MULTI-OBJECTIVE OPTIMIZATION FOR RESOURCE DRIVEN SCHEDULING IN CONSTRUCTION PROJECTS

BY

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DISSIDERATION

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ABSTRACT

Despite the many capabilities and contributions of available resource-driven scheduling techniques and models, they still suffer from a number of important limitations including their inability to (1) provide efficient resource utilization schedules that are capable of directly measuring and minimizing the negative impacts of resource fluctuations in construction projects; (2) analyze and optimize the impact of schedule acceleration strategies such as the utilization of multiple shifts on construction productivity, duration, and cost; and (3) analyze and quantify the impact of construction uncertainties on the generated project schedules in an efficient and effective manner especially for real-life large-scale construction projects.

To overcome the aforementioned limitations, the main objectives of this study are to: (1) design innovative resource leveling metrics that can overcome the limitation of existing methods and develop a robust resource leveling model that is capable of maximizing resource utilization efficiency; (2) develop an advanced resource leveling and allocation model that is capable of simultaneously maximizing resource utilization efficiency and minimizing project duration while resolving all resource conflicts; (3) formulate a robust multiple shifts scheduling model that is capable of simultaneously minimizing project time and cost while minimizing the negative impacts of shift work on productivity, safety and cost; (4) develop a robust resource fluctuation cost model that is capable of minimizing resource fluctuation costs while minimizing project duration within the specified range of project duration; (5) develop an advanced project risk assessment model that is capable of providing fast and accurate estimates for the probability of project completion for large-scale construction projects; and (6) design a prototype
multi-objective optimization system for resource driven scheduling in construction projects that integrates the research developments with commercially available project management software, Microsoft Project 2007, to facilitate their ultimate use and adoption by the construction industry.

First, innovative resource leveling metrics are developed to circumvent the limitation of existing metrics and directly measure and minimize undesirable resource fluctuation. A robust resource leveling model is formulated by incorporating the newly developed resource leveling metrics to maximize resource utilization efficiency for construction projects. The optimization model is implemented using genetic algorithms in order to optimize resource utilization efficiency.

Second, a resource leveling and allocation model is developed to simultaneously optimize resource leveling and allocation for construction projects. The model is developed as a multi-objective genetic algorithm to provide optimal tradeoffs between maximizing resource utilization efficiency and minimizing project duration while complying with all resource availability constraints.

Third, a robust multiple shifts scheduling model is formulated to simultaneously minimize project time and cost while minimizing the negative impacts of shift work on construction productivity, safety, and cost. A multi-objective genetic algorithm is utilized to implement the model in order to support construction planners in generating optimal tradeoffs among project time, cost, and labor utilization in evening and night shifts. The model is also designed to consider labor availability constraints in order to optimally distribute the limited availability of labor on the competing shifts.
Fourth, a robust resource fluctuation cost model is developed to provide the most cost effective and efficient resource utilization for construction projects. The model is developed as a novel multi-objective optimization model that is capable of modeling and minimizing overall resource fluctuation costs (i.e. idle costs, release and rehiring costs, and mobilization costs) and analyzing and optimizing the potential tradeoffs between minimizing resource fluctuation costs and minimizing project duration.

Fifth, a robust project risk assessment model is developed to overcome the limitations of existing probabilistic scheduling methods including (a) the inaccuracy limitation of the PERT method due to its “merge event bias” by incorporating an accurate multivariate normal integral method; and (b) the impractical computational time of the Monte Carlo simulation method by incorporating a newly developed approximation method. The model is named FARE (Fast and Accurate Risk Evaluation). The development of the FARE model facilitates the optimization of resource-driven scheduling while considering the impact of relevant risks and uncertainties.

Sixth, a prototype multi-objective optimization for resource driven scheduling system is developed to seamlessly integrate the aforementioned research developments with commercially available project management software, Microsoft Project 2007, to facilitate their ultimate use and adoption by the construction industry. The system is designed to (1) retrieve project scheduling data from MS Project that can be utilized in the developed optimization models, and store the generated optimization results in a binary file that can be accessed and processed by MS Project; (2) enable construction planners to benefit from and utilize the practical project scheduling and control features
in MS Project during their analysis of the optimal schedules generated by the developed models in this study; and (3) facilitate the input of project parameters and the visualization of the obtained solutions using the newly developed graphical user interface modules.

The main research developments of this study contribute to the advancement of current practice in resource scheduling and planning in construction projects and can lead to: (1) an increase in the resource utilization efficiency in construction projects which can produce significant improvements in construction productivity, cost and duration; (2) an improvement in utilizing the limited availability of resources; (3) a reduction in the duration and cost of multiple shifts operation while circumventing the negative impacts of shift work on productivity, safety, and cost; and (4) an enhancement in analyzing construction project risks in order to improve the reliability of project performance.
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# TABLE OF CONTENTS

**LIST OF TABLES** .......................................................................................................................... xi

**LIST OF FIGURES** ........................................................................................................................ xii

**CHAPTER 1**
**INTRODUCTION** .......................................................................................................................... 1

1-1 Overview ......................................................................................................................................... 1
1-2 Problem Statement ............................................................................................................................ 2
1-3 Research Objectives ........................................................................................................................ 12
1-4 Research Methodology .................................................................................................................... 13
1-5 Significance of Proposed Research ............................................................................................... 20
1-6 Thesis Organization ....................................................................................................................... 22

**CHAPTER 2**
**LITERATURE REVIEW** .................................................................................................................. 26

2-1 Introduction ....................................................................................................................................... 26
2-2 Requirements of Resource Utilization Plan in Construction Projects ........................................... 26
2-3 Requirements of Project Risk Assessment in Construction Projects ............................................ 34
2-4 Construction Resource Utilization Optimization Models ............................................................. 35
2-5 Multi-Objective Genetic Algorithms ............................................................................................... 50
2-6 Probabilistic Project Network Analysis Models .............................................................................. 52
2-7 Summary ........................................................................................................................................ 57

**CHAPTER 3**
**RESOURCE LEVELING MODEL** .................................................................................................... 59

3-1 Introduction ....................................................................................................................................... 59
3-2 Types of Resource Fluctuations ....................................................................................................... 59
3-3 New Resource Leveling Metrics ..................................................................................................... 61
3-4 Optimization Model ........................................................................................................................ 65
3-5 Model Evaluation ........................................................................................................................... 77
CHAPTER 4
RESOURCE ALLOCATION AND LEVELING MODEL ........................................ 82
4-1 Introduction ......................................................................................... 82
4-2 Initialization Phase ............................................................................. 83
4-3 Multi-Objective Optimization Phase .................................................. 85
4-4 Activity Ranking Phase ...................................................................... 86
4-5 Resource Scheduling Phase ............................................................... 87
4-6 Model Evaluation .............................................................................. 90
4-7 Summary .......................................................................................... 93

CHAPTER 5
OPTIMIZING THE UTILIZATION OF MULTIPLE SHIFTS ............................. 94
5-1 Introduction ......................................................................................... 94
5-2 Model Formulation ........................................................................... 94
5-3 Model Implementation ....................................................................... 103
5-4 Model Evaluation ............................................................................. 116
5-5 Summary .......................................................................................... 125

CHAPTER 6
RESOURCE FLUCTUATION COST MODEL ............................................... 127
6-1 Introduction ......................................................................................... 127
6-2 Scheduling Phase .............................................................................. 128
6-3 Multi-Objective Optimization Phase .................................................. 142
6-4 Model Evaluation ............................................................................. 144
6-5 Summary .......................................................................................... 148

CHAPTER 7
PROJECT RISK ASSESSMENT MODEL .................................................. 150
7-1 Introduction ......................................................................................... 150
7-2 Module 1: PERT Model .................................................................... 151
LIST OF TABLES

Table 4.1 Case study data ........................................................................................................... 92
Table 5.1 Multiple shift options ........................................................................................................... 96
Table 5.2 Activity data for the example in Figure 5.1 (Two shifts system, SS=2) ........ 102
Table 5.3 Example of activity data in a two shifts system (SS=2) ........................................ 106
Table 5.4 Activity data ....................................................................................................................... 118
Table 5.5 Sample Pareto optimal solutions ......................................................................................... 124
Table 6.1 Activity data ....................................................................................................................... 146
Table 7.1 Original Ang’s method to select the representative paths .............................................. 177
LIST OF FIGURES

Figure 1.1 Limitations of network scheduling methods....................................................... 3
Figure 1.2 Research needs and scope.................................................................................. 4
Figure 1.3 Resource leveling solutions using existing metrics ......................................... 6
Figure 1.4 Optimizing resource allocation and leveling...................................................... 7
Figure 1.5 Prototype multi-objective optimization system for resource driven scheduling in construction projects........................................................................................................... 18
Figure 1.6 Research Tasks ................................................................................................. 19
Figure 2.1 Impact of resource fluctuation and peak demand on resource fluctuation cost .................................................................................................................................................. 30
Figure 2.2 Impact of schedule changes on resource fluctuation cost and project duration .................................................................................................................................................. 33
Figure 3.1 Types of resource fluctuations ........................................................................... 60
Figure 3.2 Calculations of the new metrics......................................................................... 62
Figure 3.3 Difference between RRH and RID metrics........................................................ 64
Figure 3.4 Decision variables and optimization objectives ............................................... 67
Figure 3.5 Optimization model ........................................................................................... 71
Figure 3.6 Optimizing resource fluctuation and peak demand ........................................... 72
Figure 3.7 Activity shifts based on maximum and selected shift days M_n and S_n............. 76
Figure 3.8 Optimization results generated by new model and metrics............................... 78
Figure 3.9 Optimization results generated by existing metrics ........................................... 79
Figure 3.10 Analysis of existing resource leveling example (Son and Skibniewski 1999) by new model and metrics.......................................................................................................................... 80
Figure 4.1 Decision variables and their produced schedules ........................................84
Figure 4.2 Optimization model ....................................................................................90
Figure 4.3 Optimal solutions ......................................................................................92
Figure 5.1 Minimizing labor utilization in evening shifts ............................................101
Figure 5.2 Multi-objective optimization model ..........................................................104
Figure 5.3 Impact of resource constraint on project duration ....................................110
Figure 5.4 Activity network .......................................................................................117
Figure 5.5 Labor utilization for multiple shift options .................................................119
Figure 5.6 Pareto optimal solutions ...........................................................................123
Figure 6.1 Resource fluctuation cost (RFC) model ....................................................128
Figure 6.2 The impact of shifting activities on the float of their predecessors ..........141
Figure 6.3 Activity network .......................................................................................145
Figure 6.4 Resource utilization of early schedule ......................................................147
Figure 6.5 Pareto optimal solutions and project schedules ........................................148
Figure 7.1 Correlation between two network paths ....................................................155
Figure 7.2 Performance of the Genz’s algorithm for small to mid-size networks .......158
Figure 7.3 FARE model for a large scale construction project network......................161
Figure 7.4 Redundant links among project activities ................................................161
Figure 7.5 Three main steps to remove high probability paths ...................................163
Figure 7.6 Selecting representative paths using lower bound for mean path duration (LM) ...........................................................................................................165
Figure 7.7 Longest Path Duration Search (LPDS) algorithm ....................................169
Figure 7.8 Longest path from a given activity node (n) to the end node (E) ..........170
Figure 7.9 Fast Representative Path Search (FRPS) algorithm................................. 174
Figure 7.10 Searching for representative paths using the lowest bound for the mean path duration (LM) and the longest mean path duration (LDₙ) ........................................... 175
Figure 7.11 Experiment 1: Project network and activity data................................. 182
Figure 7.12 Probability of project completion (PTₜ) produced by FARE model and MCS for Experiment 1 ..................................................................................................................... 183
Figure 7.13 Error of results produced by FARE model compared to the results of MCS for Experiment 1 ..................................................................................................................... 184
Figure 7.14 Computational times of FARE model and MCS for Experiment 1 ........ 184
Figure 7.15 The number of selected representative paths by the FARE model for Experiment 1 ..................................................................................................................... 185
Figure 7.16 Experiment 2: Project network and activity data................................. 187
Figure 7.17 Probability of project completion (PTₜ) produced by the FARE model and MCS for Experiment 2 ..................................................................................................................... 188
Figure 7.18 Error of results produced by FARE model compared to the results of MCS for Experiment 2 ..................................................................................................................... 188
Figure 7.19 Computational times of the FARE model and MCS for Experiment 2 ...... 189
Figure 7.20 The number of selected representative paths by the FARE model for Experiment 2 ..................................................................................................................... 189
Figure 8.1 Main modules of MORDS system .............................................................. 193
Figure 8.2 Main command bars and buttons for MORDS system .......................... 195
Figure 8.3 Sample sub-command bars and buttons for the multiple shifts scheduling model in MORDS ................................................................................................................. 195
Figure 8.4 Newly created input fields and tables by MORDS system for each developed model .............................................................................................................................................................................................................................................................................................................................................. 197
Figure 8.5 Sample input fields and tables generated by MORDS system ....................... 198
Figure 8.6 GUI forms of control modules for each developed model .............................. 201
Figure 8.7 Progress bars in MORDS system ..................................................................... 202
Figure 8.8 Status of existing saved solutions .................................................................... 202
Figure 8.9 GUI form of output module for MSS model in MORDS system .................... 204
Figure 8.10 Exported solution shown in MS Project ......................................................... 205
Figure 8.11 Optimal solutions visualization forms ............................................................. 206
Figure 8.12 Optimal solutions produced by MORDS system for RL model ................. 207
Figure 8.13 Optimal solutions produced by MORDS system for RLRA model .............. 208
Figure 8.14 Optimal solutions produced by MORDS system for MSS model (Experiment 3) .............................................................................................................................................................................................................................................................................................................................................. 208
Figure 8.15 Optimal solutions produced by MORDS system for RFC model ............... 209
Figure 8.16 Probabilities of project completion produced by MORDS system for FARE model (John Doe project) .............................................................................................................................................................................................................................................................................................................................................. 209
CHAPTER 1
INTRODUCTION

1-1 Overview

Despite the widespread utilization of network scheduling techniques such as the Critical Path Method (CPM) and Precedence Diagram Method (PDM) in the construction industry, they have a number of important limitations including the inability to (1) minimize fluctuations in resource utilization levels over the project duration (Hegazy 1999b; Hiyassat 2000; Son and Mattila 2004), as shown in Figure 1.1(A); (2) consider the availability limits of construction resources during various periods of the project (Brucker et al. 1998; Jiang and Shi 2005; Kim and Ellis 2008; Zhang et al. 2006a), as shown in Figure 1.1(B); (3) analyze the impact of utilizing multiple shifts and overtime hours on construction productivity, duration, and cost (El-Rayes and Kandil 2005; Jaskowski and Sobotka 2006; Xiong and Kuang 2008), as shown in Figure 1.1(C); and (4) consider the uncertainties and risks involved in construction scheduling and cost estimating (Kannan et al. 2001; Lee and Arditi 2006; Nasir et al. 2003), as shown in Figure 1.1(D).

In order to overcome the aforementioned limitations of traditional scheduling techniques, a number of resource-driven scheduling models was developed that focused on (1) resource leveling (Ahuja 1976; Akpan 2000; Burgess and Killebrew 1962; Easa 1989; Harris 1978; Hiyassat 2000; Mattila and Abraham 1998; Son and Mattila 2004; Son and Skibniewski 1999); (2) resource allocation (Ahuja 1976; Bell and Han 1991; Doctor
Problem Statement

In order to address the limitations of existing resource-driven scheduling models, this study will focus on and thoroughly investigate five major domain problems: (1) optimizing resource leveling in order to maximize resource utilization efficiency while maintaining the original project duration; (2) optimizing resource allocation and leveling in order to minimize the negative impacts of resource availability constraints on project time while maximizing resource utilization efficiency; (3) optimizing the scheduling of multiple shifts in order to minimize the negative impacts of evening and night shifts while minimizing project time and cost; (4) optimizing resource fluctuation costs in order to provide the most cost effective and efficient resource utilization for construction projects; and (5) construction risk assessment in order to maximize the reliability of project performance, as shown in Figure 1.2.
• Crew idle time
• Idle cost ($)

• Short-term release and rehire
• Release and Rehiring cost ($)

• Unavailable resources

(A) Undesirable resource fluctuations

(B) Resource demand exceeds availability limit

(C) Negative impacts of multiple construction shifts

(D) Inability to consider uncertainty and project risk

Figure 1.1 Limitations of network scheduling methods
First, a number of resource leveling models and algorithms have been developed to improve resource utilization efficiency by reducing the level of fluctuations in resource utilization and their negative impact on construction productivity and cost. Available resource leveling models are designed to minimize resource fluctuations by shifting non-critical activities within their available floats to keep the project duration of the original early schedule unchanged. These models introduced and utilized a number of metrics to reduce resource fluctuations including: (1) sum of squares method (Ahuja 1976; Bandelloni et al. 1994; Burgess and Killebrew 1962; Harris 1978; Hegazy 1999b; Son and Skibniewski 1999); (2) absolute difference between resource consumption in
consecutive time periods (Easa 1989; Senouci and Adeli 2001; Senouci and Eldin 2004); (3) deviation between actual resource usage and a specified or a uniform resource usage (Akpan 2000; Chan et al. 1996; Chua et al. 1996; Easa 1989; Leu and Yang 1999; Mattila and Abraham 1998; Son and Mattila 2004); and (4) sum of squares of resource changes (Ahuja 1976). Despite the contributions of these models, they all focused on measuring and penalizing the difference between fluctuating resource profiles and a predetermined desirable shape such as a rectangular or a parabolic shape, as shown in Figure 1.3. Accordingly, resource leveling models that adopt these metrics produce construction schedules that (1) favor only a predetermined resource profile that is often difficult to fully achieve due to the scheduling constraints imposed on construction projects; and (2) penalize various alternative shapes of resource profiles that may produce more efficient resource utilization than those achieved by the existing metrics, as shown in Figure 1.3. As such, there is a need to develop new resource leveling metrics and models that are capable of (1) overcoming the limitations of existing ones; and (2) generating optimal schedules and resource utilizations that are not limited to the predetermined desirable resource profile shapes, as shown in Figure 1.3.
Second, a number of optimization models were developed to integrate resource leveling and resource allocation techniques in order to improve resource utilization efficiency while complying with resource availability constraints (Chan et al. 1996; Chua et al. 1996; Hegazy 1999b; Leu and Yang 1999; Senouci and Eldin 2004). These research studies introduced and utilized various metrics in their models to produce optimal schedules that provide improved resource profiles and minimum project durations while complying with resource availability constraints. Despite the significance and contributions of these research studies, there is no or little research focusing on (1) maximizing overall resource utilization efficiency by directly measuring and minimizing

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**Figure 1.3 Resource leveling solutions using existing metrics**
undesirable resource fluctuations while complying with resource availability constraints; and (2) generating feasible tradeoffs between resource utilization efficiency and project time for construction planners to enable the selection of an optimal plan that satisfies the specific requirements of the project being considered, as shown in Figure 1.4. There is an urgent and pressing need for advanced optimization models that are capable of generating optimal tradeoffs between resource utilization efficiency and project time while complying with resource availability constraints.

![Figure 1.4 Optimizing resource allocation and leveling](image)

Third, significant research advancement has been made in the area of time-cost tradeoff analysis. This led to a number of optimization model that were developed using various optimization techniques including heuristic methods, linear programming, integer programming, and genetic algorithms (GAs). These models can be classified according to their optimization objectives into models that attempted to: (1) minimize project time and cost using time-cost tradeoff analysis without resource utilization consideration (El-Rayes and Kandil 2005; Feng et al. 1997; Li et al. 1999; Xiong and Kuang 2008; Zheng et al. 2004, 2005); and (2) minimize project time and cost while
improving resource utilization efficiency (Hegazy 1999a; Hegazy and Ersahin 2001; Jaskowski and Sobotka 2006; Leu and Yang 1999; Moussourakis and Haksever 2004; Senouci and Adeli 2001; Senouci and Eldin 2004). While these studies provided significant contributions to the area of optimizing resource utilization and time-cost tradeoff analysis, there has been little or no reported research that focused on optimizing project time and cost using multiple shifts while taking into consideration minimizing the negative impacts of shift work on construction productivity, safety, and cost for construction projects. There is a pressing need for advanced new models that are capable of supporting construction planners in identifying optimum multiple shifts plan and schedules that are capable of simultaneously minimizing project time and cost and minimizing the negative impacts of shift work on construction productivity, safety, and cost while complying with resource availability constraints.

Fourth, many research studies investigated and developed optimization models to minimize construction resource fluctuations and their negative impacts using various methodologies including heuristic methods, linear programming, integer programming, and genetic algorithms (GAs). These models can be classified into three categories according to their optimization objectives: (1) maximize the conformance of fluctuating resource profile to predetermined shapes (Ahuja 1976; Bandelloni et al. 1994; Burgess and Killebrew 1962; Chan et al. 1996; Chua et al. 1996; Easa 1989; Harris 1978; Hegazy 1999b; Hiyassat 2000, 2001; Leu and Yang 1999; Mattila and Abraham 1998; Senouci and Eldin 2004; Son and Mattila 2004); (2) minimize resource idle cost to smooth resource utilization (Akpan 2000); and (3) directly measure and minimize undesirable resource fluctuation and peak demand to maximize resource utilization.
efficiency (El-Rayes and Jun 2009; Jun and El-Rayes 2009). While the aforementioned studies provided significant contributions, there has been little or no reported research that focused on (1) studying and quantifying the impact of daily resource fluctuations on resource fluctuation costs including idle costs, release and rehiring costs, and mobilization costs; and (2) modeling and optimizing potential tradeoffs between minimizing resource fluctuation costs and minimizing project duration. Akpan (2000) developed a model to improve the utilization of multiple resources by minimizing their idle cost; however the developed model did not consider the impact of resource mobilization costs and release and rehiring costs, and did not study the tradeoffs between resource fluctuation costs and project duration. El-Rayes and Jun (2009) developed resource leveling metrics to maximize resource utilization efficiency by directly measuring and minimizing resource fluctuation and peak demand; however their model did not analyze resource fluctuation costs, and did not model the tradeoffs between resource fluctuation costs and project duration. In order to address this research gap, there is a pressing need for advanced new models that are capable of supporting construction planners in identifying optimum schedules that are capable of minimizing resource fluctuation costs and analyzing and optimizing the tradeoffs between minimizing resource fluctuation costs and minimizing project duration.

Fifth, deterministic scheduling methods such as the critical path method (CPM) are widely used for project planning and control in the construction industry. These methods assume that the durations of project activities are deterministic and therefore they are incapable of considering the impact of various construction risks and uncertainties such as weather, productivity, and site conditions on the activity and project duration (Ang et
al. 1975; Faniran et al. 1998; Jaafari 1984; Mo et al. 2008; Nasir et al. 2003; Okmen and Oztas 2008). In order to overcome the aforementioned limitations of deterministic scheduling methods, a number of probabilistic scheduling methods were developed including (1) program evaluation and review technique (PERT); (2) probabilistic network evaluation technique (PNET) (Ang et al. 1975); (3) narrow reliability bounds (NRB) (Ditlevsen 1979); (4) Monte Carlo simulation (MCS) (Diaz 1989; Diaz and Hadipriono 1993; Halpin and Riggs 1992; Lee and Arditi 2006; Lu and AbouRizk 2000; Sculli 1989; Slyke 1963); and (5) simplified Monte Carlo simulation (SMCS) (Diaz and Hadipriono 1992). The program evaluation and review technique (PERT) was developed by the US Navy in 1958 as a probabilistic scheduling method that can be used to estimate the probability of project completion (Kerzner 2009). This method however has been criticized by many research studies due to its “merge event bias” limitation. This critical limitation causes the PERT method to neglect the impact of sub-critical paths on the overall probability of project completion, and thereby it often leads to optimistic results and underestimating the expected project duration (Ahuja et al. 1994; Halpin and Riggs 1992; Slyke 1963). Monte Carlo simulation (MCS) is widely used as a probabilistic scheduling method for construction projects (Diaz and Hadipriono 1993; Halpin and Riggs 1992; Lee and Arditi 2006; Lu and AbouRizk 2000; Sculli 1989; Slyke 1963). Despite its accuracy in estimating the probability of project completion, the Monte Carlo simulation method has been criticized by many researchers due to its large computation load for large scale projects (Ang et al. 1975; Guo et al. 2001; Lu and AbouRizk 2000; Mummolo 1997; Sculli 1989; Zammori et al. 2009). Other research studies in probabilistic scheduling developed approximation methods (Ang et al. 1975; Gong and
Hugsted 1993; Guo et al. 2001; Sculli and Shum 1991) and multivariate methods (Anklesaria and Drezner 1986) and combined them with the PERT method. Despite the significant contributions of the aforementioned research studies to the area of probabilistic scheduling, available models often (1) lead to optimistic results and underestimate the expected project duration by neglecting the impact of sub-critical paths on the overall probability of project completion (e.g. “merge event bias” limitation of PERT); and (2) require large computational load to simulate the randomness of project time for large scale projects and therefore they are incapable of integrating project risk assessment and scheduling optimization. Accordingly, there is a pressing need for a new probabilistic scheduling model that is capable of providing fast and accurate risk evaluation for real-life and large-scale construction projects.

Sixth, the aforementioned research developments need to be integrated in a prototype multi-objective resource driven scheduling system that is designed to interface with commercially available project management software, Microsoft Project 2007, in order to (1) provide a proof of concept of the planned research developments in this study; (2) evaluate the performance of the prototype system in optimizing resource-driven scheduling for construction projects; and (3) facilitate the ultimate use and adoption of developed models by construction planners.
1-3 Research Objectives

The primary goal of this research is to develop robust resource-driven scheduling models for optimizing resource utilization in construction projects. To accomplish this goal, the main research objectives of this study are:

1. Develop innovative resource leveling metrics that circumvent the aforementioned limitation of existing models and are capable of directly measuring and minimizing the negative impact of resource fluctuations on construction productivity and cost, and incorporate these metrics in a robust optimization model that is capable of generating optimal and practical schedules to maximize the efficiency of resource utilization in construction projects.

2. Develop a robust resource leveling and allocation model that is capable of (1) maximizing resource utilization efficiency by directly measuring and minimizing undesirable resource fluctuations; and (2) generating optimal tradeoffs between resource utilization efficiency and project duration while complying with all resource availability constraints.

3. Formulate and develop multiple-shift scheduling models that are capable of (1) minimizing the negative impacts of evening and night shifts on construction productivity, safety, and cost; (2) generating optimal tradeoffs between project duration and cost; and (3) complying with all labor availability constraints.

4. Develop a robust resource fluctuation cost model that is capable of (1) providing a cost effective and efficient resource utilization for construction projects; and (2) generating optimal tradeoffs between minimizing resource fluctuation costs (i.e. idle,
release and rehiring, and/or mobilization costs) and minimizing project duration within the specified range of project duration.

5. Develop a robust risk assessment model that circumvents the limitation of existing probabilistic scheduling methods and has the capability of providing fast and accurate risk assessment to facilitate the optimization of resource-driven scheduling for large-scale construction projects while considering the impact of relevant risks and uncertainties.

6. Integrate the aforementioned research developments in a prototype multi-objective optimization system that is capable of (1) optimizing resource-driven scheduling for construction projects; and (2) seamless integration with a commercially available project management software application, Microsoft Project 2007, to facilitate the ultimate use and adoption of developed scheduling models by construction planners.

1-4 Research Methodology

In order to achieve the aforementioned objectives, this research is organized into seven main research tasks: (1) conduct a comprehensive literature review of the latest research developments in resource-driven scheduling; (2) develop new resource leveling metrics and models to directly measure and minimize undesirable resource fluctuation so as to maximize resource utilization efficiency; (3) formulate and develop resource leveling and allocation model to maximize resource utilization efficiency while minimizing the negative impact of resource availability constraints on project time; (4) develop a robust multiple shifts scheduling model to minimize project time and cost while minimizing the negative impacts of evening and night shifts on project
performance; (5) develop a robust resource fluctuation cost model to simultaneously minimize overall resource fluctuation costs and minimize project duration within a specified range of project duration; (6) formulate an efficient risk assessment model for project networks to forecast the impact of uncertainties on overall project performance; and (7) develop a prototype multi-objective optimization system to integrate the research developments and facilitate their ultimate use by construction planners, as shown in Figure 1.6.

1-4.1. Task 1: Conduct Comprehensive Literature Review

The objective of this task is to investigate the latest research developments in planning resource utilization for construction projects in order to achieve a solid starting point for the proposed study. The work in this task is sub-divided into following three sub-tasks:

1. Review and investigate all relevant resources scheduling and project network risk analysis studies.
2. Examine and identify the limitations of available studies.
3. Explore feasibility of multi-objective optimization and risk assessment tools.

1-4.2. Task 2: Develop Resource Leveling Model

The purpose of this task is to study and develop innovative resource leveling metrics that circumvent the limitation of existing ones and has a capability of directly measuring and minimizing undesirable fluctuation in daily resource demand. This task will also formulate and implement an optimization model that is capable of searching for optimum schedules that maximize resource utilization efficiency while maintaining the
original project duration. The work in this research task is subdivided into the following four sub-tasks:

1. Explore all relevant decision variables that impact resource utilization efficiency.
2. Develop new resource leveling metrics to directly measure undesirable resource fluctuations.
3. Implement an optimization model to maximize resource utilization efficiency while complying with project time constraints.
4. Evaluate and improve the performance of the developed model.

1-4.3. Task 3: Develop Resource Allocation and Leveling Model

The purpose of this task is to develop an optimization model that integrates the developed resource leveling model and resource allocation techniques and has the capability of maximizing resource utilization efficiency while minimizing the negative impact of resource availability constraints on project time. The work in this research task is subdivided into the following four sub-tasks:

1. Investigate all relevant decision variables that impact resource utilization efficiency and project time.
2. Integrate the developed resource leveling model with resource allocation techniques.
3. Formulate and implement an optimization model to generate optimal tradeoffs between resource utilization efficiency and project time while complying with resource availability constraints.
4. Evaluate and improve the performance of the developed model.
1-4.4. **Task 4: Develop Multiple Shifts Scheduling Model**

The purpose of this task is to study and develop the metrics that are capable of quantifying and minimizing the negative impact of shift work on project performance such as productivity, safety, and cost and to develop an optimization model that is capable of generating optimal tradeoffs between project time and cost while complying with all resource availability constraints. The work in this research task is subdivided into the following four sub-tasks:

1. Investigate all relevant decision variables that affect resource utilization in multiple shifts, project time, and cost.
2. Develop objective metrics to quantify and minimize the negative impacts of evening and night shifts on construction productivity, safety, and cost.
3. Formulate and implement an optimization model to minimize project time and cost while minimizing the negative impacts of evening and night shifts on project performance while complying with all labor availability constraints.
4. Evaluate and improve the performance of the developed model.

