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MULTI-OBJECTIVE PROJECT CRASHING ALGORITHM SELECTION

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Abstract

Project crashing algorithm selection of a project is a crucial aspect of each project to decision makers striving to expedite or crash a project. In this study a new method has been introduced to choose alternatives based on the interest and preferences of decision makers due to the uncertainties of the optimal solutions of crashing algorithms. A multi criteria decision making (MCDM) technique, The Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**) is used to select the appropriate crashing algorithm. The proposed method leads the decision makers to select the desirable algorithm to their projects. An example is analysed to demonstrate the capabilities of the present method.

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1. CHAPTER ONE: INTRODUCTION

1.1 Multi-objective project crashing

Multi-objective project crashing is a process of accelerating an activity or multiple activities in order to shorten the overall durations of a project taking in to account many complicated and usually conflicting parameters/factors at a time.Though project managers' effort is to deliver projects within planned duration and budgets, delays and cost overrun occurs as a routine phenomenon at many construction projects and it can cause unavoidable dispute between owners and contractors. In other words, contractors and owners usually aim to balance between overall cost of a project and its duration. As a result, project crashing, also known as project time reduction, least-cost expending, optimized scheduling, scheduling with time constraints and time-cost trade-off has been introduced and studied. Time-cost trade-off analysis, typically leads to rational estimation of project least cost duration which is not necessarily identical to the original contractual duration. Thus, contractors and project managers often encounter the need to expedite the execution on the project under their responsibility to meet targeted milestones imposed by owners and/or to make up for lost time due to delays experienced during execution of the project. This need can also arise from the fact that "originally estimated project duration is not necessarily the least time solution nor is the least cost schedule for the project, in spite of the fact that each activity within the project was originally planned to be done in the most efficient manner"[5]. Project crashing is referred to as the shortening of the required time for accomplishing one or more of the engineering, procurement, construction start up tasks (or a total project) to serve one of the three purposes [3]:

- Reducing total design-construction time from that considered normal;
- Accelerating a schedule for owner convenience; and
- Resolving lost time after falling behind schedule.

Expediting respective duration of projects is becoming a challenging task in management of construction projects considering a set of factors in addition to the basic ones i.e. time and cost. Hence, Construction project Expediting has received a considerable attention over the last two decades. Though, a lot of methods and algorithms have been developed to address the above problem, still there is a difficulty of using appropriate algorithms/methods to both contractors and owners as these algorithms obtain different optimal solutions to a single project.

A project crashing algorithm/method is considered as a tool of project optimization which aims to shorten project schedules without changing project scope of work, in order to meet schedule constraints and objectives. Selection of proper crashing algorithm is one of the important issues of project expediting activities of achieving high performance in project delivery. The main advantage of selecting a proper crashing algorithm is to avoid crisis or other consequences due to using irrelevant algorithm which costs more than the cost of algorithm selection process especially for mega projects including thousands of activities, such as Great Renaissance Dam and Railway projects in Ethiopia.

As a result , obtaining a project crashing algorithm selection method for construction projects of reducing duration while imposing least additional direct cost keeping other factors optimal, has been of interest to this study.

1.2 Statement of the Problem

When reviewing literature on project crashing, certain issues appeared to have been left unanswered. First, though, most decision makers (DMs) frequently resort to schedule crashing but still reduced to some form of time-cost trade-off analysis, where schedule crashing is performed based on cost only. Second, although various methods and factors are proposed in the literature to solve multiple objective project crashing problems, different methods and/or algorithms consider only limited factors, such as time, cost, quality and quantity in multi colony ant algorithm, time, cost and Material Restrictions in Fuzzy Mathematical Models and Critical Path Method, and time, cost, risk and uncertainty in Fuzzy Set Theory and Contractors Judgment. This is likely because of the fact that in all these methods, crashing is still reduced to some form of analysis, where crashing is performed based on limited factors only. In other words, there is no single method considering a set of factors those managers and contractors can use to perform this important management function. Furthermore, no algorithm selection method developed to select the most optimal or optimal of the optimal solutions obtained using different algorithms. However, it is important to obtain algorithm selection method considering the essential parameters/factors will be of essence and gain more important in setting priorities for activity crashing.

1.3 Objective

1.3.1 Main objective

The main objective of this study is to obtain and provide multiple - objective project crashing algorithm selection method using the Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**).

1.3.2 Specific objective

To accomplish the main objective stated above, the specific objectives of this study are summarized as follows:

- Investigate or take look on currently used multi- objective project crashing algorithms and determine the limitations of these approaches.
- Identify the factors/parameters considered by the current algorithms and what are the contractors and project managers' actual interest during project crashing.
- Identify commonly used multi – objective crashing algorithms.

- Validate the performance of the proposed method or technique using an illustrative example.

1.4 Organization of the thesis

Chapter 2 presents a review of the literature regarding project crashing including parameters/factors considered during crashing, time- cost trade off, recently used project crashing algorithms and review on the commonly used project crashing models such as ant colony optimization (ACO), fuzzy logic model, modified adaptive weight approach (MAWA) and multi-objective optimization model (MOOM). Chapter 3 reviews the proposed methodology. Chapter 4 mainly discusses the algorithm selection analysis such as the description and computational procedure of a multi-criteria decision analysis method (**TOPSIS**), risk zoning and risk-quality interconvert ability and an illustrative example. Finally Chapter 5 presents the conclusion and recommendation of this thesis respectively.

2. CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

Multi-objective project crashing is referred to as the shortening of the required time for accomplishing one or more of the engineering, procurement, construction start up tasks (or a total project) taking various factors in to consideration, i.e. time, cost, quality, quantity, material restriction etc. The basic crashing techniques in construction projects should be developed for the purpose of reducing total design-construction time from that considered normal, accelerating a schedule for owner convenience, and resolving lost time after falling behind schedule [3].

Over the years, many research studies have been conducted to model time-cost relationship, discarding other factors. As a result, Construction planners often face the challenge of optimum resources utilization to compromise between different and usually conflicting aspects of projects such as resource availability, contractors' leverage on subcontractors who are selected to carry out the accelerated work, additional direct cost required to crash each activity from its normal duration state, risk, complexity and logistics of the work involved, number of successor of the activities and cash flow constraints etc.

Though, recent trends (i.e. multiple objective project crashing) consider some of the factors stated before in addition to time and cost but still project crashing is reduced to some form of analysis, where schedule crashing is performed based on limited factors (i.e. one algorithm consider a limited parameters/factors at a time) and using different algorithms obtain different optimal solution for a single project. As a result, it is important to obtain a method to select the best algorithm with the optimal solution from the existing to be used by both the contractors and project managers before start expediting their project.

2.2 Time-cost trade-offs

Project crashing is a challenging task, which project teams frequently face when there is a need to reduce durations of projects in an effort to meet contractual obligations, changing client needs, recover from delays experienced during project execution and/or to determine least cost project duration [11].The process of project crashing or accelerating completion of construction was originally developed by Kelly 1961 after introduction of critical path method (CPM) for planning, scheduling and controlling projects [4]. It aims at establishing the delicate balance between the overall cost of a project and its duration, to achieve the desired overall project objectives.

The process of project crashing referred to (Moselhi 1993, Evensmo and Karlsen 2008) is also known as [9]:

- ✓ Project time reduction,
- ✓ Least-cost expediting,
- ✓ Project compression or schedule compression,
- ✓ Least-cost scheduling,
- ✓ Optimized scheduling,
- ✓ Scheduling with time constraints,
- ✓ Project acceleration,
- ✓ Project time crashing or schedule crashing

The objective of the time-cost trade-off analysis is to reduce the original project duration, determined form the critical path analysis, to meet a specific deadline with the least cost. In addition to that it might be necessary to finish the project in a specific time to finish the project in a predefined deadline date, recover early delays, avoid liquidated damages, free key resources early for other projects, and avoid adverse weather conditions that might affect productivity, receive an early completion-bonus, and improve project cash flow [8]. Reducing project duration can be done by adjusting overlaps between activities or by reducing activities' duration. What is the reason for an increase in direct cost as the activity duration is reduced? A simple case arises in the use of overtime work. By scheduling weekend or evening work, the completion time for an activity as measured in calendar days will be reduced. However, extra wages must be paid for such overtime work, so the cost will increase. Also, overtime work is more prone to accidents and quality problems that must be corrected, so costs may increase. The activity duration can be reduced by one of the following actions [8]:

- ✓ Applying multiple-shifts work.
- ✓ Working extended hours (over time).
- ✓ Offering incentive payments to increase the productivity.
- ✓ Working on weekends and holidays.
- ✓ Using additional resources.
- ✓ Using materials with faster installation methods.
- ✓ Using alternate construction methods or sequence.

This duration reduction results in increasing the total direct cost of projects and in decreasing project indirect cost. It should be noted that direct costs are those costs related to putting the facility components in place, containing cost of all resources directly used in execution of project (e.g. materials, labor, equipment and subcontractors); likewise, indirect costs are the costs generally incurred whether or not productive work is actually accomplished, (e.g. office personnel, office services and supplies, site supervision, etc) and should be considered as long as the project is underway [5].

In the process of project crashing, additional resources are used to reduce the original durations of individual activities, which give rise to progressive increase of the project direct cost and steady reduction in the project indirect cost [9], as is shown in Figure 2.1. Accordingly, the resulting relationship between project total cost (direct plus indirect costs) and its duration provides project teams with useful information. Because of the above mentioned changes in project direct and indirect costs over projects' shortened duration, the project total cost versus duration curve typically depicts a valley, which identifies the optimum project duration and its associated cost, i.e. the project's least cost duration. In other words, this curve includes the project optimum duration, which coincides with the project least total cost, as well as the total additional direct cost required to crash project's schedule to any targeted duration.

