table 4.21: Risk adjustment factor associated with the critical activities

Activity	% of completion	Risk category	Category importance weight	Risk description	Risk impact	Risk likelihood	RAF
A	100	-	-	-	-	-	-
		Safety	0.2275	Accident frequency ratio	0.3064	0.724	
				Safety training	0.1953	0.822	
				Utilizing safety equipment	0.2084	0.680	
				Utilizing safety and health standards	0.2896	0.756	
		Quality	0.2103	Staff training quality	0.2048	0.756	
				Labor productivity	0.2625	0.611	
				Rework and defects	0.2559	0.567	
B	0			Raw material quality	0.2769	0.724	0.6225
		Scope	0.2867	Scope creep	0.2624	0.611	
				Integration defects	0.2651	0.381	
				Inadequate defend scope	0.1781	0.450	
				Change in legal od regularity framework	0.2942	0.332	
				Employee absence	0.1836	0.796	
		Resource	0.2753	Employee turnover	0.2361	0.756	
				Insufficient funds	0.2633	0.498	
				Depreciation of equipment	0.3169	0.724	
		Safety	0.2275	Accident frequency ratio	0.3064	0.724	
				Safety training	0.1953	0.822	
				Utilizing safety equipment	0.2084	0.680	
E	0			Utilizing safety and health standards	0.2896	0.756	0.6225
		Quality	0.2103	Staff training quality	0.2048	0.756	
				Labor productivity	0.2625	0.611	
				Rework and defects	0.2559	0.567	
				Raw material quality	0.2769	0.724	

Table 4.21: Continued.

Activity	% of completion	Risk category	Category importance weight	Risk description	Risk impact	Risk likelihood	RAF
E	0	Scope	0.2867	Scope creep	0.2624	0.611	0.6225
				Integration defects	0.2651	0.381	
				Inadequate defend scope	0.1781	0.450	
				Change in legal od regularity framework	0.2942	0.332	
		Resource	0.2753	Employee absence	0.1836	0.796	
				Employee turnover	0.2361	0.756	
				Insufficient funds	0.2633	0.498	
				Depreciation of equipment	0.3169	0.724	

The same assumptions made by Hamzeh et al. (2020) are considered here to enable a comparison. In other words, 16 risk factors are assumed for each critical activity which are grouped under four different categories including safety, quality, scope, and resource risks. Unlike Hamzeh et al. (2020) who calculated the risk performance index at the macro level based on critical and non-critical activities, risk is considered in this research at the micro level and only for critical activities. In addition to that, their model did not consider the uncertainties associated with activities beyond the reporting date. The same crisp numbers considered by Hamzeh et al. (2020) are assumed for risk impacts and their likelihoods to enable a comparison. Table 4.21 shows the risk adjustment factor RAF associated with each critical activity.

As shown in that table no RAF is considered for critical activity A because it is already completed. However, the RAF associated for the two remaining critical activities is calculated as shown in Table 4.21. The same condition is assumed for both activities enabling comparison. Accordingly, the RAF_{cr} for the remaining time to project completion is calculated as 0.6225. Equation 3.58 is employed to calculate the estimated project duration at completion. As shown in that equation, the weightings associated with the DPIcr, EDIcr, and RAFcr are required for forecasting EDAC. Since the progress monitoring period is at the third quarter of the project, the 0.2525, 0.436, and 0.3114 weights are considered for DPIcr, EDIcr, and RAFcr respectively as considered by Hamzeh et al. (2020). Table 4.22 shows the estimated time at completion utilizing the developed model.

Table 4.22: Estimated time at completion considering critical activities and their corresponding risk factors

EDM-cr performance indicators	
Performance indicators	Value
BPD	23
AD-cr$_{(t=14)}$	14
TPD-cr$_{(t=14)}$	14
TED-cr$_{(t=14)}$	7
ED-cr$_{(t=14)}$	7
DPI-cr$_{(t=14)}$	0.5
EDI-cr$_{(t=14)}$	0.5
RAFcr	0.6225
EDAC	43.73

In order to demonstrate the capability of the developed model over the models reported in the literature, a comparison is carried out with those of Lipke et al. (2009), Moselhi (2011), Khamooshi and Golafshani (2014), Wood (2018), and Hamzeh et al. (2020). Figure 4.10 shows the schedule performance associated with each of those models at the reporting date. As shown in that figure, the first three models relying on cost-based data for schedule performance evaluation resulted in over optimistic estimation of the schedule performance with values of 0.92, 0.74, and 0.91 for SPI, SPI_{cr}, and $SPI_{(t)}$, respectively. This is mainly due to non-critical activity D which has high cost overshadowing the delay of critical activities. The studies conducted by Khamooshi et al. (2014) and Hamzeh et al. (2020) both utilize the time-based data for schedule performance evaluation of the projects. However, they both considered the progress of all project activities at the reporting date, underestimating the delay of critical activities with the DPI equal to 0.75.