1-4.5. **Task 5: Develop Resource Fluctuation Cost Model**

The purpose of this task is to study and develop an optimization model that is capable of minimizing overall resource fluctuation costs and optimizing the potential tradeoffs between minimizing resource fluctuation costs and minimizing project duration in order to provide the most cost effective and efficient resource utilization on construction projects. The work in this research task is subdivided into the following four sub-tasks:
1. Investigate all relevant decision variables that affect resource fluctuation costs and project duration.

2. Develop objective metrics to quantify and minimize overall resource fluctuation costs (i.e. idle, release and rehiring, and/or mobilization costs).

3. Formulate and implement an optimization model to generate optimal tradeoffs between resource fluctuation cost and project duration within a specified range of project duration.

4. Evaluate and improve the performance of the developed model.

1-4.6. Task 6: Develop Project Risk Assessment Model

The objective of this task is to develop an efficient risk assessment model that is capable of evaluating and identifying project uncertainties. The work in this research task is subdivided into the following four sub-tasks:

1. Explore efficient methods to evaluate the uncertainties imposed on construction projects.

2. Develop objective metrics or indices to quantify the reliability of project performance.

3. Formulate and implement an efficient risk assessment model to evaluate the reliability of project performance.

4. Evaluate and improve the performance of the developed model.

1-4.7. Task 7: Develop Prototype Multi-Objective Optimization System

The goal of this task is to formulate and implement a prototype multi-objective optimization system for planning and scheduling resource utilization in construction
projects as shown in Figure 1.5. The work in this research task is subdivided into the following four sub-tasks:

1. Develop and implement a control module to integrate above developed models.
2. Integrate the developed control module with available commercial project management software.
3. Develop a graphical user interface module to facilitate the ultimate use and adoption of developed models by construction planners.
4. Evaluate and improve the performance of the developed model.

Figure 1.5 Prototype multi-objective optimization system for resource driven scheduling in construction projects
Figure 1.6 Research Tasks
1-5 Significance of Proposed Research

The proposed research is expected to have a significant impact on (1) reducing undesirable resource fluctuation and improving overall resource utilization efficiency in order to improve construction productivity and reduce project duration and cost; (2) enhancing the utilization of limited construction resources in order to reduce construction time and cost; (3) enhancing labor utilization in multiple shifts in order to improve construction productivity and safety; (4) producing the most cost effective and efficient resource utilization; and (5) increasing the reliability of project performance in order to reduce the risks of project delays.

1. Impact on resource utilization efficiency: Construction scheduling techniques such as Critical Path Method (CPM) and Precedence Diagram Method (PDM) assume unlimited supply of resources, and thereby they often produce schedules that have undesirable resource fluctuations. These resource fluctuations are impractical, inefficient and costly to implement on construction sites, as they require additional cost to hire additional workforces and/or to maintain an unproductive level of workforce on site during low demand periods. Accordingly, the proposed study is designed to develop innovative resource leveling metrics that circumvent the limitation of existing metrics and provide the capabilities of directly measuring and minimizing only undesirable resource fluctuation to maximize resource utilization efficiency. The proposed optimization model is expected to support construction planners in identifying optimal schedules that maximize resource utilization efficiency while complying with project completion constraints. This is expected to contribute to
enhance resource utilization on construction sites and significant improvements in construction productivity and cost-effectiveness.

2. Impact on the utilization of limited construction resources: The availability of construction resources is often limited due to seasonal shortages, labor disputes, equipment breakdowns, and competing demands. The proposed study is designed to develop a resource-driven scheduling model that integrates resource leveling and allocation techniques. The proposed model is expected to support construction planners in identifying optimal tradeoffs between resource utilization efficiency and project time.

3. Impact on labor utilization in multiple shifts: Construction projects are often required to be accelerated in order to achieve the benefits of early completion such as incentive for early completion, avoidance for liquidate damage, and early release of key resources for other projects (Clough et al. 2000). Multiple shifts are often used in construction projects to accomplish schedule acceleration. However, they often have negative impacts on construction productivity and safety including worker's fatigue, absenteeism, risk of injuries and accidents, and high turnover rate (Helander 1981). Moreover, additional labor for the evening and/or night shifts is often needed to supplement those working in day shifts because labor unions often restrict laborers to work no more than one shift per day. In many projects, this required additional skilled construction labor is often not available. Accordingly, this study will develop robust multiple-shift scheduling models that are capable of (1) minimizing the negative impacts of evening and night shifts on labor productivity, safety, and social disruption; and (2) minimizing project time and cost while complying with resource
availability constraints. This is expected to contribute to optimizing resource utilization in multiple shifts and to improve their productivity, cost and safety.

4. **Impact on the cost effective and efficient resource utilization plan**: The generated schedules of construction projects often require significant fluctuations in the daily resource demands on site. These fluctuations cause additional construction costs, including resource idle costs, release and rehiring costs, and/or mobilization costs. The proposed study is designed to develop a multi-objective optimization model that is capable of modeling and minimizing these resource fluctuation costs and analyzing and optimizing potential tradeoffs between minimizing these resource fluctuation costs and minimizing the project duration. This is expected to contribute to providing cost effective and efficient resource utilization for construction projects.

5. **Impact on reliability of project performance**: The proposed study is designed to develop an advanced project risk assessment model that has a capability of providing fast and accurate risk assessment for large-scale construction projects. This unique capability holds strong potential to facilitate the optimization of resource-driven scheduling while considering the impact of relevant risks and uncertainties. This can contribute to enhancing the reliability of project performance.

1-6 Thesis Organization

The organization of this report and its relation to the main research tasks of the proposed study is described as follows:

Chapter 2 presents a comprehensive literature review that investigates available resource scheduling models and risk assessment methodologies for construction
projects, examines and identifies their limitations and needs, and explores the feasibility of available multi-objective optimization and risk assessment tools.

Chapter 3 discusses the development of new resource leveling model for construction projects that is capable of maximizing resource utilization efficiency. This chapter describes the modeling of all relevant decision variables that affect resource utilization efficiency and the development of new resource leveling metrics that are capable of directly measuring and minimizing undesirable fluctuations in resource demands. This chapter also describes the formulation and implementation of an optimization model that is capable of maximizing resource utilization efficiency while complying with project time constraints.

Chapter 4 discusses the development of an integrated resource leveling and allocation model that is capable of simultaneously maximizing resource utilization efficiency and minimizing the negative impacts of the limited availability of construction resources on project time. This chapter describes the modeling of all relevant decision variables that affect resource utilization efficiency and project time. The formulation and implementation of an optimization model that is capable of generating optimal tradeoffs between resource utilization efficiency and project time is also described in this chapter.

Chapter 5 discusses the development of a resource-driven scheduling model that optimizes the utilization of multiple shifts in construction projects in order to minimize project time and cost while minimizing the negative impacts of evening and night shifts. This chapter describes the modeling of all relevant decision variables that affect scheduling and planning resource utilization in multiple shifts and the development of
metrics that enable measuring the negative impacts of shift work on project performance. The chapter also describes the formulation and development of optimization models for the utilizations of multiple labor shifts, which are capable of generating optimal tradeoffs among project time, cost, and labor utilization in multiple shifts.

Chapter 6 discusses the development of a robust resource fluctuation cost model that is capable of minimizing overall resource fluctuation costs and analyzing and optimizing the tradeoffs between minimizing resource fluctuation costs and minimizing project duration. This chapter describes the modeling of all relevant decision variables that affect overall resource fluctuation costs including idle, release and rehiring, and mobilization costs for construction resources and project duration. The formulation and implementation of an optimization model that is capable of generating optimal tradeoffs between resource fluctuation costs and project duration is also described in this chapter.

Chapter 7 discusses the development of new model for fast and accurate risk evaluation for a large scale construction project network, namely FARE that is capable of overcoming the limitation of “merge event bias” of traditional PERT method by incorporating a fast and accurate multivariate normal integral method. The chapter also describes the development of new approximation method to improve efficiency in evaluating the risk of project schedule for a large scale construction project network.

Chapter 8 presents the development of a prototype multi-objective optimization system for resource driven scheduling that is designed to integrate all aforementioned research developments with commercially available project management software, Microsoft
Project 2007. The chapter presents, four main modules, add-ins module, input module, control module, and output module that facilitate (1) optimizing resource-driven scheduling for construction projects; (2) the benefit from practical project scheduling and controlling features in commercial project management software; and (3) the ultimate use and adoption of developed models by the construction industry.

Chapter 9 presents the conclusions, research contributions, and recommended future research of the present study.
CHAPTER 2
LITERATURE REVIEW

2-1 Introduction
A comprehensive literature review has been conducted to establish a solid starting point to pursue the proposed study. The literature review focused on investigating and analyzing current practices as well as relevant research studies in planning for resource utilization in construction projects. This chapter summarizes and organizes the reviewed literature in five main sections: (1) the requirements of resource utilization plan in construction projects; (2) the requirements of project risk assessment in construction projects; (3) available resource utilization optimization models; (4) multi-objective genetic algorithms and their capability of optimizing conflicting objectives in construction engineering and management; and (5) available probabilistic project network analysis models.

2-2 Requirements of Resource Utilization Plan in Construction Projects
2-2.1 Requirements of Resource Scheduling
In order to complete a construction project at maximum efficiency of time and cost, judicious scheduling and allocation of available resources are required (Clough et al. 2000). However, the widely utilized network scheduling techniques such as Critical Path Method (CPM) and Precedence Diagram Method (PDM) assume the unlimited supply of resources, and thereby they often produce unintended high resource demands and
undesirable resource fluctuations. Harris (1978) indicated that there are several negative impacts of undesirable resource fluctuation on project performance; as (1) it causes hiring and releasing of workers in short-term basis which is troublesome, inefficient, and costly; (2) clerical costs and unemployment compensation cost occur due to hiring and releasing of labors; (3) it needs time to readjust to the working conditions of a particular job when hiring new labors; (4) there is a possibility that once released workers might find another job and not be available upon recall; (5) high-idle cost occurs when employing high-cost resource units; and (6) it produces disruption in the learning curve effects, and thereby decreases productivity (Stevens 1990). As such, undesirable resource fluctuation affects on overall project performance including productivity and cost. Moreover, high resource peak demand causes a congestion problem on site with the activities that wait for the available resources. Accordingly, it causes poor productivity, increased cost, and in the end, project delays (Hendrickson 1989). In order to minimize those negative impacts on project performance and resource utilization efficiency, there is a pressing need for developing robust models that are capable of eliminating undesirable resource fluctuation and peak demand.

2-2.2 Requirements of Resource Utilization in Multiple Shifts Work

Multiple shifts are often used in construction projects to accelerate schedules and meet project deadlines. This utilization of two or three 8-hour shifts per day is reported to provide a number of advantages, including (1) enabling the number of weekly work-hours to be almost doubled or tripled; (2) benefiting from the fact that the premium cost of an evening or night shift is often lower than that of overtime hours; and (3) minimizing overtime productivity losses that are often encountered during overtime hours due to
workers fatigue and site congestion (Hanna et al. 2008). Despite these advantages, the utilization of multiple construction shifts still suffers from a number of limitations including its negative impacts on construction cost, productivity, and safety. The utilization of multiple shifts often leads to additional costs that are required for shift premiums, nighttime lighting, quality control, and safety measures. In addition, nighttime construction disrupts the circadian rhythm of shift workers who often struggle with adapting to new sleep cycles. As a result, the utilization of evening and/or night shifts is reported to cause productivity losses due to workers fatigue, health disorders, social life disruption, lower morale, and higher accident rates (Hanna et al. 2008; Kogi 1985). For example, Folkard and Tucker (2003) found that the risk of injuries and accidents on evening shifts is higher than day shifts, and they also found that night shifts have the highest risk of injuries and accidents among the three shifts. Staffing evening and/or night shifts is another problem that confronts construction managers as most workers prefer to work on day shifts (Czeisler et al. 1982; Guerin and DelPo 2007). Moreover, recent studies found that the utilization of evening and night shifts causes higher rates of labor turnover and absenteeism which leads to project delays and cost overruns (Gomar et al. 2002; Hanna et al. 2008; Knauth 2001). In order to minimize these negative impacts of utilizing multiple shifts, the number of labor hours during the evening and/or night shifts should be minimized whenever possible.

Additionally, the utilization of multiple shifts needs to comply with labor availability constraints. Construction managers and planners need additional labor for the evening and/or night shifts in addition to those working in day shifts because labor unions often restrict laborers to work no more than one shift per day. In many projects, this required
additional skilled construction labor is often not available. The recent study by Construction User Round Table (CURT) reported that 82% of responding companies experienced shortage of skilled workers on their projects, and 78% of them indicated that the trend has worsened over the past years (Srour et al. 2006). In order to comply with these labor availability constraints, construction planners need to distribute and utilize the limited number of construction labor among multiple shifts in the most efficient and effective manner in order to maximize project performance.

Multiple shifts can also resolve resource conflicts among project activities for the same equipments by doubling or tripling their usage time (Clough et al. 2000; Oexman et al. 2002). Especially, the utilization of heavy, cost intensive, and specialized equipments are often restricted due to their lack of availability and high utilization cost. Construction planners and schedulers need to take into consideration the utilization of multiple shifts in construction projects as one of alternatives to accelerate project schedules while resolving conflicting critical equipment demands among project activities.

2-2.3 Requirements of Cost Effective and Efficient Resource Utilization

Network scheduling techniques often produce impractical and costly schedules that require significant fluctuations in the daily resource demands on site, as shown in Figure 2.1 (Harris 1978). These resource fluctuations cause additional construction costs, including (1) idle costs for construction resources that cannot be released during their non-productive time and need to be kept idle on site until they are needed at a later time (Akpan 2000), as shown in alternative 1 of Figure 2.1; (2) release and rehiring costs for construction resources that can be temporarily released during low demand periods and
rehired later when needed (Gomar et al. 2002), as shown in alternative 2 of Figure 2.1; and (3) mobilization costs such as mobilization and demobilization costs for construction equipment and clerical and training costs for construction workers to gradually mobilize/hire all the required resources until the peak demand level is reached (Karshenas and Haber 1990; Srour et al. 2006), as shown in Figure 2.1.

![Figure 2.1 Impact of resource fluctuation and peak demand on resource fluctuation cost](image)

In order to minimize the aforementioned costs of resource fluctuations (i.e., idle, release and rehiring, and/or mobilization costs), the level of resource fluctuations can be reduced by shifting the early start date of selected construction activities, as shown in Figure 2.2. This figure illustrates four alternative schedules and their resource fluctuation costs for a simple example. The first alternative (see Figure 2.2(B)) represents the early project schedule for a resource that cannot be released and rehired.
This alternative causes 13 idle resource days, requires a peak demand of 7 resources, and leads to a project duration of 8 days. The total resource fluctuation costs (RFC) of this schedule is $2,650, which includes (a) $1,950 of idle costs to retain non-productive construction resources on site during low demand periods until they are needed later on in the project; (b) no release and rehire costs; and (c) $700 of mobilization costs that are needed to gradually increase the level of resources to satisfy the maximum demand (i.e. MaxR=7) for the project and then gradually release them towards the end of project.

The second alternative represents the early project schedule for a resource that can be released and rehired. The project duration of this is 8 days and its resource fluctuation cost (RFC) is $1,600 which includes release and rehiring costs of $900 for 4 resources, and mobilization costs of $700 to hire a peak demand of 7 resources. The third alternative represents the impact of shifting the early start of activity B within its float by 3 days (see Figure 2.2(D)), which causes 4 idle resource days, requires a peak demand of 7 resources, and leads to a project duration of 8 days. The resource fluctuation cost (RFC) of the third alternative ($1,300) is less than the first two alternatives because it reduced the resource fluctuation in the schedule. In order to achieve the most cost effective and efficient resource utilization on construction projects, the impact of resource fluctuation and peak demand on resource idle costs, release and rehiring costs, and mobilization costs should be directly measured and minimized. The example in Figure 2.2(E) also illustrates that the resource fluctuation and peak demands can often be minimized by allowing an extension in the project duration. This fourth alternative shows the impact of shifting the early start of activity B by 4 days, which requires zero idle resource days, zero released and rehired resources, a peak demand
of 6 resources, and project duration of 9 days, as shown in Figure 2.2(E). Extending the project duration by 1 day in this alternative enabled it to generate the least resource fluctuation cost (RFC=$600) among the four alternatives because it produced the minimum peak resource demand and mobilization costs while eliminating resource idle costs and release and rehiring costs. As such, construction planners need to analyze and optimize potential tradeoffs between minimizing resource fluctuation costs and minimizing the project duration in order to identify and implement an optimal project schedule and resource utilization plan for construction projects.
Figure 2.2 Impact of schedule changes on resource fluctuation cost and project duration

- ** Idle days = 13 days → Idle cost = $1,950
- Released and rehired resources = 0 → Release and rehiring cost = $0
- Peak resource demand = 7 → Mobilization cost = $700
- Resource fluctuation cost (RFC) = $2,650
- Project duration = 8 day

- ** Idle days = 0 days → Idle cost = $0
- Released and rehired resources = 3 → Release and rehiring cost = $900
- Peak resource demand = 7 → Mobilization cost = $700
- Resource fluctuation cost (RFC) = $1,600
- Project duration = 8 day

- ** Idle days = 4 days → Idle cost = $600
- Released and rehired resources = 0 → Release and rehiring cost = $0
- Peak resource demand = 7 → Mobilization cost = $700
- Resource fluctuation cost (RFC) = $1,300
- Project duration = 8 day

- ** Idle days = 0 days → Idle cost = $0
- Released and rehired resources = 0 → Release and rehiring cost = $0
- Peak resource demand = 6 → Mobilization cost = $600
- Resource fluctuation cost (RFC) = $600
- Project duration = 9 day

- ** Alternative 3: Shift activity B by 3 days & resource cannot be released
- ** Alternative 4: Shift activity B by 4 days & delay project duration by 1 day
2-3 Requirements of Project Risk Assessment in Construction Projects

Critical path method (CPM) has been widely used for project planning and controlling in construction industry. This method has the capabilities of showing the precedence relationships among project activities, identifying project critical paths, providing activity float times, and generating optimized resource allocation (Okmen and Oztas 2008). However, this method has long been criticized by many researchers due to its assumption that the durations of project activities are deterministic and it is not changed by various uncertainties such as weather, productivity, site conditions, and labor skill during construction period (Ang et al. 1975; Faniran et al. 1998; Jaafari 1984; Mo et al. 2008; Nasir et al. 2003; Okmen and Oztas 2008). In real projects, these uncertainty factors always exist and can affect on the duration of construction activities. Accordingly, this limitation of critical path method (CPM) may lead to provide a construction planner with incorrect critical paths and fail to complete the project by a target time (Jaafari 1984). Therefore, reliable forecast of project completion is essential for project success, because it can provide the greater percentage of recovery in the early stage of project and provide alternative decisions for cost escalation involving time/cost tradeoffs (Ahuja and Nandakumar 1985). There is a pressing need for developing an advanced project risk assessment model that is capable of forecasting the project completion time and providing the reliable project performance.
2-4 Construction Resource Utilization Optimization Models

2-4.1 Resource Leveling Models

The primary purpose of resource leveling is to reduce peak requirements and smooth out period-to-period fluctuations in resource assignment without changing project time (Hegazy 1999b). A number of resource leveling models and algorithms have been developed to reduce the level of fluctuations in resource utilization and their negative impact on construction productivity and cost. These models introduced and utilized a number of metrics to reduce resource fluctuations including: (1) sum of squares method; (2) absolute difference between resource consumption in consecutive time periods; (3) deviation between actual resource usage and a desirable or a uniform resource usage; and (4) sum of squares of resource changes.

First, a number of research studies have utilized sum of square method to calculate total sum of squares of daily resource demands in order to reduce the level of resource fluctuation (Ahuja 1976; Bandelloni et al. 1994; Burgess and Killebrew 1962; Harris 1978; Hegazy 1999b; Son and Skibniewski 1999), as shown in Equation (2.1).

\[ M_x = \sum_{t=1}^{T} r_t^2 \]

(2.1)

Where, \( M_x \) = total sum of squares of daily resource demands; \( T \) = project duration; and \( r_t \) = daily resource demand on day (t). This equation produces minimum value when the resource profile can have exact uniform distribution (i.e. rectangular shape of resource profile). The uniform distribution of resource profile can be made when each daily
resource demand is equal to average of total sum of daily resource demands, as shown in Equation (2.2).

\[ U = \frac{\sum_{t=1}^{T} r_t}{T} \]  

(2.2)

Where, \( U \) = uniform level of resource demand.

Second, many research studies have developed resource leveling metrics to minimize absolute difference between resource consumption in consecutive time periods in order to improve resource utilization efficiency (Easa 1989; Senouci and Adeli 2001; Senouci and Eldin 2004), as shown in Equation (2.3). This equation produces minimum value when the resource profile can have exact uniform distribution.

\[ Abs-Diff = \sum_{t=1}^{T-1} |r_{t+1} - r_t| \]  

(2.3)

Third, in order to improve resource utilization efficiency, a number of research studies have attempted to minimize deviation between actual resource usage and a desirable or a uniform resource usage (Akpan 2000; Chan et al. 1996; Chua et al. 1996; Easa 1989; Leu and Yang 1999; Mattila and Abraham 1998; Son and Mattila 2004), as shown in Equation (2.4)
\[ Res-Dev = \sum_{i=1}^{r} |LU - r_i| \]  
\[ (2.4) \]

Where, \( LU \) = a desirable or a uniform level of resource demand. This equation also produces minimum value if the resource profile is exactly same as a desirable or a uniform distribution of resource profile (i.e. rectangular resource profile).

Fourth, Ahuja (1976) proposed the metrics that minimize sum of squares of resource changes to improve resource utilization efficiency, as shown in Equation (2.5). This equation produces minimum value when the resource profile has exact parabolic shape, which represents gradual build-up and run-down resource utilization during project duration.

\[ SRC = r_1^2 + \sum_{i=1}^{r-1} (r_{i+1} - r_i)^2 + r_r^2 \]  
\[ (2.5) \]

Those resource leveling metrics were incorporated in the models to minimize the level of fluctuation in resource utilization using various optimization tools including (1) heuristic methods (Ahuja 1976; Akpan 2000; Burgess and Killebrew 1962; Harris 1978); (2) linear programming (Easa 1989; Mattila and Abraham 1998); (3) integer programming (Son and Mattila 2004); (4) dynamic programming (Bandelloni et al. 1994); (5) simulated annealing (Son and Skibniewski 1999); (6) mathematical method (Senouci and Adeli 2001); and (7) genetic algorithms (Chan et al. 1996; Chua et al. 1996; Hegazy 1999b; Leu and Yang 1999; Senouci and Eldin 2004). Although these
models have made significant contributions in this area, they have attempted to minimize the difference between fluctuating resource profiles and a predetermined desirable shape such as a rectangular or a parabolic shape, and thereby the models that adopt those metrics penalized various alternative shapes of resource profiles that may produce more efficient resource utilization than those achieved by those metric (see Figure 1.3).

2-4.2 Resource Allocation Models
The objective of resource allocation is to resolve resource conflicts among project activities for same labors and equipments by rescheduling activities while keeping the unavoidable extension of the project duration to a minimum. Many research studies have developed optimization model for a resource allocation problem using various techniques including (1) heuristic methods (Ahuja 1976; Bell and Han 1991; Boctor 1990; Sampson and Weiss 1993); (2) integer programming (Talbot 1982); (3) linear programming (Mingozzi et al. 1998); (4) dynamic programming (Gavish and Pirkul 1991); (5) branch and bound algorithm (Brucker et al. 1998); (6) simulated annealing (Lee and Kim 1996); (7) genetic algorithms (Chan et al. 1996; Chua et al. 1996; Hegazy 1999b; Kim and Ellis 2008; Lee and Kim 1996; Leu and Yang 1999; Senouci and Eldin 2004); and (8) particle swarm optimization (Zhang et al. 2006b). Early attempts to solve resource allocation problems using mathematical models such as linear programming, integer programming, and dynamic programming often suffer from large scale problems required in practical application due to a phenomenon called “combinatorial explosion” (Chan et al. 1996). Heuristic methods based on priority-rule are capable of overcoming
the problem of combinatorial explosion. However, these methods cannot guarantee optimal solution, although it provides good feasible solutions. Therefore, a number of research studies have developed the models using meta-heuristic search methods such as simulated annealing (SA) and tabu search (TS), and naturally inspired algorithms such as genetic algorithms (GA) and particle swarm optimization (PSO).

Lee and Kim (1996) have applied SA, TS, and GA for resource allocation problem and compared their performance with each other. A new encoding scheme which denotes priority of each activity was developed and used in those algorithms. The analysis results showed that those algorithms outperform existing heuristic methods such as the minimum slack method in searching for optimal solution, and SA provides the best performance among three optimization algorithms.

Chan et al. (1996) have presented GA-scheduler that searches for optimal schedules that provide minimum project duration under the resource constraints using genetic algorithm (GA). The objective function was designed to minimize the deviation between the required resources and the available resources while minimizing the extension of project duration by penalizing scheduling beyond target date. This enables simultaneous optimization of resource leveling and allocation as well as “due-date” problems. The application results showed that GA-scheduler outperforms heuristic methods, and the computational time does not grow exponentially for a larger problem.

Chua et al. (1996) have developed co-evolving resource scheduling model using genetic algorithm (GA) that is capable of generating optimal schedule that minimizes project duration with respect to the resource availability profile that is configured
interactively with the schedule for minimum resource idling. The resource contacts model was designed to subdivide the entire project into separate resource contracts and control the resource hiring levels for each contract by GA. The model is capable of simultaneously searching for optimum schedules and the required resource profile that minimize project duration while providing minimum resource idling. The case study illustrated that the model also could provide schedules and corresponding resource available profiles that yield considerable savings idle resources even in multi-resource problems.

Leu and Yang (1999b) introduced new GA crossover and mutation operators, UX3 and UM3 that overcome the limitation of traditional GA operators for sequencing problems. GA-based resource constrained construction scheduling (GARCS) model that incorporates those two new GA operators was developed to generate optimal schedules that minimize project time under the resource availability constraints. The model was extended to consider time-cost tradeoff as well as resource constrained scheduling. In order to search for optimal time-cost tradeoff under the resource availability constraints, the model was developed as multi-objective GARCS that consists of six subsystems: activity duration generation subsystem, activity order generation subsystem, project cost calculation subsystem, project duration calculation subsystem, evaluation subsystem, and selection subsystem. Application examples illustrated that the model has a capability of searching for non-dominated solutions for the multi-objective resource-constrained scheduling problems after a number of trials.
Zhang et al. (2006b) have developed the model using a particle swarm optimization (PSO) to exploit both preemption and break for the resource constrained construction project with the objective of minimizing project time. The model allows the break to take place in off-working time and allows the interrupted activities not to resume soon in the next working period, and accordingly, multiple activities can share the constrained resources while the activities are interrupted. The example analysis demonstrated that the preemptive scheduling under break and resource-constraints (PSBRC) has a capability of minimizing project duration and illustrated that the PSO-based methodology for the PSRBC is effective.

Kim and Ellis (2008) presented a permutation based elitist genetic algorithm to optimize a large-scale resource constrained project scheduling. The algorithm employed the elitist strategy to preserve the best individual solution for the next generation in order to obtain an improved solution. New random number generator was developed to examine precedence feasible individuals. The model employed a serial schedule generation scheme proposed by Kelly (1963) for the permutation-based decoding. In order to demonstrate the use of present model and its capability of searching for optimal solutions in a large-scale project network, the project networks with 30, 60, and 120 activities were analyzed by the present model. The results of analysis illustrated that the present model can explore and exploit several suboptimal solutions, which may include the optimal solution, and the proposed algorithm is useful to solve the multiple resource-constrained project scheduling problems.
2-4.3 Time-Cost Tradeoff Analysis Models

Time-Cost optimization (TCO) problem has been extensively examined by a number of research studies. Various approaches have been proposed for optimizing construction time and cost including (1) heuristic methods (Fondahl 1961; Moselhi 1993; Prager 1963; Siemens 1971); (2) mathematical programming (Liu et al. 1995; Moussourakis and Haksever 2004); and (3) meta-heuristic methods (El-Rayes and Kandil 2005; Feng et al. 1997; Hegazy 1999a; Hegazy and Ersahin 2001; Jaskowski and Sobotka 2006; Leu and Yang 1999; Li et al. 1999; Li and Love 1997; Senouci and Eldin 2004; Xiong and Kuang 2008; Zhang et al. 2006b; Zheng et al. 2004, 2005). Mathematical programming such as linear programming is suitable for problems with linear time-cost relationships, but they often fail to solve the problem with discrete time-cost relationships (Feng et al. 1997). Moreover, it requires a lot of computational efforts to solve a large scale project network. Heuristic methods are able to overcome such limitation of a large scale problem, but fail to guarantee optimal solutions. Therefore, many research studies have focused on utilizing meta-heuristic methods in time-cost tradeoff analysis to overcome the limitation of heuristic methods and mathematical programming.

Liu et al. (1995) have developed optimization model using a hybrid method that integrates linear and integer programming. Linear programming was used to find lower bounds of the solutions, and then integer programming was used to obtain the exact solution. In linear programming model, the time-cost curve of each activity was identified by piecewise linear approximation. All the dominated options were eliminated when establishing the convex hull. This convex hull was then used as the set of the
constraints (lower bounds) within each activity that contributes to the linear model of the time-cost tradeoff problems. The integer programming was then used to minimize total project cost with the constraints of activity precedence and the selection of a single resource utilization option for each activity. The hybrid model was developed using Microsoft Excel to provide a construction planner with an efficient means of analyzing time-cost trade-off decisions.

Feng et al. (1997) have presented the model using genetic algorithm (GA) to search for optimal time-cost tradeoff. Pareto front approach was used to search for non-dominated solutions that simultaneously minimize project time and cost. These non-dominated solutions were founded by plotting each solution in the population and calculating the distance of each point in each generation from each segment of the convex hull of the generation. The calculated distance is then used to select the solutions in the population to reproduce the next generation solutions. The optimal time-cost curve can be founded in the final population. An example with 18 activities was analyzed by the model and it showed that the model was able to generate 95% of the optimal points on the time-cost curve.

Hegazy (1999a) have implemented GA in the commercial project management software, MS-project, using VBA language. The model was developed to search for the least cost combination of construction methods for the various tasks, considering deadline duration, late completion liquidated damages, early completion incentive, and daily indirect cost. Moreover, the model combines time-cost tradeoff with resource management procedure to schedule construction projects under the resource
availability constraints. This resource constrained scheduling was performed by the feature originally included in the commercial project management software. The results of case study illustrated that the model could produce better solution than heuristic method. This development tool provides a practical tool which can be used in practice.