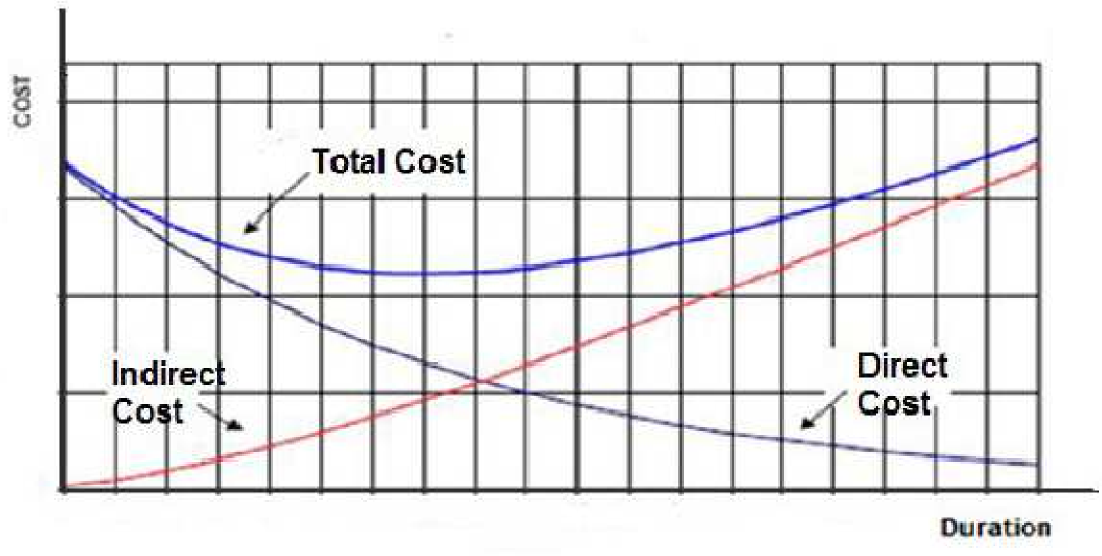


Figure 2.1: Project time-cost relation [source: Nazila (2011, 14)]

Minimization of such increased direct cost and finding the point of least-cost duration has always been of interest to researchers and professionals alike. Consequently, because of the importance of schedule crashing process in successful management of engineering, procurement and construction (EPC) projects, considerable studies were carried out to develop methods to solve this problem. This resulted in the development of a number of models to determine the least-cost project duration and/or project least-cost associated with any targeted duration e.g. Kelly 1961, Elmaghrabi 1993, Yang 2005, Geem 2010, Evensmo and Karlsen 2008, Ezeldin and Soliman 2009, Cheng, Huang and Cuong 2011. Schedule crashing is divided in to planned schedule crashing which is planned before construction starts; and unplanned, that is a result of unexpected changes to planned scope of work and in the majority of the cases the need for project acceleration is due to the later [6]. In most study we focus mainly on unplanned needs for schedule crashing. In other words, the proposed method deals with the situations where delays have been already occurred. In such situations, contractors and project managers will find themselves trending beyond their committed deadline date and are forced to crashing schedules of their projects; since in 75 percent of the cases, no extra time is granted by owners [9]. Also, it is applicable to the cases where during execution phase of the project, owners introduce changes in scope and/or pre-scribed project milestones. In either of these cases, contractors resort to use different crashing strategies to get their projects back on track. The sooner these decisions are made, the project is more likely to be succeeded to get back on track; since in early stages of project execution there are many options to solve the problem, but toward the end, available choices dwindle.

Based on Yerkes-Dodson Law, “performance increases with cognitive arousal, but only to a certain point. Performance, however, decreases when levels of arousal become too high” [9]. Considering this fact in project schedule crashing will be translated as existence of a level of schedule pressure at which performance is at a maximum. In other words, pressurizing an activity less or more than this level will lead to reduction in performance and productivity.

As such, although contractors and owners can benefit from the results of accelerating a project, that can be earlier entrance of their product to the market for owners, and avoiding penalties and/or gaining early completion bonuses for contractors, productivity and quality may be sacrificed in this acceleration process [9]. It is important to quantify the impact of schedule crashing on labor productivity and determine the factors which have the most effect on this loss of productivity for both planned and unplanned schedule accelerations.

To start crashing process, before applying any of the project crashing strategies, the relations between activities direct cost and their respective durations should be determined. Some of the relationships are continuous and discrete time–cost relationship. A continuous relationship represents an activity that can be completed at any time–cost combination along the curve. In contrast, a discrete time–cost relationship appears when only specific and distinct duration values are feasible and is more appropriate than a continuous one to model engineering project activities. It should be noted that an activity might also have hybrid of continuous and discrete time-cost relations.

Traditionally, a linear continuous relation is assumed between activities time and their respective direct cost. In this kind of relation, by decreasing activity duration from its normal duration to its crashed point, i.e. the point in which activity reaches its most compressive duration and cannot be further crashed, its associated direct cost will increase linearly (see Figure 2.2). However, this assumption might not be realistic enough for a number of construction activities. As a result a number of time-cost relations are introduced to better present each activity's special direct cost change over its crashed duration.

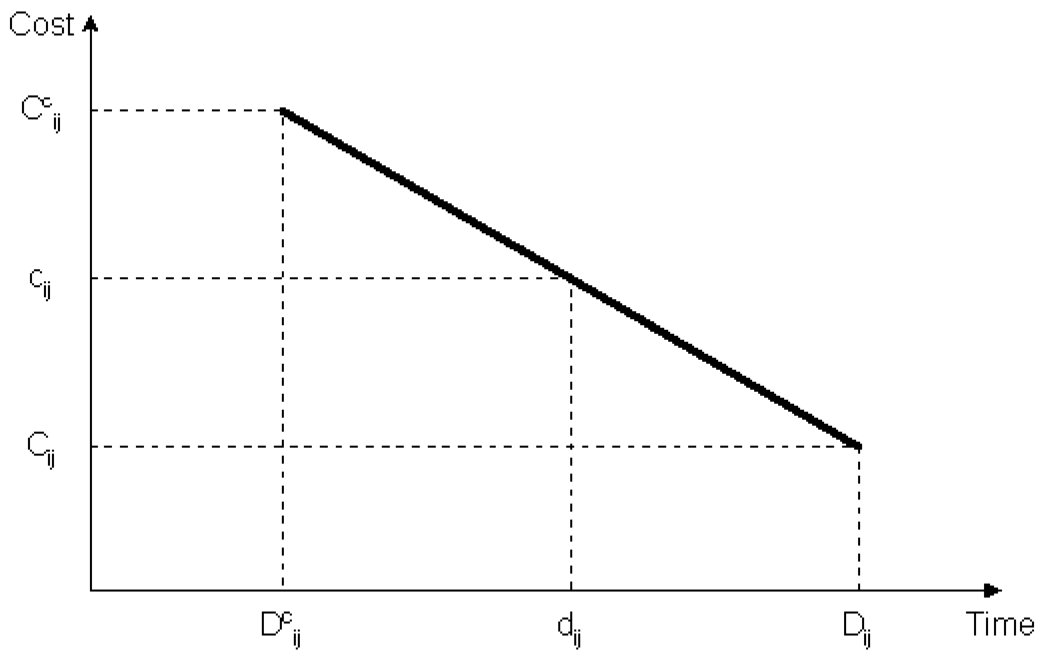
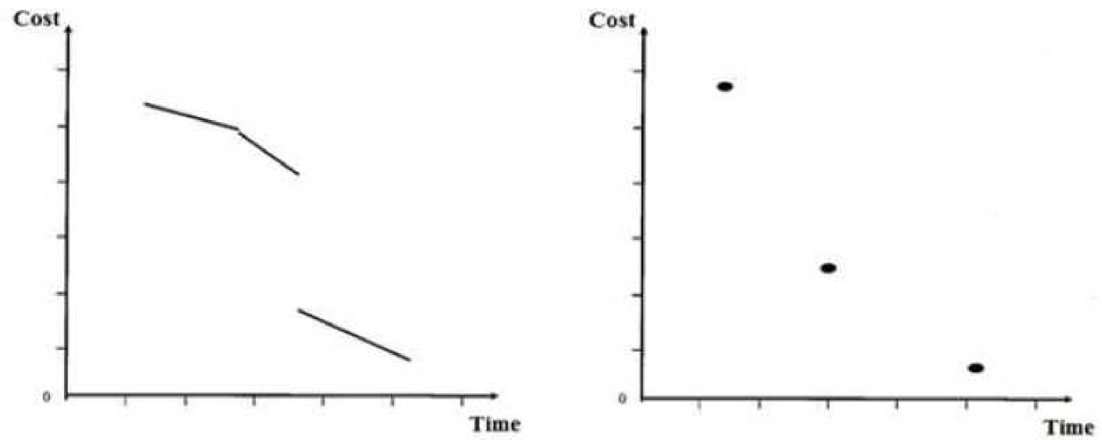


Figure 2.2: Linear activity time-cost relation [source: Nazila (2011, 18)]

- Multi-linear (Piecewise linear and linear with gaps in between which could be attributed to the use of different technologies). This kind of time-cost relation is also used frequently in the methods presented in the literature since the linearity can approximate the true cost variation without much error. Also, linear relationships allow the application of linear programming (LP) techniques, which are efficient and can guarantee a global optimal solution and finally, nonlinearity of time-cost relationships can be circumvented by piecewise linearization.
- Discrete
- Curve –linear, concave or convex (could be converted to piecewise linear) and etc.



a) Piece-wise linear b) Discrete

Figure 2.3: a) Piece-wise linear and b) discrete activity time-cost relations [source: Nazila (2011, 19)]

After each activity's time cost relations has been determined, the process of schedule crashing should be started. Contractors and/or decision makers (DMs) are then to select a method to find the best activity or the best set of activities that should be accelerated to optimize project schedule. This is usually done by means of using additional resources such as working overtime and double shifts (additional hours from existing workers), bringing expert crew or subcontracting the work, utilizing more productive equipment, using different construction methods and have a closer look at break down of the cost needed to accelerate the activities involved. Thus different methods are proposed to address the problems stated above. These methods can mainly be divided to optimization and heuristic methods as described below.

2.2.1 Optimization methods

Various optimization models are developed to solve the time-cost trade-off problem. These methods can mainly be categorized to two categories; first group are optimization methods that use different mathematical and artificial intelligence techniques to solve the time-cost trade-off problem. These methods provide good optimum or near optimum solutions but are difficult to apply and require considerable computational effort [7].

2.2.1.1 Mathematical programming

Mathematical approaches convert the project time-cost trade-off problem to mathematical problems. In other words, they convert project CPM network and its precedence and time-cost relationships into constraints and objective functions.