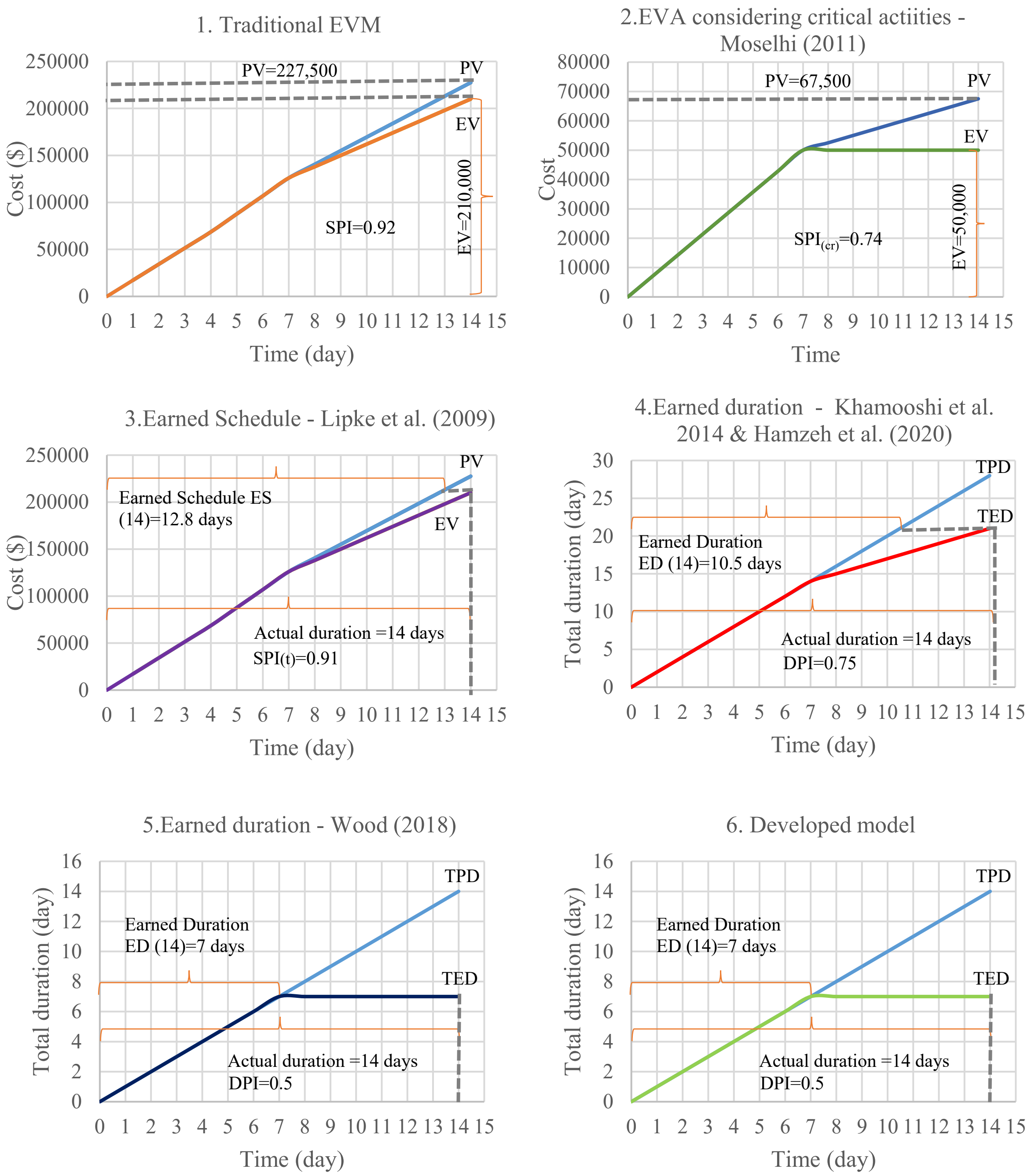


Figure 4.10: Schedule performance using cost-based and time-based data

As shown in that figure, the first three models relying on cost-based data for schedule performance evaluation resulted in over optimistic estimation of the schedule performance with values of 0.92, 0.74, and 0.91 for SPI, SPI_{cr}, and $SPI_{(t)}$, respectively. This is mainly due to non-critical activity D which has high cost overshadowing the delay of critical activities. The studies conducted by Khamooshi et al. (2014) and Hamzeh et al. (2020) both utilizes the time-based data for schedule performance evaluation of the projects. However, they both considered the progress of all project activities at the reporting date underestimating the delay of critical activities with the DPI equal to 0.75. The study conducted by Wood (2018) is the only research that considers only the earned duration of critical activities in estimating project duration at completion providing a more realistic schedule performance of the project with DPI equal to 0.5. It, however, utilized past performance data for estimating project duration at completion with no consideration of the future uncertainties. The model developed in this research addresses this limitation and estimate project duration at completion utilizing the past and future performance data of critical activities.