Li et al. (1999) have presented machine learning and genetic algorithms based system (MLGAS) that integrates a machine learning method with GA to overcome the limitations of existing GA based systems for time-cost tradeoff problems. The research study indicated that there are two limitations on existing GA models: (1) the existing models requires the user to manually craft the time-cost curves for formulating the objective functions; and (2) the systems only deal with linear time-cost relationships. The Quadratic Time-Cost Curves Discovery System (QTCD) was developed using machine learning method to automatically generate the quadratic time-cost curves from historical data and measure the credibility of each quadratic time-cost curve. The generated time-cost curves are then used to formulate the objective function, and it was optimized by the GA. The GA was improved by using multiple point crossover and variable mutation probability. This prevents the GA operations from being trapped into local optima. Case study showed that MLGAS outperforms the human expert in solving nonlinear time-cost tradeoff problems and it could produce the better solutions than the solutions produced by heuristic methods.

Zheng et al. (2004) have presented multi-objective optimization approach that simultaneously optimize project time and cost. Modified adaptive weight approach (MAWA) was developed to replace traditional fixed or random weights. The objective
functions for time and cost were integrated into a single objective for simulation. This approach overcomes the limitation of single objective time-cost tradeoff and enables GA to have greater searching pressure to resist the inherent convergence power of GA. The adaptive weights have practical meaning in representing the relative importance of each criterion for the project. These weights enable GA to search a wider range against the objectives that have a relatively small search space in previous generations. This approach can guarantee the diversity of exploration and efficiency of exploitation of historical information.

Zheng et al. (2005) have developed GA-based multi-objective optimization model that simultaneously minimizes time and cost. In order to overcome the problem of genetic drift, the model utilized Pareto ranking, niche formation, and adaptive mutation rate. The genetic drift occurs when GA converge to a single peak due to the stochastic errors during processing. The model incorporated modified adaptive weight approach (MAWA) to exert a search pressure in GA. Pareto ranking mechanism overcomes the limitation of traditional proportional selections. Niche formulation is useful for stabilizing multiple subpopulations that arise along the Pareto-optimal front, and thereby it maintains diversity of population. A computer prototype was developed as a macro in Microsoft Project to evaluate the feasibility of solutions generated by GA. The medium sized project was selected and fitted into the prototype to test the performance of model. The results confirm that the developed model is reliable to generate optimum solutions.

El-Rayes and Kandil (2005a) have presented the multi-objective optimization model for time-cost-quality tradeoff analysis. Multi-objective genetic algorithm was used in the
model to generate the optimal solutions for those conflicting objectives. The decision variables were feasible resource utilization options that include construction method, crew formation, and crew overtime policy. The construction methods include the utilization of different type of materials that have different strength. Each feasible resource utilization options have various combinations of those available options, and it provides an expected daily production rate, cost rate, and quality performance. The multi-objective genetic algorithm was implemented in the model to search for optimal resource utilization options for each activity that provides minimum project cost and time while maximizing quality performance. The model also provided visualization of tradeoffs among time, cost, and quality for the analyzed example.

Xiong and Kuang (2008) have used ant colony optimization (ACO) algorithm to solve time-cost tradeoff problem. The modified adaptive weight approach (MAWA) proposed by Zheng et al. (2004) was incorporated in the model to generate optimal time-cost tradeoff curve. ACO algorithm is inspired by ant colony behavior, and it searches optimal solutions in combinatorial problems. Each of \( m \) ants constructs one solution in every generation, and the heuristic information and pheromone information are used to select an option to perform an activity. MAWA utilizes information from the current set of solutions to generate an adaptive weight for each objective, and thereby exerts a search pressure towards the ideal point. The performance of developed model was compared with GA by two test examples. The results showed that ACO-based multi-objective approach provides an attractive alternative to solving construction time-cost optimization.
2-4.4 Multi-Objective Resource Scheduling Models

Optimizing resource leveling, resource allocation, and time-cost tradeoff analysis are often interrelated with each other. Therefore, a number of research studies have formulated the models that simultaneously optimize those conflicting objectives (Hegazy 1999b; Hegazy and Ersahin 2001; Leu and Yang 1999; Senouci and Eldin 2004).

Hegazy (1999b) have developed the optimization model that can simultaneously consider resource leveling and allocation. The model was developed using the macro language of Microsoft project to provide a project manager with an automated tool to improve the results of their familiar software. MS-project allows user to specify the priority levels for activities, and thereby resource conflicts can be resolved by the specified priority levels. These priority levels for activities were set as genes in GA, and the activities were scheduled by MS project based on the randomly generated priority levels by GA. Two resource leveling metrics, \( M_x \) and \( M_y \), were then calculated for the schedules to evaluate its level of resource fluctuation. The calculated values of two metrics were used as fitness functions in GA to optimize resource leveling. However, the resource-leveling feature of MS project schedules the activities as early as possible based on their specified priority levels. Accordingly, the model might not generate schedules that might have better level of resource utilization than those produced by MS project.

Hegazy and Ersahin (2001) have presented the spread sheet model that simultaneously considers time-cost tradeoff analysis, resource allocation, resource leveling, and cash flow management. The genetic algorithm was implemented in Microsoft Excel to
facilitate the development and the optimization. Those objectives are aggregated in one objective function, total project cost, to be minimized. Those objectives that violate the constraints were penalized using the cost term in the objective function. The model has a capability of searching for optimal schedule that minimizes the total project cost under time, cost, and resource constraints simultaneously. The results of case studies confirmed the consistency and good performance of the model.

Leu and Yang (1999) have developed the multi-criteria optimal model for construction scheduling. The model integrates time-cost trade-off model, resource allocation model, and resource leveling model. A genetic algorithm was used in the model to search for optimal solutions. Two GA operators, UX3 and UM3, were introduced and used in the model to enhance the performance of GA in searching for optimal solutions. The study also developed a resource leveling index (RLI) as an objective function to optimize multiple resources leveling. This objective function uses the penalty value (P) to prevent the violation of precedence relationships and resource overutilization. In order to search for non-dominated solution, TOPSIS, a MADM method that was proposed by Hwang and Yoon (1981) was used in the model. The performance of model was compared with traditional heuristic and mathematical models by analyzing case studies. The results showed that the GA has great advantages and performance in simultaneously optimizing multi-objectives for constructions scheduling.

Senouci and Eldin (2004) have presented an augmented Lagrangian genetic algorithm model for resource scheduling. The model considers all precedence relationships, multiple crew strategies, total project cost minimization, and time-cost tradeoff. The
model was formulated to consider both resource leveling and resource constrained scheduling. The quadratic penalty function was used to transform the resource scheduling problem to an unconstrained one. The model allows any linear or nonlinear functions for the presentation of cost-duration and resource-duration relationships. The model is capable of searching for optimal durations for each activity and construction schedules that minimize project cost while satisfying the constraints such as resource constraint, activity relationship constraint, and duration constraint. The application example showed that the developed model was able to simultaneously optimize resource leveling and allocation as well as total project cost.

2-4.5 Limitation of Available Models

Despite the significant contributions and practical features of the previous studies, there are still some limitations that need to be addressed. These limitations can be summarized as follows:

1. The aforementioned resource leveling models are incapable of maximizing resource utilization efficiency as they do not focus on directly measuring and minimizing undesirable resource fluctuation that causes the negative impacts on construction productivity and cost.

2. None of the models in the literatures was developed to generate optimal tradeoff between resource utilization efficiency and project time. Although more improved resource utilization can be achieved in the longer project duration, most of research studies have only focused on minimizing resource fluctuation in the fixed project time.
3. Available models do not consider multiple shifts operation to accelerate project schedule and analyze time-cost tradeoff for construction projects. Moreover, there are no reported researches that focus on optimizing resource utilization in multiple shifts to minimize the negative impacts of shift work on construction productivity, safety, and cost.

4. There has been little or no reported research that focused on (1) studying and quantifying the impact of daily resource fluctuations on resource fluctuation costs including idle costs, release and rehiring costs, and mobilization costs; and (2) modeling and optimizing potential tradeoffs between minimizing resource fluctuation costs and minimizing project duration. There is a pressing need to develop a robust optimization model that is capable of generating cost effective resource utilization plan for construction projects.

This research aims to overcome the above limitations in order to provide advanced models that can be used by construction engineers or planners during the planning of construction resource. The following section introduces a review of multi-objective genetic algorithms and their potential capabilities to overcome these limitations and achieve the objectives of this study.

2-5 Multi-Objective Genetic Algorithms

Genetic algorithms (GAs) have been most widely used tool to solve multi-objective construction engineering and management problems, including resource leveling, resource allocation, and time-cost tradeoff, as described earlier. A number of
researchers have developed the methods that can deal with multi-objectives in the optimization process including the modified adaptive weight approach (MAWA), the convex hull approach, and the TOPSIS. These methods are capable of searching for non-dominated optimal solution (i.e. Pareto front), and thereby they can deal with multi-objective problems. Traditional multi-objective optimization approach was to combine the two objective functions in to one function using a method for weighting those objectives. However, the problem of this approach is that the overall optimum is achieved at the dominating objective only, and thereby it is difficult to identify the proper weights for each objective (Feng et al. 1997). In order to overcome the limitation of these weighting approaches to solving multi-objective optimization problems, a number of multi-objective GA have been developed, including Strength Pareto Evolutionary Algorithm (SPEA), Pareto-Archived Evolutionary Strategy (PAES), and Non-dominated Sorted Genetic Algorithms (NSGA II) (Deb et al. 2001). Among those algorithms, it was reported that NSGA II is one of the most robust multi-objective genetic algorithms (Zitzler et al. 2001). The performance of NSGA II was tested using a multi-objective example, and it was compared to the performance SPEA II and PAES. The comparison results showed that SPEA II and NSGA II had the best overall performance (Zitzler et al. 2001). Other research studies also demonstrated that NSGA II and SPEA II outperform other multi-objective optimization algorithms (D’Souza and Simpson 2002; Hiroyasu et al. 2002; Watanabe et al. 2000). A number of research studies have successfully utilized NSGA II in construction engineering and management problems (El-Rayes and Kandil 2005; El-Rayes and Khalafallah 2005; Hyari and El-Rayes 2006; Khalafallah and El-Rayes 2006, 2008). The results of these studies illustrated that NSGA II provides
good performance in multi-objective optimization problems for construction engineering and management area.

2-6 Probabilistic Project Network Analysis Models

In order to overcome the limitations of deterministic scheduling methods, the program evaluation and review technique (PERT) was developed by the US Navy in 1958 as a probabilistic scheduling method that can be used to estimate the probability of project completion (Kerzner 2009). PERT enables planners to (a) express the uncertainty in estimating the durations of project activities by providing three duration estimates for each activity: optimistic, most likely, and pessimistic duration; and (b) analyze the impact of the probabilistic estimates of activity duration on the probability of the overall project duration. Despite its probabilistic scheduling capabilities, the PERT method has been criticized by many research studies due to its “merge event bias” limitation. This critical limitation causes the PERT method to neglect the impact of sub-critical paths on the overall probability of project completion, and thereby it often leads to optimistic results and underestimating the expected project duration (Ahuja et al. 1994; Halpin and Riggs 1992; Slyke 1963).

In order to overcome the limitation of program evaluation and review technique (PERT), a number of probabilistic scheduling methods were developed including (1) probabilistic network evaluation technique (PNET) (Ang et al. 1975); (2) narrow reliability bounds (NRB) (Ditlevsen 1979); (3) Monte Carlo simulation (MCS) (Diaz 1989); and (4) simplified Monte Carlo simulation (SMCS) (Diaz 1989). Diaz and Hadipriono (1993)
analyzed and compared the performance of these scheduling methods including PERT in estimating the probability of project completion. The comparison results showed that (a) PERT, PNET, and NRB produced more optimistic results than MCS, (b) MCS provided the most accurate estimate for the probability of project completion; and (c) SMCS produced results that are very close to MCS (Diaz and Hadipriono 1993).

Monte Carlo simulation (MCS) is widely used as a probabilistic scheduling method for construction projects (Diaz and Hadipriono 1993; Halpin and Riggs 1992; Lee and Arditi 2006; Lu and AbouRizk 2000; Sculli 1989; Slyke 1963). Despite its accuracy in estimating the probability of project completion, the Monte Carlo simulation method has been criticized by many researchers due to its large computation load for large scale projects. It requires a great number of simulation runs for accurate probability estimation and each simulation run requires on the scheduling of the entire project activities including the forward path analysis of the critical path method (CPM) to identify the project duration (Ang et al. 1975; Guo et al. 2001; Lu and AbouRizk 2000; Mummolo 1997; Sculli 1989; Zammori et al. 2009). Other research studies in probabilistic scheduling developed approximation methods (Ang et al. 1975; Gong and Hugsted 1993; Guo et al. 2001; Sculli and Shum 1991) and multivariate methods (Anklesaria and Drezner 1986) and combined them with the PERT method.

Ang et al. (1975) have developed the probabilistic network evaluation technique (PNET) to overcome the limitation of “merge event bias” of PERT. This technique considers the impact of correlations among the project network paths that have same activities. They have estimated the probability of project completion by formulating the probabilistic
project network problem as a multiple joint probabilities. In order to calculate the multiple joint probabilities for the probabilistic project network, they have identified the upper and lower bounds for the probability of project completion and then developed a new approximation method based on the correlations among project network paths. The PNET method is developed based on the following three observations: (1) The paths with long mean durations and high coefficients of variation will have the greatest significance on the probability of project completion; (2) if several paths are highly correlated with a major path, then these paths are represented by the same major path alone; and (3) if several paths have low mutual correlations, the probability of project completion can be approximated with the product of those respective path probabilities. Based on those observations, Ang et al. (1975) have approximated the probability of project completion by sorting the paths based on their mean and then evaluating the correlations among the project network paths. Application examples have illustrated that PNET has a capability of generating similar results compared to Monte Carlo simulation (MCS).

Sculli and Shum (1991) have introduced a new method to provide the approximated solution for the PERT problem. The method formulated the PERT problem as the multivariate normal probability and then obtained an approximation to the mean and standard deviation of the completion time of the network. It is assumed that all the paths in the project network are normally distributed based on the central limit theorem (CLT). New approximation method was developed to obtain the mean and variance of multivariate normal probability of project completion time using the method introduced

Gong and Hugsted (1993) have introduced a new analytical merge-event time-estimation technique, called the back-forward uncertainty-estimation (BFUE) procedure. The technique is based on the fact that a noncritical path can become a subcritical or critical path through the use of the slack time along the path. Three types of event were considered in the technique: (1) event connected with one activity end; (2) event connected with two merging paths; and (3) event connected with more than two merging paths. Based on each type of event, BFUE calculates the expected time and time variance of a project network. The BFUE procedure locates the relative start events of the relevant merging paths so that the correlation influence on the merge-event time estimation can be offset. Therefore, BFUE procedure obtains its accuracy by coping with the assumption of the independence of the relevant merging paths. The assumption of the normal distribution is applied in this technique. Also, it is assumed that the correlations between the merging paths are zero. Application examples have illustrated that BFUE produces the results closed to the results produced by the PNET and Monte Carlo simulation (MCS).

Guo et al. (2001) have developed a new analytical method, the Modified Stochastic Assignment Model (MSAM), for the prediction of project duration. The method modified the Stochastic Assignment Model (SAM) which was originally implemented in traffic assignment problem (Maher and Hughes 1997). This method applies the approximation method developed by Clark (1961) to find the longest project duration. The method
proposed by Clark (1961) enables the estimate of the mean and standard deviation of the project duration. It is assumed that the duration of project activity follows normal distribution, and the activities are not correlated with each other. MSAM methods first scan outward from the start event to the ends of all activities which leave the event. Whenever merge event occurs, MSAM determines the distribution of the maximum duration from the start event to the current event. After finishing the scanning process, it calculates the probability of project completion based on the estimated mean and standard deviation of project duration distribution. Application examples illustrated that MSAM produced similar results to MCS and PNET.

Anklesaria and Drezner (1986) have formulated the PERT project network analysis as a multivariate normal probability problem to evaluate the impact of sub-critical paths in the project network on the probability of project completion. Their method however can provide a reasonable computation time only for project networks that have fewer than seven integral m-dimensions (m ≤ 7), and therefore it approximates the probability of project completion by selecting only less than seven representative network paths. Application examples illustrated that the proposed method produced similar results compared to the results produced by Monte Carlo simulation (MCS).

As such, a number of research studies have developed and introduced various methods to overcome the limitations of "merge event bias" of PERT and to estimate the probability of project completion for the project network. Despite the significant contributions of the aforementioned research studies to the area of probabilistic scheduling, there are little or no reported research studies that focused on probabilistic
scheduling methods using the multivariate method that are capable of analyzing large scale construction projects that require the analysis of more than seven representative network paths in a practical computational time. Accordingly, there is a pressing need for a new probabilistic scheduling model that is capable of providing fast and accurate risk evaluation for real-life and large-scale construction projects.

2-7 Summary

This chapter first discusses relevant requirements of resource utilization plan in construction projects. It also illustrates that none of available resource utilization optimization models have focused on (1) directly measuring and minimizing undesirable resource fluctuation to maximize resource utilization efficiency; (2) generating optimal tradeoff between resource utilization efficiency and project time to support a construction planner in selecting the best solution that satisfies the special requirements of project being considered; (3) considering optimization of multiple shifts schedules and resource utilization for accelerating a project using time-cost tradeoff analysis; and (4) analyzing the impact of resource fluctuation and peak demand on resource utilization cost. The literature review has revealed that multi-objective genetic algorithms, NSGA II has proved to be one of the robust algorithms that outperform other available optimization algorithms. This chapter also discusses the existing approaches for the probabilistic project network analysis. It illustrates that none of the existing methods have focused on probabilistic scheduling methods using the multivariate method that are capable of analyzing large scale construction projects that require the analysis of more than seven representative network paths in a practical computational time. The
following chapters will evaluate the performance of multi-objective genetic algorithm in optimizing resource utilization in construction projects and introduce an advanced project risk assessment model.
CHAPTER 3
RESOURCE LEVELING MODEL

3-1 Introduction
The main objective of this chapter is to present the development of (1) innovative resource leveling metrics that circumvent the limitation of existing approaches and are capable of directly measuring and minimizing the negative impact of resource fluctuations on construction productivity and cost; and (2) a robust and practical optimization model that incorporates the newly developed metrics and is capable of generating optimal and practical schedules that maximize the efficiency of resource utilization in construction projects. The preset model is developed in four main tasks: (1) exploring two types of resource fluctuations; (2) formulating innovative resource leveling metrics to maximize resource utilization efficiency; (3) implementing an optimization model that is capable of generating optimal schedules that maximize resource utilization efficiency; and (4) evaluating and verifying the model performance. The following sections in this chapter describe these four main research tasks.

3-2 Types of Resource Fluctuations
Resource fluctuations can be classified based on their impact on the efficiency of resource utilization into two types: (1) acceptable fluctuations; and (2) undesirable fluctuations, as shown in Figure 3.1. Acceptable fluctuations represent gradual build-up and run-down of resources, and they can be depicted graphically by a mountain shape in the resource histogram as shown in Figure 3.1(A). In this type of fluctuation, a
contractor needs to gradually increase the level of resource utilization to satisfy resource demands during different periods of the project and then gradually release them toward the end of the project. Gradual build-up and run-down of construction resources will minimize the number of times that a contractor has to hire, layoff, and then rehire the same resources (Mattila and Abraham 1998). On the other hand, undesirable fluctuations represent temporary decreases in the demand for construction resources. This can be depicted graphically by a valley shape in the resource histogram as shown in Figure 3.1(B). In this type of fluctuation, a contractor is forced to either (1) release the additional construction resources and rehire them at a later stage when needed; or (2) retain the idle construction resources on site until they are needed later in the project. In order to generate productive and cost effective construction schedule, this undesirable fluctuation should be directly measured and minimized.

![Figure 3.1 Types of resource fluctuations](image-url)
3-3 New Resource Leveling Metrics

Two new resource leveling metrics are developed to directly measure and quantify the impact of resource fluctuations on construction productivity and cost, Release and Re-Hire (RRH) and Resource Idle Days (RID).

3-3.1 Release and Re-Hire (RRH)

This metric is designed to quantify the total amount of resources that need to be temporarily released during low demand periods and rehired at a later stage during high demand periods, as shown in Figure 3.2(B). The present model utilizes Equation (3.1) to calculate the Release and Re-Hire (RRH) metric in three sequential steps: (1) calculate the total daily resource fluctuations (HR) using Equation (3.2) which sums up all the increases and decreases in the daily resource demand, as shown in Figure 3.2(B); (2) identify the total increases in the daily resource demand (H) which is half the total daily resource fluctuations (HR); (3) determine the number of released and re-hired resources by subtracting the maximum resource demand (MRD) from the total increases in the daily resource demand (H), as shown in Equation (3.1).

\[
RRH = H - MRD = \frac{1}{2} \times HR - MRD \tag{3.1}
\]

\[
HR = \left[ r_1 + \sum_{i=1}^{T-1} |r_i - r_{i+1}| + r_T \right] \tag{3.2}
\]

\[
MRD = \text{Max}(r_1, r_2, \ldots, r_T) \tag{3.3}
\]
Where, $RRH =$ total amount of resources that need to be temporarily released and rehired during the entire project duration; $H =$ the total increases in the daily resource demand; $HR =$ the total daily resource fluctuations; $T =$ total project duration; $r_t =$ resource demand on day $(t)$; $r_{t+1} =$ resource demand on day $(t+1)$; and $MRD =$ the maximum resource demand during the entire project duration. It should be noted that this metric can be practical and useful in projects that allow the release and rehire of construction workers. In other projects that restrict this type of resource release and rehire, contractors are often required to keep the additional resources idle on site during low demand periods, as shown in Figure 3.2(A). To quantify and minimize the impact of this decision on construction productivity and cost, the following section presents the development of a new metric named Resource Idle Days (RID).

![Figure 3.2 Calculations of the new metrics](image)
3-3.2 Resource Idle Days (RID)

This metric is designed to quantify the total number of idle and non-productive resource days caused by undesirable resource fluctuations and it can be calculated using Equation (3.4). As shown in Figure 3.2(C), idle resources occur on day (t) when the resource demand on that day (t) dips to a lower level than the peak demand levels experienced prior to and after that day (t). When this dip in resource demand occurs, the idle resources on day (t) can be calculated by subtracting its resource level from the least of the peak demands that occur before or after that day as shown in Figure 3.2(C).

For example, the number of idle resources on the fifth day (t=5) in Figure 3.2(C) can be calculated by subtracting the resource level on that day ($r_5 = 2$) from the next peak level occurring on the sixth day ($r_6 = 4$). As stated earlier, this metrics can be more practical and useful than the earlier described RRH metric in projects that impose restriction on releasing and rehiring construction resources.

$$\text{RID} = \sum_{t=1}^{T} \left[ \min \{ \max (r_1, r_2, \ldots, r_t), \max (r_t, r_{t+1}, \ldots, r_T) \} - r_t \right]$$  \hspace{1cm} (3.4)

Where, $\text{RID}$ = total number of idle and non-productive resource days during the entire project duration; $T$ = total project duration; and $r_t$ = resource demand on day (t).

The two newly developed metrics (RRH and RID) are designed to address different project needs. For projects that allow the release and rehire of construction workers, RRH can be effectively utilized to directly measure and minimize the release of resources during low demand periods and rehiring them when needed at a later stage.
For other projects that restrict resource release and rehire, RID can be effectively utilized to directly measure and minimize total resource idle time on site during low demand periods. Each of the two newly developed metrics adopts a unique methodology to minimize undesirable resource fluctuations, and accordingly they can produce different schedules and resource profiles, as shown in the simple example in Figure 3.3.

While existing metrics attempt to transform fluctuating resource profile to a predetermined desirable shape (e.g. a rectangular or a parabolic), the new metrics focus on minimizing only undesirable fluctuation, and accordingly they are capable of generating more efficient resource utilizations than existing ones. These two new metrics are incorporated in a newly developed optimization model that is capable of generating optimal schedules that maximize resource utilization efficiency. The development of this optimization model is described in more detail in the following section.

![Figure 3.3 Difference between RRH and RID metrics](image-url)
3-4 Optimization Model

A robust optimization model is developed to incorporate the aforementioned new resource leveling metrics and maximize the efficiency of resource utilization in construction projects. The optimization model incorporates the two new resource leveling metrics and it is developed and organized in three main modules: (1) Initialization module to calculate an initial project schedule and the number of total float days that each activity can be delayed without delaying the overall project duration; (2) Resource Leveling module to evaluate the impact of shifting non-critical activities within their available float times on the overall resource utilization efficiency; and (3) Genetic algorithm (GA) module to search for and identify a set of optimal schedules that maximize resource utilization efficiency. These three main modules are described in more detail in the following sections.

3-4.1 Initialization Module

The main objective of this module is to calculate an initial project schedule and the total float for each activity in the project. These float times are then used to identify the upper limit on the main decision variables in this model (i.e., number of allowable shift days for each activity). Accordingly, the main decision variables in the present model are named maximum-shift-days ($M_n$) and their total number is equal to the number of non-critical activities in the project, as shown in Figure 3.4. The computation procedure in this Initialization Module is performed using the following four main steps (see Figure 3.5):
1.1) Input the planning and scheduling data for each activity, including its duration, daily resource demand, and job logic.

1.2) Calculate the early start time ($ES_n$), early finish time ($EF_n$), late start time ($LS_n$), and late finish time ($LF_n$) for each activity ($n$) based on the input data in the previous step.

1.3) Calculate the free float ($FF_n$) and total float ($TF_n$) for each activity ($n$) using Equations (3.5) and (3.6).

$$FF_n = \text{Min}_{\text{succ}ES_n} - EF_n \quad (3.5)$$
$$TF_n = LS_n - ES_n \quad (3.6)$$

Where, $FF_n$ = free float of activity ($n$); $\text{Min}_{\text{succ}ES_n}$ = the minimum early start time among all the successors of activity ($n$); $EF_n$ = early finish time of activity ($n$); $TF_n$ = total float of activity ($n$); $LS_n$ = late start time of activity ($n$); and $ES_n$ = early start time of activity ($n$).

1.4) Set a lower and upper bounds on all decision variables ($M_n$) as shown in Equation (3.7). This constraint is specified to ensure that the shift of each non-critical activity will not exceed its identified total float ($TF_n$) and accordingly will not cause an extension to the overall project duration.

$$0 \leq M_n \leq TF_n \quad (3.7)$$
The main decision variables in this model are the number of shift days for each activity \((M_n)\) and they are represented using a genetic algorithm chromosome, as shown in Figure 3.4. The impact of these decision variables on the project resource utilization efficiency is evaluated and optimized in the Genetic Algorithm module and the Resource Leveling Module which are described in more details in the following two sections.

3-4.2 Genetic Algorithm Module

The objective of this module is to search for and identify a set of optimal schedules that maximize resource utilization efficiency. Genetic algorithm is implemented in the present model due to its robust capabilities of identifying optimal and near optimal solutions in large search spaces (Deb et al. 2001; Goldberg 1989). Genetic algorithms have been used by many studies to optimize resource leveling and allocation in construction projects (Chan et al. 1996; Chua et al. 1996; Hegazy 1999b; Leu and Yang 1999).
It should also be noted that despite its widespread utilization and capabilities in identifying near optimal solutions, genetic algorithms cannot guarantee the generation of the absolute optimal solution in all cases. In this module, the genetic algorithm computations are performed using the following three main steps (see Figure 3.5):

2.1) Generate an initial set of solutions (k=1 to K) for the initial population (P_{g=1}) in the first generation (g=1). Each solution (k) consists of randomly generated values for the maximum-shift-days variable (M_1,M_2,…,M_N), and accordingly these solutions (k=1 to K) are designed to produce an initial set of feasible project schedules and resource profiles, as shown in Figure 3.4.

2.2) Evaluate the impact of each solution (k) on overall resource utilization efficiency by using the Resource Leveling Module that calculates the earlier described Release and Re-Hire (RRH) or Resource Idle Days (RID) metrics and the maximum resource demand (MRD) as shown in Equations (3.1), (3.3) and (3.4). These metrics are incorporated in the optimization function of the present model as shown in Equations (3.8) and (3.9). This optimization function is designed to incorporate a planner defined weights (W_1) and (W_2) in order to minimize the RRH or RID metrics while simultaneously minimizing the maximum resource demand (MRD). Figure 3.6 illustrates the impact of this combined optimization on the efficiency of resource utilization. Limiting the optimization to only the new resource leveling metrics can generate resource profiles that provide minimum non-productive periods while requiring a large number of resources during the
peak demand periods as shown in Figure 3.6(B). Expanding the optimization function to include the new metrics (RRH and RID) as well as the maximum resource demand (MRD) can generate improved resource profiles that provide minimum non-productive periods while keeping the peak resource demand to a minimum, as shown in Figure 3.6(D). As described earlier, construction planners can select to minimize the Release and Re-Hire (RRH) or Resource Idle Days (RID) metrics depending on the special conditions and requirements of the construction project, and accordingly they can utilize either Equation (3.8) or (3.9) in the present optimization model. The calculated value of this optimization function will be used to evaluate the fitness of each solution (k) in population (P_g) for reproducing new offspring solutions in the next step.

\[
\text{Minimize resource fluctuation and peak demand} = \min (W_1 \cdot \text{RRH} + W_2 \cdot \text{MRD}) \quad (3.8)
\]

\[
\text{Minimize resource fluctuation and peak demand} = \min (W_1 \cdot \text{RID} + W_2 \cdot \text{MRD}) \quad (3.9)
\]

Where, \(W_1\) = planner defined weight or relative importance for the RRH or RID; and \(W_2\) = planner defined weight or relative importance for the MRD. Construction planners can specify these weights of \(W_1\) and \(W_2\) to reflect the relative importance of minimizing undesirable resource fluctuations and minimizing the maximum resource demand in their projects. The relative importance of these two important objectives depends on the specific project conditions and needs and may vary from one project to another. Accordingly, the present model is designed to provide construction planners with the flexibility to
easily experiment with varying weights and analyze their impact on the generated optimal schedules.

2.3) Create the next generation population \((P_{g=g+1})\) of solutions based on the calculated fitness values using genetic operators such as selection, crossover, and mutation. The selection operation is used to identify the fittest solutions for the reproduction phase. The crossover operation is used to reproduce two new offspring solutions by swapping the parameters of the parent solutions coded in the strings at randomly determined points. The mutation operation is used to randomly change the value of one of parameters in the string to avoid convergence to local optimal solutions (Chua et al. 1996; Goldberg 1989). Steps 2.2) and 2.3) are repeated over a number of predetermined generations \((G)\) in order to generate optimal/near optimal schedules that maximize resource utilization efficiency for construction projects.
3.3) Calculate the number of selected-shift days \( S_{n^*} \) based on the updated FF\(_{n^*}\), TF\(_{n^*}\), and M\(_{n^*}\) using Eq. (9).

