Application of Multi-Criteria Decision Making Techniques in Time-Cost-Quality Trade-Off

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ABSTRACT

Discrete time-cost-quality trade-off problems (DTCQTPs) are a branch of project scheduling problem which deals with establishing a compromise between time, cost and quality. In this thesis, multi-objective optimization models, namely, genetic algorithm (GA) and improved harmony search (IHS), integrated with multiple criteria decision making (MCDM) methods are developed to solve the DTCQTPs with the aim to find the best optimal project scheduling alternative. Three different MCDM methods, e.g., evidential reasoning (ER), PROMETHEE, and TOPSIS are used to rank the Pareto-optimal solutions obtained through GA and IHS. The proposed methodology is applied to a benchmark construction project scheduling problem to investigate the efficiency of the proposed methods. The obtained results revealed that the ER approach which is a more complex MCDM methods when compared with PROMETHEE and TOPSIS can provide the DMs with a transparent view of each project scheduling alternative. Thus, detailed investigations is possible for the ER approach, while the PROMETHEE approach with a similar ranking of the solutions can be a useful substitution for the ER approach. The performance analysis showed that IHS algorithm is more efficient than GA while the former has a higher computational time.

Keywords: discrete time-cost-quality trade-off problem (DTCQTP), multi-objective optimization models, genetic algorithm (GA), improved harmony search (IHS), multiple criteria decision making models, evidential reasoning (ER), PROMETHEE, TOPSIS.

ÖZ

Ayrık zaman-maliyet-kalite ilişkileri problemleri (AZMKP), zaman, maliyet ve kalite arasında bir uzlaşma kurulması ile ilgili proje planlama problemi dalından biridir. Bu tezde, çok amaçlı optimizasyon modelleri, yani genetik algoritma (GA) ve geliştirilmiş uyum arama (GUA), çok kriterli karar verme (ÇKKV) yöntemleri ile entegre olarak en iyi optimum proje planlama alternatifini bulmak amacıyla ZKMP'ni çözmek için geliştirilmiştir. Üç farklı ÇKKV, örneğin kanıta dayanan muhakeme (KDM), PROMETHEE ve TOPSIS, GA ve GUA ile elde edilen Pareto-optimal çözümlerini sıralamak için kullanılır. Önerilen metodoloji, yöntemlerin etkinliğini araştırmak için bir kıyas inşaat projesi planlama sorunu üzerine uygulanır. Elde edilen sonuçlar, PROMETHEE ve TOPSIS'e kıyasla daha karmaşık bir ZKMP yöntemi olan KDM'nin karar vericilere (KV) her bir proje planlaması alternatifinin şeffaf görünümünü sağladığını ortaya çıkarmıştır. Böylece, PROMETHEE yaklaşımı, benzer bir sıralama çözümleri ile KDM yaklaşımı için yararlı bir ikame olabilir iken, GUA yaklaşımı için detaylı incelemeler mümkündür. Performans analizi, eskisinin daha yüksek hesaplama süresine sahip iken, GUA algoritmasının GA'dan daha verimli olduğunu göstermiştir.

Anahtar kelimeler: Ayrık zaman-maliyet-kalite ilişkileri problemleri (AZMKP), çok amaçlı optimizasyon modelleri, genetik algoritma (GA), geliştirilmiş uyum arama (GUA), çok kriterli karar verme modelleri, kanıta dayanan muhakeme (KDM), PROMETHEE, TOPSIS.

To My Lovely Family

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LIST OF ABBREVIATIONS

DTCQTP	Discrete time-cost-quality trade-off problem
MCDM	Multiple criteria decision making
GA	Genetic algorithm
NSGA-II	Non-dominated sorting genetic algorithm
AHP	Analytical hierarchy process
PERT	Project evaluation review technique
DM	Decision maker
ER	Evidential reasoning
PROMETHEE	Preference ranking organization method for enrichment evaluation
TOPSIS	Technique for order of preference by similarity to ideal solution
HS	Harmony search
IHS	Improved harmony search
HMCR	Harmony memory consideration rate
CT	Computational time
GD	Generational distance
RV	Range variance

Chapter 1

INTRODUCTION

1.1 Background of the Study

Project can be defined as a temporary endeavor being essayed, and it culminates in development of a unique product or service. Projects are done by people, constrained by limited resources, and moreover they need to be planned, executed and controlled. Projects can be expressed as a means of achieving an organization's strategic plans (PMI, 2001). Construction projects are no exception to the aforementioned definition owing to the feature of uniqueness in their nature. This refers to the fact that each construction project has its own site characteristics, weather condition, and crew of labor, and fleet of equipment. During the planning phase, an array of conditions such as technological and organizational methods, and constraints in addition to the availability of resources, must be taken into consideration to ensure that the requirements of the clients are fulfilled in terms of time, cost, and quality (Zhou, Love, Wang, Teo, & Irani, 2013).

In every construction project, one of the primary difficulties is scheduling the execution process during the planning phase which necessitates the deployment of broad and multi-criteria approaches to achieve a compromise between various and occasionally conflicting objectives, e.g., time, cost, quality, and etc. Most frequently, construction projects are entangled with circumstances in which decision makers (DMs) need to narrow down potential alternatives, and decide on an optimal solution which is a compromise between conflicting objectives. Nowadays, the competitive business environment of construction industry forces the contractors to schedule the project in an efficient manner. Regarding this, the project scheduling problems plays a vital role in the overall project success, especially in managing the organizational resources (Tavana, Abtahi, & Khalili-Damghani, 2014). Due to all the aforementioned reasons, project scheduling problems have been the subject of many research studies in operations research, meanwhile have been known as a popular playground in which a plethora of optimization techniques have been employed (Baptiste & Demassey, 2004; Ghoddousi, Eshtehardian, Jooybanpour, & Javanmardi, 2013; Monghasemi, Nikoo, Fasaee, & Adamowski, 2014; Mungle, Benyoucef, Son, & Tiwari, 2013).

1.2 Discrete Time-Cost-Quality Trade-Off Problems

Discrete time-cost-quality trade-off problems (DTCQTPs) constitute a branch of project scheduling problems, which involve multiple activity performing modes. In contrast to problems with continuous time-cost-quality trade-offs, the correlation between the time, cost, and quality of each mode of activity is expressed through a point-by-point definition. This discrete interaction defines the durations of the activities which are chosen from a set of finite number of alternatives. The discrete relationship is more favorable since for an activity, a set of feasible synthesis of resources and alternatives might be inaccessible (Eshtehardian, Afshar, & Abbasnia, 2009). For instance, for the excavation activity which might rely on heavy equipment such as bucket loader, there exist some constraints such as the limited available number of bucket loader, impractical usage of fractional number of bucket loaders i.e., 1.36 bucket loader is not sensible in real practice, and etc. The activities in the project schedule network are constrained by preceding/succeeding relationships, implying that an activity cannot be executed until all its preceding activities are accomplished (Sonmez & Bettemir, 2012; J. Xu, Zheng, Zeng, Wu, & Shen, 2012).

In general, time, cost, and quality are known as conflicting objectives in DTCQTPs with significant interdependencies and multiple trade-off sets (Eshtehardian et al., 2009). As a rule of thumb, activities' durations often can be reduced to expedite the project with some additional cost, and/or increase the duration of an activity to ensure the maintenance of quality. In this regard, DTCQTPs are appropriate for application of different multi-objective optimization techniques to make the best decisions with respect to the existing trade-offs.

In comparison with the project evaluation and review technique (PERT), which is a statistical tool to be used in project management context, DTCQTPs do not take into consideration the probability. More specifically, in PERT analysis the time, cost and quality are defined as the most pessimistic, optimistic, and most probable options. Thus, in PERT analysis, for each activity three different modes of execution are defined based on probability theory. The DM should determine the three modes in PERT by considering what are the worst, best and most probable options which are going to occur in real practice based on his own judgement, records, and predictions. However, in DTCQTPs, each activity can take any number of execution modes including the ones defined through PERT analysis. Hence, the DTCQTPs are more generalized form of PERT analysis which do not only rely on the probability but also considers the existing limitations and constraints in a common construction project.

1.3 Multiple Criteria Decision Making (MCDM) Problem

DTCQTP deals with allocating the available resources, time, cost, and quality, in an efficient manner with respect to the trade-offs between the objectives. Owing to the multidisciplinary nature of scheduling problems which are closely entwined with various non-commensurable multiple criteria, establishing which solution is the best choice to be implemented can be a difficult task (Monghasemi et al., 2014). Multiple criteria decision making (MCDM) methods provide an efficient means for supporting the choice of the preferred Pareto optimum (Mela, Tiainen, Heinisuo, & Baptiste, 2012). Also, MCDM methods help finding the Pareto-optimal solutions, also known as the social planner solution (Madani, Sheikhmohammady, Mokhtari, Moradi, & Xanthopoulos, 2014; Mela et al., 2012), in the case of multiple criteria with one decision maker or when there is perfect cooperation among the DMs (Madani & Lund, 2011). The main advantage of MCDM methods is their information handling capabilities, which facilitate the process of organizing and synthesizing the required information throughout an assessment (Løken, 2007). The aim of MCDM methods is to assist the DMs in order to facilitate the process of organizing and synthesizing the required information in an assessment, so that DMs are satisfied and confident with their decision (Løken, 2007).

1.4 Multi-Objective Optimization

The multi-objective optimization usually does not lead into a unique optimal solution, more specifically a set of Pareto-optimal solutions can be achieved. The Pareto fronts defines a set of solutions in which no solution can be improved unless sacrificing at least one of the other objectives. Each Pareto-optimal solution represents a compromise between different objectives, and generally comparing two solutions in multi-objective optimization is much more complicated than in the single-objective optimization (Mungle et al., 2013). The improved version of non-dominated sorting genetic algorithm (NSGA-II) is demonstrated to outperform other approaches, e.g. pareto archive evolutionary strategy in converging to near true Pareto front (Deb, Pratap, Agarwal, & Meyarivan, 2002). The capability of NSGA-II encourages the application of the method to be applied into more complex and real-world multi-objective optimization problems.

1.5 Significance of the Study

There is a lack of studies that have applied MCDM methods in project scheduling problems to select the best solution amongst the Pareto solutions, and in such studies only the Pareto solutions are obtained, plotted and reported; this was one of the issues that motivated the authors of this study to apply MCDM methods in solving DTCQTP to aid DMs in selecting the best schedule of the project. Thus, the present study attempts to present a comprehensive framework to integrate MCDM methods with multi-objective optimization techniques.

1.6 Aims and Scopes

The aims and scopes of the present study are as to enhance the procedure in scheduling the construction project in order to establish a trade-off between the conflicting objectives, e.g., duration of the project (time), project expenses (cost), and the attainable overall quality (quality). Here, the aim is to better the existing approaches in project scheduling by incorporating MCDM methods into the body of multi-objective optimization in order to aid the decision makers with appropriate decisions.

The aim of this study is to integrate MCDM methods into the body of multi-objective optimization models in order to improve the decision making process. The proposed method will be applied on a case problem of highway construction project to demonstrate the efficacy of the proposed model.

1.7 Limitations

As a limitation in this study is that the activities must be expressed through discrete time, cost and quality attributes. Regarding this issue, it is still a difficult task to quantify these objectives prior to start of that activity and it is entangled with several uncertainties. However, the author proposes that in future studies, fuzzy set theory can be incorporated to address the uncertainty of the input variables. On the other hand, the MCDM methods which are used here consider a single decision maker or a group of those with unique attitude towards the importance of the objectives. Therefore, it is not possible to assign different weights for each objective simultaneously. To eliminate this limitation, the MCDM methods can further be expanded to group decision making models which are efficient when the decisions are based on group rationality rather than individuality.

1.8 Questions to be Answered

The present study will be able to give answers for a few questions which are as follows:

(1) Is it possible to integrate multi-objective optimization methods with MCDM methods? In case of the possibility of this integration, how it can be done and why it can be beneficial?

(2) Which MCDM method can be more efficient in aiding the DMs in reaching the optimal project schedule alternative among possible options? What are the main features of great importance to prefer a MCDM method over any other approach?

(3) Which multi-objective optimization model, either GA or is more suitable to be used for project scheduling problems? What are the evaluation criteria to judge and investigate the difference between the performance of GA and HS?

1.9 Thesis Structure

In the following chapters the more details of the proposed methodology will be presented. Chapter 2 discusses the literature review of DCTQTPs and MCDM methods. Chapter 3 presents the methodology and the developed mathematical model to tackle the DTCQTP. Chapter 4 explains the case problem of a highway construction project and presents the required data of the benchmark case problem. In chapter 5, the proposed model of this study has been applied on the case problem to demonstrate the efficacy of the proposed model. The concluding marks are done in chapter 6 which is followed with some recommendations for future studies.

Chapter 2

LITERATURE REVIEW

2.1 DTCQTPs Backgrounds

Every construction project triggers with pre-planning of involving activities with the aim to foresee the outcomes and pre-judge about the available schedule alternatives. Various possible of schedule alternatives might vary significantly in criteria such as time (duration of project), cost (activity-related expenditures), and quality (overall satisfactory score in terms of standards). All these issues are studied in project scheduling problems to establish a compromise between the objectives to ensure the successful usage of resources leading to the overall success of the project. Therefore, project scheduling problems are a critical part in the overall success of a project, and especially in managing organizational resources (Tavana et al., 2014).

Discrete time-cost-quality trade-off problems (DTCQTPs) are a branch of project scheduling problems which comprise a project network that is represented with activities on a node network. Each activity in the project network possesses various execution modes while being constrained by preceding/succeeding relations via other activities. The correlation between time, cost, and quality for each activity execution mode is expressed via a point by point definition (Sonmez & Bettemir, 2012; J. Xu et al., 2012).

The DTCQTP solution methods can generally be categorized into two groups:

> **(a) Exact mathematical programming:** such as linear programming, integer programming, dynamic programming, and branch and bound algorithms (Erenguc, Ahn, & Conway, 2001; Moselhi, 1993);
>
> **(b) Non-exact approaches:** such as heuristic algorithms (Vanhoucke, Debels, & Sched, 2007) and meta-heuristic algorithms (Afruzi, Najafi, Roghanian, & Mazinani, 2014; Afshar, Kaveh, & Shoghli, 2007; Geem, 2010; Mungle et al., 2013; Tavana et al., 2014; Zhang & Xing, 2010).

Solving complex project scheduling problems using exact algorithms can be computationally costly and time-consuming. Heuristic optimization methods generally require less computational effort than conventional optimization methods, but cannot guarantee a global optimal solution. Meta-heuristic algorithms have been shown to be highly efficient in approximating the optimal solutions of combinatorial optimization problems in a relatively short time with a low computational effort (Czyzżak & Jaszkiewicz, 1998; Madani, Rouhani, Mirchi, & Gholizadeh, 2014).

Hapke, Jaszkiewicz, and Słowiński (1998) used Pareto Simulated Annealing to find a set of non-dominated solutions to a project scheduling problem with multi-category resource constraints. Jaszkiewicz and Słowiński (1997) applied the light beam search-discrete approach in order to aid the decision makers (DMs) to iteratively look for a solution they can agree on. Mungle et al. (2013) integrated the fuzzy clustering technique with a genetic algorithm (GA) approach in order to guide the algorithm to preserve the solutions with a higher degree of satisfaction with regards to the objectives of the problem. Afruzi et al. (2014) proposed a model for solving the discrete time-cost-quality trade-off problems in the case of limited manpower resources in which the selection of the mode of an activity is dependent on the availability of its required manpower resource in that specific period of time. Tavana et al. (2014) used a non-dominated sorting genetic algorithm (NSGA-II) and ε-constraint to solve a discrete time-cost-quality trade-off problem in which interruptions are allowed for the activities in progress and precedence relationships are generalized such as a ‘time lag’ between a pair of activities. They concluded that NSGA-II outperformed the ε-constraint method with regards to all comparison matrices.

2.2 PERT Analysis

The PERT analysis is based on three assumptions and facts that influence successful achievement of research and development program objectives. These objective are time, resources and technical performance specifications. PERT employs time as the variable that reflects planned resource-applications and performance specifications. With units of time as a common denominator, PERT quantifies knowledge about the uncertainties involved in developmental programs requiring effort at the edge of, or beyond, current knowledge of the subject.

Through an electronic computer, the PERT technique processes data representing the major, finite accomplishments (events) essential to achieve end-objectives; the inter-dependence of those events; and estimates of time and range of time necessary to complete each activity between two successive events. Such time expectations include estimates of "most likely time", "optimistic time", and "pessimistic time" for each activity. The technique is a management control tool that sizes up the outlook for meeting objectives on time; highlights danger signals requiring management decisions; reveals and defines both methodicalness and slack in the flow plan or the network of sequential activities that must be performed to meet objectives; compares current expectations with scheduled completion dates and computes the probability for meeting scheduled dates; and simulates the effects of options for decision – before decision.

In PERT analysis, the activities corresponding time, cost and quality are estimated through a probabilistic method of beta-distribution with the aid of mean and variance of the activity time, cost and quality. To meet this end, the pessimistic, optimistic and most likely completion time, cost and quality are identified. Several disadvantages are identified throughout the literature for the PERT analysis which are as follows: quantifying the time, cost and quality with the limited theoretical justifications and unavoidable defects of PERT analysis is still a time-consuming and in some case impossible (Grubbs, 1962).

There is the tendency to select the most likely activity time, cost and quality closer to the optimistic values, since the latter is often difficult to be predicted so it is chosen conservatively closer to the optimistic value. Most often the most likely activity time, cost and quality has the same relative location point in the interval of $[a, b]$. Although this provides the opportunity to simplify the PERT anaylsis it is rather followed by some assumptions which are not in-line with real practice. The PERT analysis is error-prone basically to its accompanying assumptions which can reaches up to 33% (MacCrimmon & Ryavec, 1964). So many improvements for the PERT analysis has been proposed by the researchers throughout the literature, however, to the extent of the author’s knowledge, none of the proposed modification was successful in real practice since the modifications made the distribution law rather uncertain and/or made it difficult to simulate the activity network (Golenko, 1968).

However, in DTCQTPs, the difficulties in determining the PERT three options do not exist since in the former approach the time, cost and quality objectives are determined according to the contractors' prequalification process. Different time, cost and quality options for each activity, also being known as execution modes of activities are determined for each contractor. On the other hand, the data of the DTCQTPs do exist in the literature and they can be used as the benchmark for future studies without any additional time-consuming analyses.

2.3 MCDM Backgrounds

There exist a multitude of MCDM methods that have differences in terms of theoretical background, formulation, questions, and types of input and/or output (Hobbs & Meier, 1994). Numerous studies have investigated the practical applications of various MCDM methods in different areas such as sustainable energy planning (Hadian & Madani, 2015; Madani & Lund, 2011; Pohekar & Ramachandran, 2004; Laura Read, Mokhtari, Madani, Maimoun, & Hanks, 2013), water resource planning (Hajkowicz & Collins, 2007; Mirchi, Watkins Jr, & Madani, 2010; L. Read, Inanloo, & Madani), conflict resolution (Madani, Sheikhmohammady, et al., 2014; Mokhtari, Madani, & Chang, 2012), sustainable forest management (Wolfslehner, Vacik, & Lexer, 2005), environmental management (Huang, Keisler, & Linkov, 2011; Igor Linkov & Moberg, 2011), and in the design of power generation systems (Alsayed, Cacciato, Scarcella, & Scelba, 2014; Aragonés-Beltrán, Chaparro-González, Pastor-Ferrando, & Pla-Rubio, 2014).

According to Belton and Stewart (2002), MCDM methods can be classified into three main categories:

a) value measurement methods;

b) goal, aspiration, and reference level methods; and

c) outranking methods;

In the value measurement method, each alternative is given a numerical value which indicates the solution rank in comparison with the others. Different criteria are weighted according to the accepted level of DMs in trading off between multiple criteria. Multi-attribute utility theory, proposed by Keeney and Raiffa (1976), and analytical hierarchy process (AHP), proposed by Saaty (1980), are examples of this category. Other iterative procedures that emphasize solutions which are closest to a determined goal or an aspiration level fall into the second category (e.g., TOPSIS). In general, these approaches are focused on filtering the most unsuitable alternatives during the first phase of the multi-criteria assessment process (Løken, 2007).

In the outranking methods, the alternatives are ranked according to a pairwise comparison, and if enough evidence exists to judge if alternative a is more preferable than alternative b, then it is said that alternative a outranks the b. *ELECTRE* (Roy, 1991) and *PROMETHEE* (J. P. Brans, P. Vincke, & B. Mareschal, 1986) are based on this approach of ranking.

There exists no direct approach to declare which type of MCDM method is superior since different types of inputs and outputs are generated by each method, which makes such comparisons invalid. However, it can be stated that the approach that satisfies the DMs best, and which has a user friendly interface, and can provide the DMs with sufficient confidence to translate their decisions into actions, is one that is useful (Løken, 2007). Numerous studies have been conducted to investigate the usability, and enumerate the fundamental dissimilarities, between different MCDM methods (Løken, 2007; Mela et al., 2012; Opricovic & Tzeng, 2004). In general, most studies have avoided comparing the usefulness of different approaches, and have solved particular case studies using different MCDM approaches without making any comment on the performance of the different methods. This is due to limitations stemming from limited test problems; any judgment needs rational justification to make such comparisons valid (Mela et al., 2012).