Figure 4.11 shows a comparison between the results of the developed model and those of the models referred to above.

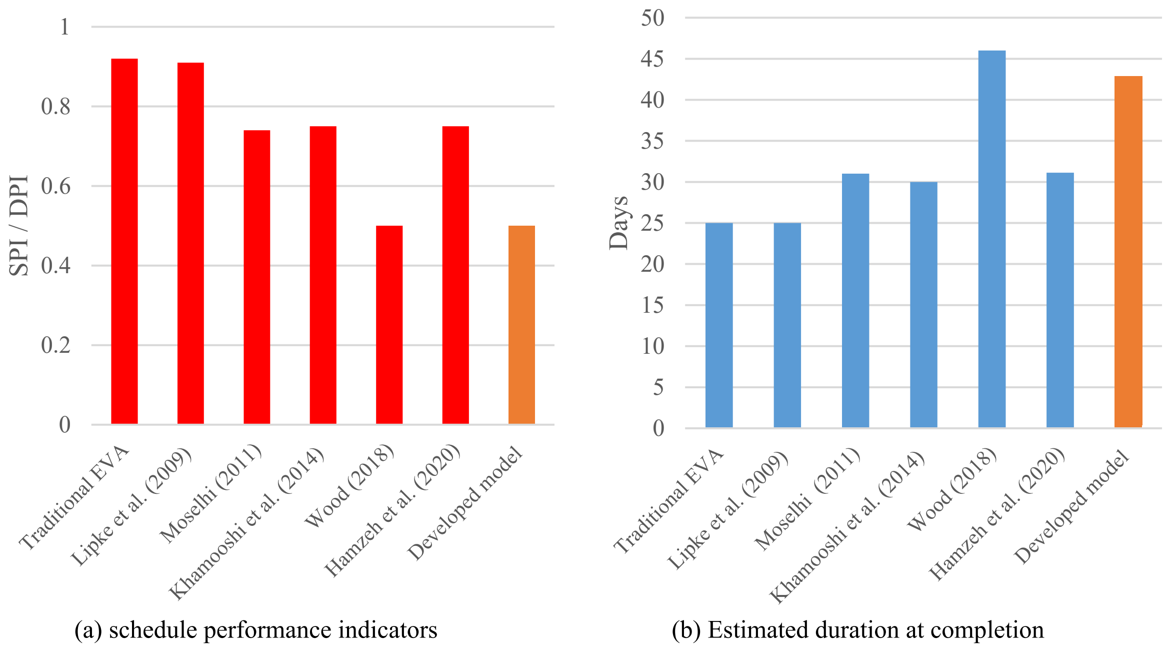


Figure 4.11: Comparisons of the estimated project duration at completion with different models.

As shown in that figure, all models confirmed that the project is behind schedule (see Figure 8-a) at the reporting date. However, each one reported a different amount of delay which in turn leads to different estimates of project duration at completion. Figure 8-b shows the estimated project duration at completion based on each model.

As shown in that figure, the developed model yielded more realistic forecasted time to completion in comparison to related models reported in the literature.

For instance, as shown in Figure 4.11, part b, the model recently proposed by Wood (2018) resulted in a pessimistic estimation of the project duration at completion with an overall estimation of 46 days. This is attributed to its assumption that considers the performance attained so far will continue to project completion, which might not occur. In contrast, the model recently proposed by Hamzeh et al. (2020) provided an optimistic estimation of the project duration at completion of 31.12 days. The reason here for that optimistic estimate is that their method does not differentiate between critical and non-critical activities in forecasting project duration at completion, which overshadows the delays of critical activities.

The developed model, on the other hand, yielded an estimate that circumvents the limitations of the above two models. It accounts for critical activities and their associated future uncertainties in forecasting project duration at completion. Accordingly, it provides project managers with a more accurate and realistic estimation of the required time to project completion and assists them in taking informed corrective actions where needed.