3.4) Shift the selected non-critical activity \( (n^*) \) and calculate its rescheduled ES\(_{n^*}'\) and EF\(_{n^*}'\) using Eq. (10) and (11).

3.5) Recalculate the free float time of all the predecessors of the selected non-critical activity \( (n^*) \) using Eq. (5).

3.6) Shift all non-critical activities?

3.7) Calculate daily resource demands for the rescheduled project.

3.8) Evaluate the impacts of shifting non-critical activities on overall resource utilization efficiency by calculating two new metrics (RRH and RID) and the maximum resource demand (MRD) using Eq. (1), (4) and (3).

Figure 3.5 Optimization model
A= Minimize undesirable fluctuation (Minimize RRH or RID)

B= Minimize the maximum resource demand (Minimize MRD)

Figure 3.6 Optimizing resource fluctuation and peak demand

3-4.3 Resource Leveling Module

The main decision variables (Mₙ) in the above Genetic Algorithm Module are passed to this module to calculate the impact of shifting non-critical activities within their float times on the overall efficiency of resource utilization using the following eight main steps (see Figure 3.5):
3.1) Recall the early start time (ES\textsubscript{n}), early finish time (EF\textsubscript{n}), free float (FF\textsubscript{n}), and total float (TF\textsubscript{n}) for all activities, which were previously calculated in the Initialization Module.

3.2) Identify all non-critical activities in the project and evaluate the impact of shifting each one of them separately on the overall efficiency of resource utilization. This process evaluates only one activity at a time (n) and covers all non-critical activities starting with the last activity and progressing backwards towards the start of the project. The order of selecting these non-critical activities for evaluation is determined using the following incremental set of primary and tie breaking rules:

i) Select the latest non-critical activity (n) with the latest LF time that has not been shifted in prior shifting cycles.

ii) If the primary rule i) creates a tie, select the non-critical activity (n) with the least total float.

iii) If rule ii) creates another tie, select the latest non-critical activity (n) that has the highest order number (n).

3.3) For each activity identified in the previous step (n), apply Equation (3.10) to calculate the number of selected-shift-days (S\textsubscript{n'}) based on the updated free float (FF\textsubscript{n'}), original total float (TF\textsubscript{n'}) and the maximum-shift-days (M\textsubscript{n'}). It should be noted that the original total float (TF\textsubscript{n'}) of each activity (n') does not change during the shifting cycles (steps 3.2 to 3.5) while the free float (FF\textsubscript{n'}) can vary if the activity successors are shifted in previous cycles as shown in Figure 3.7. Accordingly, the original total float (TF\textsubscript{n'}) of each activity (n') is calculated only
once in step 2.1) at the beginning of the genetic algorithm computations to generate the maximum-shift-days (M_{n^*}). The free float (FF_{n^*}), on the other hand, needs to be updated after each shifting cycle (step 3.5) and then used to identify the selected-shift-days (S_{n^*}) for activity (n^*) using Equation (3.10). This ensures that the selected-shift-days for activity (n^*) will not cause any additional shifts to its successor activities as shown in Figure 3.7. For example, the randomly generated maximum-shift-days for activity D by the genetic algorithm (M_D=2) is greater than its updated free float (FF_D=1) after shifting activity E in the previous cycle and accordingly can delay the early start of its successors, as shown in Figure 3.7(B). To avoid delaying its successors, the selected-shift-days for activity D (S_D=1) is calculated using Equation (3.10), as shown in Figure 3.7(C).

\[
S_{n^*} = \left\lfloor \frac{\text{FF}_{n^*} + 1}{\text{TF}_{n^*} + 1} \times M_{n^*} \right\rfloor
\]  \hspace{1cm} (3.10)

Where, \( S_{n^*} \) = selected-shift-days, the number of shift days for the selected non-critical activity (n^*); \( M_{n^*} \) = maximum-shift-days, the decision variable for the selected non-critical activity (n^*); \( \lfloor \rfloor \) = fraction truncation; and \( \text{TF}_{n^*} \) = total float of the selected non-critical activity (n^*).

3.4) Shift the selected non-critical activity (n^*) by \( S_{n^*} \) days and calculate its rescheduled early start time (ES_{n^*}') and early finish time (EF_{n^*}') as shown in Equations (3.11) and (3.12).
\[ ES_{n^*}' = ES_{n^*} + S_{n^*} \]
\[ EF_{n^*}' = EF_{n^*} + S_{n^*} \]

Where, \( ES_{n^*}' \) = rescheduled early start time of the selected non-critical activity \((n^*)\); \( EF_{n^*}' \) = rescheduled early finish time of the selected non-critical activity \((n^*)\); \( ES_{n^*} \) = the original early start time of the selected non-critical activity \((n^*)\) before the shift; and \( EF_{n^*} \) = the original early finish time of the selected non-critical activity \((n^*)\) before the shift.

3.5) Recalculate the free float time of all the predecessors of the selected non-critical activity \((n^*)\) using Equation (3.5).

3.6) Repeat the steps from 3.2) to 3.5) for all the non-critical activities in the project considering one activity at a time.

3.7) Calculate daily resource demands for the rescheduled project.

3.8) Evaluate the impact of shifting non-critical activities within their available float times on the overall resource utilization efficiency by calculating the two newly developed metrics of Release and Re-Hire (RRH) or Resource Idle Days (RID) and the maximum resource demand (MRD) using Equations (3.1), (3.3) and (3.4).

The above eight steps are repeated for each solution \((k)\) in the population \((P_g)\) of each generation \(g\). The calculated values of the two new metrics (RRH and RID) and the maximum resource demand (MRD) for each solution \((k)\) are then incorporated in the optimization function (Equation (3.8) or (3.9)) in the Genetic Algorithm Module in order
to maximize the overall efficiency of construction resource utilization. This value of the optimization function is used as the fitness value for each solution (k) to reproduce new offspring solutions in subsequent generations during the search for optimal/near optimal solutions. After a number of predetermined generations (G), each solution (k) in the final population (P_G) represents an optimal/near optimal schedule that maximizes the overall efficiency of construction resource utilization.

**Figure 3.7** Activity shifts based on maximum and selected shift days M_n and S_n.
3-5 Model Evaluation

An application example is analyzed to demonstrate the capabilities of the present model and the newly developed metrics (RRH and RID) in generating optimal resource utilization plans that outperform existing resource leveling metrics. The example includes 6 critical activities and 14 non-critical activities and has a project duration of 31 days, as shown in Figure 3.8(A). The early schedule of this example has a resource profile that includes undesirable resource fluctuations and a high peak resource demand of 21 resources as shown in Figure 3.8(B). In order to minimize these resource fluctuations and the peak resource demand, the example was optimized using a number of experiments that analyzed varying weights for $W_1$ and $W_2$ in Equations (3.8) and (3.9) that represent the relative importance of the two new metrics (RRH and RID), and the maximum resource demand (MRD), respectively. The analyzed experiments and weights include (1) $W_1=90\%$ and $W_2=10\%$; (2) $W_1=50\%$ and $W_2=50\%$; and (3) $W_1=10\%$ and $W_2=90\%$. For each of these three experiments, the present model generated an optimal schedule that completely eliminated the undesirable fluctuations that are measured by the two newly developed metrics (RRH and RID). As expected, it was also observed that increasing the weight of $W_2$ led to a reduction in the daily maximum resource demand (MRD) in the developed optimal schedule. The generated optimal schedule for experiment 1 is shown in Figure 3.8(C).
The results provided by the present model and metrics were compared to those produced by existing metrics including (1) sum of squares method ($M_s$); (2) absolute difference between resource consumption in consecutive time periods (Abs-Diff); (3) deviation between actual resource usage and a desirable or a uniform resource usage (Res-Dev); and (4) sum of squares of resource changes (SRC) as shown in Figure 3.9. The result of this comparative analysis clearly illustrates that the present model and metrics are capable of outperforming existing metrics and eliminating undesirable resource fluctuation and resource idle time. Furthermore, a number of other resource leveling examples from the literature were analyzed using the developed metrics and model. The results of this analysis confirmed the findings of the aforementioned
application example and highlighted the improvement of the new metrics over existing ones, as shown in Figure 3.10. This should prove useful to construction planners and schedulers and can contribute to enhancing the efficiency of resource utilization and improving construction productivity.

Figure 3.9 Optimization results generated by existing metrics
Figure 3.10 Analysis of existing resource leveling example (Son and Skibniewski 1999) by new model and metrics
3-6 Summary

Two new metrics for resource leveling and a robust optimization model were developed to maximize the efficiency of resource utilization in construction projects. The model is designed to search for optimal and practical schedules that minimize undesirable resource fluctuation while simultaneously minimizing the resource peak demand. The model is developed in three main modules: (1) initialization module to calculate an initial project schedule and the total float for each activity in the project; (2) genetic algorithm module to search for and identify a set of optimal schedules that maximize resource utilization efficiency; and (3) resource leveling module to evaluate the impact of shifting non-critical activities within their float times on the efficiency of resource utilization. An application example was analyzed to illustrate the use of the model and demonstrate its capabilities in generating an optimal schedule that eliminates undesirable resource fluctuations and resource idle times. This should prove useful to construction engineers and planners and can lead to significant improvements in labor productivity and cost performance in construction projects.
CHAPTER 4
RESOURCES ALLOCATION AND LEVELING MODEL

4-1 Introduction

The objective of this chapter is to present the development of an advanced multi-objective optimization model that is capable of simultaneously optimizing resource allocation and leveling. The objectives of present model are to (1) minimize project duration while resolving all resource conflicts; (2) maximize resource utilization efficiency by minimizing undesirable resource fluctuations that cause non-productive crew idle time; and (3) producing optimal/near optimal tradeoffs between project duration and resource utilization efficiency to support construction planners in generating and evaluating all feasible tradeoffs in order to select the best solution that strikes the optimal balance between maximizing resource utilization efficiency and minimizing project duration, as shown in Figure 1.4. In order to achieve those objectives, the present optimization model is developed in four main phases: (1) initialization phase that enables construction planners to input all the relevant planning and scheduling data and calculates the lower and upper bounds for the main decision variables used in the present model; (2) multi-objective optimization phase that searches for and identifies a set of optimal schedules that simultaneously maximize resource utilization efficiency and minimize project duration; (3) activity ranking phase that generates a scheduling sequence for activities to resolve all resource conflicts among project activities for the same resources; and (4) resource scheduling phase that performs resource leveling and allocation based on the scheduling sequence generated in activity ranking phase.
and the decision variables generated in multi-objective optimization phase, and evaluate
the impact of revised schedule on overall resource utilization efficiency and project
duration. The following sections in this chapter provide a concise description of those
four main phases.

4-2 Initialization Phase

The purpose of Initialization phase is to retrieve all the relevant planning and scheduling
data and calculate the lower and upper bounds for the main decision variables in the
present model. The two main decision variables, namely Priority-Value ($P_n$) and
Maximum-Shift-Days ($M_n$), are used in the present model. Priority-Value ($P_n$) is used to
prioritize each activity (n) to resolve resource conflicts. On the other hand, Maximum-
Shift-Days ($M_n$) is used to shift activities to eliminate undesirable resource fluctuation
and peak demand. Each of these two decision variables is represented using a genetic
algorithm chromosome and their total number is equal to the number of activities in the
project (N), as shown in Figure 4.1. The computation procedure in this initialization
phase is performed using the following five main steps (see Figure 4.2):

1.1) Input the planning and scheduling data for each activity, including its duration,
resource types, daily resource demand, and job logic.

1.2) Create five sets of project activities as follows:

a) $U$: Set of all the project activities ($U = \{1, 2, ..., N\}$).

b) $A_n$: Set of activities that should be completed before starting activity (n).

c) $B_n$: Set of activities that require the completion of activity (n) to start.
d) $Z_n$: Set of activities that have parallel relationships with activity (n) ($Z_n = U - A_n - B_n$)

e) $C_n$: Set of activities that are in $Z_n$ and have a resource conflict with activity (n).

1.3) Calculate the upper bound for the decision variable, Maximum-Shift-Days ($M_n$), for activity (n) ($UB_n$) using Equation (4.1).

$$UB_n = \sum_{n \in Z_n} d_n - \sum_{n \in C_n} d_n$$  \hspace{1cm} (4.1)

Where, $d_n =$ duration of activity (n).

1.4) Set the lower and upper bounds on the decision variables, $P_n$ and $M_n$ ($0 \leq P_n \leq N$, $0 \leq M_n \leq UB_n$).

1.5) Repeat steps 1.2) to 1.3) for the remaining activities in the project.

---

**Figure 4.1 Decision variables and their produced schedules**
4-3 Multi-Objective Optimization Phase

In order to simultaneously maximize resource utilization efficiency and minimize project duration, a multi-objective genetic algorithm (Deb et al. 2001) is used to implement the present model. The phase is implemented in the following five main steps:

2.1) Generate an initial set of solutions (k=1 to K) for the initial population \( P_{g=1} \) in the first generation \( (g=1) \). Each solution \( k \) consists of randomly generated values for the Priority-Value and the Maximum-Shift-Days variables \( (P_1, P_2, \ldots, P_N, M_1, M_2, \ldots, M_N) \). These solutions are designed to produce an initial set of feasible project schedules and resource profiles, as shown in Figure 4.1.

2.2) Calculate the values of the objective functions (i.e. project duration \( T \) and resource utilization efficiency, Release and Re-Hire (RRH) or Resource Idle Days (RID) shown in Equations (3.1) and (3.4)) for each solution \( k \) in the parent population \( P_g \). This step is performed using the Activity Ranking phase and the Resource scheduling phase that returns the values of the objective functions for a given set of decision variables values.

2.3) Calculate Pareto optimal rank and crowding distance for each solution \( k \) in the parent population \( P_g \) and create a new child population \( C_g \) using the genetic operators of selection, crossover, and mutation.

2.4) Evaluate the fitness functions for each solution in the newly created child population \( C_g \) in a process similar to step 2.2).

2.5) Combine child and parent populations \( C_g \) and \( P_g \) to form a newly combined population, and then select the best 50% of the members of the combined
population to form a new parent population for the next generation (P_{g+1}). This process acts as a strong form of elitism as it preserves the best solutions of the parents’ population over generations (Deb et al. 2001).

The above steps from 2.2) to 2.5) are repeated over a number of predetermined generations (G) in order to generate a Pareto optimal set of non-dominated solutions that simultaneously minimize project duration and maximize resource utilization efficiency.

4-4 Activity Ranking Phase

The main objective of this phase is to generate an activity order based on the randomly generated priority values (P_n). The serial method proposed by Kelly (1963) is employed in this phase to produce various activity orders. The phase is performed using the following eight main steps (see Figure 4.2):

3.1) Create Scheduled set (S), Unscheduled set (U), Decision set (D), and Activity-Order array (A[j]; j=0, 1,…, N-1).
3.2) Put all the project activities into set (U).
3.3) Set j=0 and select the activities that do not have predecessors from the set (U).
3.4) Move the activities selected in the previous step from set (U) to set (D).
3.5) Select activity (n*) that has the highest value of P_n from set (D) (select the activity that has the smallest activity number (n) in case of a tie) and save it in Activity-Order array (A[j]).
3.6) Move the selected activity \( \text{(n*)} \) from set \( \text{(D)} \) to set \( \text{(S)} \).

3.7) Set \( j = j + 1 \) and select the activities from set \( \text{(U)} \) if all their predecessors exist in set \( \text{(S)} \).

3.8) Repeat steps 3.4) to 3.7) for the remaining activities in set \( \text{(U)} \).

The generated Activity-Order array \( \text{(A[j])} \) is then used in the resource scheduling phase to resolve resource conflicts by defining the scheduling sequence of competing activities, which is described in more detail in the following section.

**4-5 Resource Scheduling Phase**

The main objective of this phase is to (1) perform resource allocation and leveling by scheduling each activity \( \text{(n)} \) based on the generated Activity-Order array \( \text{(A[j])} \) and the randomly generated Maximum-Shift-Days \( \text{(M_n)} \); and (2) calculate project duration \( \text{(T)} \) and overall resource utilization efficiency \( \text{(RRH or RID)} \) for the schedule. This phase is performed using the following eight main steps (see Figure 4.2):

4.1) Set \( j = 0 \) and calculate early start time \( \text{(ES}_{A[0]} \text{)} \) and early finish time \( \text{(EF}_{A[0]} \text{)} \) for the first activity in the array \( \text{(A[0])} \) using Equations (4.2) and (4.3).

\[
\text{ES}_{A[0]} = 1 \\
\text{EF}_{A[0]} = \text{ES}_{A[0]} + d_{A[0]} - 1
\]  

(4.2) (4.3)

4.2) Set \( j = j + 1 \) and calculate the earliest possible start time \( \text{(EPST}_{A[j]} \text{)} \) and the latest
possible start time (LPST_{A[j]}) for activity (A[j]) using Equations (4.4) and (4.5).

\[ EPST_{A[j]} = \begin{cases} \max\{EF_n | n \in \text{predecessors of } A[j]\}; & \text{if } A[j] \text{ has predecessors} \\ 1; & \text{otherwise} \end{cases} \]  \hspace{1cm} (4.4)

\[ LPST_{A[j]} = \max\{EF_{A[0]}, EF_{A[1]}, \ldots, EF_{A[j-1]}\} + 1 \]  \hspace{1cm} (4.5)

4.3) Calculate the total number of possible start times (TPST_{A[j]}) for activity (A[j]) in the period from EPST_{A[j]} to LPST_{A[j]} and save each possible start time in Start-Days array (SD_{A[j][i]}). Each possible start time saved in this array represents the day that the activity can start without having any resource conflicts with other activities during its duration.

4.4) Calculate Selected-Start-Time (SST_{A[j]}) for activity (A[j]) using Equation (4.6). This prevents activity (A[j]) to shift beyond its LPST_{A[j]} and cause non-productive resource utilization periods.

\[ SST_{A[j]} = \left\lfloor M_{A[j]} \times \frac{TPST_{A[j]}}{(UB_{A[j]} + 1)} \right\rfloor \]  \hspace{1cm} (4.6)

Where, \( M_{A[j]} \) = Maximum-Shift-Days for activity (A[j]); \( UB_{A[j]} \) = upper bound of \( M_{A[j]} \); and \( \left\lfloor \cdot \right\rfloor \) = fraction truncation.

4.5) Calculate early start time (ES_{A[j]}) and early finish time (EF_{A[j]}) for activity (A[j]) using Equations (4.7) and (4.8).
ES_{A[j]} = SD_{A[j]} + SST_{A[j]} \hspace{2cm} (4.7)

EF_{A[j]} = ES_{A[j]} + d_{A[j]} - 1 \hspace{2cm} (4.8)

4.6) Repeat steps 4.2) to 4.5) for the remaining activities in the project.

4.7) Calculate daily resource demands for the revised schedule.

4.8) Calculate project duration (T) using Equation (4.9) and the overall resource utilization efficiency using the two new metrics of RRH and RID using Equations (3.1) and (3.4).

\[ T = \text{Max}\{EF_1, EF_2, \ldots, EF_N\} \hspace{2cm} (4.9) \]

The above steps are repeated for each solution (k) in population (P_g) of each generation (g). The calculated values of the project duration (T) and the two new resource leveling metrics (RRH and RID) for each solution (k) are then used as the fitness value in the multi-objective optimization phase to reproduce new offspring solutions in subsequent generations during the search for optimal/near optimal solutions. After a number of specified generations (G), each solution (k) in the final population (P_G) represents non-dominant optimal/near optimal solutions that simultaneously minimize project duration (T) and maximize resource utilization efficiency (RRH or RID).
4-6 Model Evaluation

An application example is analyzed to illustrate the use of the present model and demonstrate its capabilities in generating a set of optimal tradeoff between project duration and resource utilization efficiency. The example consists of twenty activities
with varying daily resource demands and a maximum availability limit of 9 resources per day, as shown in Table 4.1. Assuming an unlimited supply of resources, early schedule of this example can be completed in 31 days and it produces a resource profile that includes undesirable fluctuations. The example was analyzed after considering the maximum availability limit of 9 resources per day using the resource leveling feature in MS Project software, and it produced a project duration of 46 days with RRH=11 and RID=42, as shown in Figure 4.3. The example was then analyzed using the present model in order to (1) minimize project duration (T) and minimize Release and Re-Hire (RRH); and (2) minimize project duration (T) and minimize Resource Idle Days (RID). As shown in Figure 4.3, the optimal solutions generated by the present model outperform the solution produced by MS project, as it provides significant reduction in the project duration as well as in RRH and RID. Each of these solutions represents an optimal schedule for the project that provides unique project duration and resource utilization efficiency. A construction planner can evaluate each of these optimal solutions and select the one that satisfies the specific requirements of the project being considered.
Table 4.1 Case study data

| Activity | Duration | Predecessors | R/day* | Activity | Duration | Predecessors | R/day*
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>6</td>
<td>-</td>
<td>2</td>
<td>K</td>
<td>1</td>
<td>C,E</td>
<td>4</td>
</tr>
<tr>
<td>B</td>
<td>3</td>
<td>-</td>
<td>3</td>
<td>L</td>
<td>2</td>
<td>E,G,H</td>
<td>8</td>
</tr>
<tr>
<td>C</td>
<td>4</td>
<td>A</td>
<td>2</td>
<td>M</td>
<td>4</td>
<td>I,K</td>
<td>5</td>
</tr>
<tr>
<td>D</td>
<td>6</td>
<td>-</td>
<td>5</td>
<td>N</td>
<td>2</td>
<td>F,L</td>
<td>3</td>
</tr>
<tr>
<td>E</td>
<td>6</td>
<td>A,B</td>
<td>3</td>
<td>O</td>
<td>3</td>
<td>L</td>
<td>6</td>
</tr>
<tr>
<td>F</td>
<td>5</td>
<td>C</td>
<td>9</td>
<td>P</td>
<td>5</td>
<td>J,M,N</td>
<td>4</td>
</tr>
<tr>
<td>G</td>
<td>2</td>
<td>D</td>
<td>3</td>
<td>Q</td>
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<td>H</td>
<td>2</td>
<td>A,B</td>
<td>5</td>
<td>R</td>
<td>2</td>
<td>J,O</td>
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<td>G,H</td>
<td>3</td>
<td>S</td>
<td>5</td>
<td>P,Q</td>
<td>2</td>
</tr>
<tr>
<td>J</td>
<td>6</td>
<td>F</td>
<td>6</td>
<td>T</td>
<td>3</td>
<td>R</td>
<td>5</td>
</tr>
</tbody>
</table>

Daily resource limit = 9

R/day: Resource demand per day

*: Solution produced by MS-Project
: Solution produced by the present model

(A) Project duration – RRH tradeoffs analysis
(B) Project duration – RID tradeoffs analysis

Figure 4.3 Optimal solutions
4-7 Summary
A robust multi-objective optimization model is developed to simultaneously optimize resource allocation and leveling in construction projects. The model is designed to search for and generate optimal and practical construction schedules that simultaneously minimize project duration and maximize resource utilization efficiency while maintaining all scheduling constraints such as job logic and daily resource limit. Two new resource leveling metrics (RRH and RID) were incorporated in the present model to directly measure and minimize undesirable resource fluctuations that cause negative impacts on construction productivity and cost. An application example was analyzed to demonstrate the capabilities of model in generating optimal trade-offs between project duration and resource utilization efficiency. This should prove useful to construction engineers and planners and can lead to significant improvements in construction productivity and costs.
5-1 Introduction

The objective of this chapter is to present the development of a robust multi-objective optimization model for scheduling multiple shifts in construction projects. The model is designed to support construction engineers and planners in generating optimal shift work plans and schedules that simultaneously (1) minimize project duration, (2) minimize cost, and (3) minimize the negative impacts of shift work for construction projects while complying with labor availability constraints. To accomplish this, the model is developed in two main stages: (1) model formulation; and (2) model implementation, which are described in more details in the following sections.

5-2 Model Formulation

The primary purpose of this development stage is to determine the main decision variables and formulate the three optimization objectives of minimizing the project duration, cost, and the negative impacts of multiple shifts.

5-2.1. Decision Variables

The present model is designed to consider all relevant decision variables on scheduling multiple shifts that have an impact on project time, cost, and labor utilization. This includes: (1) Shift-option \((S_n)\), which represents the feasible options of utilizing multiple shifts for each activity \((n)\); (2) Priority-Value \((P_n)\), which prioritizes each activity \((n)\) and
determines its scheduling sequence to resolve potential resource conflicts that are caused by the limited availability of labor; and (3) Labor-constraint \( (L_i) \), which distributes the limited number of available daily labor among the competing shifts to minimize the negative impact of labor availability constraints on project performance. The number of feasible shift options varies according to whether the activity can be constructed using one, two or three shifts per day, as shown in Table 5.1. Table 5.1 illustrates an example of feasible shift options and their typical daily work hours for labor (Popescu et al. 2003). As such, each shift utilization option has different work hours per day, production rate and cost rate, and accordingly it leads to unique duration and cost for each activity \( (n) \). Construction planners can specify the number of feasible shift options \( (S_n) \) for each activity \( (n) \) based on the type of shift system used for the project (e.g. two shifts or three shifts), as shown in Table 5.1. For example, concrete curing cannot be crashed using multiple shifts and therefore its feasible shift options can be specified to include only single shift operation (e.g. \( S_n=0: \) Single shift operation). The calculations of activity duration and cost for each Shift-option \( (S_n) \) of activity \( (n) \) are described in more details in the following section.

5-2.2. Optimization Objectives

The present model is formulated to provide the capability of simultaneously minimizing project duration, cost, and the negative impacts of utilizing multiple shifts. To this end, three main objective functions are incorporated in the present model to quantify and minimize project duration, cost, and labor utilization, as shown in Equations (5.1), (5.8) and (5.13).
Table 5.1 Multiple shift options

<table>
<thead>
<tr>
<th>Shift-Option ($S_n$)</th>
<th>Two shifts system (SS=2)</th>
<th>Work hours/day</th>
<th>Three shifts system (SS=3)</th>
<th>Work hours/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Two shifts (Day &amp; Evening Shifts)</td>
<td>15.5 hrs</td>
<td>Three shifts (Day, Evening, &amp; Night shifts)</td>
<td>22.5 hrs</td>
</tr>
<tr>
<td>1</td>
<td>One shift (Day shift)</td>
<td>8 hrs</td>
<td>Two shifts (Day &amp; Evening shifts)</td>
<td>15.5 hrs</td>
</tr>
<tr>
<td>2</td>
<td>One shift (Evening shift)</td>
<td>7.5 hrs</td>
<td>Two shifts (Day &amp; Night shifts)</td>
<td>15 hrs</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td></td>
<td>Two shifts (Evening &amp; Night shifts)</td>
<td>14.5 hrs</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td></td>
<td>One shift (Day shift)</td>
<td>8 hrs</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td></td>
<td>One shift (Evening shift)</td>
<td>7.5 hrs</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td></td>
<td>One shift (Night shift)</td>
<td>7 hrs</td>
</tr>
</tbody>
</table>

0.5 hours of meal break is not included in total work hours per day

Optimization Objective 1: Minimize Project Duration = Min \{T\}  
\[ T = \max_{n \in A} \{EF_n\} \]  
\[ ES_n = \max_{n \in \text{PRE}_n} \{EF_n\} + 1 \]  
\[ EF_n = ES_n + D_{S_n} - 1 \]  
\[ D_{S_n} = \left[ \frac{Q_n}{PD_{S_n}} \right] \]
Where, $T =$ project duration; $EF_n =$ early finish time of activity (n); $ES_n =$ early start time of activity (n); $PRE_n =$ immediate predecessors of activity (n); $D_{sn} =$ duration of activity (n) under Shift-option ($S_n$), which is rounded up to the nearest integer number; $Q_n =$ quantity of work in units of measurement for activity (n); $PD_{sn} =$ crew daily output (units/day) for activity (n) under Shift-option ($S_n$); $j =$ type of shift (e.g. $j=1$: day shift, $j=2$: evening shift, and $j=3$: night shift); $pd_{nj} =$ crew daily output (units/day) for shift ($j$) of activity (n); $SH_{sn} =$ the selected shifts by Shift-option ($S_n$); and $A_j =$ productivity adjustment factor to consider productivity losses during evening ($j = 2$) and night ($j = 3$) shifts.

The present model is designed to consider the impact of the expected productivity losses that will be encountered during evening and night shifts, as shown in Equation (5.7). Construction planners can specify the productivity adjustment factor ($A_j$) in Equation (5.7) based on the historical data or the one that is recommended by Mechanical Contractors Association of America (MCAA) Labor Estimating Manual. The manual recommends increasing man-hours for evening shifts by 20% and night shifts by 30% (Kitchens 1996). The consideration of these expected productivity losses enables construction planners to generate more reliable estimates of activity durations when
multiple shifts are utilized. It should be noted that the above calculations are based on the assumption that the same crew size and composition is utilized in every shift for activity (n).

**Optimization Objective 2:** Minimize Project Direct Cost = Min \{DC\}  \hspace{1cm} (5.8)

\[
DC = \sum_{n=1}^{N} d_{n}^{S_n}
\]  \hspace{1cm} (5.9)

\[
d_{n}^{S_n} = Q_{n} \times MC_{n} + D_{S_n} \times (LC_{S_n} + EC_{S_n})
\]  \hspace{1cm} (5.10)

\[
IC = ic_{ss} \times T
\]  \hspace{1cm} (5.11)

\[
TC = DC + IC
\]  \hspace{1cm} (5.12)

Where, \(DC\) = total project direct cost; \(N\) = total number of activities in the project; \(d_{n}^{S_n}\) = direct cost of activity (n) using Shift-option \((S_n)\); \(Q_{n}\) = quantity of work in units for activity (n); \(MC_{n}\) = material cost rate ($/unit) for activity (n); \(D_{S_n}\) = duration of activity (n) based on Shift-option \((S_n)\); \(LC_{S_n}\) = labor cost rate ($/day) based on Shift-option \((S_n)\); \(EC_{S_n}\) = equipment cost rate ($/day) based on Shift-option; \(IC\) = total project indirect cost; \(ic_{ss}\) = daily project indirect cost based on the type of shift system (SS) used in the project (e.g. SS=1 for one shift system, SS=2 for two shifts system, and SS=3 for three shifts system); and \(TC\) = total project cost.

The present model is designed to consider shift premium costs in the labor cost rate based on the selected Shift-option \((S_n)\). The operation and maintenance cost of
construction equipment can be also considered in the equipment cost rate based on the total work hours per day under Shift-option \( (S_n) \). The model enables the daily project indirect cost \( (i_{c_{ss}}) \) to vary based on the type of shift system \( (SS) \) used in the project, because operating two and three shifts per day requires more field supervision, engineering support, and quality control, and accordingly it leads to higher indirect costs than operating only one shift per day. The present model is designed to minimize the total project direct cost \( (DC) \) in its second objective function, as shown in Equation (5.8). This enables the model to generate optimal tradeoffs between the project cost \( (DC) \) and duration \( (T) \) which can then be used to calculate the total project cost \( (TC) \), as shown in Equation (5.12).