2.3.1 MCDM Methods

2.3.1.1 Evidential Reasoning

Evidential reasoning (ER) (J.-B. Yang & Singh Madan, 1994) is a generic evidence-based MCDM approach, which owes its popularity to its ability to handle problems having both qualitative and quantitative criteria and performance values associated with uncertainties due to ignorance and imperfect assessment. The ER approach has been widely applied in various areas, such as prequalifying construction contracts (Sönmez, Holt, Yang, & Graham, 2002), safety analysis of engineering systems (Wang, Yang, & Sen, 1995), drinking water distribution monitoring and fault detection (Bazargan-Lari, 2014), environmental impact assessment (Gilbuena, Kawamura, Medina, Nakagawa, & Amaguchi, 2013; Y.-M. Wang, J.-B. Yang, & D.-L. Xu, 2006), and risk analysis and assessment (Chen, Shu, & Burbey, 2014; Deng, Sadiq, Jiang, & Tesfamariam, 2011).

The ER approach uses belief structures, belief matrices, and rule/utility-based grading techniques to aggregate the input information. The main advantage of ER is that it can consistently model various types of data, e.g., quantitative (cardinal), qualitative (ordinal), certain (deterministic), and uncertain (stochastic), within a unified framework; a feature that prevents the inadvertent damage of data through the analysis process (J.-B. Yang, Wang, Xu, & Chin, 2006). ER uses a hierarchical structure consisting of attributes, and aggregated information from the bottom to the top level of the hierarchical structure based on the evidence combination rule rooted in the Dempster-Shafer theory of evidence (Shafer, 1976).

In the context of DTCQTP, time, cost, and quality are considered as three quantitative attributes in assessing the alternatives.

2.3.1.2 PROMETHEE

The underlying concept of the Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) approach was first introduced by J.-P. Brans, P. Vincke, and B. Mareschal (1986) and since then it has been widely used in various fields such as environment and waste management (Ia Linkov et al., 2006; Queiruga, Walther, Gonzalez-Benito, & Spengler, 2008), hydrology and water management (Hyde & Maier, 2006), energy management (Diakoulaki & Karangelis, 2007), business and financial management (Albadvi, Chaharsooghi, & Esfahanipour, 2007), and etc. Behzadian, Kazemzadeh, Albadvi, and Aghdasi (2010) have done an exhaustive study to uncover, classify, and interpret the current research on PROMETHEE methodologies and applications. They provided a comprehensive and rational framework for structuring a decision problem, identifying and quantifying its conflicts and synergies, clusters of actions, and highlight the main alternatives and the structured reasoning behind (Rahnama, 2014).

The advantage of the PROMETHEE decision making method is that it provides the decision makers with both complete and partial rankings of the actions, and it is well-suited for complex problems, especially those with several multi-criteria, involving a lot of human perceptions and judgments, whose decisions have long-term impact (Tuzkaya, Ozgen, Ozgen, & Tuzkaya, 2009).

The PROMETHEE-based decision making models comprises several versions such as PROMETHEE I for partial ranking of the alternatives and PROMETHEE II for complete ranking of the alternatives (Behzadian et al., 2010; Brans & Vincke, 1985). Following, several modified versions have been proposed such as PROMETHEE III suitable for interval-based ranking (Cavalcante & De Almeida, 2007; Fernández-Castro & Jiménez, 2005), PROMETHEE IV for partial/complete assessment of alternatives when the set of viable solutions is continuous, PROMETHEE V for problems with segmentation constraints (Mareschal & Brans, 1992), and so many other extensions have been proposed. In this study, PROMETHE II which is intended to provide a complete ranking of the finite set of project scheduling alternatives for DTCQTPs is used and is discussed in the following sections.

2.3.1.3 TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a very common technique in the field of MCDM which was first proposed by Hwang and Yoon (1981). The TOPSIS technique attempts to rank the alternatives based on two parameters; (a) minimum distance from the positive ideal solution; (b) farthest distance from the negative ideal solution (Dymova, Sevastjanov, & Tikhonenko, 2013). In simple words, the best solution is the one with lowest distance from the ideal solution while being as far as possible from the worst solution in that case. the TOPSIS technique has been widely used in many fields, e.g., management of supply chain (K. Govindan, Khodaverdi, & Jafarian, 2013), industrial robotic system selection

(Chaghooshi, Fathi, & Kashef, 2012), the optimal green supplier selection procedure (Kannan, Khodaverdi, Olfat, Jafarian, & Diabat, 2013).

2.4 Multi-Objective Optimization of DTCQTPs Backgrounds

2.4.1 Genetic Algorithm

Genetic algorithm (GA) is a stochastic search method applicable to optimization problems which is founded on biological behavior (Wilson, 1997b). The GA seeks to improve performance by sampling areas of the parameters space that are more likely to lead to better solution (Goldberg, 1989; Holland, 1975). All solutions should comply with three important characteristics.

(1) Feasibility which means that each decoded solution should lie within feasible region;

(2) Legality implying that decoded solutions should be in the solution space;

(3) Uniqueness by the means of not more than one solution can be obtained by decoding of each chromosome and vice versa (J Xu & Zhou, 2011).

Applying various approaches, numerous attempts have been made to solve the DTCQTPs (Afshar et al., 2007; El-Rayes & Kandil, 2005; Mungle et al., 2013; Tavana et al., 2014). The genetic algorithm (GA) is a stochastic search method applicable to optimization problems, and is based on natural selection (Wilson, 1997a). For instance, Feng, Liu, and Burns (1997) used multi-objective genetic algorithm to deal with the DTCQTP. Due to space limitations, and since the GA procedures are widely known, the steps are only briefly discussed in the following subsections.

2.4.2 Improved Harmony Search

Harmony search (HS) is a relatively newly-inspired algorithm which has been developed based on the observation that music tends to seek a perfect state of harmony.

It was first proposed by Geem, Kim, and Loganathan (2001). Since then its effectiveness and advantages have been demonstrated in various applications, and in most cases it has been shown to outperform other meta-heuristics algorithms such as GA and ant colony optimization (Geem, 2010; X. S. Yang, 2009).

The HS algorithm seeks solutions in problem search space with the aid of a phenomenon-mimicking algorithm based on the musical improvisation process which looks for harmonies with more pleasing sounds in terms of aesthetic quality. Furthermore, HS is more powerful and flexible when identifying the high performance regions of the solution space. In order to reinforce the capability of the HS algorithm in performing local searches an improved harmony search (IHS) has since been proposed to enhance the fine-tuning characteristics of the algorithm (Mahdavi, Fesanghary, & Damangir, 2007). The population-based characteristic of IHS facilitates the multiple harmonic groups to be used in parallel, which adds more efficiency in comparison with other non-population based meta-heuristic algorithms (X. S. Yang, 2009).

2.5 Combination of Optimization and MCDM Methods

Multi-objective optimization can be coupled with MCDM methods to solve multi-criteria multiple-decision-maker problems in which each decision maker has different objectives and/or assigns different weights to her decision criteria. To this end, two general approaches have been pursued in the literature (Chaudhuri & Deb, 2010). In the first approach (Bazargan-Lari, 2014; Monghasemi et al., 2014; Perera, Attalage, Perera, & Dassanayake, 2013; Tanaka, Watanabe, Furukawa, & Tanino, 1995) multi-objective optimization is first used to obtain the set of Pareto-optimal solutions and then MCDM methods are used to select the compromise solution. This approach oversimplifies the problem and fails to establish a proper linkage between multi-objective optimization and MCDM. In this case, the preferences of the decision makers are not considered at the optimization stage. Thus, some of the generated solutions might be strongly undesirable to some decision makers.

To address the above-mentioned problem, the second approach integrates MCDM methods and multi-objective optimization, resulting in a concentrated search in a region where there is a higher chance of finding solutions that are Pareto-optimal and acceptable by the decision makers. Chaudhuri and Deb (2010) proposed a novel approach to combine MCDM and multi-objective optimization that allows investigation of the different regions of the Pareto-optimal frontier first and then searching through these regions as many times as required to satisfy the decision makers. Their suggested approach, however, does not consider the non-cooperative tendencies among the decision makers (Madani, 2010). Therefore, if each decision-maker wants to select her own desirable region(s) on the Pareto-optimal frontier and seek for optimal solutions in an iterative procedure, the overall process can be very time-consuming. In some cases, finding an optimal solution that satisfies all decision makers is even impossible.

Chapter 3

METHODOLOGY

3.1 Mathematical Model to Solve DTCQTPs

The cost component for each activity can be an agglomeration of various factors which are required to complete the activities successfully. Generally, direct and indirect costs are the two main elements that constitute the overall cost of each activity. The direct cost is the overall cost spent directly in order to successfully accomplish the activities, and is directly related to the execution phase. In other terms, the direct cost is any expenditure which can be directly assigned for completing an activity, while the indirect cost can be allocated for a single activity. The direct cost of j^{th} option of i^{th} activity is denoted by $\tilde{c}_{ij}$. The cost might also consist of indirect costs $(\tilde{C}_d)$, which originate from the managerial cost of a construction organization and any other indirect costs which can be measured in cost per day. In this study, the indirect cost is assumed to be a fixed amount, and its amount varies with project duration.

Different types of construction contracting methods may also impose other types of costs, namely, tardiness penalty $(\tilde{C}_p)$ and incentive cost $(\tilde{C}_{in})$, both of which can be measured in cost per day. For any delay occurring in total project time in comparison with the DMs' desired time $(\tilde{T}_d)$, the main contractor(s) might be charged a tardiness fine on a daily basis, usually at a fixed price per day. In contrast, for any early completion, they might be rewarded for each day of this early completion period.

A thorough model to solve the DTCQTP can be expressed as:

$$\text{Minimize } f_1 = \max_{\forall p \in P} \{\tilde{T}_1, \tilde{T}_2, \ldots, \tilde{T}_n\} \tag{1}$$

$$\text{Minimize } f_2 = \sum_{i=1}^{N} \tilde{c}_{ij} + f_1 . \tilde{C}_d + \bar{u}\left(f_1 - \tilde{T}_d\right) . \left(\tilde{T}_d - f_1\right) . \tilde{C}_p + \bar{u}\left(\tilde{T}_d - f_1\right) . \left(\tilde{T}_d - f_1\right) . \tilde{C}_{in} \tag{2}$$

$$\text{Maximize } f_3 = \alpha Q_{min} + (1 - \alpha) Q_{ave} \tag{3}$$

$$Q_{min} = min\left\{\tilde{q}_{ij} : x_{ij} = 1\right\} \tag{4}$$

$$Q_{ave} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{m} q_{ij} \cdot x_{ij}}{N} \tag{5}$$

The set of $P = \{p|p = 1,2, \ldots, n\}$ is used to represent all the paths of the activity network. i_p is the i^{th} activity on path p, and n_p is the number of activities on path p. Considering all these notations the total implementation time of p^{th} path ($\widetilde{T}_p$) is the summation of the durations of all the activities on path p, which can be mathematically calculated as $\widetilde{T}_p = \sum_{i_p}^{n_p} \tilde{t}_{ij}$. Therefore, the first objective function (f_1) refers to the total project duration which is obtained by considering the maximum implementation time, $\tilde{T} = \{\tilde{T}_1, \tilde{T}_2, \ldots, \tilde{T}_n\}$, where $\tilde{T}$ represents all paths of the project network (Eq. 1).

The second objective function (f_2) represents the total project cost which is the summation of each activity cost ($\tilde{c}_{ij}$) denoting the direct cost. It is later added to the indirect cost calculated by multiplying the fixed cost of the indirect cost ($\tilde{C}_d$) with the project duration (f_1). The direct cost is any expenditure which can be directly assigned for completing an activity, while the indirect cost can be allocated for a single activity. Other cost components such as the project tardiness penalty and incentive costs are also considered. The unit step function, $\bar{u}(x)$, is either one or zero for non-negative and negative values of x, respectively. Then, the total project cost can be mathematically computed as shown in Eq. 2. x_{ij} is the index variable of i^{th} activity when performed in j^{th} option. If $x_{ij} = 1$ then the j^{th} option for i^{th} activity is selected and when $x_{ij} = 0$ it means that the j^{th} option of i^{th} activity is not selected.

The next objective function (f_3) estimates the project quality through Eq. 3. If the quality of the i^{th} activity of j^{th} option is shown by $\tilde{q}_{ij}$ the estimation of the project overall quality is a linear relationship between the minimum quality of all the selected alternatives (Q_{min}), which is calculated according to Eq. 4, and the average quality of all the chosen alternatives (Q_{ave}) which is calculated using Eq. 5. A higher value of α means a greater emphasis on the fact that the quality of no activity in the schedule is too low, while a lower value ensures that the overall project quality is aimed at not lying too far away from the average quality (Q_{ave}).

Using the α parameter ensures that the third objective (f_3) represents a close estimation of the overall project quality since only the average value might not be a good measurement of the total obtainable project quality. Therefore, if an activity with a very low quality is selected, it lowers f_3 more significantly than in the case where only average value is considered, thus automatically, throughout the optimization algorithm, an attempt is made so that not only the average quality is at a high standard, but also no activity with a very poor quality to be selected. Using the step function ensures that either the tardiness penalty or the incentive cost is added to the total cost. It must be noted that the total cost is from the viewpoint of the project's main contractor and that of the owner, meaning that incentive and tardiness costs are summed negatively and positively with the total cost, respectively. If we consider the cost from the owner's viewpoint, then the incentive cost would be negative but the tardiness cost would be positive. To take into account all the expenditures in relation to the project the first case is considered (*i.e.*, the contractors' viewpoint), which is the more common approach in DTCQTPs.

3.2 Assumptions

Throughout this thesis a few simplifying assumptions have been considered which are as follows:

(1) The indirect cost of the activities is assumed to be a fixed value per day.

(2) The relationship between the activities in the project scheduling network is only finish to start type of relationship. This means that the preceding activity should be completed prior to the start of its succeeding activities.

(3) The qualities are only the expected quality from that specific activity. Thus, it may not represent the attained quality of the project after it has been completed.

(4) It is assumed that there is no lead and/or lag time between the activities. This implies that soon after the preceding activity is done, the succeeding activities should be started.

3.3 Multi-Objective Optimization Techniques

3.3.1 Genetic Algorithm Framework

Applying various approaches, numerous attempts have been made to solve the DTCQTPs (Afshar et al., 2007; El-Rayes & Kandil, 2005; Mungle et al., 2013; Tavana et al., 2014). The GA is a stochastic search method applicable to optimization problems, and is based on natural selection (Wilson, 1997a). For instance, Feng et al. (1997) used multi-objective genetic algorithm to deal with the DTCQTP. Due to space limitations, and since the GA procedures are widely known, the steps are only briefly discussed in the following subsections.

3.3.1.1 Initial Population and Chromosome Representation

GA is a chromosome-based evolutionary algorithm, and as with its nature, the GA tries to seek better offspring from the population during each generation of evolution, as first proposed by Holland (1975). The chromosome consists of cells which are known as genes. In this study, the position of the genes indicates the number of activities, and the value of each gene represents the option which is assigned for the activity execution mode. Table 1 shows a sample of a chromosome with 6 activities.

Table 1. Structure of a chromosome

Activity Number:	1	2	3	4	5	6
Execution Mode:	3	2	4	3	2	1

The initial population of the algorithm is generated randomly, allowing the entire range of possible solutions. Here, the population size is set to 400 which is selected based on preliminary model run and it must be sufficiently large to ensure convergence to the optimal solutions. The GA has the capability to be seeded with additional set of chromosomes in the areas where optimal solutions are more likely to be found. The additional set of chromosomes are generated through running the algorithm for several times with the purpose to seed each run of the algorithm with the obtained set of chromosomes from the previous run in the last generation. The gene values can only take values which do not violate the number of options available for that activity (the upper limit). For example, if activity number 3 has only 4 options, then the gene value of the third position cannot take any value more than 4, and the values must be limited to integers in the interval of [1,4]. This representation of the chromosome ensures that no chromosome leads into infeasible solution which avoids unnecessary computational effort and results into saving time.

3.3.1.2 Crossover and Mutation Operator

During each generation, similar to the natural evolution process, a pair of 'parent' solutions is selected for breeding and producing a pair of 'child'. The crossover operator attempts to reproduce a pair of 'child' which typically shares many of the characteristics of its 'parents'. There exist various crossover operators, among which are the two point crossovers as used by Mungle et al. (2013) which was shown to be efficient in solving DTCQTPs optimization. Therefore, the two point crossover is selected as the crossover operator.

In order to preserve the diversity within the newly generated population there is the need to generate a number of solutions which are entirely different from the previous solutions. Analogous to biological mutation, the mutation operator alters only one gene in a chromosome to generate a non-identical 'child'. Swap mutation is used for the mutation operator alter the chromosomes (Cicirello & Cernera, 2013). Swap mutation operator simply changes the values of two randomly selected genes in a chromosome. In this case, the upper limit for the values of the gens is the only constraint which must be checked during the alteration of each chromosome otherwise infeasible chromosomes are produced. In the case when any value of a gene violates the upper limit, the maximum allowable value for that specific gene is replaced to ensure no 'child' leads into infeasible solution. Obviously, since the lower limit value for all the genes is 1, there is no need to check whether or not there is any value lower than 1.

3.3.1.3 Selection Procedure

GA is based on nature's survival of the fittest mechanism. The best solutions survive, while the weaker solutions perish. In order to simulate the natural selection procedure, the solution with best performance, according to its fitness function, survives and produces offspring for the next generation (Mawdesley, Al-jibouri, & Yang, 2002). The Roulette Wheel technique (Goldberg, 1989) is used in this study, which is widely used in the selection procedure of GA algorithm.

According to Roulette Wheel technique, the selection is basically done stochastically to form the basis of the next generation. For each chromosome the fitness value, which is the average utility score ($u_{ave}^{(f_1,f_2)}$) is obtained. Furthermore, each fitness value is divided by the summation of all the fitness values of the chromosomes of the existing the population. This procedure assigns the percentage of the total fitness function for each chromosome which is a measure of the strength of each chromosome. Thus, the chromosome with higher fitness percentage, has more chance to be selected.

Table 2. An example showing the Roulette Wheel selection procedure

Chromosome number	$u_{ave}^{(f_1,f_2)}$	Percentage of fitness function (%)	Share of each chromosome from the roulette wheel
1	0.11	4.15	5
2	0.43	16.22	17
3	0.95	35.84	36
4	0.63	23.77	24
5	0.53	20.00	20
summation	2.65	100	102

In order to explain the procedure of selection in roulette wheel, assume a population with only 5 chromosomes as listed in Table 2. The second column shows the fitness function value ($u_{ave}^{(f_1,f_2)}$) for each chromosome. As it can be observed, the chromosome number 1 and 3 are the weakest and strongest individuals respectively, based on their fitness function, therefore the chromosome number 1 has lowest chance to be selected with only 4.15% of the total fitness function; however the chromosome number 3 has the highest chance with 35.84% share of the total fitness function. The last column shows the share of each chromosome from the roulette wheel which is calculated by rounding the data of the third column to the nearest integer greater than or equal to the data. The summation of the shares of the chromosomes from the roulette wheel is equal to 102.

Figure 1 illustrates the roulette wheel which is divided into 102 red and black pockets. For each chromosome a number of pockets are assigned based on its share of the roulette wheel. In order to select a chromosome for the next generation a random integer is generated in the interval of $[1{,}102]$, if the random number belongs to interval $[1{,}5]$ then the chromosome number 1 is selected, and if the random number lies between the interval of $[6{,}22]$ then the chromosome number 2 is selected, and so on. Although this procedure considers higher chance of selection for the strongest chromosome, it allows the weakest chromosomes to be selected as well with a lower probability.

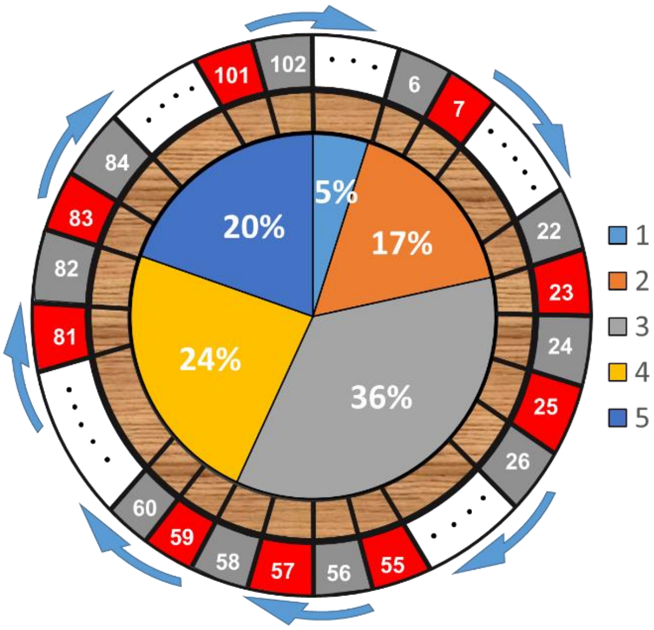


Figure 1. Roulette wheel selection procedure

3.3.1.4 Termination Criterion

In order to stop the algorithm, the termination criterion of the maximum number of generations is selected to force the algorithm to seek superior solutions continuously. The higher the maximum number of generation, the more computational effort is required; however a very low value prevents the algorithm to converge the optimal solution. Thus, based on preliminary model run the maximum number of generation is set to 500. The higher values were also tested but no improvement could be attained.