These mathematical algorithms mainly are used to obtain the optimal solutions for the time-cost trade-off problem. The main advantages of mathematical approaches include their efficiency and accuracy. However, as stated previously, formulating constraints and objective functions is time-consuming and prone to errors [10]. Furthermore, having mathematical programming knowledge is necessary to formulate these mathematical models correctly, while few construction planners are trained to perform this type of formulation, especially for large networks. These models can increase in size very rapidly and large problems may not be computationally tractable in reasonable time frames. Because of these reasons, the application of these models is limited as they are not efficient in optimizing large-scale construction projects.

2.2.1.2 Near optimum solutions

With the fast growth in computer technology and advances in artificial intelligence applications, computational optimization techniques were used more and more to solve the schedule crashing problems. In contrast with mathematical methods, these approximate methods perform well over a variety of problems. These methods are simple and easy to use, but may lead only to near optimum solutions [10]. Approximate methods utilize different techniques to carry out the schedule crashing process such as Genetic Algorithm, Particle Swarm Optimization and iterative crashing process.

These optimization methods performed well over a variety of problems as they are simple and easy to use and need less computational effort, although may lead only to near optimum solutions. Also, as explained earlier, application of these methods is time-consuming for large scale projects. Because of these reasons, heuristic methods have been introduced and used widely to solve time-cost trade-off problem.

2.2.2 Heuristic methods

The second group of project schedule crashing methods are the heuristic methods that are mainly based on rules of thumb. Although these methods are easier to model and apply, which renders them more practical for large scale projects, they do not guaranty optimal solutions.

The iterative crashing method is also one of the other approximate methods. It was first introduced by Siemens (Siemens 1971) as an effective cost slope model named SAM (Siemens Approximation Method) [2]. this method commonly considers linear, piecewise linear, discontinuous, hyperbolic or discrete relations between activity's direct cost and its duration and tends to shorten project total duration by crashing the activity with the lowest cost slope on the critical path one unit of time in each iteration. In other words, this is done by selectively crashing specific activities to shorten project duration and then incrementally crashing (i.e., shave a day off of) the selected activity where that is possible. Then it keeps track of the activity-based (direct) cost of crashing selected activity (or activities) and indirect cost savings associated with reducing overall project duration while recalculating the forward pass and check for changes in network critical path(s). The procedure of crashing ends up by reaching project least-cost duration, reaching the targeted project duration or until no further crashing is possible. Iterative crashing procedure has also been used to accelerate linear projects such as highways and pipelines. These heuristic methods performed well over a variety of problems. However, the solutions obtained by these heuristic methods do not provide the range of possible solutions, making it difficult to experiment with different scenarios for what-if analyses. Still these heuristic methods can find good solutions with far less computational effort than optimization methods. Regardless of being heuristic or optimization based, leading to optimum or near optimum solutions, none of the methods stated above take into account any factor beyond the additional direct cost required for acceleration of project activities. This has been attributed to the limited uptake and use of these methods. In fact, the lack of consideration of such factors has been attributed to the limited use, if any, of these methods in practice [1].

2.3. Factors considered during project crashing

In today's construction projects it is important to find out factors that contractors and/or decision makers(DMs) usually consider in order to accelerate their projects in the most efficient and practical manner. Appropriate set of parameters/factors selection to our project in addition to time and cost is one of the main activities to be performed before crashing started. The top seven commonly considered factors in schedule crashing are (see Figure 2.4) [7]:

- ✓ Resource availability,
- ✓ Contractors' leverage on subcontractors, who are selected to carry out the accelerated work,
- ✓ Additional direct cost required to crash each activity from its normal duration state,
- ✓ Risk,
- ✓ Complexity and logistics of the work involved,
- ✓ Number of successor of the activities and
- ✓ Cash flow constraints.

Though recent trends on project crashing algorithms reveal that the most commonly considered parameters are time, cost, risk, and quality, as can be seen from Figure 2.4 factors such as resource availability and contractor's leverage on sub-contractors who are deemed more capable of performing the accelerated work were found to be even more important than the project additional cost needed for crashing activity durations. As stated above and shown in Figure 2.4, it is more important in setting priorities for activity crashing accordingly rather than considering cost as the major factor as time-cost trade off algorithms. This perhaps explains the limited use of existing methods that consider limited parameters in practice though contractors and construction management professionals consider a wide range of factors when making decisions pertinent to shortening project durations.

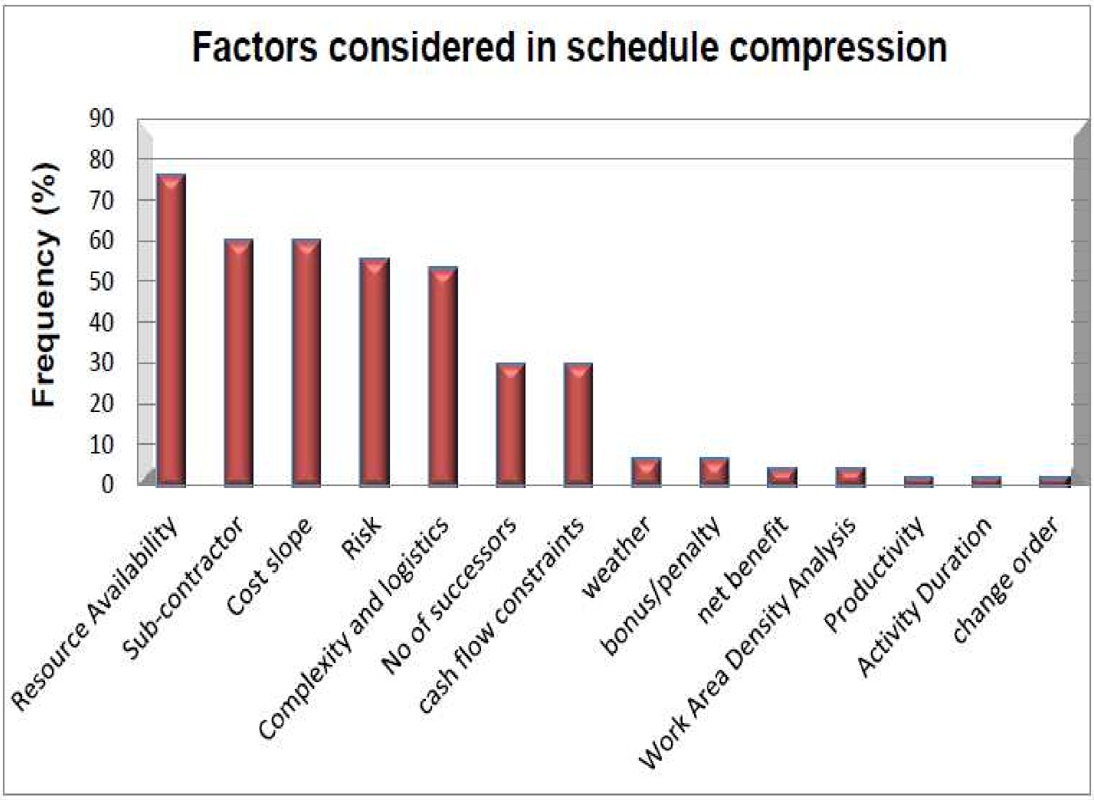


Figure 2.4: Factors considered in schedule compression [source: Roofigari (2011-b, 40)]

Result of respondents on the frequency of encountering the need to accelerate projects under their responsibility show that only 5 percent of the respondents did not encounter such a need as shown in Figure 2.5 below. These results also show that the majority of the respondents (42 percent) encounter this need in 30 to 70 percent of the projects under their responsibility ([7], 38). This clearly shows the practical importance of the schedule crashing as a critical management function.

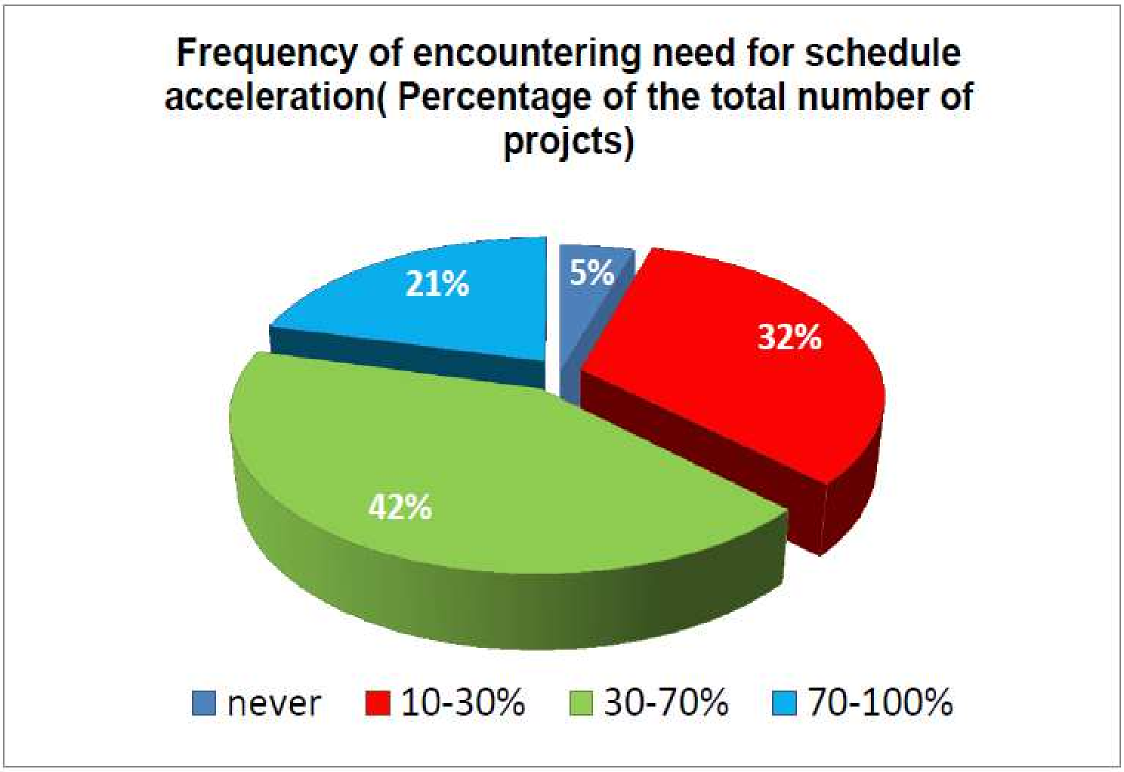


Figure 2.5: Frequency of encountering the need for schedule acceleration [source: Roofigari (2011-b, 38)]

2.4 Recently used methods of multi - objective project crashing

As stated in the introduction part of this literature review multi-objective project crashing is referred to as the shortening of the required time for accomplishing one or more of the engineering, procurement, construction start up tasks (or a total project) taking various factors in to consideration, i.e. time, cost, quality, quantity, material restriction etc and the basic crashing techniques in construction projects should be developed for the purpose of reducing total design-construction time from that considered normal, accelerating a schedule for owner convenience, and resolving lost time after falling behind schedule.