**Optimization Objective 3:** Minimize Labor Utilization in Evening and Night Shifts = Min \{LHEN\} \hspace{1cm} (5.13)

\[
LHEN = LHE + LHN \times (1 + W)
\]

if SS=3 (Three shifts system) \hspace{1cm} (5.14)

\[
LHEN = LHE
\]

if SS=2 (Two shifts system) \hspace{1cm} (5.15)

\[
LHE = \sum_{n=1}^{N} (D_{s_n} \times R_{s_{n,2}}) \times HE
\]

(5.16)

\[
LHN = \sum_{n=1}^{N} (D_{s_n} \times R_{s_{n,3}}) \times HN
\]

(5.17)

Where, \( LHEN \) = total labor hours in evening and night shifts; \( W \) = planner defined weight to represent the relative importance of minimizing total number of labor hours on night shift (e.g. \( W = 0\% \) to \( 100\% \)); \( LHE \) = total number of labor hours in evening shifts;
LHN = total number of labor hours in night shifts; \( D_n \) = duration of activity (n) based on Shift-option \( S_n \); \( R_{n,j} \) = daily labor demand of activity (n) on shift (j) under Shift-option \( S_n \); \( j \) = type of shift (e.g. \( j=1 \): day shift, \( j=2 \): evening shift, and \( j=3 \): night shift); HE = daily work hours for evening shift (e.g. 7.5 hours per day); and HN = daily work hours for night shift (e.g. 7 hours per day).

This objective function (LHEN) provides the capability of minimizing the total number of labor hours required on evening and night shifts in order to minimize the aforementioned negative impacts of utilizing these shifts. It should be noted that minimizing the project cost alone (see Equation (5.8)) does not guarantee that the minimum number of workers will be utilized in the evening and night shifts. Figure 5.1 shows a simple example that illustrates this fact and demonstrates the need for the third optimization function (Equation (5.13)) that focuses on minimizing the number of labor hours in evening and night shifts. In this example, since activity C can be operated by only day shift, there are only two possible alternatives to minimize the project duration: crashing only activity B or crashing only activity A. It should be noted that accelerating both activities A and B provides same project duration as accelerating only activity A or B. The impact of these two alternative acceleration options on the activity duration and direct cost is summarized in Table 5.2. As shown in Figure 5.1(C) and (D), the impacts of these two alternative solutions on the project cost and labor utilization are different although they produce the same project duration. The first solution (see Figure 5.1(C)) produces the minimum cost and it requires the utilization of 12 labor hours in the evening shift. On the other hand, the second solution produces the minimum labor
hours in the evening shift (i.e., 8 labor hours) and leads to a project cost that is higher than the first solution. This clearly illustrates that minimizing the project cost alone (see Equation (5.8)) does not guarantee that the minimum number of labor hours will be utilized in evening and night shifts.

As stated earlier, the utilization of a larger number of labor hours during the evening or night shifts exposes more workers to the aforementioned risks of nighttime work including the risk of accidents, injuries, health disorders, and social life disruption which often leads to additional costs and schedule delays. In order to minimize these negative impacts of evening and night shifts, the total number of labor hours in these shifts needs to be minimized while optimizing the aforementioned objectives of project duration and cost, as shown in Figure 5.1(D). To accomplish this, the present model includes this
separate and third optimization function that focuses on minimizing the utilization of labor in night and evening shifts, as shown in Equation (5.13). It should be noted that the third optimization function for the three shifts system (SS=3) shown in Equation (5.14) is designed to emphasize the minimization of labor hours in night shifts by multiplying it by a planner defined weight \((1+W)\) to inflate its impact on the optimization objective. Accordingly, the output of Equation (5.14) does not represent the actual number of labor hours in evening and night shifts. In order to analyze the actual number of labor hours in evening and night shifts, Equations (5.16) and (5.17) in the model can be used after identifying the optimum solutions.

Table 5.2 Activity data for the example in Figure 5.1 (Two shifts system, SS=2)

<table>
<thead>
<tr>
<th>Activity (n)</th>
<th>Shift-option ((S_n))</th>
<th>Feasible shift options</th>
<th>Duration ((D_{S_n}))</th>
<th>Direct Cost ((dC_{nS}))</th>
<th>Daily labor demand on shift ((j) (r^{S_n}_{n,j}))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Day (j=1)</td>
<td>Evening (j=2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A 0</td>
<td>Two shifts (Day &amp; Evening shifts)</td>
<td>4</td>
<td>$12,400</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>A 1</td>
<td>One shift (Day shift)</td>
<td>7</td>
<td>$11,600</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>B 0</td>
<td>Two shifts (Day &amp; Evening shifts)</td>
<td>3</td>
<td>$11,900</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>B 1</td>
<td>One shift (Day shift)</td>
<td>5</td>
<td>$11,300</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>C 0</td>
<td>One shift (Day shift)</td>
<td>10</td>
<td>$5,900</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>
5-3 Model Implementation

The purpose of this stage is to present the development of an optimization model that simultaneously minimizes project duration, cost, and labor utilization in evening and night shifts. To this end, the present model is implemented as a multi-objective genetic algorithm (Deb et al. 2001), and it is organized in three main modules: (1) initialization module that retrieves all relevant input data specified by the construction planner and accordingly sets a lower and upper bounds for the decision variables; (2) scheduling module that develops practical multiple shift schedules for construction projects and evaluates the impacts of the decision variables on project performance; and (3) multi-objective genetic algorithm module that searches for and identifies optimal/near optimal tradeoffs between project duration, cost, and labor utilization in evening and night shifts. The following sections describe these three main modules in more details.

5-3.1. Initialization Module

The objective of this module is to retrieve all relevant input data specified by the construction planner for utilizing multiple shifts and to set a lower and upper bounds for the optimization decisional variables. The computation procedure in this module is performed using the following three main steps (see Figure 5.2):
1.1) Input the planning and scheduling data for each activity (n), including its quantity of work \( (Q_n) \), crew daily output \( (PD_n) \) for the day shift; productivity adjustment factor \( (A_j) \) for the evening and night shifts; total number of feasible shift options \( (UBS_n) \); material cost rate \( (MC_n) \); labor cost rate \( (LC_{s_n}) \); equipment cost rate \( (EC_{s_n}) \); and daily labor demand \( (RD_{n,j}) \) on shift (j) for each feasible Shift-option \( (S_n) \). In addition, the project input data include the daily work hours for evening shifts \( (HE) \); the daily work hours for night shifts \( (HN) \); the daily project indirect cost \( (ic_{ss}) \) based on the type of shift system \( (SS) \) in the project; activity
precedence relationships; and total number of available labor (RC). The activity
duration and cost can be either specified by the construction planner or they can
be calculated using Equations (5.5) and (5.10). For the example shown in Table
5.3, the duration of activity A for each feasible Shift-option (S_n) is calculated
using Equations (5.5), (5.6) and (5.7) based on the activity input data of Q_A=2000
S.F, \( \rho d_A^1 = 300 \) S.F/day, and A_2=0.2. Similarly, the cost of activity A for each
feasible Shift-option (S_n) is calculated using Equation (5.10) based on the input
data of MC_A=$0.55/S.F, LC_0=$758/day and LC_1=$368/day.

1.2) Identify the values of the Shift-option (S_n) decision variable for each activity (n)
based on the input data, as shown in Table 5.3. The Shift-option (S_n) decision
variable represents the feasible shift options for activity (n), where each of these
options is associated with a unique activity cost, duration, and labor demand, as
shown in Table 5.3.

1.3) Set the lower and upper bounds of decision variables, Priority-Value (P_n), Shift-
option (S_n), and Labor-constraint (L_j), as shown in Equations (5.18), (5.19) and
(5.20). The impact of these three decision variables on project duration, cost, and
labor utilization are evaluated and optimized in the scheduling module and the
multi-objective genetic algorithm module, which are described in more detail in
the following two sections.

\[
0 \leq P_n \leq N-1 \quad (5.18)
\]
\[
0 \leq S_n \leq UBS_{n-1} \quad (5.19)
\]
\[
0 \leq L_j \leq RC \quad j = 1, 2, \ldots, J-1 \quad (5.20)
\]
Where, UBS\(_n\) = total number of Shift-options (S\(_n\)) for activity (n); N = total number of activities in the project; j = type of shift (e.g. j=1: day shift, j=2: evening shift, and j=3: night shift); and J = the maximum number of allowable shifts per day (e.g. J=3 for three shifts per day, and J=2 for two shifts per day).

Table 5.3 Example of activity data in a two shifts system (SS=2)

<table>
<thead>
<tr>
<th>Activity (n)</th>
<th>Total number of Shift-options (UBS(_n))</th>
<th>Shift-option (S(_n))</th>
<th>Feasible shift options</th>
<th>Duration ((D_{S_n}))</th>
<th>Direct Cost ((d_{C_n}^{s_n}))</th>
<th>Daily labor demand on shift (j) ((R_{S_n}^{j,s_n}))</th>
</tr>
</thead>
</table>
| A           | 2                                        | 0                      | Two shifts (Day & Evening) | 4                      | $4,130                   | Day (j=1): 2  
Evening (j=2): 2 |
|             |                                           | 1                      | One shift (Day)         | 7                      | $3,680                   | Day (j=1): 2  
Evening (j=2): 0 |
| B           | 2                                        | 0                      | Two shifts (Day & Evening) | 2                      | $11,950                  | Day (j=1): 4  
Evening (j=2): 4 |
|             |                                           | 1                      | One shift (Day)         | 3                      | $11,310                  | Day (j=1): 4  
Evening (j=2): 0 |
| C           | 2                                        | 0                      | Two shifts (Day & Evening) | 6                      | $16,470                  | Day (j=1): 3  
Evening (j=2): 3 |
|             |                                           | 1                      | One shift (Day)         | 9                      | $15,700                  | Day (j=1): 3  
Evening (j=2): 0 |

5-3.2. Scheduling Module

The objective of this module is to develop practical multiple shift schedules for construction projects that comply with all job logic and resource availability constraints.
and to evaluate the impact of the optimization decision variables on project performance. Accordingly, the computations in this module are performed in four main steps that are designed to (1) identify the resource availability constraint \((RCS_j)\) for each shift \((j)\) based on the Labor-constraints \((L_i)\) that are generated by the genetic algorithm module and distribute the limited number of available daily labor \((RC)\) among these competing shifts accordingly; (2) determine the execution order of each activity in the project based on its Priority-Value \((P_n)\) while complying with all project precedence relationships and job logic; (3) schedule each activity based on its identified execution order while complying with all resource availability constraints \((RCS_i)\) that are imposed on each shift \((j)\); and (4) evaluate the performance of the developed schedule in terms of project duration, total direct cost, and the labor utilization on evening and night shifts. As shown in Figure 5.2, these four main steps are performed as follows:

2.1) Calculate the resource constraints \((RCS_j)\) for each shift \((j)\) based on the values of the Labor-constraint \((L_i)\) that are generated by the genetic algorithm module. The purpose of this step is to distribute the limited number of available daily labor \((RC)\) among the competing shifts in order to minimize the negative impact of labor availability constraint \((RC)\) on project duration, as shown in Figure 5.3. The computation procedure can be performed using the following five sub-steps:

I. Identify the minimum required number of labor \((MR_j)\) for each shift \((j)\) based on the values of the Shift-option \((S_n)\) that are generated by the genetic algorithm module for all the project activities. \(MR_j\) is identified as the
maximum daily resource demand for all the activities in each shift \((j)\) using Equation (5.21). The purpose of this step is to identify the lower bound for each resource constraint \((RCS_j)\) and enable activities to perform their shift operations selected by the Shift-option \((S_n)\). For the example shown in Figure 5.3(B), if the decision variable of Shift-option \((S_n)\) is selected to be \(S_A=0, S_B=1,\) and \(S_C=0\) based on the activity data in Table 5.3, then the day shift requires at least 4 labors to perform the three activities (i.e., \(MR_1 = \max\{R_{A,1}^0=2, R_{B,1}^1=4, R_{C,1}^0=3\} = 4\)). Similarly, the evening shift in this example requires at least 3 labors (i.e., \(MR_2 = \max\{R_{A,2}^0=2, R_{B,2}^1=0, R_{C,2}^0=3\} = 3\)). Accordingly, the resource constraint \((RCS_j)\) for the day and evening shift in this example should be greater than or equal to its minimum required number of labor, respectively.

\[
MR_j = \max \{R_{n,j}^{S_n}\} \quad (5.21)
\]

Where, \(MR_j\) = minimum required number of labor for each shift \((j)\); and \(R_{n,j}^{S_n}\) = daily labor demand of activity \((n)\) on shift \((j)\) under Shift-option \((S_n)\).

II. Calculate the remaining number of labor (REM) after allocating the minimum required number of labor \((MR_i)\) for each shift \((j)\) using Equation (5.22). For the example shown in Figure 5.3(B), only 5 labors remain \((REM=5)\) from the 12 available labors \((RC=12)\) after allocating 4 labors to the day shift \((MR_1=4)\) and another 3 labors to the evening shift \((MR_2=3)\).
\[ REM = RC - \sum_{j=1}^{J} MR_j \]  

(5.22)

Where, \( RC \) = total number of available daily labor that can be distributed among all competing shifts.

III. Calculate the percentage of the remaining labor (REM) that should be allocated to the competing shifts. This percentage (\( PL_j \)) for each shift \( j \) is calculated using Equation (5.23) based on the values of the Labor-constraint that is generated by the genetic algorithm module (\( L_j \)) and the total number of available labor (RC). For the example shown in Figure 5.3(B), three additional labors will be allocated for the day shift based on 66.7% of the remaining labor (\( PR_1 = \lfloor PL_1 \times REM \rfloor = \lfloor 0.667 \times 5 \rfloor = 3 \)).

\[ PL_j = \frac{L_j}{RC} \quad j = 1, 2, \ldots, J-1 \]  

(5.23)

Where, \( j \) = type of shift (e.g. \( j=1 \): day shift, \( j=2 \): evening shift, and \( j=3 \): night shift); and \( J \) = the maximum number of allowable shifts per day (e.g. \( J=3 \) for three shifts per day, and \( J=2 \) for two shifts per day).
IV. Calculate the additional number of labors ($PR_j$) that will be allocated for each shift ($j$) based on its allocation percentage ($PL_j$) and the remaining number of labors (REM) as shown in Equations (5.24) and (5.25). For the example shown in Figure 5.3(B), three additional labors will be allocated for
the day shift \( (PR_1 = \left\lfloor PL_1 \times REM \right\rfloor = \left\lfloor 0.667 \times 5 \right\rfloor = 3) \). It should be noted that the example shown in Figure 5.3(B) utilizes a two shift system, and accordingly only Equation (5.24) is calculated. For three shifts systems, both Equations (5.24) and (5.25) should be calculated.

\[
PR_1 = \left\lfloor PL_1 \times REM \right\rfloor \quad \text{if SS=2 or 3 (Two or three shifts system)} \tag{5.24}
\]

\[
PR_2 = \left\lfloor PL_2 \times (REM - PR_1) \right\rfloor \quad \text{if SS=3 (Three shifts system)} \tag{5.25}
\]

Where, \( PR_1 \) = additional number of labors that will be allocated for the day shift; \( PR_2 \) = additional number of labors that will be allocated for the evening shift; and \( \left\lfloor \cdot \right\rfloor \) = fraction truncation.

V. Calculate the total number of labor (RCS\(_j\)) that will be allocated for each shift \( (j) \) by summing up its minimum required number of labor (MR\(_j\)) and its additional number of allocated labors (PR\(_j\)), as shown in Equations (5.26) through (5.29). For the example shown in Figure 5.3(B), a total of 7 labors is allocated for the day shift (RCS\(_1\) = MR\(_1\) + PR\(_1\) = 4 + 3 = 7). For a two shifts system (SS=2), the total number of labors allocated for the evening shift (RCS\(_2\)) can be easily calculated as the difference between the total number of available daily labor (RC) and the total number of labor allocated to the day shift (RCS\(_1\)), as shown in Equation (5.27). For a three shifts system (SS=3), the total number of labors allocated for the evening and night shifts (RCS\(_2\) and RCS\(_3\)) can be calculated in a similar manner, as shown in Equations (5.28) and (5.29).
RCS_1 = MR_1 + PR_1 \quad \text{if SS}=2 \text{ or } 3 \text{ (Two or three shifts system)} \quad (5.26)

RCS_2 = RC - RCS_1 \quad \text{if SS}=2 \text{ (Two shifts system)} \quad (5.27)

RCS_2 = MR_2 + PR_2 \quad \text{if SS}=3 \text{ (Three shifts system)} \quad (5.28)

RCS_3 = RC - RCS_1 - RCS_2 \quad \text{if SS}=3 \text{ (Three shifts system)} \quad (5.29)

The computation procedure of the above five sub-steps is designed to distribute the limited number of daily available labor (RC) among all competing shifts based on the Labor-constraint (L_i) generated by the genetic algorithm module in order to identify the resource availability constraints for the day, evening and night shifts (RCS_1, RCS_2, and RCS_3). These three resource constraints that are generated based on the genetic algorithm are then used to schedule the project activities in the following steps of this scheduling module.

2.2) Create activity scheduling order array (A[m]) based on the values of the Priority-Value (P_n) that are generated by the genetic algorithm module. The serial method proposed by Kelly (1963) is employed in this step to generate various activity orders while complying with all project precedence relationships and job logic. The computation procedure of creating activity order array (A[m]) can be performed using the eight steps described in Chapter 4-4.

2.3) Schedule each activity (n) based on the activity order array (A[m]) while complying with all the resource constraints (RCS_j) imposed on each shift (j). The computation procedure can be performed using the following six sub-steps:
I. Set $m=0$ and select the initial activity (n) in activity order array $A[m]$.

II. Calculate the early start time ($ES_n$) and early finish time ($EF_n$) for the selected activity (n) using Equations (5.3) and (5.4).

III. Set $m=m+1$ and select the next activity (n) in activity order array $A[m]$.

IV. Calculate early start time ($ES_n$) and early finish time ($EF_n$) for the selected activity (n) using Equations (5.3) and (5.4).

V. Find the latest day (LD) that activity (n) violates the resource constraint ($RCS_j$) during the period from its early start time ($ES_n$) to early finish time ($EF_n$). If activity (n) does not violate any resource constraint ($RCS_j$) during that period, go to step III. Otherwise, recalculate early start time ($ES_n'$) and early finish time ($EF_n'$) for activity (n) using Equations (5.30) and (5.31), and repeat this step until activity (n) can be scheduled without violating any resource constraint ($RCS_j$) imposed on shift (j).

\[
ES_n' = LD + 1 \tag{5.30}
\]

\[
EF_n' = ES_n' + D_{S_n} - 1 \tag{5.31}
\]

VI. Repeat the procedures from step III to V for the remaining project activities.

2.4) Calculate the three objective functions (i.e. project duration (T), total direct cost (DC), and the labor utilization in evening and night shifts (LHEN)) for the revised project schedule using Equations (5.1), (5.8), and (5.13).
The above four main steps are repeated for each solution \( (x) \) in the population \( (P_g) \) of each generation \( (g) \). The calculated values of those three objective functions are then used as the fitness values in the multi-objective genetic algorithm module for each solution \( (x) \) to reproduce new offspring solutions in subsequent generations during the search for optimal/near optimal solutions. After a number of predetermined generations \( (G) \), each solution \( (x) \) in the final population \( (P_G) \) represents an optimal/near optimal shift work plan and schedule that simultaneously minimizes the project duration \( (T) \), the project direct cost \( (DC) \), and labor utilization in the evening and night shifts \( (LHEN) \).

5-3.3. Multi-Objective Genetic Algorithm (MOGA) Module

The objective of this module is to search for and identify optimal/near optimal tradeoffs among project duration, cost, and the labor utilization in the evening and night shifts. In order to enable the generation of optimal tradeoffs among those three objectives, the present model is implemented using multi-objective genetic algorithm (Deb et al. 2001). This algorithm adopts the concept of Pareto optimality to enable multi-objective optimization and the survival of the fittest criteria to evolve solutions over a number of specified generations until it reaches optimal/near optimal solutions. The computation procedure in this module is performed using the following five main steps (see Figure 5.2):

3.1) Generate an initial set of solutions \( (x=1 \text{ to } X) \) for the initial population \( (P_{g=1}) \) in the first generation \( (g=1) \). Each solution \( (x) \) consists of randomly generated values for the three decision variables of Priority-Value \( (P_n) \), Shift-option \( (S_n) \), and Labor-
constraint \((L_i)\) as follows: \(P_1, P_2, \ldots, P_N, S_1, S_2, \ldots, S_N, L_1, L_2, \ldots, L_{J-1}\). These solutions \((x=1 \text{ to } X)\) are designed to produce an initial set of feasible project schedules and labor utilizations in various shifts.

3.2) Calculate the values of three objective functions (i.e., project duration \((T)\), project direct cost \((DC)\), and the labor hours in evening and night shifts \((LHEN)\)) for each solution \((x)\) in the parent population \((P_g)\). This step is performed by using the scheduling module that returns the values of these objective functions for a given set of decision variables.

3.3) Calculate Pareto optimal rank and crowding distance for each solution \((x)\) in the parent population \((P_g)\) and create a new child population \((C_g)\) using the genetic operators of selection, crossover, and mutation.

3.4) Evaluate the fitness functions for each solution \((x)\) in the newly created child population \((C_g)\) in a process similar to step 3.2).

3.5) Combine child and parent populations \((C_g \text{ and } P_g)\) to form a newly combined population, and then select the best 50% of the members of the combined population to form a new parent population for the next generation \((P_{g+1})\). This process acts as a strong form of elitism as it preserves the best solutions of the parent population over generations (Deb et al. 2001).

The above steps from 3.2) to 3.5) are repeated over a number of predetermined generations \((G)\) in order to generate a Pareto optimal set of non-dominated solutions for the three optimization objectives (i.e., minimizing project duration \((T)\), project direct cost \((DC)\), and labor utilization in the evening and night shifts \((LHEN)\)). Construction
planners can select the best solution that satisfies the special requirements or conditions of the project from the optimal set generated by this module.

5-4 Model Evaluation

An application example is analyzed to illustrate the use of the present optimization model and demonstrate its capabilities. The example includes 15 activities that have finish to start relationships among them, as shown in Figure 5.4. Table 5.4 illustrates activity data including allowable types of shift operation for each activity (n) and its direct cost, duration, and daily labor demand for each shift and Shift-option (S_n). In this example, every shift requires the same crew formation to perform the activities in the project and the daily work hours for the day, evening, and night shifts are 8 hours, 7.5 hours, and 7 hours, respectively. The early schedule of this example based on utilizing only single day shift operation (i.e. S_n=4) requires a project duration of 38 days and a total direct cost of $138,100, as shown in Figure 5.5(A). If all activities operate two shifts (see simple solution 1 in Figure 5.5(B)), the project can be completed in 23 days with a total direct cost of $148,500 and a total of 2587.5 labor hours in the evening shift. On the other hand, if all activities operate three shifts to accelerate the schedule (see simple solution 2 in Figure 5.5(C)), the project duration can be further reduced to 18 days with a total direct cost of $165,100 and a total of 1905 and 1778 labor hours in the evening and night shifts respectively, as shown in Figure 5.5(C).
Figure 5.4 Activity network
## Table 5.4 Activity data

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S^c_n=0: Three shifts (Day, Evening, & Night shifts), S^c_n=1: Two shifts (Day & Evening shifts), S^c_n=2: Two shifts (Day & Night shifts), S^c_n=3: Two shifts (Evening & Night shifts), S^c_n=4: One shift (Day shift), S^c_n=5: One shift (Evening shift), S^c_n=6: One shift (Night shift)
In order to minimize the project duration while simultaneously minimizing its cost and labor utilization on evening and night shifts, this example was analyzed using the developed multi-objective optimization model. Four experiments were conducted to

Figure 5.5 Labor utilization for multiple shift options
analyze the impacts of utilizing two and three shifts systems with varying labor availability constraints (RC). In the first experiment, a three shifts system (SS=3) was utilized in combination with a total of 70 available daily labors (RC=70). In order to distribute this limited number of daily labor among the three daily shifts, the lower and upper bounds of Labor-constraint ($L_j$) were set as $0 \leq L_1 \leq 70$ and $0 \leq L_2 \leq 70$ respectively. As shown in Table 5.4, each activity has 7 possible types of shift operations for this three shifts system. In order to minimize the labor utilization on evening and night shifts, the weight for night shift in Equation (5.14) were set as $W=80\%$. This weight, as stated earlier, represents that reducing the number labor hours in the night shift is 80\% more critical than the evening shift because evening shifts typically have less negative impacts on project performance compared to night shifts. The optimization results of this experiment are summarized in Figure 5.6(A) that illustrates the generated optimal tradeoff solutions among the three optimization objectives (i.e. minimizing project duration, cost, and the labor utilization in evening and night shifts). The minimum project duration achieved in this experiment significantly outperforms simple solution 2 in Figure 5.5(C), as it provides the same project duration of 18 days while providing 5.3\% reduction in the project direct cost and 27.3\% reduction in labor utilization in evening and night shifts, as shown in Table 5.5. It should be noted that operating three shifts by all activities (simple solution 2) requires additional costs to accelerate all activities including the non-critical ones that do not contribute to minimizing the overall project duration. The present model, however, is designed to identify optimal tradeoffs among minimizing project duration, cost, and labor utilization, and accordingly it will accelerate only activities that minimize the project duration while
minimizing the impact of this acceleration on project cost and labor utilization in evening and night shifts, as shown in Table 5.5.

The second experiment was conducted to analyze the impact of the two shifts system (SS=2) and the availability of 50 daily labors (RC=50) on the project performance. In the initialization module of present model, only the types of shift operations belonging to the two shift system (i.e. S_n=1, 4, and 5) were selected from the activity data in Table 5.4 and set as S_n=0, 1, and 2 respectively. The lower and upper bounds of Labor-constraint (L_1) for the day shift was set as 0 ≤ L_1 ≤ 50 and the generated optimization results of this experiment are summarized in Figure 5.6(B). The results of this analysis also confirms that the minimum project duration generated by the model significantly outperforms simple solution 1 in Figure 5.5(B), as it provides the same project duration of 23 days while providing 2.8% reduction in the project direct cost and 34.5% reduction in labor utilization in the evening shift, as shown in Table 5.5.

In the third experiment, a three shift system (SS=3) with a total of 50 daily labors (RC=50) were analyzed. The lower and upper bounds for the decision variables and the weight (W) for Equation (5.14) were set same as the experiment 1. As shown in Figure 5.6(C), the minimum project duration achieved in this experiment (19 days) is one day longer than the minimum duration solution generated in experiment 1 (18 days) due to the lower limit of labor availability. The fourth experiment was conducted to analyze the impacts of a two shift system (SS=2) with a total of 35 daily labors (RC=35) on project performance. The lower and upper bounds for the decision variables were set same as
the experiment 2. As shown in Figure 5.6(D), the minimum project duration achieved in this experiment was 25 days, which is 2 days longer than the result of experiment 2 due to the lower limit of labor availability.

The results of four experiments illustrate that the present model provides new and needed capabilities to support construction engineers and planners in (1) evaluating and identifying optimal shift systems for the project in a single run; (2) producing optimal tradeoff solutions among minimizing the project duration, cost, and the labor hours in evening and night shifts, where each solution identifies optimal schedules and shift work plans for each activity; and (3) generating optimal plans for distributing the limited availability of labor among shifts to minimize the negative impacts of labor constraint on project performance.
Figure 5.6 Pareto optimal solutions
Table 5.5 Sample Pareto optimal solutions

<table>
<thead>
<tr>
<th>Solution</th>
<th>Scheduling Sequence Activity Shift-option ($S_n$)</th>
<th>Project Duration (T)</th>
<th>Direct Cost (DC)</th>
<th>LHEN</th>
<th>Labor Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Resource Constraint in Shift j (RCS$_j$)</td>
<td></td>
<td></td>
<td></td>
<td>Evening Shift</td>
</tr>
<tr>
<td>Simple solution 1 (SS=2)</td>
<td>All activities operate two shifts</td>
<td>23</td>
<td>$148,500</td>
<td>2587.5</td>
<td>-</td>
</tr>
<tr>
<td>Simple solution 2 (SS=3)</td>
<td>All activities operate three shifts</td>
<td>18</td>
<td>$165,100</td>
<td>5105.4</td>
<td>1905</td>
</tr>
<tr>
<td>Experiment 1 (SS=3,RC=70)</td>
<td>A,C,G,K,B,F,J,D,H,L,N,E,I,M,O {0,1,0,1,0,4,0,1,1,4,0,4,0,0,0} {30, 25, 15}</td>
<td>18</td>
<td>$156,300</td>
<td>3709.8</td>
<td>1845</td>
</tr>
<tr>
<td>Experiment 2 (SS=2,RC=50)</td>
<td>B,F,A,D,E,I,C,G,H,M,K,O,L,J,N {0,1,0,0,0,1,0,1,0,1,0,1,0,0,1} {31, 19}</td>
<td>23</td>
<td>$144,300</td>
<td>1695</td>
<td>1695</td>
</tr>
<tr>
<td>Experiment 3 (SS=3,RC=50)</td>
<td>A,C,G,K,B,E,F,D,J,H,I,M,O,L,N {0,1,0,0,1,0,0,1,1,1,0,0,0,0,0} {31, 19}</td>
<td>25</td>
<td>$143,600</td>
<td>1230</td>
<td>1230</td>
</tr>
<tr>
<td>Experiment 4 (SS=2,RC=35)</td>
<td>A,C,G,K,B,F,D,E,I,H,M,O,L,J,N {0,0,1,0,0,0,0,0,1,0,1,0,1,0,0,1} {21, 14}</td>
<td>25</td>
<td>$144,800</td>
<td>1777.5</td>
<td>1777.5</td>
</tr>
</tbody>
</table>
5-5 Summary

A robust multi-objective optimization model was developed to schedule multiple shifts in construction projects. The model was designed to support construction engineers and planners in generating optimal shift work plans and schedules that simultaneously minimize project duration, cost, and the negative impacts of evening and night shifts, while complying with all job logic and labor availability constraints. The optimization model was developed in three main modules: (1) initialization module that retrieves all relevant input data specified by the construction planner and identifies the lower and upper bounds for each decision variable; (2) scheduling module that develops practical multiple shift schedules for construction projects and evaluates the impacts of decision variables on project performance; and (3) multi-objective genetic algorithm module that searches for and identifies optimal/near optimal tradeoffs between project duration, cost, and labor utilization on evening and night shifts. An application example was analyzed to illustrate the use of the model and demonstrate its capabilities in generating optimal tradeoff solutions among these three objectives. Four experiments were conducted to illustrate the impacts of the two and three shift systems with varying labor availability constraints on project performance. The results of analysis illustrate the new capabilities of present model in (1) evaluating and identifying optimal shift systems for the project in a single run; (2) producing optimal tradeoff solutions among minimizing the project duration, cost, and labor utilization on evening and night shifts, where each solution identifies an optimal schedule and multiple shift work plan for each activity; and (3) generating optimal plans for distributing the limited availability of labor among competing shifts to minimize the negative impacts of labor constraints on project
performance. These new and unique capabilities should prove useful to construction planners and should enable them to optimize the utilization of multiple shifts in order to accelerate the delivery of projects while minimizing the negative impacts of evening and night shifts on construction productivity, safety, and cost.
CHAPTER 6
RESOURCE FLUCTUATION COST MODEL

6-1 Introduction

The objective of this chapter is to present the development of a novel multi-objective optimization model that is capable of modeling and minimizing resource fluctuation costs and analyzing and optimizing the tradeoffs between minimizing resource fluctuation costs and minimizing project duration. The main objective of this resource fluctuation cost (RFC) model is to (1) analyze and minimize overall resource fluctuation costs (i.e. idle costs, release and rehiring costs, and mobilization costs); and (2) study and optimize the potential tradeoffs between minimizing the project resource fluctuation costs and project duration. To accomplish this, the RFC model is developed in two main phases: (1) scheduling phase that retrieves all relevant scheduling input data and develops practical schedules and evaluates their impacts on resource fluctuation costs and project duration; and (2) multi-objective optimization phase that searches for optimum schedules that simultaneously minimize project duration and minimize overall resource fluctuation costs within a specified range of project duration, as shown in Figure 6.1. The developments of these two main phases are described in more detail in the following sections.
6-2 Scheduling Phase

The main objective of this phase is to retrieve all relevant scheduling input data and develop practical schedules and to evaluate their impacts on overall resource fluctuation costs and project duration. To achieve this, this phase is developed in two sub-phases: (1) input data phase; and (2) resource scheduling phase which are described in more detail in the following sections (see Figure 6.1).
6-2.1 Input data phase

This input data sub-phase is designed to (a) enable construction planners to specify all relevant scheduling data that are needed to develop and analyze alternative project schedules; and (b) identify the lower and upper bounds for the optimization decision variables. This phase is performed using the following two main steps:

1.1) Input the planning and scheduling data for the project and each activity (n) as follows:

- **Resource data**, which specifies the types of utilized resources (k), and the total number of resource types (NR) that can be released and rehired during their non-productive time.
- **Idle cost (IC_k) for resource type (k)**, which represents the costs to keep construction resources idle on site during their non-productive time.
- **Release and rehiring cost (RC_k) for resource type (k)**, which specifies the costs to temporarily release resources during low demand periods and rehire them later when needed.
- **Mobilization cost (MC_k) for resource type (k)**, which represents the costs to gradually hire all the required resources until the peak demand level is reached, including the mobilization and demobilization costs for construction equipment and the training and clerical costs for workers.
- **Activity data**, which includes the duration (d_n) of each activity (n) and the daily resource demand (r_k,n) of resource type (k) for activity (n).
- **Project data**, which specifies the precedence relationships among project activities and the maximum number of days (DT) that the project can be delayed beyond its early completion time in order to perform the aforementioned tradeoff analysis between project duration and resource fluctuation cost. If the project duration is not allowed to be delayed and the analysis of these tradeoffs are not needed, the DT variable can be set to zero to limit the optimization procedure to only minimizing resource fluctuation costs while maintaining the early completion time of the project.