3.3.2 Improved Harmony Search Algorithm

Harmony search (HS) is a relatively newly-inspired algorithm which has been developed based on the observation that music tends to seek a perfect state of harmony. It was first proposed by Geem et al. (2001). Since then its effectiveness and advantages have been demonstrated in various applications, and in most cases it has been shown to outperform other meta-heuristics algorithms such as GA and ACO (Geem, 2010; X. S. Yang, 2009). The HS algorithm seeks solutions in problem search space with the aid of a phenomenon-mimicking algorithm based on the musical improvisation process which looks for harmonies with more pleasing sounds in terms of aesthetic quality. Furthermore, HS is more powerful and flexible when identifying the high performance regions of the solution space. In order to reinforce the capability of the HS algorithm in performing local searches an improved harmony search (IHS) has since been proposed to enhance the fine-tuning characteristics of the algorithm (Mahdavi et al., 2007). The population-based characteristic of IHS facilitates the multiple harmonic groups to be used in parallel, which adds more efficiency in comparison with other non-population based meta-heuristic algorithms (X. S. Yang, 2009).

Musicians have three choices when improvising harmony (Kaveh & Ahangaran, 2012):

(1) Playing a note exactly from his or her memory;

(2) Playing a note in the vicinity of the previously selected note;

(3) Selecting a note randomly;

The HS algorithm selects the value of decision variables with similar rules. In order to present the detailed procedure of IHS and its application in the DTCQTPs some notations are needed, which are as follows:

Notations:

HM	Harmony memory.
HMS	Harmony memory size.
$HMCR$	Harmony memory consideration rate.
$PAR(g_n)$	Pitch adjustment rate in generation g_n.

PAR_{min}, PAR_{max}	Minimum and maximum pitch adjustment rate respectively.
NI	Number of improvisation or new solution vector generation.
S_t	Number of no observed improvement in solutions.
g_n	Generation number, $g_n \in \{1,2,\dots,NI\}$.
NHV	New harmony vector.
$PVB^{lower}(i), PVB^{upper}(i)$	Lower and upper possible values for ith decision variable.
N	Number of decision variables.
$x_j, y_j, \acute{x}_j$	Two different solution vectors and new solution vector, respectively.
$\acute{x}_i$	ith decision variable value in NHV.

In a way that is conceptually similar to that of GA, the HS algorithm improves the solution vectors iteratively based on the existing solutions the harmony memory. The harmony memory is a matrix as shown below that comprises solution vectors which are randomly generated in the initial step of the algorithm and modified to increase fit as measured by a fitness function. The random generation of vectors enables the algorithm to search the solution space more efficiently. Each row of the harmony memory is a solution vector, $x_j = \left(x_1^j, x_2^j, \dots, x_N^j\right)$ which consists of N decision variables, set randomly initially.

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \dots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{HMS} & x_2^{HMS} & \dots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix}$$

The next steps are as follows:

3.3.2.1 Initialize the Problem and Algorithm Parameters

There are some parameters that need to be set, namely harmony memory size, harmony memory considering rate (HMCR), pitch adjustment rate, and number of improvisations (which is the stopping criterion). There is some evidence that IHS is less sensitive than other parameters in terms of the chosen parameters values, which alleviates the process of fine-tuning to attain quality solutions (X. S. Yang, 2009).

3.3.2.2 Initialize the Harmony Memory

Initially, the solution vectors in the harmony memory are generated randomly. In this study, each solution vector shows the sequence ordering of service requests, as explained above.

3.3.2.3 Improvise a New Harmony

New solution vectors, $\acute{x}_J = (\acute{x}_1, \acute{x}_2, \ldots, \acute{x}_N)$ will be generated through the improvisation step. Improvisation procedures are triggered by considering three conditions, which are as follows:

(1) Memory consideration;

(2) Pitch adjustment;

(3) Random selection;

Each of these rules are associated with different criteria which must be met in choosing a value for any decision variable.

The power of the IHS algorithm originates from the way the intensification and diversification are handled (X. S. Yang, 2009). In order to mimic the aforementioned rules in improvising a new harmony, two parameters, HMCR and pitch adjustment rate, are used with values ranging from 0.7~0.95 and 0.1~0.5 respectively. In the HS algorithm proposed by Geem, et al (Geem et al., 2001) these parameters are fixed throughout the algorithm improvisations steps, but in IHS the pitch adjustment rate value changes dynamically according to Eq.6. HMCR indicates the degree of elitism, which is the likelihood of a decision variable being selected among the existing values in the harmony memory. It reflects the intensification handling procedure through the algorithm. For instance, HMCR of 0.9 says that there will be a 90% chance of the decision variable being selected from the historically stored harmony memory and 10% chance from the entire possible range. The lower the value the slower the solutions tend to converge. Each decision variable being chosen from the harmony memory must be checked for whether or not it needs the pitch adjusted. In fact, the diversification is controlled by the usage of the pitch adjustment rate parameter through which the variable will be randomly increased or decreased if it does not violate the acceptable values. This procedure will be done for each decision variable until a new solution vector is obtained.

$$PAR(g_n) = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{NI - 1} \times (g_n - 1) \tag{6}$$

3.3.2.4 Update Harmony Memory

Every new solution vector should be evaluated in order to verify whether it dominates the worst solution vector among the harmony memory. If the new solution vector is better than the worst then it will be included in the harmony memory and then the worst one excluded. However, the determination of the worst solution in the harmony memory is done through the NSGA-II procedure which will be discussed in detail in the following parts.

3.3.2.5 Stopping Criterion

The stopping criterion is generally chosen as the maximum number of improvisations. Additionally, the maximum number of iteration where no improvement in solutions is obtained, might be combined with the previous approach. In the current research study, we used the combined approach to enable the algorithm to search for better solutions if there seems to be the chance of finding better solutions. The maximum number of improvisations should be determined based on sensitivity analysis and preliminary model runs; a higher value will increase the computational effort.

3.3.2.6 Pseudo-code for improved harmony search

The pseudo-code of IHS is elaborated as follows:

IHS algorithm procedure:	
For $i = 1\ to\ HMS$	Initialize the HM
Randomly generate solution vectors, x_j	
Evaluate f_1 and f_2	
For $i = 1\ to\ N$	Improvise a new harmony
$PAR\ = PAR(g_n)$;	
If rand() $> HMCR$	Memory consideration
$NHV(i) =$ randval$(PVB^{lower}(i), PVB^{upper}(i))$	
Else	
$D_1 =$ int(rand()$\times\ HMS) + 1$	
$D_2 = HM(D_1, i)$; $NHV(i) = D_2$;	
If rand() $< PAR$	Pitch adjustment
If rand() < 0.5	
$D_3 = NHV(i) +$ rand()$\times(PVB^{upper} - NHV(i))$;	
Else	
$D_3 = NHV(i) -$ rand()$\times(NHV(i) - PVB^{lower})$;	
Evaluate f_1 and f_2 for the NHV;	
If NHV dominates the worst solution vector in HM	Update HM
Replace worst solution vector with NHV	
$S_t = 0$;	
Otherwise $S_t = S_t + 1$;	
If $g_n \leq$ NI	Check stopping criterion
Repeat the procedures; $g_n = g_n + 1$;	
If $g_n >$ NI	
Stop the algorithm	
If $S_t \geq$ maximum number of no improvement observation	
Stop the algorithm	

3.3.3 NSGA-II Framework

Improved non-dominated sorting genetic algorithm (NSGA-II) is an evolutionary algorithm which is used to generate sets of Pareto-optimal solutions which is demonstrated to outperform other approaches, e.g., Pareto archive evolutionary strategy in converging to near true Pareto front (Deb et al., 2002). In this thesis, the proposed methodology of NSGA-II by Deb, et al. (Deb et al., 2002) has been tailored and customized to solve DTCQTP by converging to near optimal solutions. The capability of NSGA-II encourages the application of the method to be applied into more complex and real-world multi-objective optimization problems.

In the designed GA and IHS algorithms the concept of NSGA-II is used in which the fitness assignment to each solution comprises both the rank of the corresponding solution in terms of the front it belongs into and also the crowding distance parameter ($I_{[x_j]distance}$) which indicates the density of solutions in its vicinity.

In order to identify the first non-dominated front, $\bar{F}_1$, each solution needs to be compared with every other solution in the population to find if no other solution dominates the chosen one. In order to find the solutions belong to the next non-dominated fronts,Q, (2^{nd}, 3^{rd} and so on), the solutions of the previous fronts are discounted temporarily and the above procedure is then repeated. To elaborate the basic concept of NSGA-II better to mention that fast non-dominated sorting, sorts the solutions to form the non-dominated fronts and then another criterion, namely, the crowding distance is calculated. Furthermore, between two solutions of different fronts the solution within lower front is more preferable and if the fronts are identical then the one with lower crowding distance is judged to be superior. This procedure in comparing two solutions is called crowded comparison operator denoted by $\prec_n$ (Deb et al., 2002).

The crowding distance operator acts as an estimate of the density of solutions surrounding a particular solution in the population which is the average distance of the two solutions lies on both sides of the chosen point along each of the objectives. More simply, this distance is approximately equal to the perimeter of the cuboid formed by using the vertices of the nearest neighbors. Firstly, the population needs to be sorted in ascending order with respect to each objective function. The boundary solutions in each front (the solutions with smallest and highest objective function in each case) are assigned an infinite crowding distance value ($I_{[1]distance} = I_{[l]distance} = \infty$). In order to present the procedure of NSGA-II the required notations are as follows:

Notations:

S_p	set of solutions that x_j dominates
n_x, n_y	domination count indicating the number of solutions which dominate the solution x_j or y_j
$\bar{F}_i$	front ith which consists of non-dominated solutions
Q	set of solutions of $(i+1)$th front
I	set of all non-dominated solutions where $\|I\| = l$
$I_{[x_j]distance}$	crowding distance of solution x_j, $x_j \in I$
m	number of objectives, here $m = 4$
f_m^{max}, f_m^{min}	maximum and minimum values of the mth objective function respectively

The pseudo-code will then be as mentioned below:

Fast non-dominated sorting procedure:	
For each $x_j \in [\ HM, \acute{x}_j\ ]$; set $S_P = \emptyset$ and $n_x = 0$;	
For each $y_j \in [\ HM, \acute{x}_j\ ]$;	
If $(x_j \prec y_j)$ then $S_P = S_P \cup \{x_j\}$	if x_j dominates y_j, then add y_j to the set of solutions dominated by x_j.
Else if $(y_j \succ x_j)$ then $n_x = n_x + 1$	if y_j dominates x_j, then increment the domination counter of x_j.
If $n_x = 0$ then $\bar{F}_1 = \bar{F}_1 \cup \{x_j\}$	x_j belongs to the first front.
$i = 1$	initialize the front counter.
While $\bar{F}_i \neq \emptyset$; $Q = \emptyset$	Q is used to store the members of next front.
For each $x_j \in \bar{F}_i$	
For each $y_j \in S_P$; $n_x = n_x - 1$	
If $n_y = 0$ then $Q = Q \cup \{y_j\}$	y_j belongs to the next front.
$i = i + 1$; $\bar{F}_i = Q$	

By fast non-dominated sorting the fronts are identified and for the second comparison criterion the procedure is as follows:

Crowding distance assignment procedure:	
$l = \lvert I \rvert$	number of solutions in I.
For each x_j, $I_{[\ x_j]distance} = 0$	initialize the distance.
For each objective m	
$I = sort(I, m); I_{[1]distance} = I_{[l]distance} = \infty$	sort using each objective value and set the distance of first and last points equal to infinity.
For each x_j where $j = 2$ to $(l - 1)$	
$I_{[\ x_j]distance} = I_{[\ x_j]distance} + (I_{[\ x_{j+1}],m} - I_{[\ x_{j-1}],m})/(f_m^{max} - f_m^{min})$	for all remaining points distance will be calculated.

By obtaining the two comparison criteria the new harmony vector is compared by the comparison operator $(\prec_n)$ to check if it is better than the worst solution vector exists in the harmony memory. In multi-objective optimization where there exists conflict among the objectives the Pareto-optimal solutions can be extremely numerous meanwhile it might be tedious for the decision makers in order to attain at last one compromise solution.

3.4 Multiple Criteria Decision Making Models

3.4.1 Evidential Reasoning Framework

MCDM methods are an efficient means of handling the information which facilitates the simultaneous consideration of multiple criteria to assess potential alternatives; this eliminates the time-consuming and costly iterative procedures of reviews and feedback during the planning phase of a construction project. Numerous methods have been developed and utilized to deal with the MCDM problems such as additive utility (value) function methods (Keeney & Raiffa, 1976), outranking methods (Guitouni, Martel, Bélanger, & Hunter, 2008), and Evidential Reasoning (ER) (Bazargan-Lari, 2014).

In the ER approach, alternatives are subdivided into attributes which are influential in assessing the overall performance of those alternatives. The attributes use belief structures and belief matrices; this enables the ER approach to deal with different types of attributes, e.g., qualitative, uncertain etc. The attributes form a hierarchical structure in which the top level is the overall performance of each alternative. In order to evaluate the overall performance, the ER approach begins by aggregating the information from the bottom level of the hierarchical structure, based on the rule and utility information transformation techniques for each level. The levels are defined through the hierarchical structure of the attributes.

D. L. Xu (2012) outlined four general steps in applying the ER approach:

(1) A comprehensive understanding of the MCDM problem is attained to identify and determine the multiple attributes which can be conflicting;

(2) The belief structure of the attributes are transformed into a unified belief structure according to the weight of each attribute. This procedure utilizes the rule or utility technique in aggregating the information;

(3) Based on the aggregated information, the average utility score of each alternative is calculated. The alternative with the highest average utility score is defined as the best solution; and

(4) Distributed assessment outcomes, utility scores, or utility intervals, if some information is missing, are generated. In this step, the solution with the highest utility score is preferred over the solutions with lower corresponding values.

In general, the output of any multi-objective optimization technique is a collection of non-dominated solutions which are called the Pareto-optimal solutions. The Pareto solutions share one common characteristic: no improvement in any objective can be obtained without sacrificing at least one of the other objectives (Eshtehardian et al., 2009). On the other hand, in problems with conflicting objectives, there might be numerous Pareto-optimal solutions. In this case it is extremely tedious for the DMs to investigate each solution one by one to agree on one optimal solution without using any systematic multi-criteria assessment technique.

Mungle et al. (2013) employed a fuzzy clustering technique to find the best alternative, which is near the best value in each objective, while being far away from the worst possible values to establish a compromise between the conflicting objectives. This is a very simple procedure to determine the most appropriate alternative. However, the DMs are not able to cooperate with each other, nor can they express their own unique weights for each objective. Another limitation of this approach is that it cannot deal with various types of criteria via qualitative and uncertain attributes. Hence, it is believed that by using the ER approach the solution space of the problem can be ranked, and the highest ranked solutions can be investigated for the potential of being accepted. However, it must be noted that the solution with the highest rank according to one DM might not have a strong chance of being accepted as the optimal solution if the other DMs assess the same solution with a much lower rank. Therefore, there is a need to establish a balance between the powers of the DMs in selecting the optimal solution.

Various quantitative and/or qualitative attributes must be identified by the DMs to form the hierarchical structure of the overall performance. The attributes can simply be the problem objectives; in this case time, cost, and quality are the attributes. However, other types of attributes can be incorporated into the problem, such as the compatibility of the alternative with the company's strategic and management plan, the health and safety issue of the alternative etc. Another capability of the ER approach is to consider ignorance as a type of uncertainty which originates from the situation in which some participants (DMs) do not give any response to a specific attribute, for reasons such as having no knowledge about that specific subject (D. L. Xu, 2012).

The ER approach is based on the Dempster-Shafer theory of evidence (Shafer, 1976), and the decision theory for dealing with various types of criteria of both a quantitative and qualitative nature in decision making (Bazargan-Lari, 2014). The ER approach has also been applied in research areas such as regional hospital solid waste assessment

(Abed-Elmdoust & Kerachian, 2012), and determining the best layout of water quality monitoring stations (Bazargan-Lari, 2014). In order to implement the ER approach, the following steps must be followed:

(1) The expectations and requirements of the stakeholders and DMs should be investigated to identify the multiple assessment criteria of the MCDM problem. This preliminary step is vital in order to assure that the influential factors are identified for the specific problem under consideration. This procedure necessitates a full comprehension of the DMs preferences, which are reflected in the weights of each attribute. In addition, various types of contributing attributes (e.g., quantitative, qualitative, precise numbers, fuzziness, uncertainty, belief structures and comparison numbers) are gathered. For example, the cost of construction equipment might be precise while the cost of the excavation might be expressed within a range. The technical ability of a subcontractor might be expressed as a belief structure for which it might be 'Good' to a degree of belief of 34%, and simultaneously be 'Very Good' with a degree of belief of 63%, which is expressed as $\{$(Good, 0.34), (Very Good, $0.63)\}$. The summation of both degrees of belief is equal to 97% $(0.34\% + 0.63\%)$ with 3% as ignorance. Due to lack of knowledge about the technical capability of a subcontractor, some might prefer not to assess that criterion, which is called 'lack of evidence', in which case the summation of probability does reach to one.

The belief structure of each attribute is determined in this step. Implementing the rule or utility techniques of information aggregation, the belief structure of the attributes is transformed into a unified belief structure. As in Figure 2, the 'Very Good' and 'Very

Bad’ are assigned one and zero respectively, and the other grades may/may not be evenly distributed.

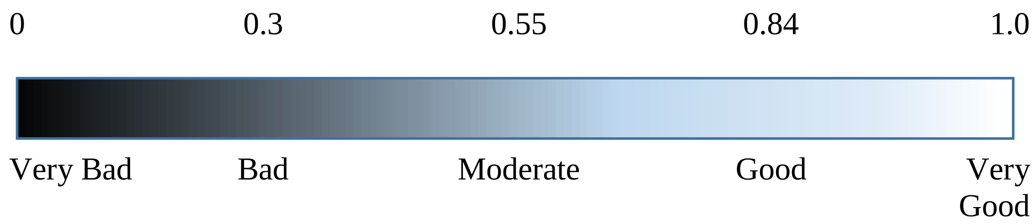


Figure 2. Utility-based preference function

(2) The assessment information of various types of criteria is aggregated to obtain the total assessment for each alternative based on the ER framework and formulations.

(3) The utility scores, or utility intervals in the case of missing information, are developed. Utility based ranking can judge the overall performance of each alternative by considering the influential attributes simultaneously through a systematic and rational prioritizing methodology. The procedure identifies the best schedule alternative for the project, which is the most favored overall by the DMs, as the final acceptable solution is a trade-off between the preferences of the DMs.

The bottom level attributes are called basic attributes. The weight assigned to the ith basic criterion (W_i) reflects the importance of that criterion in the assessment of the general criterion. W_i can be determined by different approaches (e.g., pair-wise comparison, directly by the decision makers, Entropy, etc.). Since the weights express the relative importance, the normalized values are more useful than the absolute values (D. L. Xu, 2012). The normalized weight of ith basic attribute, ω_i, is calculated using Eq.7:

$$\omega_i = \frac{W_i}{\sum_{i=1}^{L} W_i} \quad , \quad i \in \{1,2,\dots,L\} \tag{7}$$

$$\text{S.T. } 0 \leq \omega_i \leq 1 \quad , \quad \sum_{i=1}^{L} \omega_i = 1$$

The linguistic terms such as ‘worst’, ‘good’, and so on are called grades where the whole set of grades is defined as $H = \{H_n, n = 1,2,\dots,N\}$. The analytical format of the ER algorithm has been demonstrated by Guo, Yang, Chin, and Wang (2007) and Y. M. Wang, J. B. Yang, and D. L. Xu (2006) to be able to calculate the combined degrees of belief namely, β_n and β_H without using the recursive ER algorithm, which increases computational time and effort. The proposed method uses the analytical format of the ER algorithm to calculate the combined degree of belief, β_n of the nth grade, where $n \in \{1,2,\dots,N\}$ and β_H represents the incompleteness assessment of the whole set of H. β_n and β_H can be calculated using Eqs.8 and 9, respectively:

$$\beta_n = \frac{\prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1,j\neq n}^{N} \beta_{i,j}\right) - \prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1}^{N} \beta_{i,j}\right)}{\sum_{n=1}^{N}\prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1,j\neq n}^{N} \beta_{i,j}\right) - (N-1)\prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1}^{N} \beta_{i,j}\right) - \prod_{i=1}^{L}(1-\omega_i)} \tag{8}$$

$$\beta_H = \frac{\prod_{l=1}^{L}\left(1-\omega_i \sum_{j=1}^{N} \beta_{i,j}\right) - \prod_{l=1}^{L}(1-\omega_l)}{\sum_{n=1}^{N}\prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1,j\neq n}^{N} \beta_{i,j}\right) - (N-1)\prod_{i=1}^{L}\left(1-\omega_i \sum_{j=1}^{N} \beta_{i,j}\right) - \prod_{i=1}^{L}(1-\omega_i)} \tag{9}$$

The degree of belief of the ith basic criterion for the jth grade is denoted by $\beta_{i,j}$, and N is the number of grades of set H. In order to rank the alternatives, it is necessary to translate the combined degrees of belief and the incomplete assessment (β_n and β_H)

into one single utility score. Hence, it is necessary to generate numerical values equivalent to the belief structure:

$$u_{max} = \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_n + \beta_H) u(H_N)$$

$$u_{min} = (\beta_1 + \beta_H) u(H_1) + \sum_{n=2}^{N} \beta_n u(H_n) \tag{10}$$

$$u_{ave} = \frac{u_{max} + u_{min}}{2}$$

where u_{max}, u_{min}, and u_{ave} are the maximum, minimum, and the average utility score. $u(H_n)$ is a function showing the utility score of the nth grade. For example, if $n = 5$, and all the grades are spaced equally in the interval of [0,1], then $u(H_n) = \{0, 0.25, 0.5, 0.75, 1$. It is noticeable from Equation (10) that if there is no incomplete assessment ($\beta_H = 0$), all three cases of maximum, minimum, and average utility scores are exactly the same and can be determined by using the following equation:

$$u_{max} = u_{min} = u_{ave} = \sum_{n=1}^{N} \beta_n \cdot u(H_n) \tag{11}$$

Since the ER approach might seem rather too complex for non-specialists, in Table 3 a stepwise example showing the procedures of the ER approach in evaluating a solution is solved. In this example, a solution with the time and cost value of 155 days, and $140,000 respectively is shown to have a contribution of 32.2% to the overall performance of the solution when both attributes are considered simultaneously.