Over the years, many research studies have been conducted to model time-cost relationship, discarding other factors. As a result, Construction planners often face the challenge of optimum resources utilization to compromise between different and usually conflicting aspects of projects. Though, recent trends (i.e. multiple objective project crashing) consider the quality, quantity, risk, uncertainty and others in addition to time and cost but no single method of project crashing considering the stated factors into account at a time.

In this part of the literature, review of the recent literature on special methods/algorithms, along with their assumptions and limitations, used for multi-objective project crashing in addition to time and cost are presented. Many articles and studies conducted on multi-objective project crashing have been reviewed. Research conducted [12], develops a new metaheuristic multi-colony ant algorithm for the optimization of three objectives time-cost quality as a trade off problem. The model is also applicable to two objectives time – cost trade off problem. [4] Mainly discusses how fuzzy mathematical models may be used to generate construction project schedules and how to incorporate restrictions that are defined by decision makers (DMs) on items such as materials, time, and cost. Time-cost trade-offs may also be incorporated into schedules using fuzzy mathematical models, which facilitate time-cost trade-off analysis. Fuzzy mathematical models that allow the multi-objective optimization of project schedules considering constraints such as time, cost, and unexpected materials shortages were used to verify commonly used methodologies for finding the minimum completion time for projects. The research also used a heuristic procedure for material allocation and sensitivity analysis to test material shortage, which increase the cost of construction and delay the completion time of projects. [11] Presents a new method developed for schedule crashing of construction projects. The method accounts for risk and uncertainties associated with crash cost and it considers contractors' judgment. It allows contractors to: 1) perform risk analysis for different schedule crashing plans; and 2) perform different scenarios expressing vagueness and imprecision of estimated crash cost using a set of measures and indices. The method combines Fuzzy Set Theory and contractors' judgment in setting priorities for the crashing process of project schedules.

2.5 Multi criteria decision making

Decision making is the study of identifying and choosing alternatives based on the values and preferences of the decision maker. Making a decision implies that there are alternative choices to be considered, and in such a case we want not only to identify as many of these alternatives as possible but to choose the one that best fits with our goals, objectives, desires, values, and so on[28].

Consider a multi-attribute decision making problem with *m* criteria and *n* alternatives. Let $\mathbf{C}_1,\ldots,\mathbf{C}_m$ and $\mathbf{A}_1,\ldots,\mathbf{A}_n$ denote the criteria and alternatives, respectively. A standard feature of multi-attribute decision making methodology is the *decision table* as shown below. In the table each row belongs to a criterion and each column describes the performance of an alternative. The score a_{ij} describes the alternative $\mathbf{A}_j$ against criterion $\mathbf{C}_i$. For the sake of simplicity we assume that a higher score value means a better performance since any goal of minimization can be easily transformed into a goal of maximization.

As shown in decision table, weights $w_1,\ldots,w_m$ are assigned to the criteria. Weight w_i reflects the relative importance of criteria $\mathbf{C}_i$ to the decision, and is assumed to be positive. The weights of the criteria are usually determined on subjective basis. They represent the opinion of a single decision maker or synthesize the opinions of a group of experts using a group decision technique, as well.

The values $x_1,\ldots,x_n$ associated with the alternatives in the decision table are used in the MAUT methods (see below) and are the final ranking values of the alternatives. Usually, higher ranking value means a better performance of the alternative, so the alternative with the highest ranking value is the best of the alternatives.

Table 2.1: The decision table

$$
\begin{array}{cc|cccc|}
 & & x_1 & \cdot & \cdot & x_n \\
 & & \mathbf{A}_1 & \cdot & \cdot & \mathbf{A}_n \\
\hline
w_1 & \mathbf{C}_1 & a_{11} & \cdot & \cdot & a_{m1} \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
w_m & \mathbf{C}_m & a_{m1} & \cdot & \cdot & a_{mn} \\
\hline
\end{array}
$$

Multi-attribute decision making techniques can partially or completely rank the alternatives: a single most preferred alternative can be identified or a short list of a limited number of alternatives can be selected for subsequent detailed appraisal.

Besides some monetary based and elementary methods, the two main families in the multi-attribute decision making methods are those based on the Multi-attribute Utility Theory (MAUT) and Outranking methods.

The family of MAUT methods consists of aggregating the different criteria into a function, which has to be maximized. Thereby the mathematical conditions of aggregations are examined. This theory allows complete compensation between criteria, i.e. the gain on one criterion can compensate the lost on another [29]. The concept of outranking was proposed by Roy (1968). The basic idea is as follows. Alternative **A***i* outranks **A***j* if on a great part of the criteria **A***i* performs at least as good as **A***j* (concordance condition), while it's worse performance is still acceptable on the other criteria (non-discordance condition). After having determined for each pair of alternatives whether one alternative outranks another, these pair wise outranking assessments can be combined into a partial or complete ranking.

Contrary to the MAUT methods, where the alternative with the best value of the aggregated function can be obtained and considered as the best one, a partial ranking of an outranking method may not render the best alternative directly. A subset of alternatives can be determined such that any alternative not in the subset be outranked by at least one member of the subset. The aim is to make this subset as small as possible. This subset of alternatives can be considered as a shortlist, within which a good compromise alternative should be found by further considerations or methods.

2.6 Project crashing models

Project crashing has received a considerable attention over the last 20 years. As a result, a number of methods and algorithms have been developed to address specific problems using different models. A review of the models that have been developed is conducted and some of the models used for project crashing algorithm development are discussed below.

2.6.1 Ant colony optimization (ACO) model

In recent years, evolutionary and meta-heuristic algorithms have been extensively used as search and optimization tools in various problem domains, including science, commerce, and engineering. Ease of use, broad applicability, and global perspective may be considered as the primary reason for their success. Ant colony optimization algorithms are inspired by the fact that ants are able to find the shortest route between their nest and a food source, even though they are almost blind [30].

In general, ACO algorithms employ a finite size of artificial ants with defined characteristics which collectively search for good quality solutions to the problem under consideration. Starting from an initial state, selected according to some case-dependent criteria, each ant builds a solution which is similar to a chromosome in a genetic algorithm.

While building its own solution, each ant collects information on its own performance and uses this information to modify the representation of the problem, as seen by the other ants [30]. The ant's internal states store information about the ant's past behaviour, which can be employed to compute the goodness/value of the generated solution. Artificial ants are permitted to release pheromone while developing a solution or after a solution has fully been developed, or both. The amount of pheromone deposited is made proportional to the goodness of the solution an artificial ant has developed (or is developing). Rapid drift of all the ants towards the same part of the search space is avoided by employing the stochastic component of the choice decision policy and the pheromone evaporation mechanism. In order to simulate the pheromone evaporation, the pheromone persistence coefficient (ρ) is defined which enables greater exploration of the search space and minimizes the chance of premature convergence to suboptimal solutions. A probabilistic decision policy is also used by the ants to direct their search towards the most interesting regions of the search space.

The level of stochasticity in the policy and the strength of the updates in the pheromone trail determine the balance between the exploration of new points in the state space and the exploitation of accumulated knowledge [30].

Let $\tau_{ij}(t)$ be the total pheromone deposited on path ij at time t, and $\eta_{ij}(t)$ be the heuristic value of path ij at time t according to the measure of the objective function. Transition probability from node i to node j at time period t may be defined as [30].

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\propto}[\eta_{ij}(t)]^{\beta}}{\sum[\tau_{ij}(t)]^{\propto}\,[\eta_{ij}(t)]^{\beta}} & if\ j \in allowed \\ 0 & otherwise \end{cases}$$

Where α and β are parameters that control the relative importance of the pheromone trail versus a heuristic value. Let q be a random variable uniformly distributed over [0, 1], and q0∈ [0, 1] be a tunable parameter. The next node j that ant k chooses to go is [30].

$$j = \begin{cases} \arg\ \max\left\{[\tau_{il}(t)]^{\propto}[\eta_{il}(t)]^{\beta}\right\} & if\ q \leq\ q_o \\ J & othrwise \end{cases}$$

Where J = a random variable selected according to the probability distribution of p (t) ij. The pheromone trail is changed globally. Upon completion of a tour by all ants in the colony, the global trail updating is done as follows:

$$\tau_{ij}(t+1) \leftarrow \rho.\tau_{ij}(t) + \Delta\tau_{ij}$$

Where 0 ≤ ρ ≤ 1; ρ = evaporation (i.e., loss) rate, the symbol ← is used to show the next iteration and $\Delta\tau_{ij}$ represents the updating value of

$$\Delta\tau_{ij} = \begin{cases} \dfrac{Q}{f(k)} & if\ edge(i,j) is\ traversed\ by\ the\ k_{th}\ ant \\ 0 & otherwise \end{cases}$$

Where Q is a constant, representing the amount of pheromone an ant put on the path after an exploitation, and f (k) is the value of objective in each iteration.

2.6.2 Fuzzy set theory

Fuzzy set theory was developed specifically to deal with uncertainties that are not statistical in nature [19]. The concept of fuzzy sets theory differs from that of the conventional crisp sets mainly in the degree by which an element belongs to a set. In the crisp set theory, the members of a crisp set would not be members unless their membership was full in that set (i.e., their membership is assigned a value of one) While, in the fuzzy set theory, set elements are described in a way to permit a gradual transition from being a member of a set to a non member. Each element has a degree of membership ranging from zero to one, where zero signifies non membership and one indicates full membership.