CHAPTER 5: CONCLUSION

5.1. Summary and Concluding Remarks

This research introduces a comprehensive risk-based framework that houses five newly developed models, encompassing management functions from project front-end to reporting its progress, through its planning and scheduling. The framework has five newly developed models: risk maturity evaluation, contingency estimation, markup estimation, scheduling with time-interruption-cost trade-off analyses, and earned value management (EVM) analysis.

The first model presented a novel decision support model for evaluating the risk management maturity level of construction organizations. It can assist construction organizations to have a clear view of their capabilities and weaknesses in risk management processes and help them in recognizing areas that need improvements. Unlike the existing risk maturity models reported in the literature, the developed model considered different relative weights for the responses provided by different individuals. It accounted for the authority level of the participants and their level of involvement in their risk management processes. This unique aspect of the developed model allows construction organizations to assign a higher weight to the responses provided by individuals who are at portfolio or program levels of the organization and have an adequate knowledge of risk management, which in turn leads to a more accurate and reliable evaluation of the risk maturity level of the organization. Moreover, the developed model is capable of accounting for the interdependency between the risk maturity attributes and for the subjectivity and imprecision in the responses of the participants involved in its development.

The second model presented a novel method for estimating project cost contingency considering correlations among project cost items, either subjective or objective, and performs the calculations with or without using Monte Carlo simulation. As such, the method provides considerable flexibilities in estimating project contingency to accommodate situations where data needed for the use of MCS may not be available. It is particularly useful when using subjective correlations. The results of its application on examples adopted from the literature demonstrated its good accuracy in comparison with other methods.

The third model introduced new pattern recognition techniques for estimating project markup. The analysis results indicate that the developed Artificial Neural Network (ANN) model outperformed the Multiple Regression (MR) model, and that the developed Neuro-Fuzzy Inference System (ANFIS) model outperforms both.

The fourth model presented a novel multi-objective optimization method that considers simultaneously the trade-offs between four objectives: project duration, project cost, crew work interruptions and interruption costs. The developed model identifies the optimum crew formations at the unit execution level in repetitive construction projects accounting for crew availability. It introduces a novel activity relaxation free float that considers the effect of postponing the early finish dates of repetitive activities on crew work interruptions. The introduced float allows for calculating the required crew productivity rate that minimizes crew work interruptions, without delaying the successor activities and without impacting the optimized project duration.

The fifth model presented a novel method for monitoring and estimating schedule performance employing past performance data of critical activities as well as their future uncertainties. The developed model introduces a new risk adjustment factor (RAFcr) that quantifies the impact of future uncertainties of critical activities in estimating project duration at completion. The introduced (RAFcr) overcomes the prime limitation of EDM in its reliance on past performance data only. This particular aspect of the developed model provides project managers with more accurate and realistic estimation of the required time to project completion and assists them in taking early corrective actions, as needed. The results of the illustrative example highlight the contributions of the developed model in its accurate and realistic estimate of time to completion.

5.2. Research Contributions

The main contributions of this research are:

- Developing a new model for risk maturity evaluation of construction organizations that accounts for individuals' level of authority in the organization and their level of expertise in risk management.
- Developing a novel contingency estimation model that considers correlations among project cost items subjectively and objectively, and performs the calculations with or without using Monte Carlo simulation.
- Providing a comparative study on the use of Multiple Regression (MR), Artificial Neural Network (ANN) and Adaptive Nero-Fuzzy Inference System (ANFIS) techniques for estimating project markup considering need for work, job uncertainty, job complexity, market condition, and owner capability.
- Developing a new multi-objective optimization model that considers simultaneously trade-offs among project duration, project cost, crew work interruptions and interruption costs.
- Introducing a new activity activity-relaxation free float that allows for calculating the required crew productivity rate that minimizes crew work interruptions without delaying successor activities and without impacting the optimized project duration.
- Developing a new risk-based earned duration management model (RBEDM) for monitoring and estimating schedule performance of projects considering critical activities only and their associated risk factors.
- Introducing a new risk adjustment factor RAF_{cr} which quantifies the impact of future uncertainties associated with critical activities in estimating project duration at completion.

5.3. Opportunities for Future Work

Based on the research conducted, future work may consider:

- Conducting a sensitivity analysis to investigate the impact of the organization risk maturity level on on-time and within budget delivery of construction projects.

- Conducting a sensitivity analysis to investigate the effect of the diverse qualitative variation range in the correlation coefficients between pairs of cost items on the accuracy of the estimated contingency.

- Considering the effect of non-critical activities with short float (near critical activity) on the estimated project duration at completion.

- Considering the feedback loop for continuous improvement of the developed models making use of the results obtained from one model and its impact on the remaining models.

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