Table 3. ER evaluation procedure to rank the Pareto-optimal solutions

The ER approach evaluates a solution with the corresponding values for the objectives as follows:

Objectives:	Time (day)	Cost ($)	Quality (%)
Values:	125	139,000	70.40

Step 1. Identify the worst and best possible values for the attributes (e.g., time, cost, and quality).

	Time (day)	Cost ($)	Quality (%)
Best:	104	112,500	96.43
Worst:	135	171,980	65.50

Step 2. Assign normalized weights for each attribute.

Attributes:	Time	Cost	Quality
ω_i:	0.3128	0.3806	0.3048

Step 3. Calculate the belief structure for each attribute as shown in Figure 3. The x-axis indicates the grades, e.g., 'Worst', 'Poor', 'Average', 'Good', 'Best' and the corresponding values for each attribute. The quality of 94% lies between 'Good' and 'Best' grades with the quality values of 88.7% and 96.43%, respectively. This attribute belongs to 'Best' grade with 68% belief, and with 32% degree of belief belongs to grade 'Good'. The same procedure is done for the time and cost attributes. The belief structures for each attribute are as below:

Belief structures of the attributes.

Grades:	Worst	Poor	Average	Good	Best
Time	0	84	16	0	0
Cost	0	0	78	22	0
Quality	0	0	0	32	68

Step 4. Calculate the combined degree of belief β_n based on Eq.10, since there is no incomplete assessment $\beta_H = 0$.

Grades:	Worst	Poor	Average	Good	Best
β_n:	0.0	0.244	0.377	0.186	0.193

Step 5. Calculate the utility scores according to Eq.11.

$$u_{max} = u_{min} = u_{ave} = 0.402$$

The average utility score indicates that the solution satisfies DMs to an extent of 40.2% when considering all the attributes simultaneously.

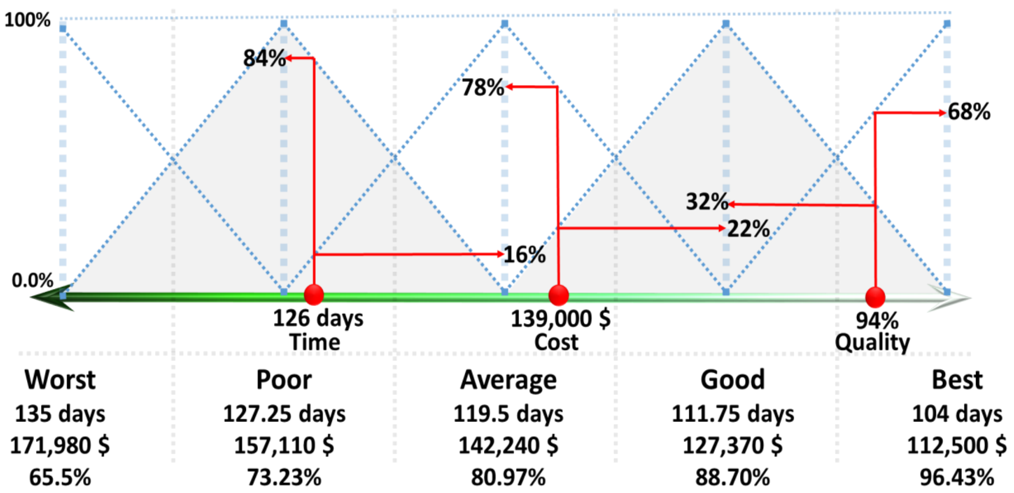


Figure 3. Transferring each attribute to belief structure

3.4.2 PROMETHEE Decision Making Model

Decision making techniques are very useful in all facets of engineering such as economic (Turskis & Zavadskas, 2011), environmental management (Gregory et al., 2012), green supplier evaluation (Kannan Govindan, Rajendran, Sarkis, & Murugesan, 2013), system engineering and management (Parnell, Driscoll, & Henderson, 2011), and etc. Following the pioneering research done by Brans and Vincke (1985) PROMETHEE-based decision making models have successfully been applied in many fields and several researchers have used them decision making problems (Behzadian et al., 2010).

The basic principle of PROMETHEE II is based on a pairwise comparison of alternatives along each recognized criterion. Alternatives are evaluated according to different criteria, which have to be maximized or minimized. The steps in developing a PROMETHEE II-based decision making model are as follows:

3.4.2.1 Weights of the Influential Criteria

As mentioned earlier, the DTCQTP is an interdisciplinary subject involving various and occasionally conflicting objectives, e.g., time, cost, and cost which need to be simultaneously optimized. The involving DMs might express their expected importance towards each objective by assigning normalized weight to each objective.

Based on the importance of time, cost, and quality of the construction project, and the decision makers' levels of importance for each criterion, the weights can be specified to be used in the model to select the best project scheduling alternative. Here, the benchmark case problem of DTCQTP adapted from Feng et al. (1997) is selected. According to Monghasemi et al. (2014) the following weights for the objectives are considered.

Table 4. Normalized weights of the objectives

Objectives:	Time	Cost	Quality
Normalized weights:	0.3128	0.3806	0.3048

3.4.2.2 Preference Function

In the process of MCDM problem, occasionally the DM needs to provide his/her preferences over a set of n decision alternatives via pairwise comparison of the alternatives with respect to a single criterion. The preferences relations are a useful means of expressing the DM's preference information (Chakeri, Dariani, & Lucas, 2008), due to their simplicity as they only require comparison of two alternatives with respect to a single criterion.

Several different preference functions have been defined with different characteristics (Figueira, Greco, & Ehrgott, 2005; Podvezko & Podviezko, 2011) which are:

(1) Usual criterion which is used when the decision maker cannot allocate importance for the differences between criteria values and only seems to know the formula “the more the better” (Podvezko & Podviezko, 2010);

(2) U-shape function which is suitable for strict comparison of any two alternative (among two criteria the one with better value has complete preference which is 1, while the other one is assigned 0 preference);

(3) V-shape/linear function which accounts for moderate comparison and in contrary with U-shape function it establishes a linear correlation between the point of indifference, 0, and the point of strict preference, 1;

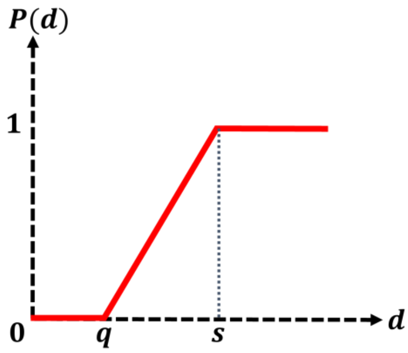
(4) Level criterion;

(5) V-shape with indifference preference, and;

(6) Gaussian criterion.

The concepts and characteristics of these preference functions can be found in Podvezko and Podviezko (2010). Here, the V-shape with indifference preference function is chosen since in addition to moderate comparison, it also defines a range of indifference for comparison and due to all these reasons, it is the most valuable preference function which has attracted the largest number of theoretical and practical applications for evaluations carried out by PROMETHEE methods (Podvezko & Podviezko, 2010). Following, these features will be explained and explicitly described.

The range of values of preference functions $P_i(d) = P_i\big(d_i(a\,, b)\big)$ falls between zero and one. Values of the functions reveal the level of preference of one alternative over another. Shapes of functions depend on boundary parameters q and s, which are chosen by a decision-maker for each criterion i, namely q_i for the lower and s_i for the upper boundary of the argument thus making two alternatives a and b indifferent in respect of the criteria R_i when the difference between values of criteria r_{ia} and r_{ib} for these alternatives $d_i(a\,, b) = r_{ia} - r_{ib}$ is smaller than the boundary parameter q_i and thus making the alternative a of the strict preference in favour of the alternative b when the difference between criteria values r_{ia} and r_{ib} for these alternatives $d_i(a\,, b) = r_{ia} - r_{ib}$ is greater than the boundary parameter s_i . When the difference falls between q_i and s_i preference criterion of the alternative a in respect of the alternative b varies between zero and one. Figure 4 shows the V-shape with indifference preference function.



$$\boldsymbol{P(d)} = \begin{cases} \mathbf{0} & \boldsymbol{d \le q} \\ \dfrac{\boldsymbol{d-q}}{\boldsymbol{s-q}} & \boldsymbol{q < d \le s} \\ \mathbf{1} & \boldsymbol{d > s} \end{cases}$$

Figure 4. V-shape with indifference pereference function

3.4.2.3 Calculation of the Global Preference Index

For each pair of alternatives a and b, the pair-wised comparison, $\pi(a, b)$, is calculated as follows:

$$\forall a, b \in A \qquad \pi(a,b) = \sum_{i=1}^{m} \omega_i \cdot P_i\big(d_i(a\,,b)\big) \tag{12}$$

Where A is the finite set of existing alternatives, and $\pi(a,b)$ denotes the preference of a over b and is simply a weighted sum of $P_i\big(d_i(a\,,b)\big)$ values for each criterion. The greater the $\pi(a,b)$ value, the more preference alternative a has in comparison with b.

3.4.2.4 Calculation of the Outranking Flows

In the next step, rank of the alternative a among a finite set of other alternatives is based on calculating the value of preference of a over the other alternatives, and also the value for not preferring a over the other ones. These are called positive outranking flow, $\varphi^+(a)$, and negative outranking flow, $\varphi^-(a)$, respectively. The net outranking flow, $\varphi(a)$, is then calculated as shown in Equation (15) which shows the overall/net preference of alternative a over all the other existing alternatives. These are calculated as follows:

$$\varphi^+(a) = \frac{1}{n-1}\sum_{x \in A} \pi(a,x) \tag{13}$$

$$\varphi^-(a) = \frac{1}{n-1}\sum_{x \in A} \pi(x,a) \tag{14}$$

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \tag{15}$$

3.4.3 TOPSIS Ranking Model

TOPSIS is a very common technique in the field of multi-criteria decision making which was first proposed by Hwang and Yoon (1981). The TOPSIS technique attempts to rank the alternatives based on two parameters; (a) minimum distance from the positive ideal solution; (b) farthest distance from the negative ideal solution (Dymova et al., 2013). In simple words, the best solution is the one with lowest distance from the ideal solution while being as far as possible from the worst solution in that case.

the TOPSIS technique has been widely used in many fields, e.g., management of supply chain (K. Govindan et al., 2013), industrial robotic system selection (Chaghooshi et al., 2012), the optimal green supplier selection procedure (Kannan et al., 2013). In this study, the TOPSIS technique is integrated to the body of GA and IHS algorithm in order to rank the Pareto-optimal solutions obtained from multi-objective optimization techniques. The procedure of TOPSIS in evaluating n number of alternatives against m number of objectives is described as below:

Step 1: Assign normalized weights w_j to the jth objective, where $\sum_{j=1}^{m} w_j$.

Step 2: Normalize the jth objective of the ith solution (f_{ij}), where the normalized value is obtained through Eq.16:

$$n_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{n} {f_{ij}}^2}} \qquad i = 1,2,\dots,n \quad \text{and} \quad j = 1,2,\dots,m \tag{16}$$

Step 3: Calculate the weighted normalized value of each objective for the solutions using Eq.17:

$$v_{ij} = w_j \cdot n_{ij} \ , \quad i = 1,2,\dots,n \quad \text{and} \quad j = 1,2,\dots,m \tag{17}$$

Step 4: Sort the weighted normalized values for each criterion to determine the positive ideal solution, $V^+ = \{v_j^+ | v_1^+, v_2^+, \dots, v_m^+\}$, and the negative ideal solution, $V^- = \{v_j^- | v_1^-, v_2^-, \dots, v_m^-\} v$.

Step 5: Calculate the distance of each solution from the positive ideal solution (V^+), and negative ideal solution (V^-) according to Eq.18:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2}$$
$$d_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2} \qquad i = 1,2, \dots, \mathrm{n} \qquad (18)$$

Step 6: calculate the relative closeness coefficient for the $i$the solution (CC_i) using Eq.19:

$$0 \leq CC_i = \frac{d_i^+}{d_i^+ + d_i^-} \leq 1 \qquad i = 1,2, \dots, \mathrm{n} \qquad (19)$$

The closeness coefficient determines which solution has the highest rank on the basis that the lth solution is better than the kth solution if and only if $CC_l > CC_k$.

Chapter 4

CASE PROBLEM

4.1 Description of the Benchmark Case Problem

To verify and demonstrate the efficacy of the proposed model to integrate the MCDM methods, namely, ER, PROMEHTHEE, and TOPSIS, into DTCQTPs, a highway construction project activity network consisting of 18 activities, first proposed by Feng et al. (1997), was adapted. The activity on the node network diagram of the case study is illustrated in Figure 5. Mungle et al. (2013) modified the data to account for the quality associated with each of the options of the activities. The corresponding time, cost, and quality for each mode of activities are listed in Table 5. The indirect cost is assumed to be 50$ per day with the due date being taken as 121 days. The incentive reward and the tardiness penalty are $\$120/\mathrm{day}$ and $\$200/\mathrm{day}$, respectively. The relative importance, α, between Q_{min} and Q_{ave} is taken as 0.4 which ensures that no activity in the schedule is preferred that has a quality lower than the average quality of all the selected options for the activities.

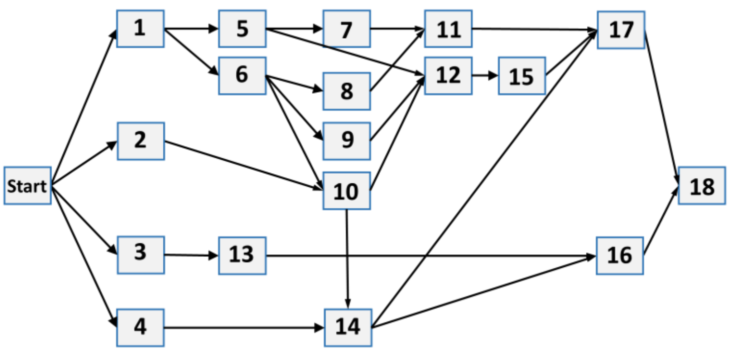


Figure 5. 18-activity on node network representation of the case example

As indicated in Table 5, each activity in DTCQTPs are associated with multiple execution modes, where time, cost, and quality for each activities' options are identified. The costs of the activities include only the direct cost. In DTCQTP the solution space increases exponentially for medium and large size problems as the options for the activities increase (Tavana et al., 2014). In this case example, each activity possesses approximately 3.4 alternatives, leading to 3.6 billion possible activity schedules for the entire project. Hence, the solution space is extremely large so that exact mathematical optimization models might be time-consuming, while the meta-heuristic approaches such as GA and IHS can be more efficient in terms of time saving.

Table 5. Data of the 18-activity network case example

#	Preceding activities	Options-(time (day), cost ($), quality (%))				
		1	2	3	4	5
1	-	(14,2400,100)	(15,2150,90)	(16,1900,86)	(21,1500,77)	(24,1200,63)
2	-	(15,3000,98)	(18,2400,87)	(20,1800,81)	(23,1500,77)	(25,1000,60)
3	-	(15,4500,100)	(22,4000,80)	(33,3200,62)	-	-
4	-	(12,45000,99)	(16,35000,74)	(20,30000,59)	-	-
5	1	(22,20000,100)	(24,17500,93)	(28,15000,77)	(30,10000,61)	-
6	1	(14,40000,95)	(18,32000,76)	(24,18000,59)	-	-
7	5	(9,30000,97)	(15,24000,70)	(18,22000,61)	-	-
8	6	(14,220,95)	(15,215,83)	(16,200,75)	(21,208,68)	(24,120,61)
9	6	(15,300,100)	(18,240,97)	(20,180,81)	(23,150,71)	(25,100,63)
10	2,6	(15,450,94)	(220,400,79)	(33,320,63)	-	-
11	7,8	(12,450,96)	(16,350,72)	(20,300,61)	-	-
12	5,9,10	(22,2000,99)	(24,1750,89)	(28,1500,70)	(30,1000,62)	-
13	3	(14,4000,99)	(18,3200,73)	(24,1800,60)	-	-
14	4,10	(9,3000,100)	(15,2400,79)	(18,2200,63)	-	-
15	12	(16,3500,100)	-	-	-	-
16	13,14	(20,3000,97)	(22,2000,89)	(24,1750,81)	(28,1500,72)	(30,1000,67)
17	11,14,15	(14,4000,98)	(18,3200,73)	(24,1800,62)	-	-
18	16,17	(9,3000,98)	(15,2400,75)	(18,2200,63)	-	-

To seek for the Pareto-optimal solutions two multi-objective optimization techniques, namely, GA and IHS, based on the powerful NSGA-II procedure are developed. Although the two approaches should be able to converge the near true Pareto-optimal front, GA and IHS have different performance criteria in terms of speed of convergence, and etc. Thus, to draw a comparison between GA and IHS, both of these techniques are utilized. The performance analysis of GA and IHS are done by calculating factors such as computational time (CT), generational distance (GD), and range variance (RV) (Zitzler, Deb, & Thiele, 2000). These quantitative metrics address speed of convergence, convergence degree, and sparse-degree of the non-dominated solutions respectively. Mungle et al. (2013) have investigated the performance of multi-objective genetic algorithm, fuzzy clustering based genetic algorithm, and combined scheme-based multi-objective particle swarm optimization, concluding that the fuzzy clustering based genetic algorithm outperforms the other two methods with respect to both GD and RV; however the CT is approximately 4 times greater in fuzzy clustering based genetic algorithm. Therefore, in this thesis, these performance analysis factors are calculated for both GA and IHS, separately. The results indicate that IHS algorithm is more efficient in converging the Pareto-optimal front when compared with GA. The results are presented in the following chapter.

4.2 Measuring the Quality

Mungle et al. (2013) proposed the methodology to quantify the expected quality from an activity. The quality is taken as a measurable factor, which can be quantified by decomposing the overall quality objectives into its main attributes and criteria relating to the project activities. To quantify the expected quality of an activity after it has been completed, some quality indicators should be first defined and identified. Since, the case problem is related to highway construction, some quality based contractor pre-qualification factors can be introduced. As an example, a few of these quality measurements and their quality indicators are listed in Table 6.

Some quality indicators have been determined in a few studies in the context of contractor prequalification system as proposed by Anderson and Russell (2001). They proposed a framework through which the long term performance of the outcome of the project is linked to its quality indicators. This quality indicators can be determined based on expert judgments, stakeholders' expectations and project specifications. Subsequently, the identification of the quality indicators should be followed by some measurement procedures. The measurement procedure can consists of some performance tests and laboratory or on-site experiments. Accordingly, the obtained results from these quality measurement approaches can be stored and recorded in a similar procedure with time and cost analysis from past construction projects of identical nature (Mungle et al., 2013). In order to handle these quality indicators the collected quality measurements are then used in AHP method to determine the quality of each subcontracting alternative to perform the construction activity as shown in Figure 6.

Table 6. Quality measurement and its indicators

Construction activity	Quality measurement	Measurement methods of indicators
Bituminous pavement	Asphalt content	Measure through ignition oven
	Air void	Super-pave gyratory compactor test
	Void in mineral aggregate	Super-pave gyratory compactor test
	Ride quality	Measure by profilometer
	In-place air void	Measure through use of cores
Concrete pavement	Compressive strength	Compression test
	Flexural strength	Split cylindrical test
	Ride quality	Measure by profilometer
	Thickness	Measure through use of cores

Figure 6 proposes the framework to measure the expected quality of a contractor which is assigned for an activity. The framework measure the quality based on the previously recorded data of project done by the assigned contractor for projects with identical nature. For each specific activity, the quality indicators and its measurement methods are identified as mentioned earlier. Then by using the AHP method as proposed by Mungle et al. (2013) the expected quality of that activity is measured. The AHP is able to identify the importance weights for each quality indicator (Aragonés-Beltrán et al., 2014).