A fuzzy set, A, is defined as a set of pairs, [x, $y_A(x)$], where x is an element in the universe of discourse X, and $y_A(x)$ is the degree of membership associated with element x. When the (variable) universe of discourse (X) is discrete and finite, a fuzzy set A in this universe is denoted by:

$$A = \left\{\frac{Y_A(x_1)}{x_1} + \frac{Y_A(x_2)}{x_2} + \cdots + \frac{Y_A(x_n)}{x_n}\right\}$$

In the case where X is a continuous and infinite variable, the degree of membership can be represented by a function, commonly known as membership function, membership functions can take various shapes and forms, A is denoted by:

$$A = \left\{\int \frac{y_A(x)}{(x)}\right\}$$

The numerator is the membership value in set A associated with the element of the universe indicated in the denominator. The plus signs in the first notation are not the algebraic ’add’ but are a function-theoretic union.

Similarly, the integral sign in the second notation is not an algebraic integral but a continuous function-theoretic union for continuous variables.

A continuous fuzzy set contains two properties: convexity and; normality. The convexity means that the membership function has only one distinct peak, while the normality ensures that at least one element in the set has a degree of membership equal to 1.0. Fuzzy sets can take various shapes; however, linear approximations such as the trapezoidal and triangular shapes are frequently used [23]. A trapezoidal fuzzy set can be represented by a four points (*a, b, c, d*) (figure 2.6), where *a* and *d* are the lower and upper bounds, *b* and *c* are the lower and upper middle values, respectively. Also, a triangular fuzzy set considered as a special case of the trapezoidal fuzzy set with *b* = *c* (figure 2.6). The membership function can be formulated as:

$$y_A(x) = \begin{cases} \dfrac{x-a}{b-a} & a < x < b \\ 1 & a \le x \le b \\ \dfrac{x-d}{c-d} & c < x < d \\ 0 & otherwise \end{cases}$$

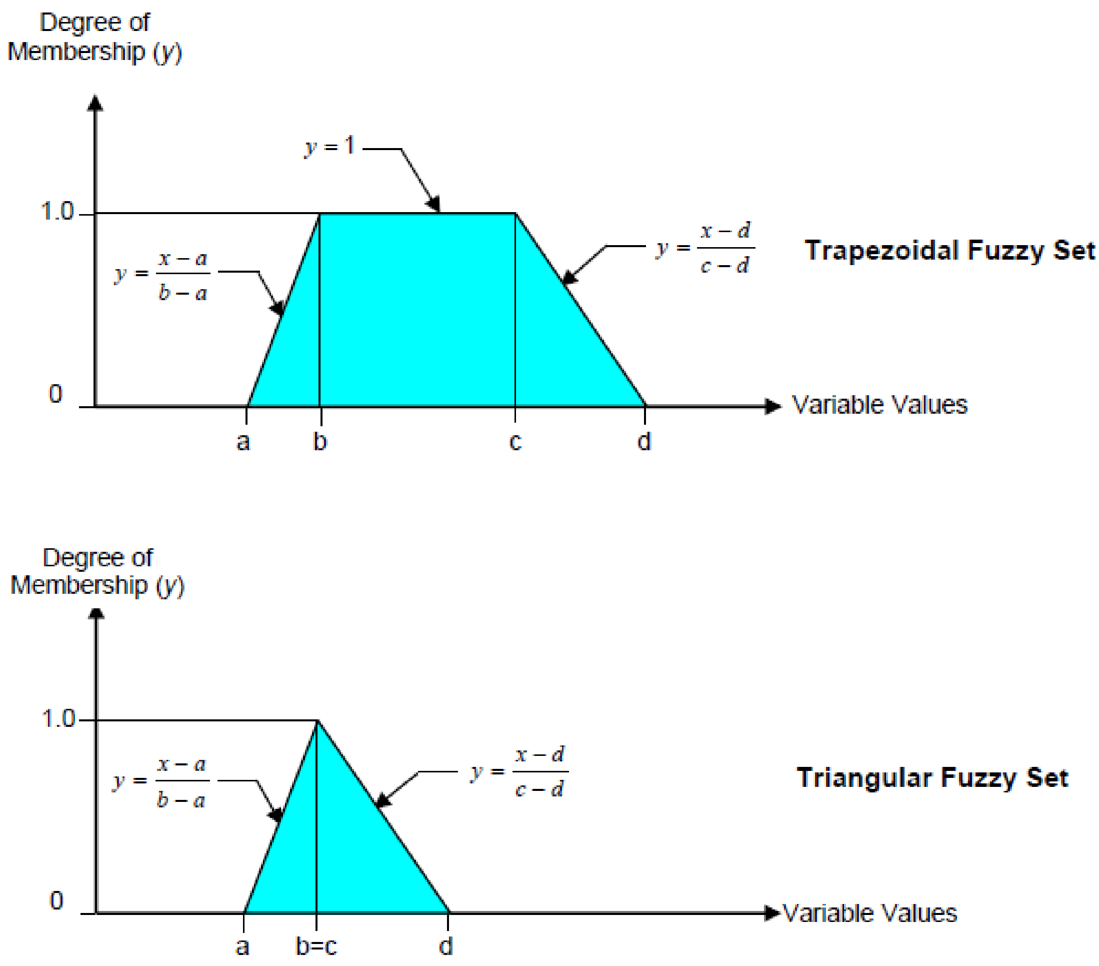


Figure 2.6: Fuzzy Set Representation

Graphically, a membership function can be represented by a variety of shapes, such as bells, triangles, or trapezoidal, but it is usually convex. For a given value y_A(x)= 0 means that x has a null membership in fuzzy set A, and y_A(x)= 1 means that x has full membership. These membership functions can be determined subjectively; the closer an element to satisfy the requirements of a set, the closer its grade of membership is to 1, and vice versa [24].

A fuzzy linguistic variable is defined as a variable, the values of which are words, phrases, or sentences in a given language. For example, material flow can be considered as linguistic variable with values such as "low flow", "medium flow", or "high flow", while numerical variables use numbers as values. Since words are usually less precise than numbers, linguistic variables provide a method to characterize complex systems that are ill defined to be described in traditional quantitative terms [26]. A linguistic variable is defined by the name of a variable X and a term set T(x) of the linguistic values of X with each value being a fuzzy number defined on universe of discourse U. For example, if Equipment Flow is a linguistic variable - the number of equipment moving among the different facilities on the construction site in a day - then its term sets, T(equipment flow), are "Low," "Medium," and "High," where each term is characterized by a fuzzy set in a universe of discourse U=[0,100] for example figure 2.7.

A membership function can be established for each of these linguistic values using a certain shape on a certain range as fit for given conditions. The three functions are grouped together in the figure as a fuzzy set family for fuzzy variable equipment flow. Figure 2.7 shows that 7 equipment flow belongs to the linguistic variables (High, Medium, and

Low) with membership values of (0, 0.8, 0.3), respectively. Using the maximum value to find the fuzzy set that this equipment flow value belongs to, 7 equipment flows belongs to the fuzzy set "Medium" with a membership value of 0.8. Because the fuzzy set concept is intended to remedy the drawbacks of the traditional clear-cut or brittle way of defining a semantic term, there always exists some overlap between membership functions within a fuzzy set family for a linguistic variable.

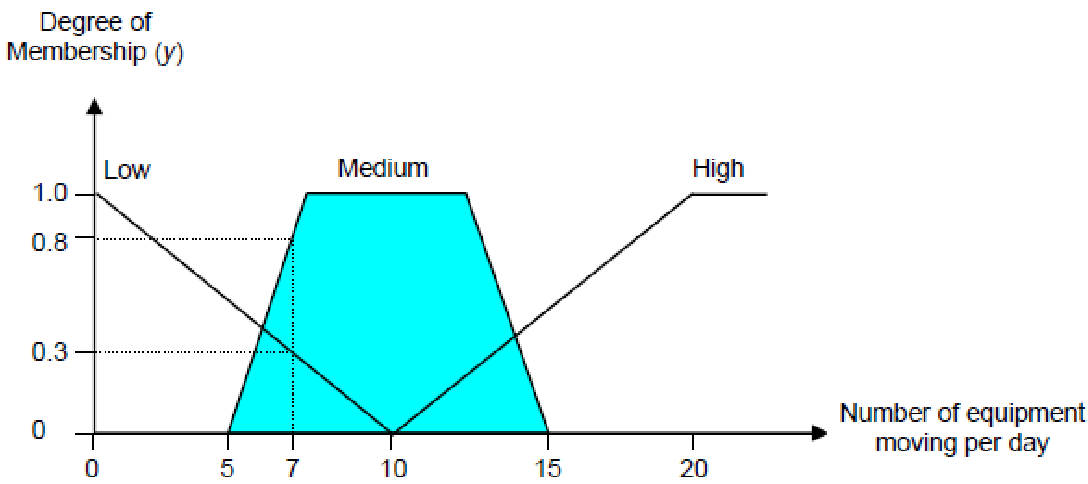


Figure 2.7: Fuzzy Sets for Linguistic Variable "Equipment Flow"

Fuzzy set theory is very useful in modelling complex and vague systems. The basic idea is that artificial logic systems can be developed to emulate the linguistic way human think and judge. In this context, the fuzzy logic approach is intended to streamline the decision analysis process and produce an evaluation according to the decision-makers value system and judgement, while maintaining simplicity and tractability. Fuzzy set theory is a tool that transforms this linguistic control strategy into a mathematical control method. Mamdani in 1974 was first used fuzzy control. It has been applied successfully in many areas such as plant layout, project scheduling, evaluating alternative construction technology and contract selection strategy and other civil engineering applications.

Fuzzy rules define the value or levels of preference of a decision-maker facing uncertain results. In developing fuzzy rules, a decision-maker exercises his or her subjective preference to determine the standing of various uncertain outcomes for the conditions of an operation. In general, the number of rules used in controlling a system using fuzzy control is as given in the following equation.

$R = (m)^{v}$

Where: R= number of rules, m= number of membership functions, and v= number of input variables. Fuzzy logic for decision making is represented by operations over fuzzy decision rules, which have the general form:

IF precondition 1 **AND** precondition 2 **AND**…………

THEN consequence 1 **AND** consequence 2 **AND** ……….A fuzzy decision rule has certain preconditions; each is to be matched with given facts, as well as certain consequences that result when the preconditions are met.

Each precondition or consequence in a rule includes an instance of the fuzzy variable involved. Consider the example of determining the size of a diesel hammer for driving concrete piles based on the given pile length and ground condition. Two preconditions (pile length, ground condition) and one consequence (hammer size) is involved as variables. One rule may read: IF the pile is long AND the ground is hard, THEN use a heavy hammer. The three words long, hard, and heavy are instances of linguistic values of the fuzzy variables [25].