1.2) Identify the lower and upper bounds of the two decision variables in the optimization model: Shift-days ($S_n$) and Release-option ($R_k$). The Shift-days variable ($S_n$) is used by the present model to identify the optimal shift for each activity (n) while the Release-option variable ($R_k$) is used to identify whether to retain resource (k) on site during its idle time or release and rehire it. The computation procedure used to identify the lower and upper bounds for these two decision variables is summarized in the following eight sub-steps:

I. Calculate the early start time ($ES_n$) and the early finish time ($EF_n$) for each activity (n) based on its input data, as shown in Equations (6.1) and (6.2).

\[
ES_n = \text{Max}_{n':\text{PRE}_n} \{ EF_{n'} \} + 1 \quad (6.1)
\]

\[
EF_n = ES_n + d_n - 1 \quad (6.2)
\]

Where, $\text{PRE}_n = $ set of immediate predecessors of activity (n); and $d_n =$
duration of activity (n).

II. Compute the duration of the early completion schedule (T) using Equation (6.3).

\[ T = \max_{n \in \text{All}} \{ EF_n \} \]  

(6.3)

III. Calculate the maximum allowable project duration (MT) based on the maximum number of days (DT) that the project can be delayed beyond its early completion time in order to perform the aforementioned tradeoff analysis between project duration and resource fluctuation cost, as shown in Equation (6.4). This enables the present model to search for and identify optimal schedules that produce further reductions in the resource fluctuation costs within the specified tradeoff range for the project duration.

\[ MT = T + DT \]  

(6.4)

IV. Calculate the late start time (LS_n) and the late finish time (LF_n) for the last activities in the project that do not have successors, as shown in Equations (6.5) and (6.6). It should be noted that the last activities can be scheduled as late as the maximum allowable project duration (MT) that was identified in the previous step.

\[ LF_n = MT, \quad n \in \text{LAST} \]  

(6.5)
\[ LS_n = LF_n - d_n + 1, \quad n \in LAST \]  

(6.6)

Where, MT = the maximum allowable project duration; LAST = set of activities that do not have successors (i.e. last activities); and \( d_n \) = duration of activity \( (n) \).

V. Calculate the late start time \( (LS_n) \) and the late finish time \( (LF_n) \) for each activity \( (n) \) using Equations (6.7) and (6.8).

\[ LF_n = Min \{ LS_{n'} \} - 1 \quad n \in SUC_n \]  

(6.7)

\[ LS_n = LF_n - d_n + 1 \]  

(6.8)

Where, \( SUC_n \) = set of immediate successors of activity \( (n) \); and \( d_n \) = duration of activity \( (n) \).

VI. Calculate the maximum number of float days \( (TF_n) \) that each activity \( (n) \) can be shifted without violating the maximum allowable project duration \( (MT) \), as shown in Equation (6.9).

\[ TF_n = LS_n - ES_n \]  

(6.9)

VII. Identify the lower and upper bounds for the first decision variable of Shift-days \( (S_n) \) for each activity \( (n) \) based on its identified total float, using Equation (6.10). The total number of variables representing \( (S_n) \) in the
present model is equal to the total number of activities (N) in the project, and it is represented using a genetic algorithm chromosome in the multi-objective optimization phase.

\[ 0 \leq S_n \leq TF_n \] (6.10)

VIII. Determine the lower and upper bounds for the second decision variable of Release-option \((R_k)\) for each releasable type of resource \((k)\) using Equation (6.11). This decision variable represents whether resource \((k)\) will be released and rehired (if \(R_k = 1\)) or kept idle on site (if \(R_k = 0\)) in order to achieve the most cost effective and efficient resource utilization for the project. The total number of variables representing \((R_k)\) in the present model is equal to the total number of resources \((NR)\) that can be released and rehired during their non-productive time.

\[ 0 \leq R_k \leq 1 \] (6.11)

The above eight steps enable the present model to identify the lower and upper bounds for these two decision variables in order to consider all possible project schedules within the specified set of project durations that ranges between the early completion schedule duration \((T)\) and the maximum allowable project duration \((MT)\). The impacts of these two decision variables, Shift-days \((S_n)\) and Release-option \((R_k)\) on the project duration and the resource fluctuation cost \((RFC)\) are evaluated in the resource scheduling phase.
and the multi-objective optimization phase which are described in more details in the following two sections.

6-2.2 Resource scheduling phase

The main objectives of the resource scheduling phase are to (1) develop practical schedules based on the decision variables, Shift-days ($S_n$) and Release-option ($R_k$), generated by the multi-objective optimization phase; and (2) evaluate the impact of the generated schedules on the project duration and the resource fluctuation costs. The computation procedure in this phase is performed using the following four main steps:

2.1) Create Scheduling-Sequence array (SS[$m$]) to determine the sequence of shifting the project activities within their available float times using the following eight sub steps that topologically sort the project activities in a backward pass starting with the last activities and progressing through the network towards the start activities:

I. Create a Scheduled set (S), an Unscheduled set (U), a Decision set (D), and a Scheduling-Sequence array (SS[$m$]).

II. Place all activities into the Unscheduled set (U).

III. Set $m=0$ and select the activities that do not have successors from the Unscheduled set (U).

IV. Move the activities selected in the previous step from the Unscheduled set (U) to the Decision set (D).

V. Select activity ($n^*$) that has the highest activity ID number (ID) from the
Decision set (D) and save it in the Scheduling-Sequence array (SS[m]).

VI. Move the selected activity (n*) from the Decision set (D) to the Scheduled set (S).

VII. Set m=m+1 and select the activities from the Unscheduled set (U) if all their successors exist in the Scheduled set (S).

VIII. Repeat the procedures from step IV to VII for the remaining activities in the Unscheduled set (U).

The above eight sub-steps are designed to determine the shift and scheduling sequence of the project activities. This scheduling sequence considers the impact of shifting activities on the floats of their predecessors in order to generate all possible project schedules without violating any precedence relationship among the project activities. For the example shown in Figure 6.2, the free floats (FFₙ) of activities A and B are affected by the schedule of their succeeding activity C, and accordingly activity C should be shifted before shifting activities A and B. After shifting activity C, the floats of activities A and B should be recalculated to enable their shift within these updated floats. It should be noted that there is no precedence relationship between activities A and B, and accordingly shifting either of them does not affect the float of the other. Their scheduling sequence therefore can be either A → B or B → A, however the above steps determines the scheduling sequence for such activities based on their activity ID numbers (e.g. activity B has higher ID number than activity A and therefore activity B is scheduled first).
2.2) Reschedule each activity \((n)\) based on the decision variable, Shift-days \((S_n)\), free float days \((FF_n)\), and Scheduling-Sequence array \((SS[m])\). The computation procedure can be performed using the following eight sub-steps:

I. Set \(m=0\) and select activity \((n)\) in Scheduling-Sequence array \((SS[m])\).

II. Calculate the free float \((FF_n)\) for activity \((n)\) before its shift using Equation (6.12).

\[
FF_n = \begin{cases} 
MT - EF_n & n \in \text{LAST} \\
\min \{ ES_{n'} - EF_n - 1 \} & n \not\in \text{LAST}
\end{cases}
\] (6.12)

Where, \(MT\) = the maximum allowable project duration; \(SUC_n\) = set of immediate successors of activity \((n)\); and \(d_n\) = duration of activity \((n)\); and \(\text{LAST}\) = set of last activities that do not have successors.

III. Calculate the percentage of shift days \((PD_n)\) for activity \((n)\) within its available free float \((FF_n)\) using Equation (6.13). It should be noted that the decision variable, Shift-days \((S_n)\), is designed to shift activity \((n)\) within its total float \((TF_n)\) in order to generate all possible schedules within the specified range of project duration. In other word, the total float \((TF_n)\) represents the maximum number of days that activity \((n)\) can possibly shift when its successors are scheduled at their late start times \((LS_n)\) and late finish times \((LF_n)\). However, if its successors are not scheduled on their late times, activity \((n)\) should be scheduled only within its available free float.
(FF\(_n\)) to comply with its precedence relationships with its successors. For the example shown in Figure 6.2(C), since activity C is not scheduled on its late start time (LS\(_C\)) and late finish time (LF\(_C\)), the updated free floats (FF\(_n\)) of its predecessors (activities A and B) are not equal to their total float (TF\(_n\)). Accordingly, activities A and B should not be shifted beyond their updated free float (FF\(_n\)) to maintain their precedence relationships with their successor, activity C. In order to shift those activities without violating their precedence relationships, the percentage of shift days (PD\(_n\)) for activity (n) is designed to proportionally shift activity (n) within its available free float (FF\(_n\)) based on its total float (TF\(_n\)) and the decision variable, Shift-days (S\(_n\)). For the example shown in Figure 6.2(D), the percentage of shift days for activity B is 66.7% (PD\(_B\) = S\(_B\)/TF\(_B\) = 2/3) based on its Shift-days decision variable (S\(_B\) = 2) and its total float (TF\(_B\) = 3). This value is then used in the next step to determine the number of days to shift activity (n) within its available free float (FF\(_n\)).

\[
PD_n = \begin{cases} 
\frac{S_n}{T_{F_n}} & T_{F_n} > 0 \\
0 & T_{F_n} = 0
\end{cases} \quad (6.13)
\]

IV. Calculate the number of shift days (SD\(_n\)) for activity (n) using Equation (6.14), which determines the number of days to shift activity (n) within its updated free float (FF\(_n\)) based on its percentage of shift days (PD\(_n\)) calculated in the previous step. For the example shown in Figure 6.2(C) and
6.2(D), the updated free float for activity B after shifting activity C is 2 days \( (FF_B = 2) \) which means that activity B can only be shifted within this updated free float \( (FF_B) \) to maintain its precedence relationships with its successor. Accordingly, the number of shift days for activity B \( (SD_B = 1) \) is calculated based on its percentage of shift days \( (PD_B) \) and the updated free float \( (FF_B) \), as shown in Figure 6.2(D).

\[
SD_n = \left\lfloor PD_n \times FF_n \right\rfloor
\]  

(6.14)

Where, \( \left\lfloor \ \right\rfloor \) = fraction truncation.

V. Recalculate the early start time \( (ES'_n) \) and the early finish time \( (EF'_n) \) for each activity \( (n) \) based on the number of shift days \( (SD_n) \) as shown in Equations (6.15) and (6.16).

\[
ES'_n = ES_n + SD_n
\]  

(6.15)

\[
EF'_n = EF_n + SD_n
\]  

(6.16)

VI. Set \( m=m+1 \) and select the next activity \( (n) \) in the Scheduling-Sequence array \( (SS[m]) \).

VII. Repeat the procedures from step II to VI for the remaining activities in the Scheduling-Sequence array \( (SS[m]) \).

VIII. Calculate daily resource demands for each type of resources based on the generated schedule.

138
2.3) Evaluate the impact of the generated schedule on project duration ($T'$) using Equation (6.17).

$$T' = \text{Max}_{n \in All}\{EF'_n\}$$  
(6.17)

2.4) Evaluate the impact of the generated schedule on resource fluctuation costs (RFC) using Equation (6.18). The total number of temporarily released and rehired resources (RRH) and the total resource idle days (RID) caused by resource fluctuations are calculated in the present model based on the procedures developed in Chapter 3-3, as shown in Equations (6.23) and (6.24). It should be noted that Equations (6.20) and (6.21) calculate idle costs and release and rehiring costs based on the decision variable, Release-option ($R_k$) for each resource type ($k$) that can be released and rehired.

$$RFC = \sum_{k=1}^{K} (TIC_k + TRC_k + TM C_k)$$  
(6.18)

$$MaxR_k = \text{Max}\{r_{k,1}, r_{k,2}, \ldots, r_{k,j}, \ldots, r_{k,T}\}$$  
(6.19)

$$TIC_k = \begin{cases} 
0 & \text{if } k \in \text{RR and } R_k = 1 \\
RID_k \times IC_k & \text{otherwise}
\end{cases}$$  
(6.20)

$$TRC_k = \begin{cases} 
RRH_k \times RC_k & \text{if } k \in \text{RR and } R_k = 1 \\
0 & \text{otherwise}
\end{cases}$$  
(6.21)

$$TM C_k = MaxR_k \times MC_k$$  
(6.22)
\[ R_{ID_k} = \sum_{t=1}^{T} \left[ \min\{ \max(r_{k,1}, r_{k,2}, \ldots, r_{k,t}), \max(r_{k,1}, r_{k,2}, \ldots, r_{k,T}) \} - r_{k,t} \right] \]  

(6.23)

\[ RRH_k = \frac{1}{2} \times HR_k - \max R_k \]  

(6.24)

\[ HR_k = \left[ r_{k,1} + \sum_{t=1}^{T-1} \left| r_{k,t} - r_{k,t+1} \right| + r_{k,T} \right] \]  

(6.25)

Where, \( TIC_k \) = total idle cost for resource type (k); \( TRC_k \) = total release and rehiring cost for resource type (k); \( TMC_k \) = total mobilization cost for resource type (k); \( \max R_k \) = the maximum level of demand for resource type (k) during the entire project duration; \( r_{k,t} \) = demand of resource type (k) on day (t); \( RR \) = set of all types of resources that can be released and rehired during their non-productive time; \( R_k \) = , Release-option decision variable generated by the multi-objective optimization phase; \( MC_k \) = mobilization cost ($/resource) for resource type (k); \( IC_k \) = idle cost ($/resource/day) for resource type (k); \( RC_k \) = release and rehiring cost ($/resource) for resource type (k); \( RID_k \) = total number of idle and non-productive days for resource type (k) during the entire project duration; \( RRH_k \) = total number of resource type (k) that need to be temporarily released and rehired during the entire project duration; and \( HR_k \) = the total daily resource fluctuations for type (k).

The above four main steps are repeated for each possible scheduling solution generated by the multi-objective optimization phase in order to calculate the two objective functions: project duration (T) and resource fluctuation cost (RFC). These two
values of the objective functions are then used in the multi-objective optimization phase to evaluate the fitness of each solution and reproduce new offspring in subsequent generations during the search for optimal/near optimal tradeoffs between those two optimization objectives. After a number of predetermined generations, each solution in the final population represents optimal/near optimal schedule that simultaneously minimizes project duration (T) and resource fluctuation cost (RFC) within the specified range of project duration. The process of multi-objective optimization phase is described in more details in the following section.

Figure 6.2 The impact of shifting activities on the float of their predecessors
Multi-Objective Optimization Phase

The objective of this phase is to search for optimum schedules that simultaneously minimize project duration and minimize overall resource fluctuation cost within the specified range of project duration. In order to simultaneously optimize these two objectives, the present model is developed using a multi-objective genetic algorithm (Deb et al. 2001). This algorithm has been successfully used as a multi-objective optimization tool by many studies for optimizing construction resource utilization (El-Rayes and Kandil 2005; El-Rayes and Khalafallah 2005; Hyari and El-Rayes 2006; Jun and El-Rayes 2009). The algorithm utilizes the survival of the fittest criteria to evolve solutions over a number of specified generations and the concept of Pareto optimality to enable multi-objective optimization. This multi-objective optimization phase is designed to interact with the resource scheduling phase to evaluate the fitness of each solution in the population of every generation by calculating the two objective functions: project duration (T) and resource fluctuation cost (RFC). The solutions in the population of last generation provided by this phase represent optimal schedules for each activity that produce a minimum resource fluctuation cost (RFC) while minimizing the project duration (T). The computation procedure in this phase is performed using the following three main steps (see Figure 6.1):

1. **Initialization**: this step generates an initial set of solutions for the initial population in the first generation. Each solution (i.e. chromosome) consists of randomly generated values for the decision variables of Shift-days ($S_n$) and Release-option ($R_k$) as follows: $S_1, S_2, ..., S_N, R_1, R_2, ..., R_{NR}$.
2. **Fitness function evaluation**: this step evaluates the fitness of each solution in the population by calculating the values of their two objective functions: project duration ($T$) and resource fluctuation cost ($RFC$) using the aforementioned resource scheduling phase, as shown in Figure 6.1.

3. **Reproduction**: this step selects the most-fit solutions (i.e. new offspring) in the parent population based on the fitness criteria, Pareto optimal rank and crowding distance for each solution, and reproduces a new child population using the genetic operators of crossover and mutation. The fitness of each solution in the newly created child population is then evaluated in a similar process to step 2, and the child and parent populations are combined to form newly combined populations. From the combined population, the best 50% solutions are selected to form a new parent population for the next generation. This process represents elitism that preserves the best solutions of the parent population over generations (Deb et al. 2001).

The above steps from 2 to 3 are repeated over a number of predetermined generations in order to generate a Pareto optimal set of non-dominated solutions that simultaneously minimize project duration ($T$) and resource fluctuation cost ($RFC$) for construction projects within the specified range of project duration. A construction planner can select the best plan that satisfies the special requirements of a project from the optimal set generated by this phase.
6-4 Model Evaluation

An application example is analyzed to illustrate the use of the present model and demonstrate its capabilities in generating optimal tradeoffs between project duration \( T \) and resource fluctuation cost \( RFC \). The example includes 20 activities that have finish to start relationships, as shown in Figure 6.3. The project activities utilize four types of resources including labors and equipments that are not allowed to be released and rehired during the construction of this application example, as shown in Table 6.1. The early schedule of this example project can be completed in 50 days and it has undesirable resource fluctuations and peak demand, as shown in Figure 6.4. This undesirable resource fluctuation causes $105,200 of total resource fluctuation costs \( RFC \), which includes $79,650 of total resource idle cost \( TIC \) and $25,550 of total mobilization cost \( TMC \) for all utilized labor and equipment. It is assumed that the maximum number of days \( DT \) that the project can be delayed for this example is 10 days, and accordingly the tradeoff between resource fluctuation costs and project duration can be analyzed and optimized for project durations that range from 50 to 60 days.

The present model generated four Pareto optimal (i.e. non-dominated) solutions for this example, as shown in Figure 6.5. Each of these solutions identifies an optimal schedule for the project activities, and it provides a unique and non-dominated optimal tradeoff between resource fluctuation costs \( RFC \) and project duration \( T \). The generated results show that the model was capable of reducing the resource fluctuation costs \( RFC \) of the early schedule by almost 32.7% from $105,200 to $70,800 while keeping
the project duration unchanged at 50 days, as shown in Figure 6.5. This minimum resource fluctuation costs (RFC) that was achieved at a project duration of 50 days can be further reduced to $54,300 (48.4% reduction from the early completion schedule) when the project duration is allowed to be extended to 58 days, as shown in Figure 6.5. The optimal tradeoff solutions produced by the present model enable a construction planner to select an optimal schedule that provides the best performance for the project. The results of this analysis clearly illustrate the new capabilities of present model in generating optimal schedules that minimize resource fluctuation cost as well as analyzing and optimizing the tradeoffs between the project duration and resource fluctuation costs. These new capabilities enable construction planners to quantify and minimize the costs of resource fluctuation costs and should contribute to enhancing the cost-effectiveness and optimal delivery of construction projects.

![Figure 6.3 Activity network](image)
## Table 6.1 Activity data

<table>
<thead>
<tr>
<th>ID</th>
<th>Activity (n)</th>
<th>Duration</th>
<th>Daily resource demand</th>
<th>Labor</th>
<th>Equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>k=2</td>
</tr>
<tr>
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<td>5</td>
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<td>C</td>
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<td>7</td>
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<td>T</td>
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<td>4</td>
<td>7</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Idle cost ($/resource/day)</th>
<th>$100</th>
<th>$200</th>
<th>$450</th>
<th>$800</th>
</tr>
</thead>
<tbody>
<tr>
<td>Release and rehiring cost ($/resource)</td>
<td>$150</td>
<td>$250</td>
<td>$700</td>
<td>$1000</td>
</tr>
<tr>
<td>Mobilization cost ($/resource)</td>
<td>$50</td>
<td>$100</td>
<td>$1,000</td>
<td>$2,000</td>
</tr>
</tbody>
</table>
Figure 6.4 Resource utilization of early schedule

Project duration (T) = 50 days
Resource fluctuation cost (RFC) = $105,200
Total resource idle cost (TIC) = TIC₁+TIC₂+TIC₃+TIC₄ = $79,650
Total mobilization cost (TMC) = TMC₁+TMC₂+TMC₃+TMC₄ = $25,550
A multi-objective optimization model was developed to support construction planners in generating optimal project schedules that minimize resource fluctuation costs on construction sites. The model provides the capability of quantifying and minimizing three main types of resource fluctuation costs: (a) idle costs for construction resources that cannot be released during their non-productive time; (b) release and rehiring costs for construction resources that can be temporarily released during low demand periods and rehired later when needed; and (c) mobilization and demobilization costs for construction equipment and labor. The model is also designed to analyze and optimize potential tradeoffs between minimizing resource fluctuation costs and minimizing the project duration. The model was developed in two main phases: (1)
scheduling phase that generates practical construction schedules and evaluates their impact on resource fluctuation costs and project duration; and (2) multi-objective optimization phase that searches for and identifies optimum schedules that simultaneously minimize project duration and minimize overall resource fluctuation costs. The model was implemented using a multi-objective genetic algorithm that utilizes the survival of the fittest criteria to evolve solutions over a number of specified generations and the concept of Pareto optimality to enable multi-objective optimization. An application example was analyzed to illustrate the use of the developed model and demonstrate its capabilities in generating optimal tradeoffs between minimizing the project duration and minimizing resource fluctuation costs. These new and unique capabilities should prove useful to construction planners and is expected to minimize the additional and unnecessary resource fluctuation costs in construction projects.
CHAPTER 7
PROJECT RISK ASSESSMENT MODEL

7-1 Introduction

The objective of this chapter is to present the development of a novel probabilistic scheduling model that enables fast and accurate risk evaluation for real-life and large-scale construction projects. The model is named “Fast and Accurate Risk Evaluation” (FARE) and is designed to overcome the limitations of existing probabilistic scheduling methods including (a) the inaccuracy limitation of the PERT method due to its “merge event bias” by incorporating an accurate multivariate normal integral method; and (b) the impractical computational time of the Monte Carlo simulation method by incorporating a newly developed approximation method. First, the multivariate normal integral method is incorporated in the FARE model to enable evaluating the impact of correlation among the network paths on the probability of project completion ($PT_i$) by calculating multiple joint probabilities that all network path durations will not exceed the specified target time. Second, a newly developed approximation method is incorporated in the FARE model to ensure that its computational time is practical for large-scale construction projects. Accordingly, the FARE model consists of three main modules: (1) PERT model to formulate the project network as a multivariate normal probability problem to overcome the limitation of the “merge event bias” of PERT; (2) fast and accurate multivariate normal integral method to efficiently and effectively estimate the probability of project completion by a specified target time based on the formulated multivariate normal probability problem; and (3) a newly developed approximation
method to provide an approximate and accurate estimate for the probability of project completion for large scale construction projects. The following sections describe the development of these three main modules in more detail.

7-2 Module 1: PERT Model

The objective of this module is to formulate the traditional PERT method as a multivariate normal probability problem to overcome its "merge event bias" limitation. The PERT model in FARE is developed using similar assumptions to those of the traditional PERT method as follows:

I. Beta distribution is used to represent the probability of the duration of activity \((n)\) and it can be determined by using three point estimates: optimistic \((a)\), most likely \((m)\), and pessimistic \((b)\) durations. The optimistic \((a)\) and pessimistic \((b)\) points represent the extreme ends of the probability distribution (i.e. 0% and 100% percentile), and the most likely \((m)\) point represents the mode. Research studies have shown that the duration of many construction activities can be represented by a beta distribution (AbouRizk et al. 1991, 1994).

II. The mean \((\mu_n)\) and standard deviation \((\sigma_n)\) for the duration of activity \((n)\) can be calculated by using Equations (7.1) and (7.2).

\[
\mu_n = \frac{(a_n + 4 \cdot m_n + b_n)}{6} \tag{7.1}
\]

\[
\sigma_n = \frac{(b_n - a_n)}{6} \tag{7.2}
\]
III. Based on the above mean ($\mu_n$) and standard deviation ($\sigma_n$) for the duration of activity (n), two shape parameters, $\alpha_n$ and $\beta_n$, for the beta distribution can be calculated using the method of moment (Bain and Engelhardt 1991), as shown in Equations (7.3) and (7.4).

\[
\alpha_n = \left(\frac{\mu_n - a_n}{b_n - a_n}\right) \cdot \left(\frac{\mu_n - a_n (b_n - \mu_n)}{\sigma_n^2} - 1\right) \quad (7.3)
\]

\[
\beta_n = \left(\frac{b_n - \mu_n}{\mu_n - a_n}\right) \cdot \alpha_n \quad (7.4)
\]

IV. The mean ($\mu_k$) and variance ($\sigma_k^2$) of the duration of path (k) in the project network can be calculated using Equations (7.5) and (7.6). It should be noted that if activities are not correlated with each other, then the variance ($\sigma_k^2$) of path (k) can be simply calculated by summing up the duration variances ($\sigma_n^2$) of all the activities on path (k), as shown in Equation (7.7). The traditional PERT method assumes that the project activities are statistically independent.

\[
\mu_k = \sum_{n=1}^{N} a_{k,n} \mu_n \quad (7.5)
\]

\[
\sigma_k^2 = \sum_{n=1}^{N} a_{k,n} \sigma_n^2 + \sum_{n=1}^{N} \sum_{n'=n+1}^{N} a_{k,n} a_{k,n'} \rho_{n,n'} \sigma_n \sigma_{n'} \quad (7.6)
\]

\[
\sigma_k^2 = \sum_{n=1}^{N} a_{k,n} \sigma_n^2 \quad \text{if all activities are statistically independent} \quad (7.7)
\]
Where, $a_{k,n}=1$ if activity $(n)$ is contained in path $(k)$, otherwise $a_{k,n}=0$; $\rho_{n,n'}$ = correlation between activity $(n)$ and $(n')$; and $N$ = total number of project activities.

V. If a large number of activities are included in the network path and the activities are not correlated (i.e. independent), the probability distribution of the sum of the activity durations along the network path can be approximated to a normal distribution based on the Central Limit Theorem (CLT). Miller (1964) has indicated that at least ten activities are required in the network path to support the normal distribution assumption for the path duration based on the CLT. Most construction projects clearly have more than ten activities in their network paths, and therefore, the normality assumption for the distribution of path duration can be justified by the CLT.

Based on the above assumptions, the PERT problem can be formulated as a multiple joint probability problem (Ang et al. 1975; Anklesaria and Drezner 1986; Sculli and Shum 1991) as shown in Equation (7.8).

\[
PT_t = P(T_1 \leq t, T_2 \leq t, \ldots, T_k \leq t, \ldots, T_K \leq t) \tag{7.8}
\]

Where, $PT_t$ = probability of project completion by a specified target project duration $(t)$. $T_k$ = duration of path $(k)$; and $t$ = target project duration.