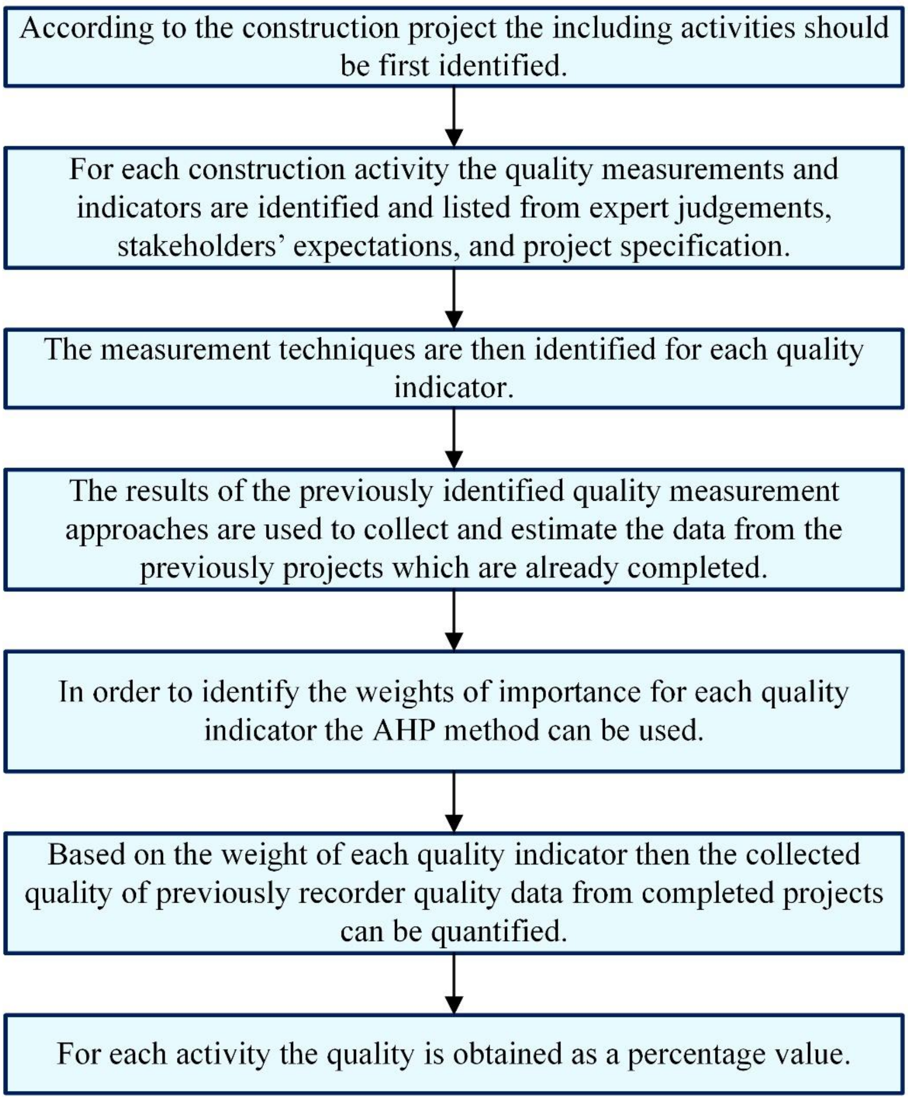


Figure 6. Framework of measuring the expected quality of contractors

Chapter 5

RESULT AND DISCUSSION

As the next stage in integrating MCDM methods into multi-objective techniques, the obtained Pareto-optimal project scheduling alternatives are ranked based on the ER, PROMETHEE, and TOPSIS methods. The novelty of employing the aforementioned MCDM methods in the context of project scheduling provides more practical solutions. Moreover, the DTCQTPs have been shown to have the potential of being solved by integrating both multi-objective optimization techniques and MCDM methods.

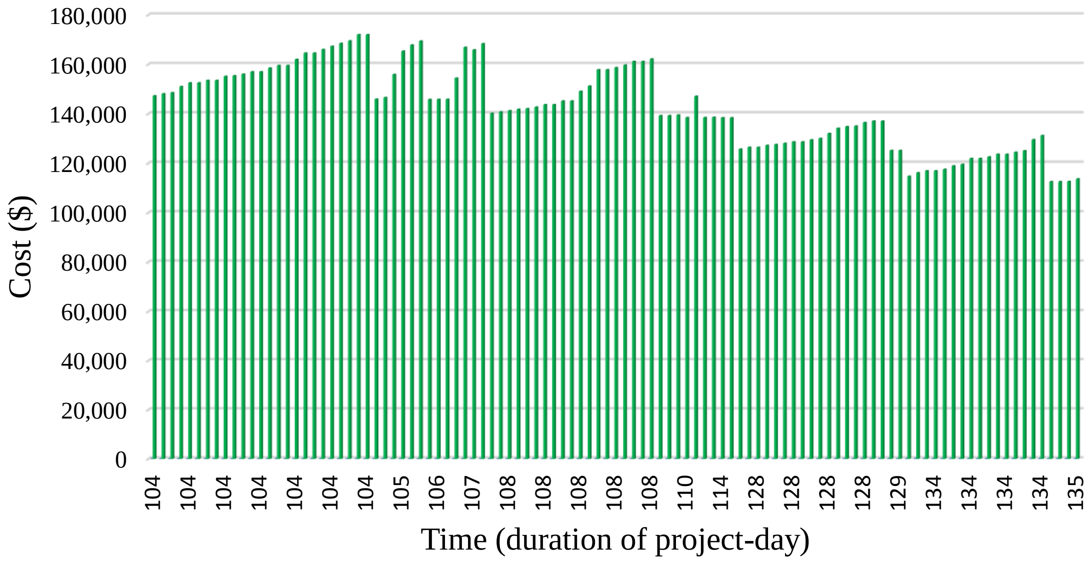
The proposed GA and IHS multi-objective optimization algorithms with NSAG-II-based procedure to solve DTCQTPs were coded in MATLAB R2013a. The GA algorithm parameters are set as follows: $n_{Pop} = 300$ with $Generation = 1{,}000$, $P_c = 0.9,\ P_m = 0.1$. The mean program running time, without any attempt to improve the computational time, was 7.80 minutes on a personal computer (Intel Core i5-3230M with CPU 2.6GHz with 4GB memory), which is an acceptable time in comparison with the solution space consisting of almost 3.6 billion possible scenarios, and only searching 0.0081% of the total number of potential solutions to obtain the Pareto solutions.

The IHS algorithm parameters are determined based on sensitivity analysis and preliminary model runs for sufficient iterations are set as follows: $HMS =$

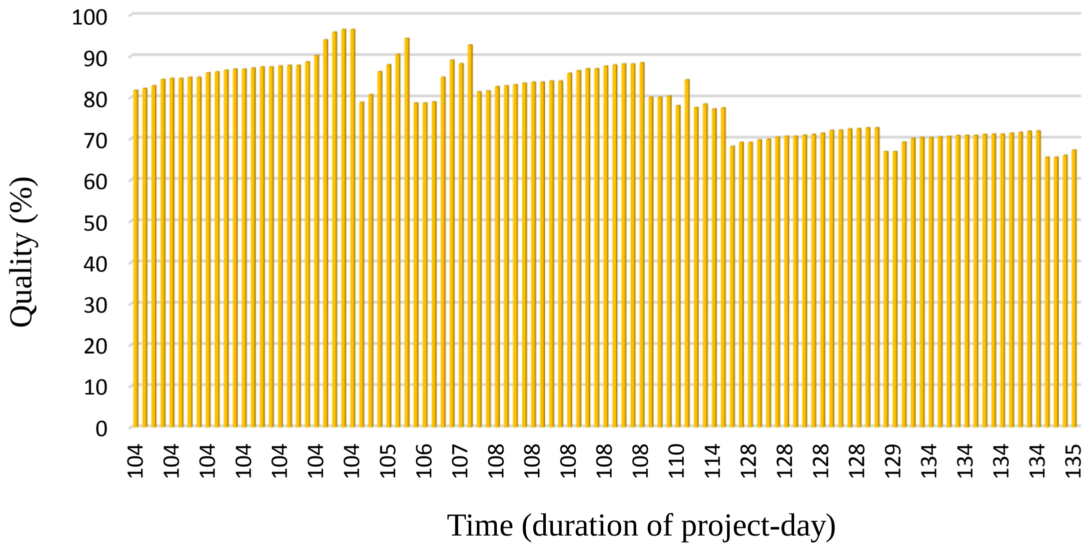
$40, HMCR = 0.9, PAR_{min} = 0.1, PAR_{max} = 0.8, NI = 10{,}000$.The mean program running time in this case was 17.41 minutes on the same computer platform. In comparison with the GA algorithm the IHS is more time-consuming with almost 9.10 minutes longer computational time.

The proposed algorithms were able to find the same Pareto solutions in 16 optimization trials out of the total 20 that were performed; this implies that the proposed approach is able to attain the same global Pareto optimal solutions with 80% accuracy. In the remaining four trials, the Pareto solutions were in a maximum of three points which were not global optimum points. This arose due to the stochastic nature of the proposed multi-objective optimization models. However, in comparison with the low percentage of search space and significant solution space, the accuracy of the algorithms is noteworthy.

In every 16 runs of the algorithm, exactly 105 Pareto solutions were identified; due to space limitations they are plotted in two sub-figures (a and b) of Figure 7. To simplify reading the data from the figures the Pareto solutions are initially sorted according to the time objective, and the solutions with identical time objectives are then sorted with respect to the cost objective. Figure 7.a shows the cost objective *vs.* time of the project, while in Figure 7.b the same Pareto solutions are shown in terms of quality *vs.* time objective. The Pareto solutions obtained for the 18 activity network benchmark case study of DTCQTP are provided in Appendix. A. This can be used for future research studies.



(a)



(b)

Figure 7. Pareto-optimal solutions. (a) cost vs. time; (b) quality vs. time

The weights of the objectives are in-line with those proposed by Monghasemi et al. (2014) which are shown in Figure 8. The weights are 0.3128, 0.3806, and 0.3048 for time, cost, and quality objectives, respectively. As indicated in Figure 8 the cost objective is the highest important criterion while the quality is the lowest one. This is also true in real practice where the monetary issues plays a vital role in evaluating and accepting the construction project scheduling alternatives, while the lowest attention is paid to the overall quality of the project. On the other hand, the duration of the construction projects can directly affect the overall cost, where any delay in the project can add indirect cost to the project. With this respect, these weights are assigned for the objectives in all the MCDM methods proposed here, namely, ER, PROMETHEE, and TOPSIS, in order to preserve the consistency of the results. In addition, these same weights can provide the opportunity of comparing the performance of these proposed MCDM methods.

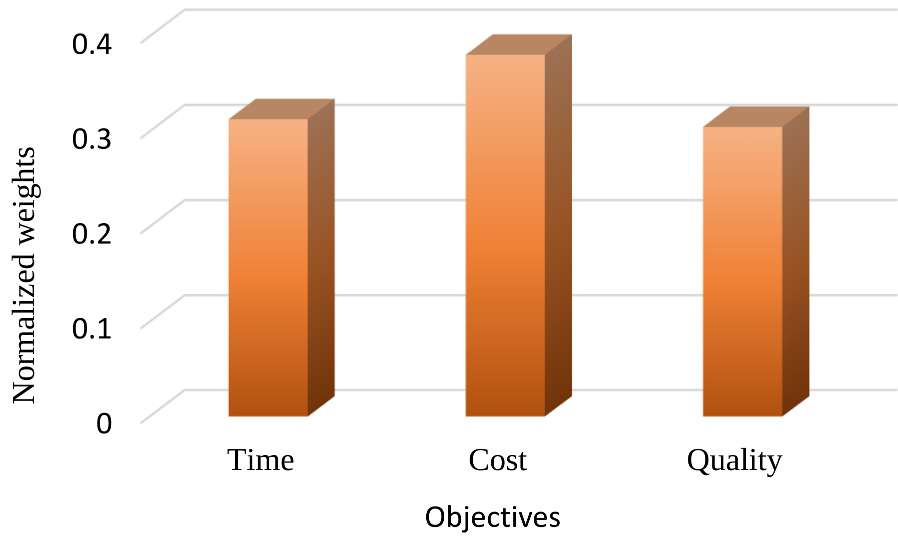
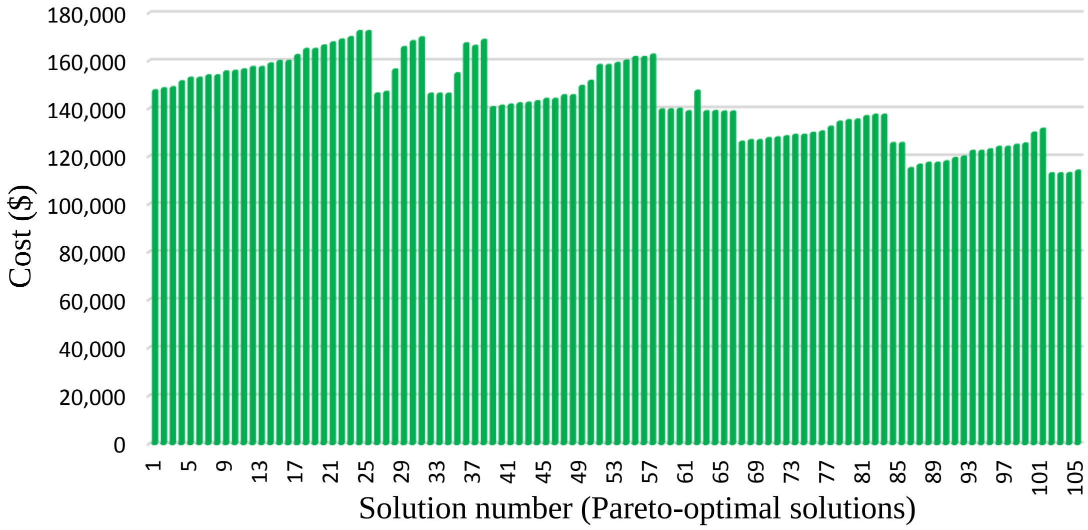


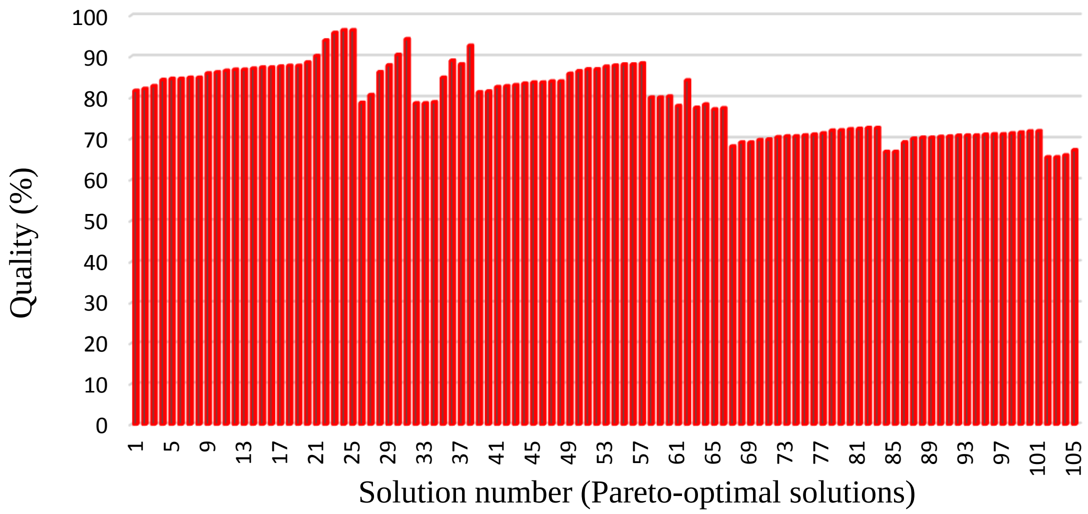
Figure 8. Normalized weights of the objectives, namely, time, cost, and quality

The obtained 105 Pareto-optimal solutions are shown in two sub-figures, a and b, in Figure 9. In Figure 9a, the cost objective is plotted against the duration of the project. Accordingly, as the project duration increases the cost of the project is reduced. From Figure 9a it is noticed that the from the 1st solution up to the 25th solution there is an increase in the overall cost of the project; however, it must be noticed that these 25 project scheduling alternatives have the same 104 days for the duration of the project, and the increase in the cost is due to the increase in the quality. The 1st solution with the quality of 81.70% has a lower cost when compared with the 25th solution with the quality of 96.43%, although both of these alternatives have the project duration of 104 days.

In real practice, if two different project scheduling alternatives have the same duration, the one with higher quality is obviously more costly. On the other hand, any increase in the project duration leads into the reduction in the construction cost. With this respect, as noticed in Figure 9a, a similar behavior should be expected from the quality objective, which can be seen as in Figure 9b. Therefore, where there exist an increasing trend in the cost objective among the solution, the same trend can be tracked when the quality is considered.



(a)



(b)

Figure 9. Pareto-optimal solutions; (a) cost vs. the number of Pareto-optimal solutions; (b) quality vs. the number of Pareto-optimal solutions

To rank the Pareto-optimal solution based on the ER approach, the overall performance of each project scheduling alternative is calculated, denoting the degree to which each alternative is acceptable when considering all the criteria, namely, time, cost, and quality, simultaneously. Thereby, to assess the overall performance of each solution, one must provide a hierarchical structure to relate the time, cost, and quality attributes with their associated normalized weights to the overall performance criterion

(Figure 10). The solutions are then ranked according to the utility scores obtained for the overall performance.

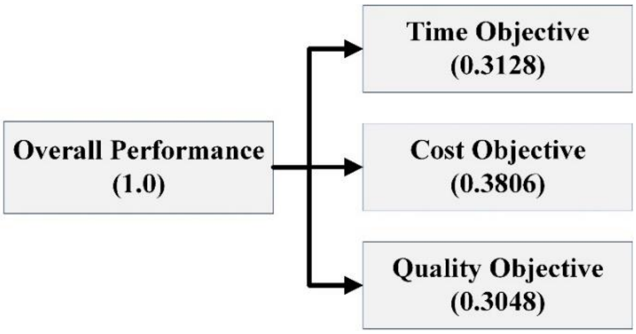


Figure 10. Hierarchical structure of overall performance assessment criteria

Based on the ER approach the 105 obtained Pareto-optimal project scheduling alternatives are ranked, and their overall ER assessment scores are shown in Figure 11. The higher the ER assessment score the better the overall performance of the alternative. This is quite interesting that from the 67^{th} solution there is a significant drop in the overall ER assessment where the 67^{th} solution has 40.05% overall ER score.

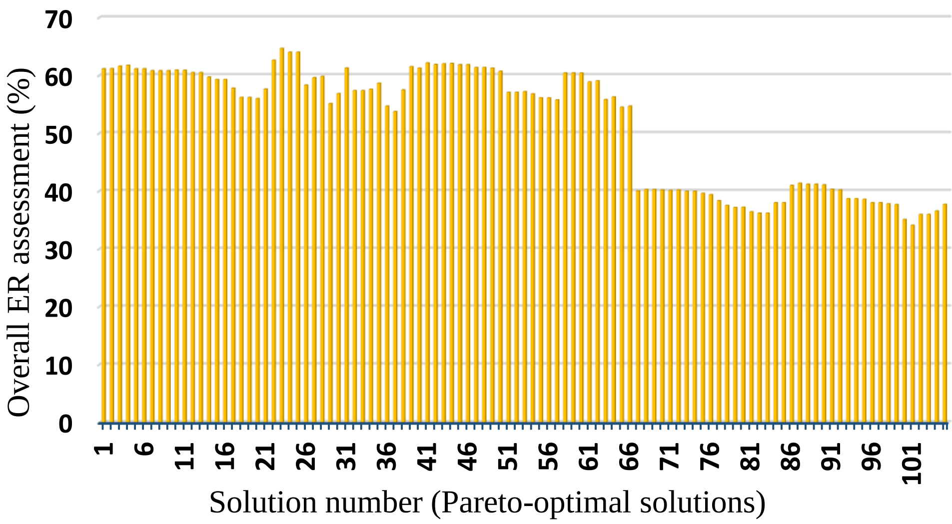
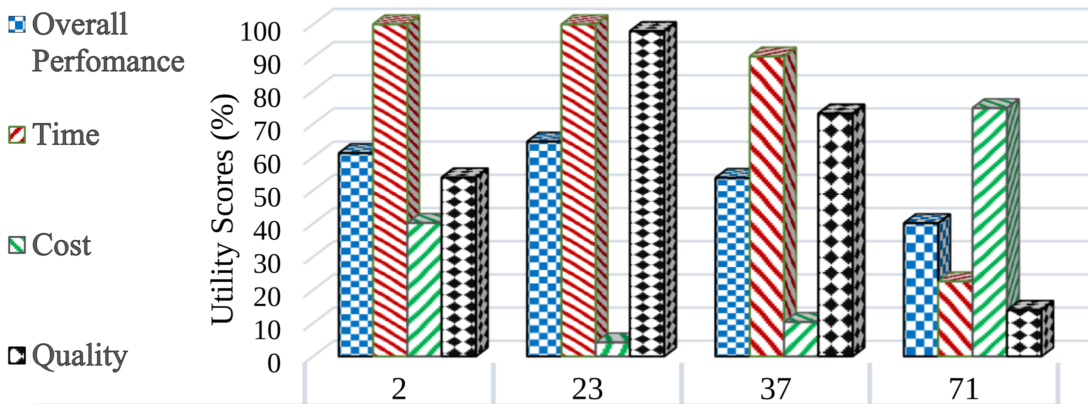


Figure 11. ER evaluation results for the Pareto-optimal solutions

The 23rd Pareto solution possesses the highest utility score (64.67%; Figure 11), which denotes that this alternative for scheduling the project satisfies the overall performance considering all the objectives simultaneously within 64.67%. However, this may not be sufficient for a final decision to select the best solution, since each solution needs to be investigated to identify its weak and strong points regarding each objective. In fact, the ER approach has the capacity to provide DMs with a transparent view of the performance of each objective in each criterion. Therefore, in the following steps of selecting the best solution, one must more deeply investigate the solutions.

Among the Pareto solutions, the 2nd, 23rd, 37th, and 71st solutions were selected to show how the overall assessment is done. The corresponding utility scores with respect to each objective in addition to the overall performance of each solution are plotted in Figure 12, where it can be seen that the 23rd solution has the highest utility score in both time and quality objectives with 100% and 97.96%, respectively. However, the cost objective of this solution has the lowest performance in being only 4.2% cost objective. Hence, the 23rd solution might not be desirable to be implemented since its performance with respect to the cost objective is extremely low. On the other hand, the 71st solution has an overall utility score of 40.11%, which is also quite low to be selected, and the 37th solution does not have an acceptable performance in terms of the cost objective (with only 10.34% for the utility score) either. With a thorough investigation, the DMs can select the most appropriate solution with a similar approach in an iterative attempt to obtain the solution that fits well with the DMs' expectations (e.g., additional data can be gathered to modify the weights of the objectives). This procedure can be continued in order to arrive at a consensus on a Pareto solution to be selected.