A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. This process is known as the fuzzy inference engine. As shown in figure 2.8, fuzzy decision-making system consists of four principal components [22]. These components are; 1) fuzzification; 2) Inference; 3) composition; and 4) defuzzification.

Fuzzification is a procedure that converts raw data from the practical world into membership functions (natural language, e.g., high, low, very low, etc.). The membership functions are then fed into the inference engine [21]. In the inference sub-process, the firing strength of each fuzzy rule is calculated. This is based on the degree to which the input elements meet the preconditions of a rule, which is measured by the fetched membership values from the fuzzy set concerned. The firing strength of a rule determines how much its consequence can be applied to the output value. The output membership function of a rule is clipped off at a height corresponding to the firing strength of that rule.

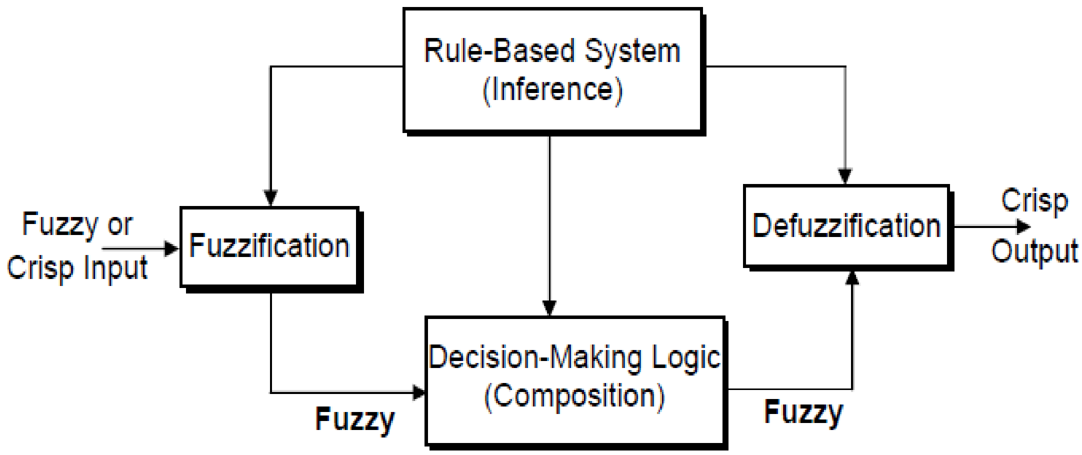


Figure 2.8: Fuzzy Decision-Making System

In the composition sub-process, all the fuzzy subsets assigned to the output variable (after the implication of the firing strength) are combined together to form a single fuzzy subset for the output variable. The union (maximum operator) is used to aggregate the overall consequence of all the rules [20]. The defuzzification sub process, is the method by which the output aggregated consequence (overall membership function) converts into crisp (non-fuzzy) value. There are many defuzzification methods that can used to defuzzify the overall membership function, such as the center of area, the largest of the maximum, the smallest of the maximum, or the mean of the maximum[27].

2.6.3 Multi-objective optimization model (MOOM)

When an optimization problem involves more than one objective function, the task of finding one (or more) optimum solution(s), is known as the Multi-Objective Optimization Problem (MOOP). In problems characterized by more than one conflicting objective, there is no single optimum solution; instead there exists a set of solutions which are all optimal, called the *Optimal Pareto front*.

A general multi-objective optimization problem is defined as follows (minimization case):

$$\begin{aligned} &\min && f(x) = [f_1(x), f_2(x), \dots, f_M(x)] \\ &\textit{subject to} && \varepsilon(x) = [e_1(x), e_2(x), \dots, e_L(x)] \geq 0 \\ & && x_i^{(L)} \leq x_i \leq x_i^{(U)}, i = 1, \dots, N, \end{aligned}$$

Where x = (x_1, x_2. . . x_N) is the vector of the N *decision variables*, M is the number of *objectives* f_i, L is the number of *constraints* e_j , and $x_i^{(L)}$ and $x_i^{(U)}$ are respectively the lower and upper bound for each decision variables x_i. Two different solutions are compared using the concept of *dominance*, which induces a *strict partial order* in the objective space F. Here a solution ''a'' is said to dominate a solution ''b'' if it is better or equal in all objectives and better in at least one objective. For the minimization case we have:

$$f(a) \prec f(b) \;\; iff \begin{cases} f_i(a) \leq f_i(b) & \forall_i \in 1, \dots, M \\ \exists_j \in 1, \dots, M & f_i\,(a) < f_j\,(b) \end{cases}$$

Optimization is an important concept in science and engineering. The construction industry is one of the prominent areas benefiting from it for efficient and effective execution of projects, for instance. Optimization is applied in the design and scheduling of HVAC systems, the design of structural systems and components, building layout, acoustic design, and the design of construction site layout [31].

The ultimate goal of a multi-objective optimization algorithm is to identify solutions in the Pareto optimal set. However, identifying the entire Pareto optimal set, for many multi-objective problems, is practically impossible due to its size. In addition, for many problems, especially for combinatorial optimization problems, proof of solution optimality is computationally infeasible. Therefore, a practical approach to multi-objective optimization is to investigate a set of solutions (*the best-known Pareto set*) that represent the Pareto optimal set as much as possible. With these concerns in mind, a multi-objective optimization approach should achieve the following three conflicting goals [9].

1. The best-known Pareto front should be as close possible as to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.

2. Solutions in the best-known Pareto set should be uniformly distributed and diverse over of the Pareto front in order to provide the decision maker a true picture of trade-offs.

3. In addition, the best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

2.6.4 Modified adaptive weight approach (MAWA)

The Modified Adaptive Weight Approach (MAWA) was proposed by Zheng, Ng and Kumaraswamy (2004) to deal with the multi-objective traditionally-time-cost trade-off problem (TCTPs) [32]. It utilizes some useful information from the current population to generate an adaptive weight for each objective, and thereby exerts a search pressure towards the ideal point. Under the MAWA (Zheng, Ng and Kumaraswamy, 2004), the adaptive weights are formulated through the following four conditions [32]

1. For $Z_c^{max} \neq Z_c^{min}$ and $Z_t^{max} \neq Z_t^{min}$;

$$V_c = \frac{Z_c^{min}}{Z_c^{max} - Z_c^{min}}$$

$$V_t = \frac{Z_t^{min}}{Z_t^{max} = Z_t^{min}}$$

$$v = v_c + v_t, \quad w_c = \frac{V_c}{V} \;, W_t = {}^{V_t}/_{V}, \;\; W_c + W_t = 1$$

2. For $Z_c^{max} = Z_c^{min}$ and $Z_t^{max} = Z_t^{min}$;

$w_c = w_t = 0.5$

3. For $Z_t^{max} = Z_t^{min}$ and $Z_c^{max} \neq Z_c^{min}$

$w_c = 0.1$, $w_t = 0.9$

4. For $Z_t^{max} \neq Z_t^{min}$ and $Z_c^{max} = Z_c^{min}$

$w_c = 0.9$, $w_t = 0.1$

Zheng, Ng and Kumaraswamy (2004) propose a fitness formula in accordance with the proposed adaptive weight:

$$f(x) = w_t \frac{Z_t^{max} - Z_t + \beta}{Z_t^{max} - Z_t^{min} + \beta} + w_c \frac{Z_c^{max} - Z_c + \beta}{Z_t^{max} - Z_t^{min} + \beta}$$

Here, β = random number (between 0 and 1).

Where, Z_c^{max}, Z_t^{max}= maximal value for the objective of total cost and time, respectively, in the current population; Z_c^{min}, Z_t^{min} = minimal value for the objective of total cost and time, respectively, in the current population; w_c, w_t = adaptive weights, respectively, on cost and time derived from the last generation, υ_c, υ_t = value for the criterion of cost and time respectively; υ = value for the project; w_c = adaptive weight for the criterion of cost; and w_t = adaptive weight for the criterion of time, Z_C represents the total cost of the x th solution in the current population; Z_t represents the time of the x th solution in the current population.

2.7 Research gap

When reviewing the literature on multi-objective project crashing, potential areas of expansion were found. Most of the research studies presented in this literature have provided significant contributions to solve project crashing problem considering only limited and different factors in different algorithms, though researches reveal that contractors and decision makers (DMs) intuitively consider a set of factors such as Resource availability, Contractors' leverage on subcontractors, who are selected to carry out the accelerated work, Additional direct cost required to crash each activity from its normal duration state, Risk, Complexity and logistics of the work involved, Number of successor of the activities and Cash flow constraints etc, which shows there are still certain gaps in the literature on project crashing that remain unanswered. That is, in all of the various methods that are proposed in the literature, project crashing is still reduced to some form of analysis, where schedule crashing is performed based on limited factors. This way, one algorithm discard factors considered by another algorithm and all these methods do not satisfy considerations of contractors and project managers when they plan to crash respective duration of their projects. In reality some of the various objectives are related to time, cost, performance, material allocation, risk and uncertainty etc. To address the above objectives and other new factors locally and internationally, the current study proposes to show how to select the most optimal algorithm out the existing and commonly used algorithms using the Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**) method, which is a multi-criteria decision analysis method based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. It is a method of compensatory aggregation that compares a set of alternatives by identifying weights for each criterion, normalising scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion. An assumption of TOPSIS is that the criteria are monotonically increasing or decreasing. Normalisation is usually required as the parameters or criteria are often of incongruous dimensions in multi-criteria problems. Compensatory methods such as TOPSIS allow trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion. This provides a more realistic form of modelling than non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs.

3. CHAPTER THREE: PROPOSED METHODOLOGY

3.1 Introduction

This chapter describes the methodology adopted in this research in relation to the objectives. The proposed methodology for multi-objective project crashing algorithm selection, composed of TOPSIS method, consists of three steps. These are:

1. Identify the factors/parameters considered by the current algorithms and what are the contractors and project managers' actual interest during project crashing.
2. Identify commonly used multi – objective crashing algorithms.
3. Validate the performance of the proposed method or technique using an illustrative example.

Research methods employed in this study include literature review and case study and the research procedure applied in this research is highlighted below.