Equation (7.8) represents the probability that the durations of all network paths are less than the target project duration $(t)$. However, it should be noted that there are often
more than two different paths in the project network that share the same activities, and accordingly there are correlations between these paths, as shown in Figure 7.1. This correlation between two different paths can be calculated using Equation (7.9). If project activities are statistically independent, then the second term in Equation (7.10) becomes zero, and thereby, the covariance between the two paths can be calculated by using only the variance ($\sigma_n^2$) of duration of common activities between the two paths as shown in Equation (7.11) (Ang et al. 1975).

\[
\rho_{k,l} = \frac{\text{Cov}_{k,l}}{\sigma_k \sigma_l}
\]  \hfill (7.9)

\[
\text{Cov}_{k,l} = \sum_{i=1}^{N} a_{k,n} a_{l,n} \sigma_n^2 + \sum_{n=1}^{N} \sum_{n'=1}^{N} a_{k,n} a_{l,n'} \rho_{n,n'} \sigma_n \sigma_{n'}
\]  \hfill (7.10)

\[
\text{Cov}_{k,l} = \sum_{n=1}^{N} a_{k,n} a_{l,n} \sigma_n^2 \quad \text{if all activities are statistically independent}
\]  \hfill (7.11)

Where, $\rho_{k,l}$ = correlation between path (k) and path (l); $\text{Cov}_{k,l}$ = covariance between path (k) and path (l); $a_{k,n}=1$ if activity (n) is on path (k), otherwise $a_{k,n}=0$.

If the correlations among the network paths partly exist, then the multiple joint probabilities shown in Equation (7.8) become the multivariate normal integral problem based on the Central Limit Theorem (CLT) (Anklesaria and Drezner 1986; Sculli 1989). Accordingly, the FARE model is formulated as a multivariate normal integral problem to
consider the impact of correlations among the network paths on the probability of project completion \( PT_i \).

Figure 7.1 Correlation between two network paths

7-3  Module 2: Fast and Accurate Multivariate Normal Integral Method

As stated earlier, the multiple joint probability problem shown in Equation (7.8) can be formulated as a multivariate normal probability as shown in Equation (7.12). The primary objective of this module is to solve the multivariate normal probability shown in Equation (7.12) for PERT networks using the efficient multivariate normal integral method (Genz 1992).

\[
PT_i = \frac{1}{\sqrt{\Sigma}} \int_{-\infty}^{t_1} \int_{-\infty}^{t_2} \cdots \int_{-\infty}^{t_m} \exp \left( -\frac{1}{2} T^T \Sigma^{-1} T \right) \, dT_1 dT_2 \cdots dT_m
\]  

(7.12)
Where, \( m \) = total number of network paths in the project network; \( T \) = a vector of correlated path durations \( (T_k) \) (i.e. random variable); \( T^\top \) = transpose of \( T \); \( t \) = target project duration; and \( \Sigma \) = \((m \times m)\) covariance matrix for the path duration \( (T_k) \).

It should be noted that the multivariate normal probability problem requires multiple integrations, where the total number of integrals in the Equation (7.12) is equal to the total number of paths in the project network. The numerical computation of the above multivariate normal probability is often a difficult and time-consuming task especially for a large-scale network that includes a large number of \( m \)-dimensional integrals. In real-life construction projects, the network often includes a large number of paths that can reach tens of millions, and accordingly this increases the number of \( m \)-dimensional integrals in the multivariate normal probability shown in Equation (7.12). Therefore, an efficient method for multivariate normal probability is essential to provide fast and accurate estimate of probability of project completion for PERT networks. To address this issue, the algorithm developed by Genz (1992) is employed in the present model. This algorithm provides an efficient procedure for calculating the multivariate normal integral by simplifying the domain of integration in Equation (7.12) through transforming its original integral into an integral over a unit hyper-cube. Compared to other existing algorithms, the Genz algorithm is capable of providing (a) more efficient computation for large \( m \)-dimensional multivariate normal integral problems; and (b) an estimate of the error bound for the estimated multivariate normal probability (Genz 1992). This error bound provides a confidence interval for the estimate of the multiple integrations in Equation (7.12) by a sampling method. In the FARE model, the recent developments
and enhancements in the Genz algorithm that incorporate quasi-random rule for the multiple integrations (Genz 2010) were incorporated and coded in C programming language. This enables the FARE model to analyze the probability of project completion for large-scale construction project networks while considering the impact of correlation among the network paths on the probability of project completion (PT_i) to overcome the limitation of “merge event bias” of PERT.

The performance of the implemented Genz algorithm in the FARE model was analyzed using varying sizes of m-dimensional multivariate normal probability problems, as shown in Figure 7.2. The results of this analysis show that the Genz algorithm provides fast and accurate estimates of multivariate normal probability even for mid-size project networks that include up to 16,000 paths and require m-dimensional multiple integrations, where m = 16,000. Although the Genz algorithm is capable of providing fast and accurate estimates of multivariate normal probability for small to mid-size networks, it still requires a large computational effort and memory (RAM) to solve real-life large-scale construction project networks that often include tens of millions of paths similar to the second example that is analyzed later in this chapter, which includes 971 activities and approximately 77 million paths. In order to address this computational time and memory (RAM) challenge, a new approximation method is developed to provide an approximate probability of project completion (PT) and it is described in more detail in the following section.
7-4 Module 3: New Approximation Method for a Large Scale Project Network

The objective of this module is to provide an approximate estimate for the probability of project completion for large-scale construction project networks that include tens of millions of network paths. A new approximation method is developed based on the two following principles:

i. Paths that have very high probability of completion time (e.g. $P(T_k \leq t) \geq 0.99 \approx 1.00$) do not significantly affect the probability of project completion ($PT_t$), as shown in Equation (7.8).

ii. If several paths are highly correlated with a path that has the lowest probability of completion time $P(T_k \leq t)$ among them, then this path is considered a major path that
can be used to represent and replace the other highly correlated paths that have higher probability of completion time (Ang et al. 1975).

Based on these principles, a new approximation method is designed to (1) remove paths that have very high probability of completion time (e.g. \( P(T_k \leq t) \geq 0.99 \approx 1.00 \)) from the analysis; (2) remove highly correlated paths from the analysis and replace them with representative paths that have the lowest probability of completion time among the correlated paths; and (3) approximate the estimate of the probability of project completion (\( PT_t \)) by a specified target time based on the selected representative paths to improve the efficiency of evaluating the risk of large scale project networks. To this end, the new approximation method is developed in four main phases, as shown in Figure 7.3: (1) initialization; (2) removal of high probability paths; (3) removal of highly correlated paths; and (4) probability approximation, which are described in more detail in the following sections.

7-4.1 Initialization

The purposes of initialization phase are to (1) specify the upper probability bound (UP) and the upper correlation bound (UC) that can be used to select representative paths from all existing paths in the project network; and (2) to reduce the redundant links in the project network. This phase is performed using the following three main steps:

1.1) Specify target project duration (t) for the network.

1.2) Specify the upper probability bound (UP) and the upper correlation bound (UC).

The purpose of the upper probability bound (UP) is to remove paths that have
higher probability than UP from the analysis since they do not significantly affect on the probability of project completion ($PT_i$), as stated earlier. On the other hand, the purpose of the upper correlation bound (UC) is to remove paths that are highly correlated with a major path and their correlations are higher than UC.

1.3) Remove redundant links in the project network using the transitivity reduction method. Redundant relationships often exist among many project activities in CPM diagrams (Nassar and Hegab 2006). These redundant links create many redundant paths in the project network, which can be dominated by other paths. For example, the duration of redundant path 1–3 in Figure 7.4 can never be longer than the duration of path 1–2–3, and therefore, these redundant paths should be removed from the network analysis.
2. Removal of high probability paths
• Remove paths that have probability of completion time greater than UP \( P(T_k \leq t) > UP \) without enumerating all existing paths in the network

3. Removal of highly correlated paths
• Remove paths that are highly correlated with a major path (i.e., remove path \( i \) that has a correlation with a major path \( j (\rho_{ij}) \geq UC \))

4. Probability approximation
• Estimate the approximate probability of project completion \( PT_t \) by a specified target project duration \( t \) using Genz’s algorithm based on the selected representative paths

Figure 7.3 FARE model for a large scale construction project network

![Diagram of FARE model](image)

Figure 7.4 Redundant links among project activities

![Diagram of redundant links](image)
7.4.2 **Removal of high probability paths**

The objectives of this phase is to identify and remove network paths that have higher probability of completion time \( P(T_k \leq t) \) than the upper probability bound (UP) and utilize only the remaining paths in the network analysis. A simple method to achieve this objective is to enumerate and analyze the probabilities of completion time for all existing paths in the project network. This method, however, is inefficient and requires high computational effort especially for large-scale construction project networks which often include a very large number of paths. In order to ensure efficiency in accomplishing these objectives, a new method is designed to perform the following three main steps, as shown in Figure 7.5: (1) transform the upper probability bound (UP) to an equivalent lower bound for mean path duration (LM) that can be used to search for and identify network paths that have a lower probability of completion time than UP; (2) find the longest mean path duration (\( LD_n \)) for each activity (n) and the largest variance (LV) in the network to enable identifying LM and searching for paths that have greater mean of path duration (\( \mu_k \)) than LM; and (3) select representative paths that have lower probability of completion time \( P(T_k \leq t) \) than UP using LM and \( LD_n \). The main reason of using the lower bound for the mean of path duration (LM) and the longest mean of path duration (\( LD_n \)) in these three steps is to improve the efficiency of searching for representative paths without enumerating all existing paths in the network by utilizing the principal of optimality (Bellman 1957). These three main steps and their computations are described in more detail in the following sections.
1. Transform the upper probability bound (UP) to an equivalent lower bound for mean path duration (LM)

2. Find the longest mean path duration (LD_n) and the largest variance (LV) in the network

3. Select representative paths that have P(T_k ≤ t) < UP without enumerating all existing paths in the network based on LM and LD_n

**Longest path duration search (LPDS) algorithm**

**Fast representative path search (FRPS) algorithm**

Figure 7.5 Three main steps to remove high probability paths

7-4.2.1  *Step 1: Transform the upper probability bound (UP) to an equivalent lower bound for mean path duration (LM)*

The main objective of this step is to transform the upper probability bound (UP) identified in the initialization phase to an equivalent lower bound for mean path duration (LM) that can be used to search for and retain network paths that have lower probability of completion time than UP. These network paths can be identified by searching for paths that have mean path durations (μ_k) that are greater than LM, as shown in Figure 7.6. The upper probability bound (UP) can be transformed to an equivalent lower bound for mean path duration (LM) using Equations (7.13) through (7.16). First Equation (7.13) can be used to comply with the upper probability bound (UP) specified earlier in the initialization phase to ensure that the FARE model selects representative paths (k) that have probability of completion time P(T_k ≤ t) that are less than the UP. The terms in Equation (7.13) can then be reorganized as shown in Equations (7.14) and (7.15) in order to identify the mean of path duration (μ_k) as a function of the target project duration (t), the standard deviation of path duration (σ_k), and the inverse of the standard normal distribution function for the upper bound (Φ^{-1}(UP)), as shown in Equation (7.15).
Since the mean path duration ($\mu_k$) in Equation (7.15) depends on the standard deviation of path duration ($\sigma_k$), then the lower bound for the mean path duration (LM) can be identified by using the largest variance of path durations (LV), as shown in Equation (7.16).

$$P(T_k \leq t) = \Phi \left( \frac{t - \mu_k}{\sigma_k} \right) \leq UP$$  \hspace{1cm} (7.13)

$$\frac{t - \mu_k}{\sigma_k} \leq \Phi^{-1}(UP)$$  \hspace{1cm} (7.14)

$$\mu_k \geq \begin{cases} t - \Phi^{-1}(UP) \cdot \sigma_k & \text{if } UP > 0.5 \\ t_k & \text{if } UP = 0.5 \\ t + \Phi^{-1}(UP) \cdot \sigma_k & \text{if } UP < 0.5 \end{cases}$$  \hspace{1cm} (7.15)

$$LM = t - \Phi^{-1}(UP) \cdot \sqrt{LV}$$  \hspace{1cm} (7.16)

Where, $\Phi(\cdot) = \text{standard normal cumulative distribution function}$; $\Phi^{-1}(\cdot) = \text{inverse of standard normal cumulative distribution function}$; and $LV = \text{the largest variance of path durations in the entire network}$, which can be identified using the next step.

The value of LM identified in this step will be used in the following main steps to select and analyze only representative paths that have mean path durations ($\mu_k$) that are greater than LM such as paths 1 and 2 in the simple example shown in Figure 7.6. It should be noted that identifying network paths that have greater mean path duration ($\mu_k$)
than LM does not guarantee that all these identified paths will have lower probability of completion time \( P(T_k \leq t) \) than UP, as shown in the case of path 2 in Figure 7.6. This may occur because LM is derived using the largest variance of path duration (LV) in the network, as shown in Equation (7.16). Accordingly, the FARE model is designed to reexamine this initial set of identified network paths based on LM by calculating their probability of completion time \( P(T_k \leq t) \) to ensure the final selection and retention of representative paths that have lower probability of completion time \( P(T_k \leq t) \) than UP, as shown in Figure 7.6. The detailed procedure of selecting representative paths based on LM is described in the following sections.

\[
LM = t - \Phi^{-1}(UP) \cdot \sqrt{LV} = 20 - \Phi^{-1}(0.99) \cdot \sqrt{7} = 13.845
\]

\[
\mu_1 = 15, \sigma_1^2 = 2.6458, P(T_1 \leq 20) = 0.9706
\]

\[
\mu_2 = 14, \sigma_2 = 2.00, P(T_2 \leq 20) = 0.9987
\]

\[
\mu_3 < LM \quad \text{but} \quad P(T_3 \leq 20) > UP
\]

\[
\mu_4 < LM \quad \text{but} \quad P(T_4 \leq 20) > UP
\]

**Figure 7.6 Selecting representative paths using lower bound for mean path duration (LM)**
7-4.2.2 Step 2: Find the longest mean path duration (LDₙ) for each activity node (n) and the largest variance (LV) in the network

The objectives of this step are to identify (1) the longest mean path duration (LDₙ) from a given activity node (n) to the end node (E) to facilitate the search for paths that have greater mean path duration (μᵢ) than LM; and (2) the largest variance (LV) of path duration in the network to enable the calculation of the lower bound for mean path duration (LM) using Equation (7.16). In order to achieve these objectives, a new algorithm named “longest path duration search” (LPDS) is developed, as shown in Figure 7.7. In this algorithm, the start (S) and end (E) nodes are assumed to be dummy activities that have zero mean duration (μᵢ) and zero variance (σᵢ²), and they do not have predecessor nodes and successor nodes, respectively. One simple approach to search for the longest mean path duration (LDₙ) in the project network is to use CPM calculations, which can be efficient in identifying the longest path for the entire project network. The CPM computations, however, are inefficient to identify the longest mean path duration (LDₙ) from a given intermediate node (n) to the end node (E), as shown in Figure 7.8. This requires focusing the CPM computations only on a sub-network that starts from node (n) until the end node (E) and removing all other activities and their precedence relationships from the analysis. For the example shown in Figure 7.8, identifying the longest mean path duration (LDₙ) from node 8 to the end node (E) requires focusing the CPM computations on the highlighted sub-network that consists of only activities, 8, 15, 17, 18, 13, 14, and E and only the precedence relationships among them. This requires the removal of unrelated activities and precedence relationships from the CPM analysis, as shown in Figure 7.8. This modification of the
original network is inefficient and time consuming, and therefore a new algorithm is developed to improve the efficiency of searching for the longest mean path duration \((LD_n)\) from a given activity node \((n)\) to the end node \((E)\), as shown in Figure 7.7.

The newly developed LPDS algorithm is designed to search for the longest path for each sub-network starting from a given activity node \((n)\) and ending with the end node \((E)\) using a method similar to the Depth-First-Search method (Cormen 2001). First, the developed LPDS algorithm sets the path duration \((PD_n)\) of all activities in the sub-network equal to zero, as shown in Figure 7.7. The algorithm then calculates the path duration starting from a given activity node \((n)\) by progressing forward through its first successor node \((S_n)\) and going deeper and deeper until it reaches the end node \((E)\) in the sub-network. The algorithm then moves backward through the sub-network until it reaches the given activity node \((n)\) in order to identify and analyze all successor nodes and paths that were not examined in the previous cycles and revise all path durations \((PD_n)\) accordingly (see Figure 7.7). These steps are repeated until the algorithm analyzes all nodes \((n)\) and their successors \((S_n)\) in the sub-network. Upon the completion of this analysis, the LPDS algorithm calculates the longest mean path duration \((LD_n)\) from a given activity \((n)\) to the end node \((E)\) as the longest path duration \((PD_E)\) from node \((n)\) to the end node \((E)\), as shown in Figure 7.7. As such, the newly developed LPDS algorithm uses a method similar to the forward pass calculation of critical path method (CPM) when calculating the path duration \((PD_n)\) for each activity \((n)\) to find the longest mean path duration \((LD_n)\) and focuses on one sub-network at a time to improve the efficiency of searching for the longest path in the sub-network that starts from a given activity node \((n)\) to the end node \((E)\), shown in Figure 7.7.
It should be noted that this algorithm can find the longest mean path duration \((LD_n)\) as well as the largest variance \((LV)\) of path duration by setting the given activity node \((n)\) equal to start node \((S)\) and then considering the variance \((\sigma_i^2)\) of activity duration instead of the mean \((\mu)\) of activity duration. Accordingly, this algorithm can also be used to identify the largest variance \((LV)\) in order to enable the calculation of the lower bound for mean path duration \((LM)\) using Equation (7.16).
Set the path duration \( (PD_n) \) of all activity nodes \((n=1 \text{ to } N) = 0\)

Set current node \((n) = \text{the given activity node } (n)\)

Set previous node \((P_n)\) of current node \((n) = \text{current node } (n)\)

Set the path duration \((PD_n)\) of current node \((n) = \text{the mean of activity duration } (\mu_n) \text{ of current node } (n)\)

Current node \((n)\) has successor nodes \((S_n)\)?

Select the first successor node \((S_n)\) of current node \((n)\)

Analyze the selected successor node \((S_n)\) to determine whether to update its path duration \((PD_{Sn})\) by calculating the expected path duration \((EPD_{n,Sn})\)

\[
EPD_{n,Sn} = PD_n + \mu_{Sn}
\]

Where, \( \mu_{Sn} = \text{Mean of activity duration of successor node } (S_n) \)

\(EPD_{n,Sn} > PD_{Sn}\)?

Yes

Update the path duration \((PD_{Sn})\) of successor node \((S_n)\) = \(EPD_{n,Sn}\)

No

Set previous node \((P_{Sn})\) of successor node \((S_n)\) = current node \((n)\)

Set current node \((n)\) = successor node \((S_n)\)

Next successor node \((S_n)\) that was not analyzed in the previous cycles?

Yes

Select the next successor node \((S_n)\) that was not analyzed in the previous cycles.

No

Previous node \((P_n)\) ≠ current node \((n)\)?

Yes

Set current node \((n) = \text{previous node } (P_n)\)

No

Current node \((n)\) has successors nodes \((S_n)\) that were not analyzed in the previous cycles?

No

End

Find the longest mean path duration \((LD_n)\) for the given activity \((n)\) by setting \(LD_n = \text{the path duration } (PD_e) \text{ of end node } (E)\)

Figure 7.7 Longest Path Duration Search (LPDS) algorithm
Figure 7.8 Longest path from a given activity node (n) to the end node (E)

7.4.2.3 Step 3: Select representative paths that have lower probability of completion time $P(T_k \leq t)$ than UP based on LM and $LD_n$

The objectives of this step is to select representative paths that have lower probability of completion time $P(T_k \leq t)$ than UP using LM and $LD_n$ without enumerating all existing paths in the network. To this end, a new algorithm named “fast representative paths search” (FRPS) is developed, as shown in Figure 7.9. This algorithm starts with calculating the lower bound for the mean path duration (LM) using Equation (7.16) and the largest variance of path duration (LV) which is identified using the newly developed
LPDS algorithm summarized in Figure 7.7. After identifying LM, the LPDS algorithm is again used to calculate the longest mean path duration (LD_n) from each activity node (n) to the end node (E), as shown in Figure 7.9. These calculated values of LM and LD_n are then used in the newly developed FRPS algorithm to search for paths that have greater mean of path duration (μ_k) than LM without enumerating all existing paths in the network.

The principal of optimality is utilized when determining whether to analyze each successor node (S_n) by calculating the expected longest mean path duration (ELD_{n,S_n}), as shown in Figure 7.9. If the expected longest mean path duration (ELD_{n,S_n}) is shorter than LM, then all paths branching from the successor activity (S_n) will have shorter mean path duration (μ_k) than LM, because the longest mean path duration (LD_n) represents the largest value of mean of path duration in the sub-network that starts from node (n) until the end node (E). Therefore, these successor nodes (S_n) will not be analyzed to search for representative paths in the network. This ensures efficiency when searching for and selecting representative paths in a large scale network.

A simple example is shown in Figure 7.10 to illustrate how the aforementioned three steps are performed in this phase to identify and remove high probability paths and retain only representative paths that have lower probability of completion time P(T_k ≤ t) than the upper probability bound (UP). As shown in Figure 7.10, the first step is performed to transform the upper probability bound (UP) to an equivalent lower bound for mean path duration (LM) using Equation (7.16). The second step is then performed to calculate (1) the longest mean path duration (LD_n) from a given activity node (n) to the end node (E); and (2) the largest variance (LV) in the network using the newly
developed LPDS algorithm. The third and last step in this phase is then performed to search for and identify representative paths that have lower probability of completion time $P(T_k \leq t)$ than the upper probability bound (UP) using the newly developed FRPS algorithm.

As shown in Figure 7.10, the third step starts by calculating the lower bound for the mean path duration (LM) for this project (LM = 26.021 days) based on the specified target project duration (t=33 days) and the upper probability bound (UP=0.99) using Equation (7.16). After identifying LM, the FRPS algorithm identifies the longest mean path duration ($LD_n$) from each activity node (n) to the end node (E) using the LPDS algorithm (e.g., $LD_{16} = 11$ and $LD_{15} = 7$). Whenever the FRPS algorithm analyzes a given activity node (n) in the network, it determines whether to analyze its successor node ($S_n$) by comparing the expected longest mean path duration that passes through that successor node ($ELD_{n,Sn}$) and the lower bound for the mean path duration (LM). If $ELD_{n,Sn}$ is less than LM, then successor node ($S_n$) will not be analyzed because all the paths branching from this successor activity node will have lower mean of path duration than LM and accordingly will have higher probability of completion time $P(T_k \leq t)$ than the upper probability bound (UP).

For example, current node 7 in Figure 7.10 has two successors (nodes 16 and 15) and the longest mean path duration ($LD_n$) from these successor nodes to the end node have been identified by the LPDS algorithm to be $LD_{16} = 11$ and $LD_{15} = 7$. Similarly, the path mean duration ($PM_n$) from the start activity (S) to activity (n) was calculated in previous cycles to be $PM_7 = 4+8+5 = 17$, as shown in the shaded activity nodes (S-1-4-7) in
Accordingly, the expected longest mean path duration ($ELD_{n,Sn}$) through node 7 and these two successor nodes can be calculated to be $ELD_{7,16} = PM_7 + LD_{16} = 28$ days and $ELD_{7,15} = PM_7 + LD_{15} = 24$ days, as shown in Figure 7.10. As stated earlier, the path that have smaller mean of path duration ($\mu_k$) than LM always have higher probability of completion time $P(T_k \leq t)$ than the upper probability bound (UP). Therefore, activity node 15 should not be analyzed, because all the paths branching from activity node 15 will have smaller mean of path duration ($\mu_k$) than the lowest bound for the mean of path duration (LM). If the current node does not have successor nodes, then the probability of completion time $P(T_k \leq t)$ for the searched path is identified in order to ensure the selection of representative paths that have lower probability of completion time $P(T_k \leq t)$ than UP, as shown in Figure 7.9 and Figure 7.10. As such, this phase searches for representative paths without enumerating all existing paths in the network by using the newly developed LPDS and FRPS algorithms, and therefore it can ensure the achievement of efficiency in searching for representative paths that have lower probability of completion time $P(T_k \leq t)$ than UP in the network. It should be noted that the number of identified representative paths in this stage can be further reduced by removing highly correlated paths which is described in more detail in the next phase.
Set the path mean (\(PM_n\)) and the path variance (\(PV_n\)) for all activity nodes (\(n=1\) to \(N\)) = 0

Set previous node (\(P_n\)) of current node (\(n\)) = current node (\(n\))

Calculate the path mean duration (\(PM_n\)) and variation duration (\(PV_n\)) for current node (\(n\))

\[
PM_n = PM_{Pn} + \mu_n \\
PV_n = PV_{Pn} + \sigma_n^2
\]

Where, \(n-1\) = former current node

Calculate probability of completion time \(P(T_k \leq t)\) for the searched path (\(k\)) that has the mean of path duration (\(\mu_k\)) ≥ LM

\[
P(T_k \leq t) = \Phi \left( \frac{t - PM_k}{\sqrt{PV_k}} \right)
\]

Select the first successor node (\(S_n\)) of current node (\(n\))

Analyze the selected successor node (\(S_n\)) by calculating its expected longest mean path duration (\(ELD_{n,S_n}\)) based on the longest mean path duration (\(LD_{S_n}\)) of successor node (\(S_n\))

\[
ELD_{n,S_n} = PM_n + LD_{S_n}
\]

Set previous node (\(P_{S_n}\)) of successor node (\(S_n\)) = current node (\(n\))

Set current node (\(n\)) = successor node (\(S_n\))

Calculate the lower bound for the mean path duration (LM) using Equation (16)

Find the longest mean path duration (\(LD_n\)) from each activity node (\(n\)) to the end node (E)

Start

The longest path duration search (LPDS) algorithm

End

Figure 7.9 Fast Representative Path Search (FRPS) algorithm
The upper probability bound (UP) = 0.99  
Target project duration (t) = 33 days

Step 1. Transform the upper probability bound (UP) to an equivalent lower bound for mean path duration (LM):

\[ LM = t - \Phi^{-1}(UP) \cdot \sqrt{LV} \text{ if UP} > 0.5 \]

Step 2. Find the longest mean path duration (LD_n) and the largest variance (LV) in the network:

- The largest variance of path durations (LV):
  \[ \sigma^2 = 1 \]
  \[ 1 + 3 + 1 + 3 + 1 = 8 \]

- Path that has the largest value of standard deviation (\( \sigma_k \)):
  \[ \mu_{15} = 4 \]
  \[ 3 \]
  \[ 0 \]
  \[ LD_{15} = 4 + 3 + 0 = 7 \text{ days} \]

Step 3. Select representative paths that have lower probability of completion time \( P(T_k \leq t) \) than UP without enumerating all existing paths in the network based on the LM and LD_n:

- Calculate the lowest bound for the mean of path duration (LM):
  \[ LM = 33 - \Phi^{-1}(0.99) \cdot \sqrt{8} = 26.02 \]

- Calculate the expected longest mean path duration (ELD_n,S_n) for successor nodes (S_n) at current activity node (7) using LD_n:

  \[ PM_7 = 17 \]
  \[ LD_{16} = 11 \]
  \[ ELD_{7,16} = PM_7 + LD_{16} = 28 \text{ days} \]
  \[ ELD_{7,15} = PM_7 + LD_{15} = 24 \text{ days} \]
  \[ LD_{15} = 7 \]

  \[ ELD_{7,15} = 24 < LM \Rightarrow \text{Activity node (15) will not be analyzed, because all the paths branching from the successor activity node (15) will have lower mean of path duration} \]

- Select the representative paths (k) that have the probability of completion time \( P(T_k \leq t) \) smaller than UP:

  \[ P(T_k \leq t) = \Phi \left( \frac{t - PM_k}{\sqrt{PV_k}} \right) \leq UP \]

Figure 7.10 Searching for representative paths using the lowest bound for the mean path duration (LM) and the longest mean path duration (LD_n)
7-4.3 Removal of highly correlated paths

The objective of this phase is to remove highly correlated paths from the analysis and replace them with a representative path that has the lowest probability of completion time among the correlated paths. The original method of Ang et al. (1975) is modified in this phase to improve the accuracy of estimating the probability of project completion (PT\(_t\)). The original method introduced by Ang et al. (1975) first sorts the paths in a descending order based on their mean path duration (\(\mu_k\)), and then selects representative paths based on their correlations, as shown in Table 7.1. When there are two highly correlated paths, the original method selects the path with the higher mean path duration (\(\mu_k\)) as a representative path. This method, however, does not guarantee the selection of representative paths that have lower probabilities of completion time \(P(T_k \leq t)\) compared to other highly correlated paths. For the example shown in Table 7.1, path 6 has a lower probability of completion time \(P(T_k \leq t)\) than path 5, which means that the impact of path 6 on the probability of project completion (PT\(_t\)) is more critical and significant compared to path 5. Therefore, path 5 should be removed and represented by path 6. However, the original Ang’s method removes path 6 and selects path 5 as the representative because it sorts the paths in a descending order based on their mean duration (\(\mu_k\)). In order to overcome this limitation, this phase sorts the paths in an ascending order of their probability of completion time \(P(T_k \leq t)\), and then selects representative paths based on their correlation using a similar procedure to the original Ang’s method. Upon the completion of this phase, the approximate probability of project completion (PT\(_t\)) can be estimated in the next phase.
Table 7.1 Original Ang’s method to select the representative paths

<table>
<thead>
<tr>
<th>Path (k)</th>
<th>$\mu_k$</th>
<th>$\sigma_k$</th>
<th>$P(T_k \leq 80) = \Phi((80-\mu_k)/\sigma_k)$</th>
<th>Path Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$\rho_{1,k}$ $\rho_{3,k}$ $\rho_{5,k}$</td>
</tr>
<tr>
<td>1</td>
<td>78</td>
<td>12.2</td>
<td>0.2560</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>76</td>
<td>12.2</td>
<td>0.3114</td>
<td>0.995</td>
</tr>
<tr>
<td>3</td>
<td>67</td>
<td>3.85</td>
<td>0.7821</td>
<td>0.1 1</td>
</tr>
<tr>
<td>4</td>
<td>67</td>
<td>3.85</td>
<td>0.7821</td>
<td>0.2 0.992</td>
</tr>
<tr>
<td>5</td>
<td>66</td>
<td>3.85</td>
<td>0.8506</td>
<td>0.1 0.1 1</td>
</tr>
<tr>
<td>6</td>
<td>66</td>
<td>12.09</td>
<td>0.6296</td>
<td>0.3 0.95 0.992</td>
</tr>
<tr>
<td>7</td>
<td>66</td>
<td>3.71</td>
<td>0.8595</td>
<td>0.995 0.07 0.06</td>
</tr>
<tr>
<td>8</td>
<td>66</td>
<td>3.87</td>
<td>0.8493</td>
<td>0.995 0.07 0.5</td>
</tr>
</tbody>
</table>

If UC=0.99, Paths 2, 7, and 8 are represented by Path 1
Path 4 is represented by Path 3
The representative paths selected by original Ang’s method = Path 1,3, 5
Path 6 is represented by Path 5, however, $P(T_5 \leq t) > P(T_6 \leq t)$

7-4.4 Probability approximation

The objective of this phase is to estimate the approximate probability of project completion ($P(T_i)$) by a specified target project duration based on the selected representative paths. The Genz’s algorithm is used to estimate this approximate probability ($P(T_i)$) while considering the correlations among the selected representative paths.
7-5 Model Evaluation

Two application examples are analyzed to illustrate the use of the developed FARE model and demonstrate its capabilities in providing fast and accurate estimates for the probability of project completion (PT\textsubscript{1}) for real-life and large-scale project networks. The performance of the FARE model in analyzing these two examples was conducted using an Intel Xeon CPU 1.86GHZ processor with a 4GB RAM. Monte Carlo simulation (MCS) was also used to analyze these two examples to enable a comparison between the MCS and the FARE model results in order to (a) evaluate the accuracy of the FARE model in estimating the probability of project completion (PT\textsubscript{1}) by a specified target project duration (t); and (b) compare the computational time of the FARE model and the MCS method.