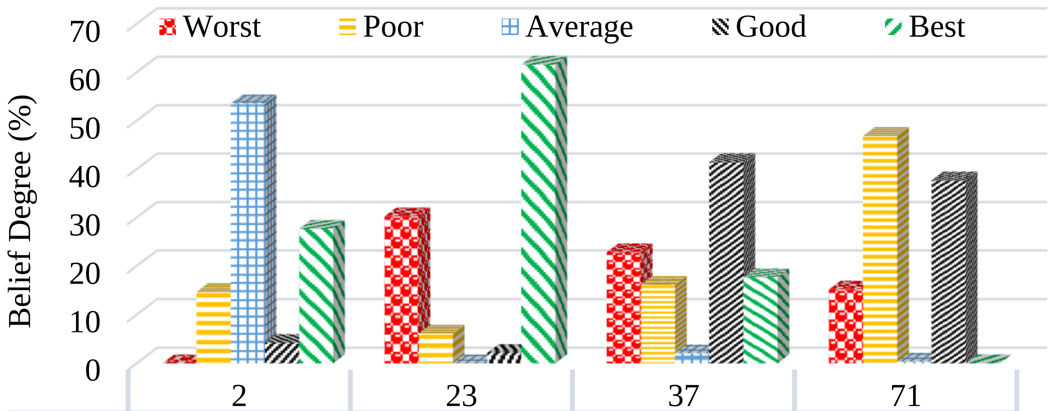
The ER approach facilitates the procedure of investigating the overall performance of each solution by providing more details of the solution performance with respect to each objective. The preconception of DMs about the performance of each solution gives more confidence to the DMs to implement their chosen project schedule, and thus more efficiently manage organizational resources.



	2	23	37	71
Overall Perfomance	61.19	64.67	53.75	40.11
Time	100.00	100.00	90.32	22.58
Cost	40.18	4.20	10.34	74.77
Quality	53.90	97.96	73.17	14.00

Figure 12. Utility scores for 2nd, 23rd, 37th, and 71st Pareto solutions with respect to each objective

As mentioned earlier, the ER approach is able to provide DMs with informative output data indicating the weak points of each alternative at any desired level. In this study, we divided the overall performance into five grades viz ‘worst’, ‘poor’, ‘average’, ‘good’, and ‘best’, which are equally spaced in the interval [0,1]. These five grades can be used to reflect the combined belief degree β_n (Figure 13). On this basis, the overall performance of the 23rd solution is believed to belong to the ‘best’ grade with a degree of 61.56%. On the other hand, the 23rd solution has the highest degree of belief of the ‘worst’ grade with 30.22%, in comparison with the 2nd, 37th, and 71st solutions with degrees of belief for the ‘worst’ grade of 0.0%, 22.81% and 15.17%, respectively. As a result, the DMs might decide not to select the 23rd solution as the best solution although it has the highest utility score. In this case, the DMs can apply improvement strategies to better the performance of the 23rd solution or start investigating another solution. Figure 12 and Figure 13 show it to be more advisable to implement the 2nd solution since it has an acceptable utility score with respect to the overall performance (61.19%), and its combined degrees of belief are high in terms of the 'average' and 'best' grades (53.55% and 27.64%, respectively) with a zero value for the 'worst' grade. Since there is no incomplete assessment, $\beta_H = 0$.



	2	23	37	71
Worst	0	30.22	22.81	15.17
Poor	14.66	6.11	16.09	46.84
Average	53.55	0	2.04	0.34
Good	4.15	2.11	41.41	37.64
Best	27.64	61.56	17.66	0

Figure 13. Combined degrees of belief (β_n) for 2nd, 23rd, 37th, and 71st Pareto solutions with respect to the overall performance

To summarize, the ER approach is highly efficient in identifying the performance of each alternative, and it enables the DMs to form a transparent and rational judgment about the best alternative. Using the ER approach in construction project scheduling provides more efficient management strategies, and the DMs can be more confident about their selected alternative since the DMs have a clear understanding of the performance of each alternative. In the present case study, we observed that although the 23rd solution had the highest utility score, it was not advisable to select it as the best solution since it has a very high degree of belief in the 'worst' grade. With further investigation, the 2nd solution was chosen to be more rational and practicable for the DMs.

The same procedure for ranking the obtained Pareto-optimal project scheduling alternatives have been done based on the PROMETHEE approach. According to Figure 14, the 23rd solution has the highest PROMETHEE score, with 0.114 while the 101st solution has the lowest PROMETHEE score of -0.164. Both ER and POROMTHEE approaches selected the 23rd and 101st project scheduling alternatives as the best and worst choices. Therefore, since both MCDM methods have led into the same solution it is ca be concluded that both of these methods are consistent; however the ER approach was able to provide the DMs with exhaustive further evaluation results. On the other hand, the ER approach is more complicated than the PROMETHEE method where the later one is more user-friendly and is applicable in various fields of knowledge.

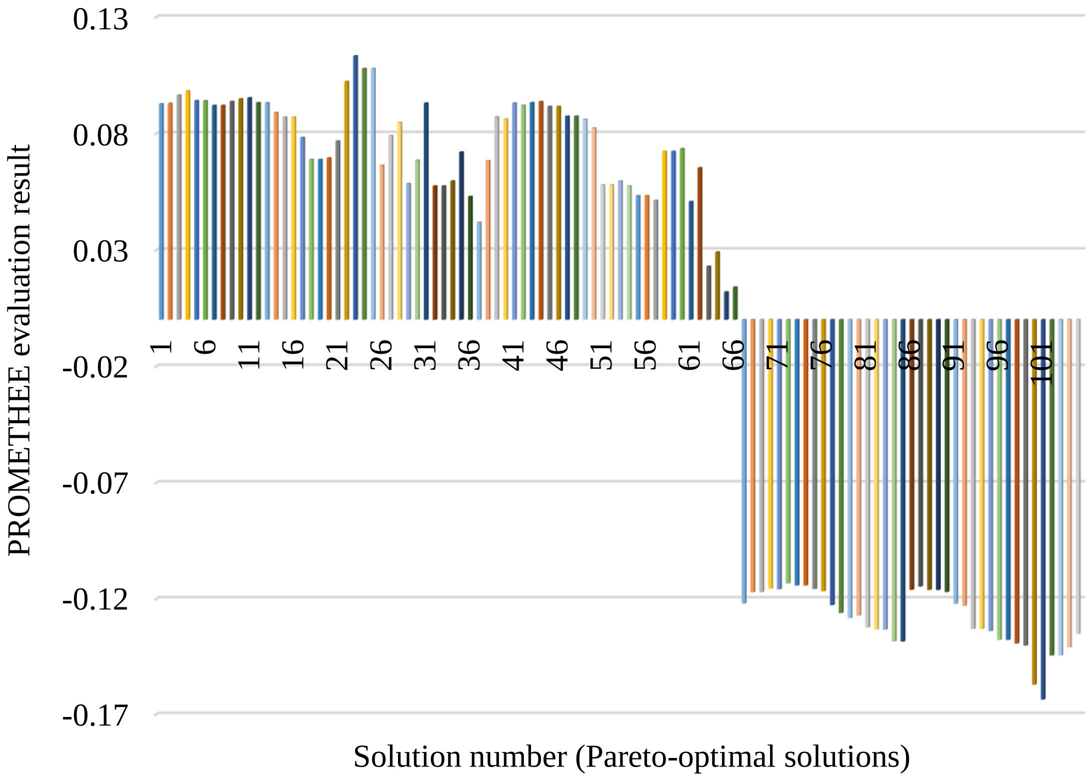


Figure 14. PROMETHEE ranking for the Pareto-optimal project scheduling alternatives

The TOPSIS procedure although it is quite more simpler than ER and PROMETHEE MCDM methods, the results vary from those two, where the 24th solution is selected by the TOPSIS method as the best optimal project scheduling alternative. According to Figure 15, as the overall performance of the solutions declines as the number of solutions increases. The 24th and 103rd solution with 0.7 and 0.3 calculated TOPSIS scores, respectively, are the best and worst project scheduling choices among the Pareto-optimal solutions.

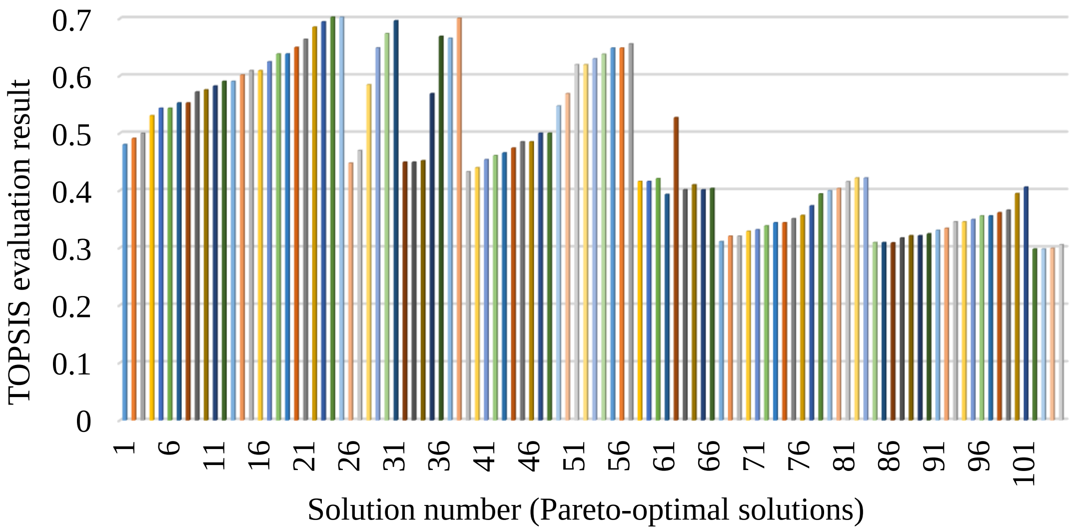


Figure 15. TOPSIS ranking for the Pareto-optimal project scheduling alternatives

5.1 Comparing the Three MCDM Methods

The 23rd, 24th, 22nd, and 41st project scheduling alternatives, as the four best solutions selected by the MCDM methods have been compared with each other as shown in Table 7. Accordingly, the ER and PROMETHEE methods are seemed to have identified 23rd, 24th, 22nd, and 41st solutions as the best solutions, respectively. Therefore the ER and PROMETHEE methods are seemed to have similar evaluation procedure to rank the alternatives. However, the TOPSIS method, has chosen 24th, 23rd, 22nd, and 41st as the best solutions, respectively.

Table 7. Evaluation results of 23rd, 24th, 22nd and 41st Pareto-optimal solutions which are the four best project scheduling alternatives

	MCDM methods			Evaluation of the best 4 solutions (%) based on:		
	ER	PROMETHEE	TOPSIS			
#	Overall	Phi	CC	ER	PROMETHEE	TOPSIS
23	64.67	0.113	0.694	100.0	100.0	98.8
24	64.02	0.108	0.702	99.0	95.2	100.0
22	62.65	0.102	0.685	96.9	90.3	97.5
41	62.15	0.093	0.454	96.1	82.1	64.6

In order to graphically illustrate the differences in the evaluation of the ER, PROMETHEE, and TOPSIS methods, in Figure 16 the overall assessment score obtained from each MCDM method has been plotted for 23rd, 24th, 22nd, and 41st solutions, respectively. Referring to Figure 16, the evaluation of the 23rd solution does not have too much difference for the ER, PROMETHEE, and TOPSIS methods. However, as the solutions' overall assessment scores fall down, it seems that the difference between these MCDM methods assessment scores increase, according to the 41st solution. However, in general not a specific trend can be tracked down, for example in the 24th and 22nd solutions the ER and TOPSIS evaluation scores do not differ significantly, while the PROMETHEE method has lower evaluation scores in the both cases. On the other hand, according to 23rd and 41st solutions the ER and PROMETHEE evaluation scores are rather too similar, while in these cases the TOPSIS is different. Therefore, there is no specific trend to be observed.

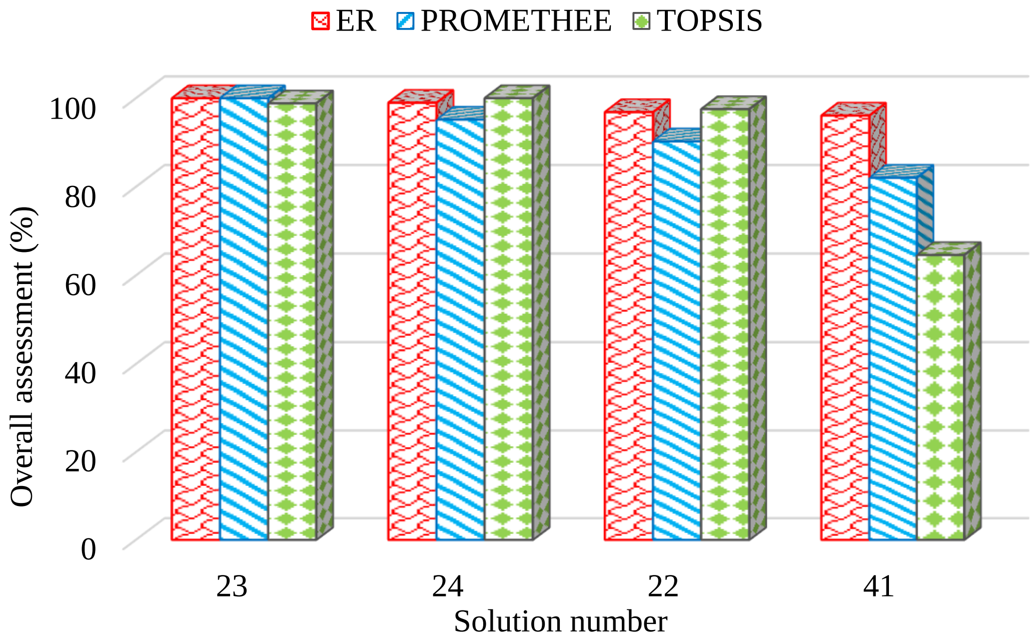


Figure 16. Comparison of 23rd, 24th, 22nd and 41st Pareto-optimal solutions which are the four best project scheduling alternatives

Furthermore, in order to investigate the difference between the analysis procedures of the ER, PROMETHEE and TOPSIS, other 4 solutions, 23rd, 48th, 60th, and 105th Pareto-optimal solutions, where selected. They are chosen randomly from the whole range of the highest and lowest ranked solutions. As listed in Table 8, all the three MCDM methods have ranked the 23rd, 48th, 60th, and 105th solutions from the best to the worst rank solutions. This concludes that the ER, PROMMETHEE and TOPSIS methods have identical overview to identify the whole range of the highest and lowest rank possible.

Table 8. Evaluation results of 23rd, 48th, 60th and 105th Pareto-optimal solutions

	MCDM methods			Evaluation of the selected 4 solutions (%) based on:		
	ER	PROMETHEE	TOPSIS			
#	Overall	Phi	CC	ER	PROMETHEE	TOPSIS
23	64.67	0.113	0.694	100.0	100.0	98.8
48	61.38	0.087	0.500	94.9	90.6	71.2
60	60.42	0.073	0.421	93.4	85.6	60.0
105	37.71	-0.135	0.305	58.3	10.2	43.9

Further investigations show that the PROMETHEE approach has ranked the 105th solution with -0.135 with a corresponding value of 10.2%, while the ER and TOPSIS methods have evaluated the 48th solution with 58.3% and 43.9%, respectively. Therefore, PROMETHEE approach in contrast with the ER and TOPSIS, degrades the lower ranked solution more significantly. This means that the DMs might only rely on the 105th solution by 10.2% if the PROMETHEE was used, while in contrast the ER and TOPSIS methods provide the DMs with 58.3% and 43.9% levels of confidence, respectively. This is illustrated in Figure 17 in which there a steep drop in the PROMETHEE evaluation score as in the 105th solution.

In addition, the comparison of the ER and TOPSIS reveals that although 48th, 60th, and 105th solutions with 94.9%, 93.4%, and 58.3% ER evaluation scores and 71.2%, 60%, 43.9% TOPSIS evaluation scores, respectively, as in Table 8, the TOPSIS method provides a lower level of confidence for the DMs when the rank of the solutions gets poorer. This can be noticed in Figure 17, where in every cases the TOPSIS score is lower than the ER evaluation score.

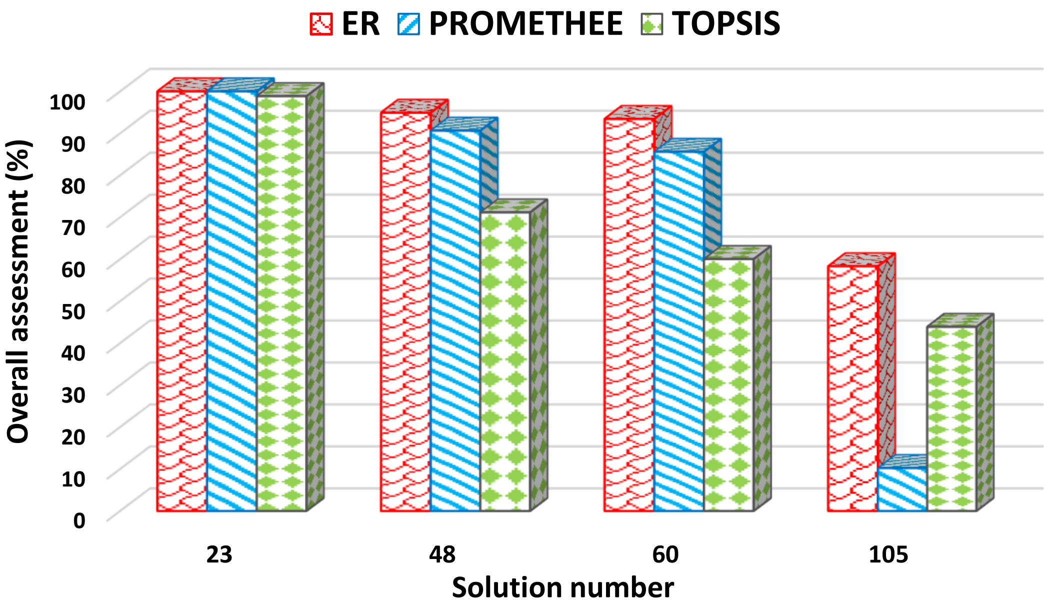


Figure 17. Comparison of 23rd, 48th, 60th and 105th Pareto-optimal solutions

5.2 Comparison of the Multi-Objective Optimization Models

To compare the efficiency of the multi-objective optimization models of GA and IHS a comparison is drawn by obtaining the performance of the proposed method. A benchmark example of DTCQTP which is solved by various approaches viz multi-objective genetic algorithm (Feng et al., 1997), fuzzy clustering based genetic algorithm (Mungle et al., 2013), and combined scheme-based multi-objective particle swarm optimization (Zhang & Xing, 2010) is considered. The performance analysis can be done by investigating the factors such as computational time (CT), generational distance (GD), and range variance (RV) (Zitzler et al., 2000). These quantitative metrics address speed of convergence, convergence degree, and sparse-degree of the non-dominated solutions respectively. Mungle et al. (2013) have investigated the performance of multi-objective genetic algorithm, fuzzy clustering based genetic algorithm, and combined scheme-based multi-objective particle swarm optimization, concluding that the fuzzy clustering based genetic algorithm outperforms the other two methods with respect to both GD and RV; however the CT is approximately 4 times greater in fuzzy clustering based genetic algorithm.

The GD parameter measures the speed of the algorithm in converging the near optimal solutions. Based on the definition given by Zitzler et al. (2000) it is defined as in Equation (20). The number of solutions in the first front in the lth generation is denoted by $\left|F_1^l\right|$. $(d_e)_i$ is the minimum 1-norm distance of the ith solution from the solutions in the true pareto solutions (F_1^{true}), where $i \in \{1,2,\ldots,\left|F_1^l\right|\}$, and it is calculated according to Equation (21). The true Pareto solutions are considered to be the same as the results reported by Geem (2010) which was also used as the basis of comparison by Mungle et al. (2013). f_k^i and f_k^j are the corresponding values for the kth objective function of ith and jth solution respectively where $k \in \{1,2,\ldots,obj\}$. Here, since only two objectives exist, i.e. time and cost, $k \in \{1,2\}$. The RV parameter is calculated based on Equation (22) with all the same parameters of the GD except for $\bar{\bar{d}}_e$ which is simply the average of all $(d_e)_i$. A smaller value for both GD and RV indicates a higher convergence degree and diversity degree respectively. A zero value for GD means absolute convergence and for RV indicates uniform distribution of Pareto solutions (Zitzler et al., 2000). The CT parameter is the duration that the algorithm takes to obtain the final results. This parameter is sensitive to the computer environment and hardware configurations and therefore the comparison needs to be done in the same computer environment.

$$GD = \sqrt{\frac{\sum_{i=1}^{\left|F_1^l\right|} {(d_e)_i}^2}{\left|F_1^l\right|^2}} \tag{20}$$

$$(d_e)_i = \left\{d_e \middle| \min\left\{\sum_{k=1}^{obj}\left|f_k^i - f_k^j\right|\right\} \text{ , } j = 1,2,\ldots,|F_1^{true}|\right\} \tag{21}$$

$$RV = \sqrt{\frac{\sum_{i=1}^{|F_1^l|}\left(\bar{\bar{d}}_e - (d_e)_i\right)^2}{|F_1^l| - 1}} \tag{22}$$

$$\bar{\bar{d}}_e = \frac{\sum_{i=1}^{|F_1^l|}(d_e)_i}{|F_1^l|} \tag{23}$$

By considering the same algorithm parameters by which the previous benchmark in DTCQTP was solved the performance analysis parameters are obtained as in Table 9. The GD and RV parameters are significantly lower for the GA and IHS used in this thesis with an average values of 2.63, 4.13 and 2.04, 3.23, respectively, out of 20 runs of the algorithm. With respect to this, both GA and IHS is demonstrated to be highly efficient in converging the near optimal solutions and in diversity of the Pareto solutions.