3.2 Research procedure

The first objective is to examine and recognize a set of variables/parameters that contractors and decision makers (DMs) intuitively consider during expediting their projects.

The second objective is to examine the current practice for time-cost tradeoffs algorithms and identify the deficiencies of the existing practice. In this step, literatures relating to the existing algorithms for time-cost problems including the single-objective time-cost trade off problems and multi-objective time-cost optimization algorithms are reviewed.

The third objective is to obtain and provide multiple - objective project crashing algorithm selection method using the Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**).

To achieve this objective, the available crashing algorithms are reviewed and the most common ones are selected. Finally, the method is validated through a case study and ranks are determined using TOPSIS method.

3.3 Research methods

3.3.1 Literature review

Literature review is a common method used by researchers at the initial stage of any research studies including the field of project management. It serves to summarize previous findings for the purpose of improving professional practice or for creating generalization through integration of empirical research [33].

For the aim of examining the current techniques and practice of multi-objective project crashing algorithms, a review of literatures concerning the project crashing algorithms is unavoidable. The suitable algorithms for the proposed method are also determined from the literature review.

3.3.2 Case study

To demonstrate the usefulness or to test the concept and performance of the proposed method for decision aiding processes related to project crashing a case study is considered which was originally introduced by Feng et al. 1992 and then the same used by Zheng et al.2005 for stochastic construction time-cost-risk trade-off analysis and other researchers use it in their study using different algorithms for the last two decades.

3.4 Summary

The methods used in this research have been outlined in this chapter in relation to the research objectives. Further details introduced and elaborated in relevant chapters of this thesis.

4. CHAPTER FOUR: ALGORITHM SELECTION ANALYSIS

4.1 Introduction

The present study was motivated by the desire to provide a method of project crashing algorithm selection for a project which takes into account various factors during expediting. This chapter presents the findings of a literature review that investigates the present study efforts in the areas of multi – objective project crashing; time, cost, quality, risk and other parameters analysis and algorithms used for project crashing. Firstly, Importance of Project Crashing Algorithm Selection is discussed followed by the description and computational procedure of a multi-criteria decision analysis method (**TOPSIS**). Then risk zoning and risk-quality interconvert ability is reviewed. Finally, a single project commonly considered by various researches in the last two decades using different crashing algorithms for multi-objective optimization is conducted as an illustrative example.

4.2 Importance of project crashing algorithm selection

The selection of an appropriate crashing algorithm is not an easy task and depends on the decision problem, as well as on the objectives of the decision makers. Sometimes the simpler the method are the better But complex decision problems may require complex methods, as well.

In this paper, a multi-criteria decision analysis method (**TOPSIS**) is used as screening devices to determine which crashing algorithm in the alternatives is the most appropriate to a project.

To introduce the importance of algorithm selection in project crashing, it is better to consider a simple and understandable example to illustrate the concept first.

Example: Consider the problem of finding a new condominium house for a family in Addis Ababa. The decision maker(s) might have decided upon some objectives: a lot of living space, an acceptable price, good residential area, mode of transportation alternatives and so on. How do the decision maker(s) decide?

The Multiple–Criteria Decision making (MCDM) model consists of various elements, depending on the nature of the decision problem as shown in Figure 4.1, depict the elements which are often found.

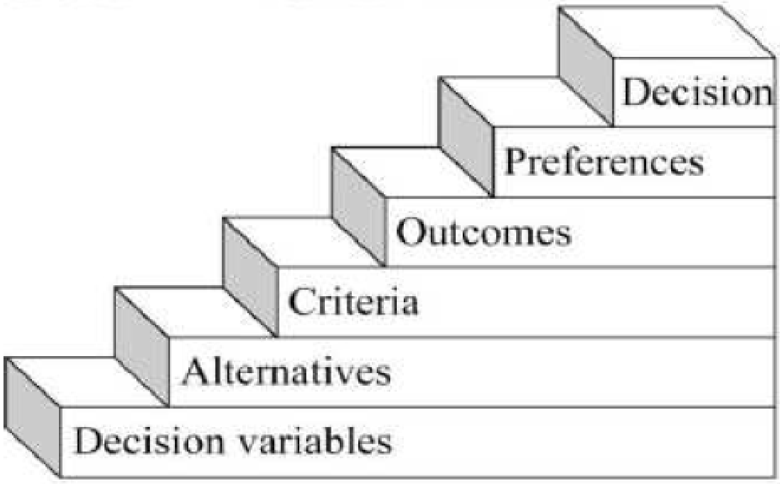


Figure 4.1: Elements of MCDM models

Though a decision maker(s) have to follow the basic elements starting from decision variables up to decision, but since my objective is to show how to select crashing algorithm which is the preference in the MCDM models let me assume all information concerning alternatives and criteria for the house purchase as shown in the decision matrix in Table 4.1 and show how to select the house.

Table 4.1: Decision matrix for the house-purchase

Criteria Alternatives	C_1: Number of rooms	C_2: Condition	C_3: Age[years]	C_4:Price [birr]	C_5:Distance to center [km]
A_1: Ayat	3	good	5	400000	15
A_2:Semit	2	Very good	7	250000	10

A_3: Arat kilo	3	Poor	2	300000	5
A_4: Gerji	1	Fair	10	230000	7
A_5:Sengatera	2	Very good	4	350000	2

In this example there are five alternatives, A_1 to A_5 evaluated by five criteria,C_1 to C_5. Note that the second criterion "condision" is qualitative which can translated to numerical values. The raws of this decision matrix represents the out comes of the alternatives defined by the dimensions C_1 to C_5.

In Multiple–Criteria Decision making (MCDM) it assumed that the decision maker(s) takes a decision by looking not at the alternatives directly but at their outcomes. Therefore the decision maker's preferences are defined in outcome space [31].

Thus this means that for the house purchase the decision maker's preferences or selection do not depend on the houses as such but on their price, size, condition in residential areas, and other factors.

Likewise in project crashing algorithm selection the decision maker takes a decision by looking not at the alternative algorithms directly but at their outcomes and this is the main objective of this paper.

4.3 The TOPSIS method

4.3.1 Description of the method

There are a variety of multiple criteria techniques to aid selection in conditions of multiple criteria. The Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**) is one of the best techniques for Multi criteria decision making (MCDM). TOPSIS is a multiple criteria method to identify solutions from a finite set of alternatives based upon simultaneous minimization of distance from an ideal point and maximization of distance from a nadir point [13]. TOPSIS was initially presented by Hwang and Yoon and Yoon and Hwang.

In this method, options are graded based on ideal solution similarity. If an option is more similar to an ideal solution, it has a higher grade. Ideal solution is a solution that is the best from any aspect that does not exist practically and we try to approximate it. Basically, for measuring similarity of a design (or option) to ideal level and non-ideal, we consider distance of that design from ideal and non-ideal solution. TOPSIS was applied to financial investment in advanced manufacturing systems, in manufacturing applications, case selecting a manufacturing process, mobile phone selection, selection of contractors, supplier selection, selecting robotic processes and material handling system. It has also been used to compare company performances and financial ratio performance within a specific industry.

The main advantages of using TOPSIS method are [14]:-

- ✓ It is simple to use.
- ✓ It takes into account all types of criteria (subjective and objective).
- ✓ It is rational and understandable.
- ✓ The computation processes are straight forward.
- ✓ The concept permits the pursuit of best alternatives criterion depicted in a simple mathematical calculation.

In this method, given 'm' options (alternatives) $A_{i,}$ each of which depends on 'n' parameters (criteria) f_j whose values are expressed with positive real numbers X_{ij} is assessed and compared and then the best option is selected. In this technique, it is assumed that the ideality of each index increases or decreases, monotonously. TOPSYS method builds on the assumption that *mxn* decision-making matrix O includes m-alternatives and n-criteria.

$$
O = \begin{array}{c|cccccc}
 & f_1 & f_2 & \cdots & f_j & \cdots & f_n \\
\hline
a_1 & x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\
a_2 & x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
a_i & x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
a_m & x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \\
 & & & & & & \\
 & \begin{pmatrix} \max \\ \min \end{pmatrix} & \begin{pmatrix} \max \\ \min \end{pmatrix} & & \begin{pmatrix} \max \\ \min \end{pmatrix} & & \begin{pmatrix} \max \\ \min \end{pmatrix}
\end{array}
$$

Figure 4.2: General mxn decision-making matrix

4.3.2 Geometrical image of the method

Figure 4.3 shows the initial arrangement of alternatives in TOPSIS method for n = 2. Parameter $X_1 = X_1^*$ has a monotonically increasing preference, and parameter $X_2 = X_2^{\Diamond}$ has a monotonically decreasing preference. The positive A*and negative $A^{\Diamond}$ ideal solution are located at diagonally opposite positions. The best solution is the alternative A_7 [15].