In the first experiment, a project network from the literature (O'Brien and Plotnick 1999) was analyzed by the FARE model and MCS. This project has 181 activities and its network includes a total of 4006 paths, as shown in Figure 7.11. Based on the activity durations in the original project, the project duration was calculated to be 229 day (O'Brien and Plotnick 1999). In this example, the most likely duration (m) of each activity was specified to be identical to the original activity durations listed in O'Brien and Plotnick (1999). The optimistic (a) and pessimistic (b) durations for each activity in this example were specified to have varying degrees of skewness in the distributions, as shown in Figure 7.11. Based on these three point estimates, the mean duration (\(\mu_i\)) and its standard deviation (\(\sigma_i\)) were calculated for each activity using Equations (1) and (2). The target project durations (t) for this project were set to range from 227 days to 283 days. In this example, the transitivity reduction method could not find any redundant
links in the project network. First, Monte Carlo simulation (MCS) was used to analyze the probability of project completion ($PT_t$) for these specified target project durations ($t$). The maximum number of iterations ($N_{MCS}$) for the MCS was set to 30,000 and, it was set to automatically terminate the iteration if the coefficient of variance (C.O.V) of probability of project completion ($PT_t$) is smaller than 0.005. MCS generates random durations for each activity based on its corresponding distribution and then uses these generated durations to calculate the project duration ($T_p$) using CPM calculations. The probability of project completion ($PT_t$) for the specified target project duration ($t$) was calculated in the simulation by using Equation (7.17).

$$PT = \frac{M}{n_{MCS}}$$ (7.17)

Where, $n_{MCS} =$ total number of iterations conducted by MCS; and $M =$ total number of times that the project duration ($T_p$) is shorter than the target project duration ($t$) during the simulation. It should be noted that the total number of iterations conducted by MCS ($n_{MCS}$) can be smaller than the specified maximum number of iterations ($N_{MCS}$) due to the termination setting. The results produced by the MCS are compared to those generated by the FARE model, as shown in Figure 7.12.

The FARE model was also used to analyze this example using 500 quasi random points and various combinations of the upper probability bound (UP) and the upper correlation bound (UC) to study the sensitivity of the FARE model results (accuracy and
computational time) to these two input parameters. The results generated by the FARE model are compared to those produced by the MCS in terms of the probability of project completion ($PT_t$) for all analyzed target project durations ($t$), as shown in Figure 7.12. The error of the FARE model compared to the MCS was calculated by subtracting the probability estimated by MCS from the probability estimated by the present model. The error values of the FARE model for all the analyzed combinations of UP and UC values are summarized in Figure 7.13.

The results show that setting UP=1 and UC=1 (which selects only representative paths that have the probability of completion time $P(T_k \leq t)$ smaller than 100%) produced very close results to the MCS (see Figure 7.11(A)), with an error less than 2%, as shown in Figure 7.13(A). The analysis results also show that setting UP=0.999 and UC=1 produced similar accuracy to those generated using UP=1 and UC=1, but with much faster computational time, as shown in Figure 7.14(B). For this combination of UP and UC, the FARE model was able to estimate the probability of project completion ($PT_t$) in less than 1 second compared to a computational time of 57 seconds for the MCS which represents 98% reduction in the computational time when the target project durations were less than 250 days, as shown in Figure 7.14. For other combinations of UP and UC, the FARE models also provided very close results compared to those generated by MCS, as shown in Figure 7.12. For example, using a combination of UP=1 and UC=0.95 produced results that had an error less than 2% within 0.2 second which represents 99.6% reduction in the computational time compared to MCS, as shown in Figure 7.13(B). The results of this analysis also show that setting too low value for UP leads to significant reduction in the number of selected representative paths which
increases the error in the estimate of project completion probability ($P_{T_i}$). For example, UP=0.95 and UC=1 selected excessively small numbers of representative paths ($K$) in the high range of project target durations, and thereby it produced errors up to 7% when only one representative path was selected ($K=1$), as shown in Figure 7.13(A). This UP and UC setting selects no representative paths (i.e., $K=0$) beyond the target project duration of 257 days, and thereby the FARE model could not estimate the probability of project completion ($P_{T_i}$) in that range, as shown in Figure 7.13(A). The reason is that many paths in the project network may have high probability of completion time $P(T_k \leq t)$ in the longer range of target project durations ($t$), and thereby setting too low UP in the FARE model causes it to select a very small number of representative paths, as shown in Figure 7.15. Based on the findings of this analysis, the UP variable should be set to larger values in the case of long target project durations in order to select a reasonable number of representative paths and produce accurate probability of project completion ($P_{T_i}$). Moreover, setting too low value for UC also leads to the selection of excessively small numbers of representative paths and increases the error in the estimate of project completion probability ($P_{T_i}$), as shown in Figure 7.13(B), and accordingly the UC variable should be 0.9 or higher.
Figure 7.11 Experiment 1: Project network and activity data
Figure 7.12 Probability of project completion ($PT_t$) produced by FARE model and MCS for Experiment 1
Figure 7.13 Error of results produced by FARE model compared to the results of MCS for Experiment 1

Figure 7.14 Computational times of FARE model and MCS for Experiment 1
In the second experiment, a large-scale construction project network was analyzed using a real-life construction schedule of the Business Instructional Facility (BIF) at the University of Illinois at Urbana-Champaign. The project scheduling network has 971 activities and it includes 76,945,592 (≈ 77 million) paths, as shown in Figure 7.16. Based on the original activity duration in the schedule, the project duration for this project is 594 days. The same method used in the first experiment was also used in this experiment to set the three duration estimates for each activity. The mean activity duration ($\mu_i$) and standard deviation ($\sigma_i$) were then calculated using Equations (7.1) and (7.2). The range of target project durations ($t$) for this project was set from 615 days to 810 days. The transitivity reduction method in the FARE model was able to identify and remove 139 redundant links in this project network. Monte Carlo simulation (MCS) was also used to analyze the probability of project completion ($PT_t$) for the specified range of
target project durations (t) for this example. The maximum number of iterations (N_{MCS}) for MCS was set to 30,000 and, it was set to automatically terminate if the coefficient of variance of probability of project completion (P_{T,t}) is smaller than 0.005. The probability of project completion (P_{T,t}) for the specified range of target project durations (t) was calculated using Equation (7.17) and the results produced by MCS are illustrated in Figure 7.17.

The FARE model was also used to analyze this example using 1000 quasi random points. Various combinations of the upper probability bound (UP) and the upper correlation bound (UC) were used according to the specified target project duration (t) to select a reasonable number of representative paths in the network for the analysis, as shown in Figure 7.17. As shown in Figure 7.17, the FARE model was able to produce very similar results to those generated by MCS with an error less than 3%, as shown in Figure 7.18. These accurate results were generated by the FARE model in a significantly shorter computational time than the MCS, as shown in Figure 7.19. The FARE model was able to reduce the computational time by more than 94% from 272 seconds to less than 16 seconds, as shown in Figure 7.19. The FARE model was able to achieve this significant reduction in the computational time (more than 94%) as a result of utilizing the aforementioned algorithms that were able to reduce the number of analyzed paths in this example from 77 million to less than 900, as shown in Figure 7.20. These significant reductions in the number of analyzed network paths and the computational time were accomplished by the FARE model while keeping its estimate errors less than 3%. Accordingly, this fast and accurate risk evaluation (FARE) model is
expected to significantly improve the efficiency and practicality of utilizing probabilistic scheduling techniques for real-life and large-scale construction projects.

Figure 7.16 Experiment 2: Project network and activity data
Figure 7.17 Probability of project completion ($PT_t$) produced by the FARE model and MCS for Experiment 2

Figure 7.18 Error of results produced by FARE model compared to the results of MCS for Experiment 2
Figure 7.19 Computational times of the FARE model and MCS for Experiment 2

Figure 7.20 The number of selected representative paths by the FARE model for Experiment 2
7-6 Summary

A novel probabilistic scheduling model was developed to enable fast and accurate risk evaluation for real-life and large-scale construction projects using the multivariate normal integral method. The model is named FARE and is designed to overcome the limitations of existing probabilistic scheduling methods including (a) the inaccuracy limitation of the PERT method due to its “merge event bias” by incorporating an accurate multivariate normal integral method; and (b) the impractical computational time of the Monte Carlo simulation method by incorporating a newly developed approximation method. The model was developed in three main modules: (1) PERT model to formulate the project network as a multivariate normal probability problem to overcome the limitation of the “merge event bias” of PERT; (2) fast and accurate multivariate normal integral method to efficiently and effectively estimate the probability of project completion by a specified target time based on the formulated multivariate normal probability problem; and (3) a newly developed approximation method to provide an approximate and accurate estimate for the probability of project completion for large scale construction projects. Two application examples were analyzed to illustrate the use of the developed model and demonstrate its capabilities in providing an accurate estimate for the probability of project completion \( (PT_t) \) in a reasonable time for a real-life large scale project network. The results of this analysis illustrate the new capabilities of the present model in providing accurate estimates for the probability of project completion \( (PT_t) \) for a specified target project duration with a significant reduction in computational time for large scale construction projects. For the large application example that included 971 activities, the FARE model was able to reduce
the computational time by more than 94% compared to Monte Carlo Simulation. The FARE model was able to achieve this significant reduction in the computational time as a result of utilizing the newly developed algorithms that were able to reduce the number of analyzed paths in this network example from 77 million to less than 900. These significant reductions in the number of analyzed network paths and the computational time were accomplished by the FARE model while keeping its estimate errors less than 3% compared to Monte Carlo Simulation. These new and unique capabilities of the developed FARE model should prove useful to construction planners and should enable them to efficiently and effectively analyze risks during the planning and scheduling of real-life large-scale construction projects.
CHAPTER 8

MULTI-OBJECTIVE OPTIMIZATION FOR RESOURCE DRIVEN SCHEDULING SYSTEM

8-1 Introduction

This chapter presents the development of a practical Multi-objective Optimization for Resource Driven Scheduling system, named MORDS that seamlessly integrates the research developments made in this study with commercially available project management software, Microsoft Project 2007. The main objective of the present system is to enable construction planners to optimize construction resource utilization and analyze the risks involved in construction project schedules in order to provide reliable and improved project performance. To this end, the MORDS system is designed to provide a number of unique capabilities, including (1) providing effective interface between the newly developed models in this study and commercially available project management software, Microsoft Project 2007, to facilitate their ultimate use and to benefit from the practical scheduling and control features of existing software; (2) automating the development of tradeoff charts among the conflicting optimization objectives to facilitate the selection of optimal solutions that address the specific project needs; and (3) supporting the visualization of generated optimal schedules through seamless integration with commercially available project management software, Microsoft Project 2007.
In order to provide the aforementioned capabilities, the system is implemented and integrated in four main modules: (1) add-ins module to create user friendly graphical command bars and buttons for each developed models and integrate them in MS Project; (2) input module to facilitate the input of all relevant data for the developed models; (3) control module to support construction planners in optimizing resource utilization and analyzing the risks involved in project schedule based on the retrieved input data; and (4) output module to facilitate the selection of optimal schedules and the visualization of the generated optimal solutions on MS Project, as shown in Figure 8.1. These four modules are described in more detail in the following sections.
8-2 Add-Ins Module

The main objective of this module is to create user friendly graphical command bars and buttons for each developed model and deploy and integrate them in MS Project. Visual Studio Tools for Office (VSTO) with C#.net was used to develop the command bars and buttons for each model in MS Project. VSTO enables the creation of user friendly graphical command bars and buttons, the deployment of externally developed modules in Microsoft office products as a COM Add-Ins interface. It should be noted that once MORDS system is installed in MS Project, this module automatically creates main command bars and buttons for the developed models and deploys them to MS Project whenever MS Project is executed. Five main command buttons with one main command bar were created and deployed in MS Project to call and execute each developed model from MS Project, as shown in Figure 8.2. Each of these main command buttons generates sub-command bars and buttons based on the selected model, as shown in Figure 8.3. These command buttons are designed to call and execute the input module, control module, and output module for each developed model in order to generate and visualize the identified optimal solutions and the probability of project completion for the planned project. The following sections describe each of these modules in more detail.
Figure 8.2 Main command bars and buttons for MORDS system

Figure 8.3 Sample sub-command bars and buttons for the multiple shifts scheduling model in MORDS
8-3 Input Module

The main objective of this module is to facilitate the input of all relevant data for the developed models. MS Project has a practical feature that enables users to create customized fields and tables for the task and resource input data. This feature is utilized in this module to automatically create customized input fields and generate tables in MS Project to enable construction planners to specify the input data for each developed model. Figure 8.4 illustrates new input fields and tables created by the MORDS system for each developed model. It should be noted that the resource leveling (RL) model and resource leveling and allocation (RLRA) model do not require additional input fields to retrieve their required input data from the existing fields in MS Project. Other models, however, require additional input fields to enable the optimization of resource utilization and risk analysis for construction schedules. For example, the multiple shifts scheduling model requires a number of additional input fields such as cost data for day shift (Cost (D)), productivity adjustment factor for evening shift (P.A (E)), and shift type, as described in Chapter 5. Figure 8.5 illustrates sample input fields and tables generated by the MORDS system for each developed model in MS Project. As such, MORDS system automatically creates input fields and generates tables in MS Project to facilitate the input of all the required data (e.g. duration, cost, and resource data) for the developed models.
Figure 8.4 Newly created input fields and tables by MORDS system for each developed model
Generate resource input fields and tables for RFC model

(A) Input fields and tables for RFC model

Generate task input fields and tables for MSS model

(B) Input fields and tables for MSS model

Generate task input fields and tables for FARE model

(C) Input fields and tables for FARE model

Figure 8.5 Sample input fields and tables generated by MORDS system
8-4 Control Module

The main purpose of this module is to support construction planners in optimizing resource utilization and analyzing the risks involved in project scheduling based on the retrieved input data. To this end, this module is designed to (1) import all relevant input data (e.g. precedence relationship, duration, resource demand) specified in the input fields and tables from MS Project; (2) specify the initial parameters for the optimization algorithm and the Genz’s algorithm; and (3) perform the developed models to optimize resource utilization and estimate the probability of project completion for the planned project. This module provides graphical user interface (GUI) forms using Visual C# .net to benefit from its advanced programming capabilities in order to facilitate the integration of developed models with MS Project.

Each model has its own GUI form in the control module to guide construction planners to specify the necessary parameters to execute the developed models, as shown in Figure 8.6. For example, the GUI form of the control module for the resource leveling (RL) model enables planners to specify the type of resource leveling metric they wish to use (RRH and RID), their relative importance weights, and resource peak demand to simultaneously minimize resource fluctuations and peak demand. Similarly, the GUI form of the control module for the fast and accurate risk evaluation (FARE) model first requires input data, including the probability upper bound (UP), correlation upper bound (UC), and target project duration (T) to evaluate the probability of project completion (PT) for the planned project. In order improve the efficiency, the output module of the FARE model is combined in the GUI form of its control module to enable construction
planners to promptly analyze and store the evaluated results, as shown in Figure 8.6(E).

It should be noted that the GUI forms of control modules for the three resource optimization models including the resource leveling (RL) model, resource leveling and allocation (RLRA) model, and multiple shifts scheduling (MSS) model enable planners to select and import resource names that need to be optimized from the available list stored in MS Project, as shown in Figure 8.6. In addition, the GUI forms of the control modules for the optimization models (i.e., RL, RLRA, MSS, and RFC) are designed to gather the main genetic algorithm parameters, including (1) population size; (2) generation number; (3) crossover probability; and (4) mutation probability.

After specifying all necessary parameters for each model, the control module invokes the optimization algorithm for the optimization models and the Genz’ algorithm for the risk assessment model by enabling planners to click the optimization button and simulation buttons in the GUI form of control module forms, as shown in Figure 8.6. Before executing the process of optimization for the RL, RLRA, MSS, and RFC models, their control modules first import all relevant input data specified in the input fields and tables. The MORDS system is designed to provide a practical feature that shows the progress status for the tasks that require a long processing time such as importing input data, genetic algorithm computations, and Genz’s algorithm computations, as shown in Figure 8.7. Moreover, the control module provides the capability of retrieving existing saved solutions for the project and shows its status on the GUI form of control module, as shown in Figure 8.8. After optimizing the resource utilization and analyzing the risks for the planned project, the control module automatically executes the output modules
to display the list of optimal solutions and the calculated probability of project completion through the new GUI forms of output modules.

Figure 8.6 GUI forms of control modules for each developed model
Figure 8.7 Progress bars in MORDS system

Figure 8.8 Status of existing saved solutions
8-5 Output Module

The output module is implemented in the MORDS system to facilitate the selection of optimal schedules for the planned project and the visualization of the generated optimal solutions in MS Project. To this end, this module is designed with new GUI forms to implement the necessary interface functions in two main phases: (1) export phase that retrieves all the generated optimal solutions and exports the selected solution to MS Project; and (2) visualization phase that graphically illustrates the selected optimal solutions on scattered plot charts. The following two sections describe these two phases in more detail.

8-5.1. Export phase

The export phase is designed to (1) retrieve the optimal solutions generated by the optimization algorithm and the project completion probabilities calculated by the Genz’s algorithm; and (2) export the selected solutions to MS project. This phase is implemented with new GUI form to list all the solutions generated by the developed models, as shown in Figure 8.9. This list table has a feature to sort the values stored in each column by clicking at the head of each column. This enables planners to easily find the solutions that have minimum or maximum values for each objective function. In order to export the selected solutions to MS Project, a user only needs to double click on one of the listed solutions shown in the list table which invokes MS Project to display the schedule of the selected solution as a Gantt chart, as shown in Figure 8.10. For RL, RLRA, RFC, and MSS models, the existing leveling delay field in MS Project was used to shift activities within their float to represent the optimal solutions using Gantt chart.
MSS model exports not only leveling delay field data but also shift option field data to represent the optimal shift option for each activity for the planned project. This phase also enables planners to save the retrieved optimal solutions and the calculated probabilities of project completion to a binary file which can be retrieved and analyzed later.

![Figure 8.9 GUI form of output module for MSS model in MORDS system](image)

Figure 8.9 GUI form of output module for MSS model in MORDS system
8-5.2. **Visualization phase**

The visualization phase is designed to graphically display the retrieved solutions using scattered plot charts in order to facilitate the selection of optimal solutions that address the specific project needs. Microsoft Chart control was implemented in this phase to illustrate the retrieved solutions on the charts, as shown in Figure 8.11. The visualization phase of the MSS model is designed to plot not only the optimal values of each objective function, but also labor hours utilized in evening and night shifts to enable construction planners to easily identify and select optimal solutions that satisfy the specific requirements of project.
Figure 8.11 Optimal solutions visualization forms

8-6 Model Evaluation

In order to evaluate the performance of developed MORDS system, the same application examples in the previous chapters were used and analyzed by MORDS system. For the RL, RLRA, MSS, and RFC optimization models, the results of this
analysis illustrates that the optimal solutions generated by the MORDS system were exactly the same as the ones shown in the previous chapters. For the FARE model, the MORDS system also produced similar results to the one shown in Chapter 7. It should be noted that the MORDS system seamlessly integrates the developed models with MS Project, and thereby it maximizes the benefit from the practical features in MS Project, such as resource grouping, critical activity sorting, and bar chart styles.

Figure 8.12 Optimal solutions produced by MORDS system for RL model
Figure 8.13 Optimal solutions produced by MORDS system for RLRA model

Figure 8.14 Optimal solutions produced by MORDS system for MSS model (Experiment 3)
Figure 8.15 Optimal solutions produced by MORDS system for RFC model

Figure 8.16 Probabilities of project completion produced by MORDS system for FARE model (John Doe project)
8-7 Summary

This chapter presented the development of a multi-objective optimization for resource driven scheduling (MORDS) system that facilitates the optimization of resource utilization and the risk assessment of construction projects. The system was developed in four main modules: (1) add-ins module to create user friendly graphical command bars and buttons for each developed models and deploy them in MS Project; (2) input module to facilitate the input of all relevant data for the developed models; (3) control module to optimize resource utilization and analyze the risks involved in project schedule based on the retrieved input data; and (4) output module to facilitate the selection of optimal schedules for the planned project and the visualization of the generated optimal solutions in MS Project. Application examples were analyzed to illustrate the use of the model and demonstrate its capabilities in: (1) generating optimal tradeoff solutions for the RL, RLRA, MSS, and RFC models; (2) visualizing the optimal tradeoff solutions using scattered plots; and (3) providing seamless integration with commercially available project management software, Microsoft Project 2007, to enable construction planners to visualize the generated solutions and to benefit from the practical features of MS Project. These capabilities should provide useful to construction planners and contribute to advance the optimization of resource utilization and the risk assessment for construction projects.
CHAPTER 9

CONCLUSION

9-1 Conclusions

The present research study focused on multi-objective optimization for resource driven scheduling in construction projects and developed a number of novel models, including: (1) an innovative resource leveling model that incorporates newly developed resource leveling metrics and directly measure and minimize undesirable resource fluctuations in order to maximize resource utilization efficiency; (2) an advanced resource leveling and allocation model that simultaneously maximize resource utilization efficiency and minimize project duration while resolving all resource conflicts; (3) a robust multiple shifts scheduling model that simultaneously minimize project time and cost while minimizing the negative impacts of shift work on project performance; (4) a robust resource fluctuation cost model that simultaneously minimize overall resource fluctuation costs and project duration within a specified range of project durations; (5) an advanced project risk assessment model that provides fast and accurate estimates for the probability of project completion to facilitate the integration with the optimization models; and (6) a practical multi-objective optimization for resource driven scheduling system named “MORDS”.

First, an innovative resource leveling model was developed in order to maximize resource utilization efficiency for construction projects. Two new resource leveling metrics, namely release and rehire (RRH) and resource idle days (RID), were
developed and incorporated in the model to circumvent the limitation of existing metrics and directly measure and minimize undesirable resource fluctuation. RRH is designed to quantify the total amount of resources that need to be temporarily released during low demand periods and rehired at a later stage during high demand periods. On the other hand, RRH is designed to quantify the total number of idle and non-productive resource days caused by undesirable resource fluctuations. The optimization model was implemented using genetic algorithms to maximize resource utilization efficiency by simultaneously minimizing undesirable resource fluctuations and peak demand.

Second, the study developed an advanced resource leveling and allocation model to simultaneously optimize resource leveling and allocation. The model is capable of simultaneously minimizing project duration and maximizing resource utilization efficiency while resolving all resource conflicts. The model was developed as a multi-objective genetic algorithm to provide the capability of identifying optimal tradeoffs between project duration and resource utilization efficiency.

Third, a robust multiple shifts scheduling model is developed to simultaneously minimize project duration, minimize cost, and minimize the negative impacts of shift work on project performance while complying with labor availability constraints. The model was implemented as a multi-objective genetic algorithm to support construction engineers and planners in (1) evaluating and identifying optimal shift systems for the project in a single run; (2) producing optimal tradeoff solutions among minimizing the project duration, cost, and labor utilization on evening and night shifts, where each solution
identifies an optimal schedule and multiple shift work plan for each activity; and (3) generating optimal plans for distributing the limited availability of labor among competing shifts to minimize the negative impacts of labor constraints on project performance. These new and unique capabilities should prove useful to construction planners and should enable them to optimize the utilization of multiple shifts in order to accelerate the delivery of projects while minimizing the negative impacts of evening and night shifts on construction productivity, safety, and cost.

Fourth, a robust resource fluctuation cost model was developed to minimize resource idle costs, release and rehiring costs, and mobilization costs; and to analyze and optimize the potential tradeoffs between minimizing these resource fluctuation costs and minimizing the project duration. The model was designed to specify the maximum number of days (DT) that the project can be delayed beyond its early completion time in order to perform the tradeoff analysis between project duration and resource fluctuation cost. The model was implemented using multi-objective genetic algorithms to search for and identify optimal construction schedules that provide optimal tradeoffs between project duration and resource fluctuation costs.

Fifth, a new model for fast and accurate risk evaluation for scheduling large-scale construction projects was developed. The model is named FARE and it uses the multivariate normal integral method to estimate the probability of project completion for PERT project networks. The model was designed to consider the impact of correlations among the network paths on the probability of project completion (PT) to overcome the
“merge event bias” issue of traditional PERT method. It was also designed to provide construction planners with fast and accurate risk evaluation for large-scale construction projects by developing a new approximation method.

Sixth, a prototype multi-objective optimization for resource driven scheduling system named “MORDS” was developed to seamlessly integrate the aforementioned research developments with commercially available project management software, Microsoft Project 2007. The system was designed to deploy the developed models as user friendly COM Add-ins interface in MS Project. This seamless integration enables construction planners to benefit from and utilize the practical project scheduling and control features in MS Project during their analysis and execution of the generated optimal schedules. In addition, the system provides enhanced visualization of the generated optimal tradeoff solutions using scattered plots to enable construction planners to easily identify and select the solutions that satisfy the specific project needs.

The aforementioned research products contribute to the advancement of current practice in construction resource planning and scheduling and can lead to: (1) an increase in the resource utilization efficiency in construction projects which can produce significant improvements in construction productivity, cost and duration; (2) an improvement in utilizing the limited availability of resources; (3) a reduction in the duration and cost of multiple shifts operation while circumventing the negative impacts of shift work on productivity, safety, and cost; and (4) an enhancement in analyzing construction project risks in order to improve the reliability of project performance.
9-2 Research Contributions

The main research contributions of this study can be summarized as follows:

1. Development of innovative resource leveling metrics that circumvent the limitation of existing approaches and are capable of directly measuring and minimizing the negative impact of resource fluctuations on construction productivity and cost.
2. Formulation of a robust optimization model that incorporates the newly developed resource leveling metrics and is capable of generating optimal and practical schedules that maximize the efficiency of resource utilization in construction projects.
3. Development of a robust resource leveling and allocation model that is capable of (a) maximizing resource utilization efficiency by directly measuring and minimizing undesirable fluctuations in resource profiles; and (b) generating optimal tradeoffs between resource utilization efficiency and project duration while resolving all resource conflicts.
4. Development of a robust multiple shifts scheduling model that is capable of searching for optimal multiple shift work plans and schedules that minimize project duration and cost while minimizing labor hours in evening and night shifts and complying with labor availability constraints.
5. Development of a robust resource fluctuation cost model that is capable of modeling and minimizing resource fluctuation costs and analyzing and optimizing the potential tradeoffs between minimizing resource fluctuation costs and minimizing project duration.
6. Development of an advanced project risk assessment model that circumvents the limitation of existing methods and enables fast and accurate risk evaluation during the scheduling of real-life large-scale construction projects.

7. Integration of the aforementioned research developments in a prototype multi-objective optimization for resource driven scheduling system that is capable of (a) optimizing resource-driven scheduling for construction projects; and (b) seamless integration with commercially available project management software, Microsoft Project 2007, to facilitate the ultimate use and adoption of developed scheduling models by construction planners.

9-3 Future Research

9-3.1 Improvements to the resource leveling model

The present research study developed new resource leveling metrics and models to maximize resource utilization efficiency for construction projects. To this end, two new alternative resource leveling metrics, Release and Rehire (RRH) and Resource Idle Days (RID), were developed to support construction planners in optimizing resource utilization based on the ability to release and rehire resources. For example, if resources cannot be released and rehired during low demand periods due to labor union restrictions for example, then the RID metric can be used to minimize resource idle days during their low demand periods. The current model assumes that the ability to release and rehire resources remains the same throughout the project duration. Future research can explore if this assumption need to be changed for some projects that may
allow these restrictions on the release and rehire of resources to vary from one project period to another and how the model formulation can be changed accordingly.

9-3.2 Improvements to the FARE model

The present research study developed a fast and accurate risk evaluation (FARE) model to evaluate the risks involved in construction project networks. The model requires users to specify appropriate values for upper probability bound (UP) and upper correlation bound (UC) in order to improve the accuracy in estimating the probability of project completion and speed up its computational time. Future research is needed to explore new methods that can automatically specify those bounds in order to improve the efficiency of the current FARE model and seamlessly integrate it with optimization models. One of these new methods can explore setting a number of representative paths that is needed to provide accurate estimate of probability of project completion for the network in a reasonable time, and then identifying the corresponding values for upper probability bound (UP) and upper correlation bound (UC) based on the specified target project duration (t).

Furthermore, future research to improve the current FARE model can focus on considering the impact of correlations between project activities to enhance its risk assessment capabilities. Factors such as weather, labor skills, site conditions, and management can affect the duration of construction activities (Wang and Demsetz 2000). For example, if adverse weather occurs during concrete forming, it is also expected that the same weather conditions will affect other sensitive activities that are scheduled during the same period of the project duration. Accordingly, construction
activities can be clustered based on the aforementioned factors that are shared among them such as weather, site condition, crew efficiency, and equipment performance. Correlations among the activities in each cluster can then be estimated and incorporated in the FARE model to provide more reliable estimate of uncertainties and risks in the project duration.

Future research to improve the FARE model can also focus on expanding it to enable its utilization during the control stage of construction projects by gathering actual project performance data during the completed phases of the project and evaluating the impact of this actual data on the uncertainties and risks of the remaining project schedule.

9-3.3 Integration of MORDS with Building Information Modeling (BIM)

The present MORDS system was developed using MS Project, which has a limitation on retrieving building space information. Space can be another constraint for the optimization of resource driven scheduling in construction projects. For example, allocating too many resources in the limited space causes space congestion problems, and thereby it negatively affects productivity, safety, and cost. In order to address this issue, future research can focus on retrieving space information from building information models (BIM) and utilizing this information in the MORDS system to optimize resource utilization for construction projects in order to improve construction productivity, safety, and cost.
9.3.4 **Optimization using multi-core computing techniques**

The present research study developed optimization models resource-driven scheduling and analyzed their performance using single core computing. In order to facilitate the use and adoption of developed models for large-scale construction projects, future research can focus on utilizing multi-core computing techniques in the optimization process such as OpenMP and GPU based CUDA programming to improve the efficiency and practicality of the developed models in optimizing resource driven scheduling for large-scale construction projects. This future research can provide significant contributions to facilitate the adoption and utilization of the developed optimization models by construction practitioners for large scale construction projects.
LIST OF REFERENCES


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