Although the IHS algorithm outperforms the GA, fuzzy clustering based genetic algorithm, combined scheme-based multi-objective particle swarm optimization, and multi-objective genetic algorithm both GD and RV parameters, its computational time is slightly greater than the later algorithms. GA has a greater computational time in comparison with combined scheme-based multi-objective particle swarm optimization and multi-objective genetic algorithm, and meanwhile it has a lower computational time in comparison with IHS, and fuzzy clustering based genetic algorithm. In general, both GA and IHS approaches seem to be significantly more efficient in finding the optimal solutions based on the performance analysis.

Table 9. Performance analysis metrics values

Algorithm	Performance analysis metrics		
	Generational distance (GD)	Range variance (RV)	Computational time (CT, minutes)
fuzzy clustering based genetic algorithm	3.12	5.72	14.12
combined scheme-based multi-objective particle swarm optimization	4.73	9.58	3.42
multi-objective genetic algorithm	5.68	10.16	4.43
IHS*	2.04	3.23	17.41
GA (NSGA-II)*	2.63	4.13	7.80

*The proposed methodology of this study.

Chapter 6

CONCLUSION AND RECOMMENDATION

This thesis aims to provide an exhaustive framework to improve the construction project scheduling by incorporating multi-objective optimization techniques, e.g., GA and IHS, which are integrated with MCDM methods, namely, ER, PROMETHEE, and TOPSIS. In order to investigate the viability of all these methods in construction project scheduling a benchmark case problem adapted from Feng et al. (1997) was solved.

The obtained results show that, first of all, the MCDM methods are highly efficient in ranking the project scheduling alternatives, and the DMs can be provided with higher level of confidence to implement the selected solution in real practice. Since, multi-objective optimization techniques, such as GA and IHS which are used here, are able to obtain a set of non-dominated solutions, being called as the Pareto-optimal solutions, there is the need to take one more step ahead to select the best optimal solution among the achieved Pareto-optimal set of solutions. The obtained results of this thesis, demonstrate that the MCDM methods can be highly efficient in ranking the Pareto-optimal solutions.

Secondly, the GA and IHS algorithms are compared against each other to identify which multi-objective optimization technique is more efficient to be used in project scheduling problem. This comparison revealed that although the IHS algorithm is more time-consuming in converging the true Pareto-optimal solutions, higher performance is achieved, when compared with GA. However, both of these techniques were able to identify the same 105 Pareto-optimal solutions while GA was faster in terms of computational effort.

Throughout the literature, there exist various optimization algorithms which are all efficient in reaching the global Pareto-optimal solutions. Some of these algorithms might be more suitable for a solving a case problem while the others might not be easily adaptable. Searching through the literature of DTCQTPs reveals that various and different types of algorithm have been already used, when GA is the most exploited optimization technique. Here, the GA was also shown to be a faster approach in comparison with the newly-inspired IHS algorithm.

Thirdly, the ER approach is rather a complex MCDM method while the TOPSIS is too simple in terms of mathematical formulations. On the other hand, the PROMETHEE approach which is simpler in comparison with the ER method, has given a similar rank for the solutions. Thus, it is proposed that the PROMETHEE approach can be a highly efficient approach in evaluating the solutions. Therefore, in DTCQTPs the PROMETHEE approach can be efficiently used in comparison with the more complex method of ER. The TOPSIS method although it is very simple, still it is not as efficient as PROMETHEE and ER approaches.

Fourthly, the ER approach can evaluate each solution without the need of comparison with any other solution. This provides each specific solution with a final score which does not depend on the other available solutions. Thus, the DMs are more confident with the selected solution of the ER approach rather than those selected by

PROMETHEE and TOPSIS. The ER approach although it is more complex, it has some advantages over the other techniques as it provides a detailed scoring and ranking for each solution in terms of each objective. Thus, the DMs are able to identify the weak points of each solution and if possible they can apply some improvement strategies. For example, if any solution shows that it has a poor performance in the one objective, the DMs can come up with some strategies, e.g., additional resource assignment for a specific period of project time to overcome the weak points more efficiently.

In the literature, there exist various optimization algorithms which are or have been used already to tackle with DTCQTPs. These techniques might be able to reach the global Pareto-optimal solutions, however they can only form the Pareto frontier utmost without any further guidance to select the best choice among possible and available alternatives. The integration of MCDM methods with multi-objective optimization methods has been discussed in other fields such as water resource management, forest management, green energy planning, and etc. Hence, this thesis answers specifically to the question that why not using MCDM methods in construction project scheduling in the context of DTCQTPs. The framework proposed here, is able to establish a successful linkage between the optimization algorithms and MCDM methods. This enables the DMs to move into a further step where the decision making process of selecting the best alternative is done through a comprehensive framework.

Lastly, the ER approach ranks the solutions with a higher confidence level in comparison with both PROMETHEE and TOPSIS methods. Therefore, in the later approaches, a poor ranked solution might have a greater chance of being selected in comparison with the ER approach. For instance, in all the obtained results, the ER approach has ranked the solutions with a higher value than the other two methods. However, this merely due to the fact that the ER approach does not depend on pair-wise comparison.

6.1 Recommendations

Incorporating MCDM methods to more efficiently schedule the construction projects can be beneficial, especially in large-scale projects. The author recommend the practitioners to improve the quality of their decisions by applying MCDM methods. To overcome some limitations of this study, and as future directions for researchers or experts, the uncertainties in modeling the project scheduling problems can be addressed by using fuzzy-based MCDM methods, such as fuzzy PROMETHEE or fuzzy ER. Lastly, computer-aided decision making processes discard the current error-prone decision making procedures.

The highly efficient performance in solving DTCQTPs obtained using the ER approach provided the authors of this study with the aspiration of developing a computer system to emulate the decision-making ability of DMs using the ER approach. Another idea is to establish approaches that can help construction contractors and decision-makers to develop more efficient subcontracting plans during the bidding process via the development of multiple criteria assessment procedures. This would be useful because the bidding and evaluation process of a construction project can be a tedious and time-consuming process with no well-established criteria and approaches.

REFERENCES

Abed-Elmdoust, A., & Kerachian, R. (2012). Regional hospital solid waste assessment using the evidential reasoning approach. *Science of the Total Environment, 441*, 67-76.

Afruzi, E. N., Najafi, A. A., Roghanian, E., & Mazinani, M. (2014). A multi-objective imperialist competitive algorithm for solving discrete time, cost and quality trade-off problems with mode identity and resource-constrained situations. *Computers & Operations Research, 50*, 80–96. doi: http://dx.doi.org/10.1016/j.cor.2014.04.003

Afshar, A., Kaveh, A., & Shoghli, O. R. (2007). Multi-objective optimization of time–cost–quality using multi-colony ant algorithm. *Asian journal of civil engineering (building and housing), 8*(2), 113–124.

Albadvi, A., Chaharsooghi, S. K., & Esfahanipour, A. (2007). Decision making in stock trading: An application of PROMETHEE. *European Journal of Operational Research, 177*(2), 673-683.

Alsayed, M., Cacciato, M., Scarcella, G., & Scelba, G. (2014). Design of hybrid power generation systems based on multi criteria decision analysis. *Solar Energy, 105*, 548-560.

Anderson, S. D., & Russell, J. S. (2001). *Guidelines for warranty, multi-parameter, and best value contracting*.

Aragonés-Beltrán, P., Chaparro-González, F., Pastor-Ferrando, J.-P., & Pla-Rubio, A. (2014). An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based multi-criteria decision approach for the selection of solar-thermal power plant investment projects. *Energy, 66,* 222-238.

Baptiste, P., & Demassey, S. (2004). Tight LP bounds for resource constrained project scheduling. *OR Spectrum, 26*(2), 251-262.

Bazargan-Lari, M. R. (2014). An evidential reasoning approach to optimal monitoring of drinking water distribution systems for detecting deliberate contamination events. *Journal of Cleaner Production, 78*(1), 1-14.

Behzadian, M., Kazemzadeh, R. B., Albadvi, A., & Aghdasi, M. (2010). PROMETHEE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research, 200*(1), 198-215.

Belton, V., & Stewart, T. J. (2002). *Multiple criteria decision analysis: an integrated approach*. Boston: Kluwer Academic Publications

Brans, J.-P., & Vincke, P. (1985). Note—A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making). *Management science, 31*(6), 647-656.

Brans, J.-P., Vincke, P., & Mareschal, B. (1986). How to select and how to rank projects: The PROMETHEE method. *European Journal of Operational Research, 24*(2), 228-238.

Brans, J. P., Vincke, P., & Mareschal, B. (1986). How to select and how to rank projects: The Promethee method. *European Journal of Operational Research, 24*(2), 228–238.

Cavalcante, C., & De Almeida, A. (2007). A multi-criteria decision-aiding model using PROMETHEE III for preventive maintenance planning under uncertain conditions. *Journal of Quality in Maintenance Engineering, 13*(4), 385-397.

Chaghooshi, A. J., Fathi, M. R., & Kashef, M. (2012). Integration of fuzzy Shannon's entropy with fuzzy TOPSIS for industrial robotic system selection. *Journal of Industrial Engineering and Management, 5*(1), 102-114.

Chakeri, A., Dariani, A. N., & Lucas, C. (2008). *How can fuzzy logic determine game equilibriums better?* Paper presented at the Intelligent Systems, 2008. IS'08. 4th International IEEE Conference.

Chaudhuri, S., & Deb, K. (2010). An interactive evolutionary multi-objective optimization and decision making procedure. *Applied Soft Computing, 10*(2), 496–511.

Chen, Y., Shu, L., & Burbey, T. J. (2014). An Integrated Risk Assessment Model of Township-Scaled Land Subsidence Based on an Evidential Reasoning Algorithm and Fuzzy Set Theory. *Risk Analysis, 34*(4), 656-669.

Cicirello, V. A., & Cernera, R. (2013). *Profiling the Distance Characteristics of Mutation Operators for Permutation-Based Genetic Algorithms.* Paper presented at the FLAIRS Conference.

Czyzżak, P., & Jaszkiewicz, A. (1998). Pareto simulated annealing—a metaheuristic technique for multiple-objective combinatorial optimization. *Journal of Multi-Criteria Decision Analysis, 7*(1), 34-47.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *Journal of Evolutionary Computation, IEEE Transactions, 6*(2), 182-197.

Deng, Y., Sadiq, R., Jiang, W., & Tesfamariam, S. (2011). Risk analysis in a linguistic environment: a fuzzy evidential reasoning-based approach. *Expert Systems with Applications, 38*(12), 15438-15446.

Diakoulaki, D., & Karangelis, F. (2007). Multi-criteria decision analysis and cost–benefit analysis of alternative scenarios for the power generation sector in Greece. *Renewable and Sustainable Energy Reviews, 11*(4), 716-727.

Dymova, L., Sevastjanov, P., & Tikhonenko, A. (2013). A direct interval extension of TOPSIS method. *Expert System Applications, 40*(12), 4841-4847.

El-Rayes, K., & Kandil, A. (2005). Time–cost–quality trade-off analysis for highway construction. *Journal of Construction Engineering and Management, 131*(4), 477–486.

Erenguc, S. S., Ahn, T., & Conway, D. G. (2001). The resource constrained project scheduling problem with multiple crashable modes: An exact solution method. *Naval Research Logistics, 48*(2), 107-127.

Eshtehardian, E., Afshar, A., & Abbasnia, R. (2009). Fuzzy-based MOGA approach to stochastic time-cost trade-off problem. *Journal of Automation in Construction*, *18*(5), 692-701.

Feng, C. W., Liu, L., & Burns, S. A. (1997). Using genetic algorithms to solve construction time–cost trade-off problems. *Journal of Computing in Civil Engineering, 11*(3), 184–189.

Fernández-Castro, A., & Jiménez, M. (2005). PROMETHEE: an extension through fuzzy mathematical programming. *Journal of the Operational Research Society, 56*(1), 119-122.

Figueira, J., Greco, S., & Ehrgott, M. (2005). *Multiple criteria decision analysis: state of the art surveys* (Vol. 78): Springer Science & Business Media.

Geem, Z. W. (2010). Multiobjective optimization of time-cost trade-off using harmony search. *Journal of Construction Engineering and Management, 136*(6), 711–716.

Geem, Z. W., Kim, J. H., & Loganathan, G. V. (2001). A new heuristic optimization algorithm: Harmony search. *Simulation, 76*(2), 60-68.

Ghoddousi, P., Eshtehardian, E., Jooybanpour, S., & Javanmardi, A. (2013). Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm. *Automation in Construction, 30*, 216–227.

Gilbuena, R., Kawamura, A., Medina, R., Nakagawa, N., & Amaguchi, H. (2013). Environmental impact assessment using a utility-based recursive evidential reasoning approach for structural flood mitigation measures in Metro Manila, Philippines. *Journal of environmental management, 131*, 92-102.

Goldberg, D. E. (1989). *Genetic algorithm in search*. Massachusetts: Addison-Wasley.

Golenko, D. (1968). Statistical Methods in Network Planning and Control: Nauka, Moscow.

Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production, 47*, 345-354.

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2013). Multi criteria decision making approaches for green supplier evaluation and selection: a literature review. *Journal of Cleaner Production*.

Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., & Ohlson, D. (2012). *Structured decision making: a practical guide to environmental management choices*: John Wiley & Sons.

Grubbs, F. E. (1962). Letter to the Editor-Attempts to Validate Certain PERT Statistics or "Picking on PERT". *Operations Research, 10*(6), 912-915.

Guitouni, A., Martel, J. M., Bélanger, M., & Hunter, C. (2008). Multiple criteria courses of action selection. *Military Operations Research, 13*(1), 35–50.

Guo, M., Yang, J. B., Chin, K. S., & Wang, H. W. (2007). Evidential reasoning based preference programming for multiple attribute decision analysis under uncertainty. *European Journal of Operational Research, 182*(3), 1294–1312.

Hadian, S., & Madani, K. (2015). A system of systems approach to energy sustainability assessment: Are all renewables really green? *Ecological Indicators, 52*, 194-206.

Hajkowicz, S., & Collins, K. (2007). A review of multiple criteria analysis for water resource planning and management. *Water Resources Management, 21*(9), 1553-1566.

Hapke, M., Jaszkiewicz, A., & Słowiński, R. (1998). Interactive analysis of multiple-criteria project scheduling problems. *European Journal of Operational Research, 107*(2), 315–324.

Hobbs, B. F., & Meier, P. M. (1994). Multicriteria methods for resource planning: an experimental comparison. *IEEE Transaction on Power Systems, 9*(4), 1811–1817.

Holland, J. H. (1975). *Adaption in Natural and Artificial Systems*. Ann Arbor: University of Michigan Press.

Huang, I. B., Keisler, J., & Linkov, I. (2011). Multi-criteria decision analysis in environmental sciences: ten years of applications and trends. *Science of the Total Environment, 409*(19), 3578-3594.

Hwang, C. L., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications.*: Springer-Verlag, New York, U.S.A.

Hyde, K. M., & Maier, H. R. (2006). Distance-based and stochastic uncertainty analysis for multi-criteria decision analysis in Excel using Visual Basic for Applications. *Environmental Modelling & Software, 21*(12), 1695-1710.

Jaszkiewicz, A., & Słowiński, R. (1997). The LBS-Discrete Interactive Procedure for Multiple-Criteria Analysis of Decision Problems *Multicriteria Analysis*: Springer Berlin Heidelberg.

Kannan, D., Khodaverdi, R., Olfat, L., Jafarian, A., & Diabat, A. (2013). Integrated fuzzy multi criteria decision making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain. *Journal of Cleaner Production, 47*, 355-367.

Kaveh, A., & Ahangaran, M. (2012). Discrete cost optimization of composite floor system using social harmony search model. *Journal of Applied Soft Computing, 12*, 372-381.

Keeney, R. L., & Raiffa, H. (1976). *Decisions with multiple objectives: preferences and value trade-offs*. NewYork: Wiley.

Linkov, I., & Moberg, E. (2011). *Multi-criteria decision analysis: environmental applications and case studies*: CRC Press.

Linkov, I., Satterstrom, F., Kiker, G., Seager, T., Bridges, T., Gardner, K. H., . . . Meyer, A. (2006). Multicriteria decision analysis: a comprehensive decision approach for management of contaminated sediments. *Risk Analysis, 26*(1), 61-78.

Løken, E. (2007). Use of multicriteria decision analysis methods for energy planning problems. *Renewable and Sustainable Energy Reviews, 11*(7), 1584–1595.

MacCrimmon, K. R., & Ryavec, C. A. (1964). An analytical study of the PERT assumptions. *Operations Research, 12*(1), 16-37.

Madani, K. (2010). Game theory and water resources. *Journal of Hydrology, 381*(3), 225-238.

Madani, K., & Lund, J. R. (2011). A Monte-Carlo game theoretic approach for multi-criteria decision making under uncertainty. *Advances in water resources, 34*(5), 607-616.

Madani, K., Rouhani, O. M., Mirchi, A., & Gholizadeh, S. (2014). A negotiation support system for resolving an international trans-boundary natural resource conflict. *Environmental Modelling & Software, 51*, 240-249.

Madani, K., Sheikhmohammady, M., Mokhtari, S., Moradi, M., & Xanthopoulos, P. (2014). Social planner's solution for the Caspian Sea conflict. *Group Decision and Negotiation, 23*(3), 579-596.

Mahdavi, M., Fesanghary, M., & Damangir, E. (2007). An improved harmony search algorithm for solving optimization problems. *Applied Mathematics and Computation, 188*(2), 1567–1579.

Mareschal, B., & Brans, J. P. (1992). PROMETHEE V: MCDM problems with segmentation constraints: ULB--Universite Libre de Bruxelles.

Mawdesley, M. J., Al-jibouri, S. H., & Yang, H. (2002). Genetic algorithms for construction site layout in project planning. *Journal of Construction Engineering and Management, 128*(5), 418-426. doi: http://ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9364(2002)128:5(418)

Mela, K., Tiainen, T., Heinisuo, M., & Baptiste, P. (2012). Comparative study of multiple criteria decision making methods for building design. *Advanced Engineering Informatics, 26*(4), 716–726.

Mirchi, A., Watkins Jr, D., & Madani, K. (2010). Modeling for watershed planning, management, and decision making. *Watersheds: management, restoration and environmental impact (Vaughn JC ed). Nova Science Publishers, Hauppauge, NY, USA*.

Mokhtari, S., Madani, K., & Chang, N.-B. (2012). *Multi-criteria decision making under uncertainty: application to the California's Sacramento-San Joaquin delta problem.* Paper presented at the) 2012 World Environmental and Water Resources Congress.

Monghasemi, S., Nikoo, M. R., Fasaee, M. A. K., & Adamowski, J. (2014). A Novel Multi Criteria Decision Making Model for Optimizing Time-Cost-Quality Trade-off Problems in Construction Projects. *Expert Systems with Applications*.

Moselhi, O. (1993). Schedule compression using the direct stiffness method. *Canadian Journal of Civil Engineering, 20*, 65–72.

Mungle, S., Benyoucef, L., Son, Y. J., & Tiwari, M. K. (2013). A fuzzy clustering-based genetic algorithm approach for time-cost-quality trade-off problems: A case study of highway construction project. *Journal of Engineering Applications of Artificial Intelligence, 26*(8), 1953-1966.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research, 156*(2), 445–455.

Parnell, G. S., Driscoll, P. J., & Henderson, D. L. (2011). *Decision making in systems engineering and management* (Vol. 81): John Wiley & Sons.

Perera, A., Attalage, R., Perera, K., & Dassanayake, V. (2013). A hybrid tool to combine multi-objective optimization and multi-criterion decision making in designing standalone hybrid energy systems. *Applied Energy, 107*, 412-425.

PMI. (2001). *A Guide to the Project Management Body of Knowledge, Inc*. Newtown Square, PA.: Project Management Institute.

Podvezko, V., & Podviezko, A. (2010). Dependence of multi-criteria evaluation result on choice of preference functions and their parameters. *Technological and economic development of economy, 16*(1), 143-158.

Podvezko, V., & Podviezko, A. (2011). PROMETHEE I method application for identification of the best alternative. *Business: Theory and Practice/Verslas: Teorija ir Praktika, 10*(2), 84-92.

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews, 8*(4), 365–381.

Queiruga, D., Walther, G., Gonzalez-Benito, J., & Spengler, T. (2008). Evaluation of sites for the location of WEEE recycling plants in Spain. *Waste Management, 28*(1), 181-190.

Rahnama, M. R. (2014). (Municipal Ranking based on Developmental Indices using PROMETHEE and Factor Analysis (Case study: Kerman, Iran. *Magnt Research Report, 2*.

Read, L., Inanloo, B., & Madani, K. Assessing the Stability of Social Planner Solutions in Multi-Participant Water Conflicts *World Environmental and Water Resources Congress 2013* (pp. 2329-2337).

Read, L., Mokhtari, S., Madani, K., Maimoun, M., & Hanks, C. (2013). *A multi-participant, multi-criteria analysis of energy supply sources for Fairbanks, Alaska.* Paper presented at the Proceedings of the 2013 World Environmental and Water Resources Congress.

Roy, B. (1991). The outranking approach and the foundations of electre methods. *Theory and Decision, 31*(1), 49-73.

Saaty, T. L. (1980). *The analytic hierarchy process: planning, priority setting, resource allocation*. New York: McGraw-Hill.

Shafer, G. (1976). *A Mathematical Theory of Evidence*. Princeton University Press, Princeton, NJ, U.S.A.

Sönmez, M., Holt, G., Yang, J., & Graham, G. (2002). Applying evidential reasoning to prequalifying construction contractors. *Journal of management in Engineering, 18*(3), 111-119.

Sonmez, R., & Bettemir, Ö. H. (2012). A hybrid genetic algorithm for the discrete time–cost trade-off problem. *Expert Systems with Applications, 39*(13), 11428–11434.

Tanaka, M., Watanabe, H., Furukawa, Y., & Tanino, T. (1995). *GA-based decision support system for multicriteria optimization.* Paper presented at the Systems, Man and Cybernetics, 1995. Intelligent Systems for the 21st Century., IEEE International Conference on.

Tavana, M., Abtahi, A. R., & Khalili-Damghani, K. (2014). A new multi-objective multi-mode model for solving preemptive time–cost–quality trade-off project scheduling problems. *Journal of Expert Systems with Applications, 41*(4), 1830-1846.

Turskis, Z., & Zavadskas, E. K. (2011). Multiple criteria decision making (MCDM) methods in economics: an overview. *Technological and economic development of economy*(2), 397-427.

Tuzkaya, G., Ozgen, A., Ozgen, D., & Tuzkaya, U. (2009). Environmental performance evaluation of suppliers: A hybrid fuzzy multi-criteria decision approach. *International Journal of Environmental Science & Technology, 6*(3), 477-490.

Vanhoucke, M., Debels, D., & Sched, J. (2007). The discrete time/cost trade-off problem: extensions and heuristic procedures *Journal of Schedulinng., 10*(4-5), 311-326.

Wang, J., Yang, J., & Sen, P. (1995). Safety analysis and synthesis using fuzzy sets and evidential reasoning. *Reliability Engineering & System Safety, 47*(2), 103-118.

Wang, Y.-M., Yang, J.-B., & Xu, D.-L. (2006). Environmental impact assessment using the evidential reasoning approach. *European Journal of Operational Research, 174*(3), 1885-1913.

Wang, Y. M., Yang, J. B., & Xu, D. L. (2006). The evidential reasoning approach for multiple attribute decision analysis using interval belief degrees. *European Journal of Operational Research, 175*(1), 35-66.

Wilson, J. M. (1997a). A genetic algorithm for the generalized assignment problem. *Operation and Research Society, 48*(8), 804-809.

Wilson, J. M. (1997b). A genetic algorithm for the generalized assignment problem *Journal of Operation and Research Society, 48*(8), 804-809.

Wolfslehner, B., Vacik, H., & Lexer, M. J. (2005). Application of the analytic network process in multi-criteria analysis of sustainable forest management. *Forest Ecology and Management, 207*(1), 157-170.

Xu, D. L. (2012). An introduction and survey of the evidential reasoning approach for multiple criteria decision analysis. *Annals of Operations Research, 195*(1), 163-187.

Xu, J., Zheng, H., Zeng, Z., Wu, S., & Shen, M. (2012). Discrete time–cost–environment trade-off problem for large-scale construction systems with multiple modes under fuzzy uncertainty and its application to Jinping-II Hydroelectric Project. *International Journal of Project Management, 30*(8), 950–966.

Xu, J., & Zhou, X. (2011). *Fuzzy-Like Multiple Objective Decision Making* (Vol. 263). Berlin Heidelberg: Studies in Fuzziness and Soft Computing, Springer-Verlag.

Yang, J.-B., & Singh Madan, G. (1994). An evidential reasoning approach for multiple-attribute decision making with uncertainty. *Systems, Man and Cybernetics, IEEE Transactions on, 24*(1), 1-18.

Yang, J.-B., Wang, Y.-M., Xu, D.-L., & Chin, K.-S. (2006). The evidential reasoning approach for MADA under both probabilistic and fuzzy uncertainties. *European Journal of Operational Research*, *171*(1), 309-343.

Yang, X. S. (2009). *"Harmony Search as a Metaheuristic Algorithm", in: Music-Inspired Harmony Search Algorithm: Theory and Applications* (Z. W. Geem Ed. Vol. 191). Berlin: Springer Berlin Heidelberg.

Zhang, H., & Xing, F. (2010). Fuzzy-multi-objective particle swarm optimization for time–cost–quality tradeoff in construction. *Journal of Automation in Construction, 19*(8), 1067-1075.

Zhou, J., Love, P. E. D., Wang, X., Teo, K. L., & Irani, Z. (2013). A review of methods and algorithms for optimizing construction scheduling. *Journal of the Operational Research Society, 64*, 1091–1105.

Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multi-objective evolutionary algorithms: empirical results. *Evolutionary Computation, 8*(2), 173–195.

APPENDICES

Appendix A: 105 Pareto-optimal solutions obtained from GA and IHS and corresponding decison variables

#	Objectives			Decision Variables																	
	Time (day)	Cost ($)	Quality (%)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	104	147230	81.70	1	3	2	2	3	1	2	1	1	1	1	1	2	1	1	3	1	1
2	104	148080	82.17	1	2	2	2	3	1	2	1	1	1	1	1	2	1	1	2	1	1
3	104	148525	82.83	1	3	1	2	3	1	2	2	1	1	1	1	1	1	1	3	1	1
4	104	150980	84.33	1	1	1	2	3	1	2	1	1	1	1	1	1	1	1	1	1	1
5	104	152480	84.60	1	1	1	2	2	1	2	1	1	1	1	1	1	1	1	2	1	1
6	104	152480	84.60	1	1	1	2	2	1	2	1	1	1	1	1	1	1	1	2	1	1
7	104	153480	84.87	1	1	1	2	2	1	2	1	1	1	1	1	1	1	1	1	1	1
8	104	153480	84.87	1	1	1	2	2	1	2	1	1	1	1	1	1	1	1	1	1	1
9	104	155130	85.93	1	2	1	2	3	1	1	1	1	1	1	1	1	1	1	3	1	1
10	104	155380	86.20	1	2	1	2	3	1	1	1	1	1	1	1	1	1	1	2	1	1
11	104	155980	86.57	1	1	1	2	3	1	1	1	1	1	1	1	1	1	1	2	1	1
12	104	156980	86.83	1	1	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1
13	104	156980	86.83	1	1	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1
14	104	158480	87.10	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	2	1	1
15	104	159480	87.37	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1
16	104	159480	87.37	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1
17	104	161980	87.60	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	104	164530	87.77	1	3	1	1	3	1	1	1	1	1	1	1	1	1	1	3	1	1
19	104	164530	87.77	1	3	1	1	3	1	1	1	1	1	1	1	1	1	1	3	1	1
20	104	165980	88.60	1	1	1	1	3	1	1	1	1	1	1	1	1	1	1	2	1	1
21	104	167280	90.17	1	3	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1
22	104	168480	93.93	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1
23	104	169480	95.80	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
24	104	171980	96.43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
25	104	171980	96.43	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
26	105	145880	78.77	2	4	2	2	3	1	2	3	1	1	2	1	2	2	1	4	1	1
27	105	146550	80.67	2	3	2	2	3	1	2	1	1	1	1	1	2	2	1	3	1	1
28	105	155900	86.23	2	1	1	2	3	1	1	1	1	1	1	1	1	1	1	2	1	1
29	105	165300	87.90	2	2	1	1	3	1	1	1	1	1	1	1	1	1	1	2	1	1
30	105	167795	90.43	2	2	1	1	2	1	1	2	1	1	1	1	1	1	1	2	1	1
31	105	169400	94.27	2	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
32	106	145800	78.63	3	4	2	2	3	1	2	3	1	1	2	1	2	2	1	4	1	1
33	106	145800	78.63	3	4	2	2	3	1	2	3	1	1	2	1	2	2	1	4	1	1
34	106	145815	78.90	3	4	2	2	3	1	2	2	1	1	2	1	2	2	1	4	1	1
35	106	154365	84.87	3	3	1	2	3	1	1	2	1	1	1	1	1	1	1	3	1	1
36	106	166865	89.03	3	3	1	1	2	1	1	2	1	1	1	1	1	1	1	3	1	1
37	107	165830	88.13	1	2	1	1	3	1	1	1	2	1	1	1	1	1	1	2	1	1
38	107	168330	92.67	1	2	1	1	2	1	1	1	2	1	1	1	1	1	1	2	1	1
39	108	140160	81.33	1	3	2	2	3	2	2	1	1	1	1	1	2	1	1	2	1	1
40	108	140760	81.53	1	2	2	2	3	2	2	1	1	1	1	1	2	1	1	2	1	1
41	108	141210	82.60	1	3	1	2	3	2	2	1	1	1	1	1	1	1	1	3	1	1

#	Objectives			Decision Variables																	
	Time (day)	Cost ($)	Quality (%)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
42	108	141810	82.80	1	2	1	2	3	2	2	1	1	1	1	1	1	1	1	3	1	1
43	108	142060	83.07	1	2	1	2	3	2	2	1	1	1	1	1	1	1	1	2	1	1
44	108	142660	83.43	1	1	1	2	3	2	2	1	1	1	1	1	1	1	1	2	1	1
45	108	143660	83.70	1	1	1	2	3	2	2	1	1	1	1	1	1	1	1	1	1	1
46	108	143660	83.70	1	1	1	2	3	2	2	1	1	1	1	1	1	1	1	1	1	1
47	108	145160	83.97	1	1	1	2	2	2	2	1	1	1	1	1	1	1	1	2	1	1
48	108	145160	83.97	1	1	1	2	2	2	2	1	1	1	1	1	1	1	1	2	1	1
49	108	149060	85.83	1	2	1	2	3	2	1	1	1	1	1	1	1	1	1	1	1	1
50	108	151160	86.47	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	2	1	1
51	108	157810	86.93	1	2	1	1	3	2	1	1	1	1	1	1	1	1	1	3	1	1
52	108	157810	86.93	1	2	1	1	3	2	1	1	1	1	1	1	1	1	1	3	1	1
53	108	158660	87.57	1	1	1	1	3	2	1	1	1	1	1	1	1	1	1	2	1	1
54	108	159660	87.83	1	1	1	1	3	2	1	1	1	1	1	1	1	1	1	1	1	1
55	108	161160	88.10	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	2	1	1
56	108	161160	88.10	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	2	1	1
57	108	162160	88.37	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1
58	109	139230	80.03	2	3	2	2	3	2	2	1	1	1	1	1	2	2	1	3	1	1
59	109	139230	80.03	2	3	2	2	3	2	2	1	1	1	1	1	2	2	1	3	1	1
60	109	139480	80.30	2	3	2	2	3	2	2	1	1	1	1	1	2	2	1	2	1	1
61	110	138480	78.00	3	4	2	2	3	2	2	3	1	1	2	1	2	2	1	4	1	1
62	110	147045	84.23	3	3	1	2	3	2	1	2	1	1	1	1	1	1	1	3	1	1
63	113	138455	77.57	2	4	2	2	3	2	2	2	1	1	2	1	2	2	1	4	2	1
64	113	138555	78.37	2	4	2	2	3	2	2	2	1	1	1	1	2	2	1	4	2	1
65	114	138360	77.17	3	4	2	2	3	2	2	3	1	1	2	1	2	2	1	4	2	1
66	114	138375	77.43	3	4	2	2	3	2	2	2	1	1	2	1	2	2	1	4	2	1
67	128	125690	68.13	2	4	3	3	4	2	3	3	2	2	2	2	3	3	1	5	2	2
68	128	126405	69.10	2	4	3	3	4	2	3	2	2	2	2	2	3	2	1	4	2	2
69	128	126405	69.10	2	4	3	3	4	2	3	2	2	2	2	2	3	2	1	4	2	2
70	128	127205	69.70	2	4	2	3	4	2	3	2	2	2	2	2	3	2	1	4	2	2
71	128	127505	69.83	2	3	2	3	4	2	3	2	2	2	2	2	3	2	1	4	2	2
72	128	128005	70.40	2	3	2	3	4	2	3	2	2	2	2	2	3	2	1	2	2	2
73	128	128605	70.60	2	2	2	3	4	2	3	2	2	2	2	2	3	2	1	2	2	2
74	128	128605	70.60	2	2	2	3	4	2	3	2	2	2	2	2	3	2	1	2	2	2
75	128	129405	70.83	2	3	2	3	4	2	3	2	2	2	2	2	2	2	1	2	2	2
76	128	130005	71.03	2	2	2	3	4	2	3	2	2	2	2	2	2	2	1	2	2	2
77	128	132005	71.33	2	2	2	3	4	2	2	2	2	2	2	2	2	2	1	2	2	2
78	128	134105	72.00	2	4	2	2	4	2	3	2	2	2	2	2	2	2	1	2	2	2
79	128	134755	72.07	2	2	2	2	4	2	3	2	2	2	2	2	2	2	1	3	2	2
80	128	135005	72.33	2	2	2	2	4	2	3	2	2	2	2	2	2	2	1	2	2	2
81	128	136405	72.43	2	3	2	2	4	2	2	2	2	2	2	2	2	2	1	2	2	2
82	128	137005	72.63	2	2	2	2	4	2	2	2	2	2	2	2	2	2	1	2	2	2
83	128	137005	72.63	2	2	2	2	4	2	2	2	2	2	2	2	2	2	1	2	2	2
84	129	125148	66.83	3	5	3	3	4	2	3	4	2	2	3	2	3	3	1	5	2	2

#	Objectives			Decision Variables																	
	Time (day)	Cost ($)	Quality (%)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
85	129	125148	66.83	3	5	3	3	4	2	3	4	2	2	3	2	3	3	1	5	2	2
86	134	114705	69.13	2	4	2	3	4	3	3	2	2	2	2	2	3	2	1	4	2	2
87	134	116105	70.03	2	2	2	3	4	3	3	2	2	2	2	2	3	2	1	2	2	2
88	134	116905	70.27	2	3	2	3	4	3	3	2	2	2	2	2	2	2	1	2	2	2
89	134	116905	70.27	2	3	2	3	4	3	3	2	2	2	2	2	2	2	1	2	2	2
90	134	117505	70.47	2	2	2	3	4	3	3	2	2	2	2	2	2	2	1	2	2	2
91	134	118905	70.57	2	3	2	3	4	3	2	2	2	2	2	2	2	2	1	2	2	2
92	134	119505	70.77	2	2	2	3	4	3	2	2	2	2	2	2	2	2	1	2	2	2
93	134	121905	70.80	2	3	2	3	3	3	3	2	2	2	2	2	2	2	1	2	2	2
94	134	121905	70.80	2	3	2	3	3	3	3	2	2	2	2	2	2	2	1	2	2	2
95	134	122505	71.00	2	2	2	3	3	3	3	2	2	2	2	2	2	2	1	2	2	2
96	134	123605	71.10	2	2	2	3	2	3	3	2	2	2	2	2	3	2	1	2	2	2
97	134	123605	71.10	2	2	2	3	2	3	3	2	2	2	2	2	3	2	1	2	2	2
98	134	124405	71.33	2	3	2	3	2	3	3	2	2	2	2	2	2	2	1	2	2	2
99	134	125005	71.53	2	2	2	3	2	3	3	2	2	2	2	2	2	2	1	2	2	2
100	134	129505	71.80	2	2	2	2	3	3	2	2	2	2	2	2	2	2	1	2	2	2
101	134	131155	71.87	2	3	2	2	2	3	2	2	2	2	2	2	2	2	1	3	2	2
102	135	112500	65.50	3	5	3	3	4	3	3	5	3	2	3	2	3	3	1	5	2	2
103	135	112500	65.50	3	5	3	3	4	3	3	5	3	2	3	2	3	3	1	5	2	2
104	135	112580	65.97	3	5	3	3	4	3	3	3	3	2	3	2	3	3	1	5	2	2
105	135	113640	67.23	3	4	3	3	4	3	3	3	2	2	3	2	3	3	1	4	2	2

Appendix B: Ranks of the Pareto-optimal solutions according to the ER, PROMETHEE, and TOPSIS methods

ER		PROMETHEE		TOPSIS	
#	Overall	#	Phi	#	CC
23	64.67	23	0.113309	24	0.702331
24	64.02	24	0.107841	25	0.702331
25	64.02	25	0.107841	38	0.700458
22	62.65	22	0.102292	31	0.696016
41	62.15	4	0.098213	23	0.694248
44	62.07	3	0.09639	22	0.68501
43	62.02	11	0.095275	30	0.673613
42	61.90	10	0.094802	36	0.668828
45	61.87	5	0.094051	37	0.665498
46	61.87	6	0.094051	21	0.663674
4	61.77	9	0.093659	57	0.655748
3	61.62	44	0.093606	20	0.649581
39	61.52	43	0.093215	29	0.648636
47	61.38	12	0.093153	55	0.648351
48	61.38	13	0.093153	56	0.648351
31	61.30	31	0.093021	18	0.638047
49	61.28	41	0.092986	19	0.638047
40	61.28	2	0.092892	54	0.637673
2	61.19	1	0.092664	53	0.629652
5	61.16	42	0.092072	17	0.624349
6	61.16	7	0.092011	51	0.619502
1	61.16	8	0.092011	52	0.619502
10	60.93	45	0.091566	15	0.609072
11	60.90	46	0.091566	16	0.609072
9	60.83	14	0.088991	14	0.601361
7	60.82	47	0.087404	12	0.590294
8	60.82	48	0.087404	13	0.590294
50	60.73	39	0.087078	28	0.584486
12	60.50	15	0.086951	11	0.582078
13	60.50	16	0.086951	10	0.575481
58	60.45	40	0.086164	9	0.571843
59	60.45	49	0.086033	35	0.568963
60	60.42	28	0.084698	50	0.568859
28	59.84	50	0.082344	7	0.552607
14	59.73	27	0.079002	8	0.552607
27	59.64	17	0.078219	49	0.547389
15	59.30	21	0.076701	5	0.54346
16	59.30	60	0.073416	6	0.54346
62	59.08	58	0.072274	4	0.530466
61	58.89	59	0.072274	62	0.527125
35	58.65	35	0.071971	47	0.499751
26	58.34	20	0.069406	48	0.499751
17	57.80	18	0.068785	3	0.499708
21	57.65	19	0.068785	2	0.490724
34	57.62	30	0.068495	45	0.48478
38	57.51	38	0.06822	46	0.48478
32	57.39	26	0.06634	1	0.480037
33	57.39	62	0.065243	44	0.473876
53	57.19	34	0.059535	27	0.46957
51	57.08	53	0.059494	43	0.465449
52	57.08	29	0.058437	42	0.460796

ER		PROMETHEE		TOPSIS	
#	Overall	#	Phi	#	CC
30	56.86	51	0.057879	41	0.453782
54	56.82	52	0.057879	34	0.451807
64	56.30	32	0.057395	32	0.449329
18	56.21	33	0.057395	33	0.449329
19	56.21	54	0.057373	26	0.447585
55	56.13	55	0.053211	40	0.439743
56	56.13	56	0.053211	39	0.432605
20	56.00	36	0.052875	82	0.42168
63	55.82	57	0.051171	83	0.42168
57	55.77	61	0.050748	60	0.420515
29	55.14	37	0.04178	58	0.415657
36	54.71	64	0.029023	59	0.415657
66	54.71	63	0.022919	81	0.415319
65	54.53	66	0.013974	64	0.409862
37	53.75	65	0.011916	101	0.405848
87	41.37	72	-0.11338	66	0.403574
88	41.20	73	-0.11429	80	0.403391
89	41.20	74	-0.11429	63	0.401176
90	41.09	87	-0.11475	65	0.400942
86	40.99	70	-0.1157	79	0.399502
91	40.33	75	-0.11581	100	0.394557
68	40.29	71	-0.11591	78	0.393887
69	40.29	86	-0.11616	61	0.39303
92	40.22	88	-0.11619	77	0.373046
70	40.21	89	-0.11619	99	0.365656
72	40.21	76	-0.11672	98	0.361151
71	40.11	90	-0.1171	76	0.356266
67	40.05	68	-0.1172	96	0.355518
73	39.97	69	-0.1172	97	0.355518
74	39.97	67	-0.12208	75	0.350666
75	39.63	91	-0.12223	95	0.34926
76	39.39	77	-0.12276	93	0.345178
93	38.70	92	-0.12314	94	0.345178
94	38.70	78	-0.12621	73	0.343576
95	38.59	80	-0.12733	74	0.343576
77	38.35	79	-0.12839	72	0.338199
96	38.01	81	-0.13246	92	0.333911
97	38.01	93	-0.13308	71	0.331417
84	38.01	94	-0.13308	91	0.330324
85	38.01	82	-0.13337	70	0.328669
98	37.81	83	-0.13337	90	0.324213
105	37.71	95	-0.13399	88	0.320991
99	37.70	105	-0.13528	89	0.320991
78	37.53	96	-0.13785	68	0.320132
80	37.22	97	-0.13785	69	0.320132
79	37.18	84	-0.13853	87	0.317011
104	36.58	85	-0.13853	67	0.310733
81	36.43	98	-0.13936	84	0.308992
82	36.20	99	-0.14028	85	0.308992
83	36.20	104	-0.14107	86	0.308517
102	35.98	102	-0.14456	105	0.30535
103	35.98	103	-0.14456	104	0.299038
100	35.10	100	-0.15717	102	0.297669

ER		PROMETHEE		TOPSIS	
#	Overall	#	Phi	#	CC
101	34.11	101	-0.1636	103	0.297669