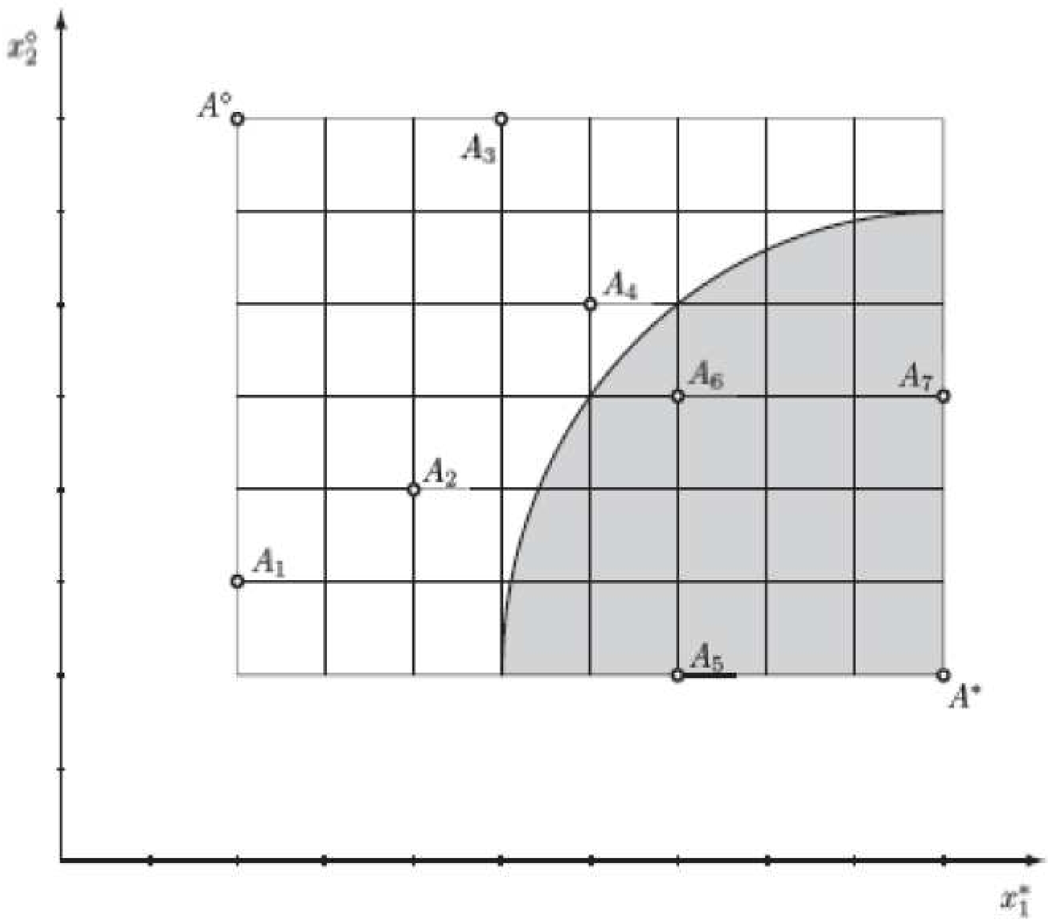


Figure 4.3: Geometrical representation of TOPSIS method

[Source: Z. Pavić and V. Novoselac (2013, 6)]

TOPSIS is a compensatory method. These kinds of methods allow the compromise between different criteria, where a bad result in one criterion can be compensated by a good result in another criterion [17]. An assumption of TOPSIS method is that each criterion has either a monotonically increasing or decreasing preference [18]. Due to the possibility of criteria modelling, compensatory methods, certainly including TOPSIS, are widely used in various sectors of multi-criteria decision making.

4.3.3 Computational procedure for TOPSIS method

Step1. Calculate the normalized decision matrix. The normalized value n_{ij} is calculated as:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, \ldots, m; j = 1, \ldots, n$$

$$\begin{array}{c|cccccc}
 & f_1 & f_2 & \cdots & f_j & \cdots & f_n \\
\hline
a_1 & r_{11} & r_{12} & \cdots & r_{1j} & \cdots & r_{1n} \\
a_2 & r_{21} & r_{22} & \cdots & r_{2j} & \cdots & r_{2n} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
a_i & r_{i1} & r_{i2} & \cdots & r_{ij} & \cdots & r_{in} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
a_m & r_{m1} & r_{m2} & \cdots & r_{mj} & \cdots & r_{mn} \\
 & \begin{pmatrix}\max\\ \min\end{pmatrix} & \begin{pmatrix}\max\\ \min\end{pmatrix} & & \begin{pmatrix}\max\\ \min\end{pmatrix} & & \begin{pmatrix}\max\\ \min\end{pmatrix}
\end{array}$$

Figure 4.4: normalized decision matrix

Step2. Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as:

$v_{ij} = w_j n_{ij}$, i =1… m; j =1…n,

Where w_j is the weight of the j^{th} attribute or criterion, and $\sum_{j=1}^{n} w_j = 1$

Step3. Determine the positive ideal and negative ideal solution

$A^+ = \{V_1^+, \dots, V_n^+\} = \{(maxV_{ij}/i\epsilon I), (minV_{ij}/i\epsilon J)\}$,

$A^- = \{V_1^-, \dots, V_n^-\} = \{(minV_{ij}/i\epsilon I), (maxV_{ij}/i\epsilon J)\}$,

Where I is associated with benefit criteria, and J is associated with cost criteria.

Step4. Calculate the separation measures, using the *n*-dimensional Euclidean distance. The separation of each alternative from the positive ideal solution is given as,

$$d_i^+ = \{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2\}^{0.5}, i = 1, \dots, m$$

Similarly, the separation from the negative ideal solution is given as

$$d_i^- = \{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2\}^{0.5}, i = 1, \dots, m.$$

Step5. Calculate the relative closeness to the ideal solution, where the relative closeness of the alternative A_i with respect to A^+ is defined as

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad , \quad i = 1, \dots \dots m$$

Since $d_i^+ \geq 0$ and $d_i^- \geq 0$, then, clearly, $C_i \in [0, 1]$

Step6. Rank the preference order. For ranking alternatives using this index, we can rank alternatives in decreasing order.

4.4 Risk factor zone, risk factor value and risk- quality interconvert ability

4.4.1 Risk factor zone and risk factor value

All construction projects always have certain risks and uncertainties as its unavoidable nature though it is possible to reduce it. Risk assessment in a project is a complex subject which requires to identifying influencing factors, quantifying the associated potential impact of the identified risk; and implementing measures to manage and mitigate the potential impact.

Table 4.2: Rating Risk impact on a schedule on a three- level scale

Scale	Risk Impact (R-I)	Risk on schedule of project
1	Low	Over all project delay <5% less delay
2	intermediate	Over all Project delay<5-25% (some delay)
3	Very High	Over all project delay>25% (delay)

[Source: Rajesh, Shweta, and Dubey. (2012, 196)]

The risk factors have been classified into 6 zones based on the P-I matrix and the risk classified in the zone having lowest impact and probability is ignored. The exclusion is based on the practice in industry. From the P-I matrix it is the zone with value 1. All other groups are divided according to the corresponding results.

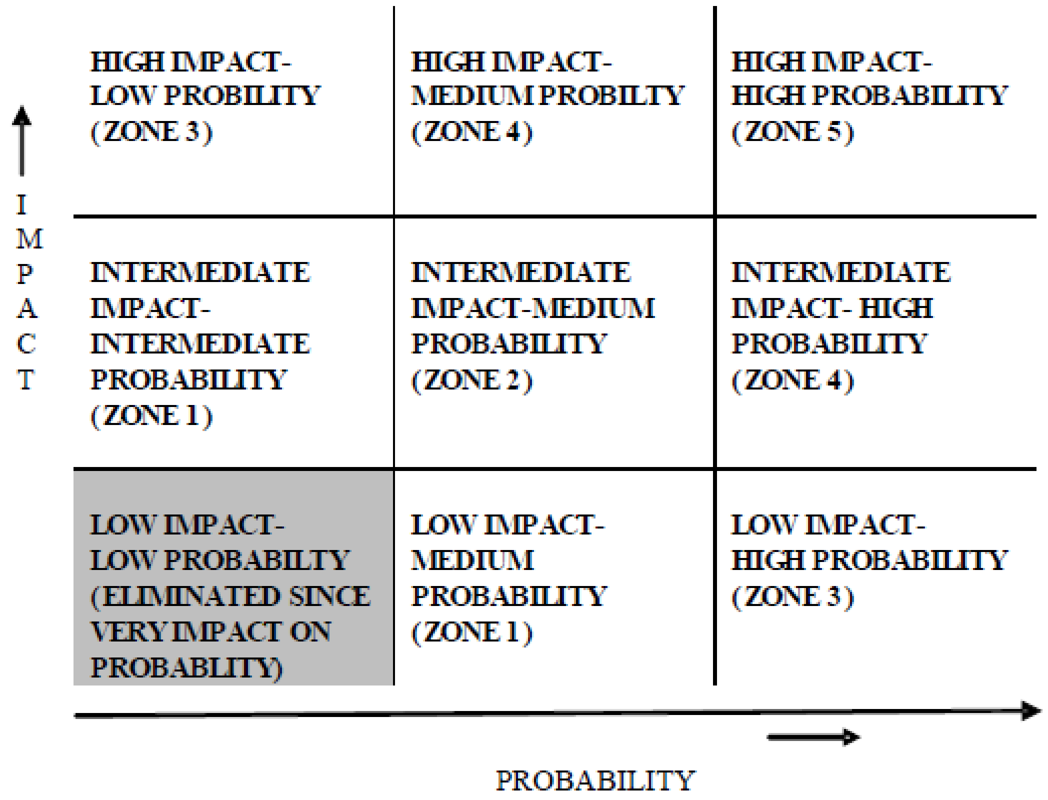


Figure 4.5: risk factor zone [Source: Rajesh, Shweta, and Dubey. (2012, 196)]

Table 4.3: Probability – Impact (P-I) Matrix

Probability	Impact		
HP = 3	LI	II	HP
IP = 2	3	6	9
LP = 1	2	4	6
	1	2	3

[Source: Rajesh, Shweta, and Dubey. (2012, 196)]

Table 4.4: Based upon analysis the various risk zones have been classified.

Risk Factor Zone	***Risk Factor Value***
Zone -1	00-0.10
Zone – 2	0.11-0.20
Zone – 3	0.21-0.35
Zone – 4	0.36-0.45
Zone – 5	>0.60

[Source: Rajesh, Shweta, and Dubey. (2012,196)]

4.4.2 Interconvert ability of quality and risk parameters

This conversion is based on the comparative study and opinion analysis from experts, project managers, building construction contractors and construction management consultants. Risk analysis and management in construction depend mainly on intuition, judgement and experience [12]. Quality is also one of the most important factors while performing project crashing which needs to be quantified and incorporated with other parameters like risk. Hence, we can use the conversion factors listed in table 4.5 and any intermediate values can be obtained by interpolation.

Table 4.5: Risk-Quality interconvert ability

Quality Parameter	Risk Factor Zone	Risk Factor Values
96 -100	Zone 1	0.10
90 -95	Zone 2	0.20
80 – 90	Zone 3	0.35
70 – 79	Zone 4	0.45
< 60	Zone 5	0.60

[Source: Rajesh, Shweta, and Dubey. (2012,196)]

4.5 Illustrative example

To demonstrate the usefulness or to test the concept and performance of the above-mentioned method for decision aiding processes related to project crashing an illustrative example is considered as a case study.

Table 4.6: project's detailed information

Activity	Precedence activity	Resource options	Duration (days)	Cost (dollars)
Site preparation		1	14	23,000
		2	20	18,000
		3	24	12,000
Forms and rebars	1	1	15	3,000
		2	18	2,400
		3	20	1,800
		4	30	1,200
		5	60	600
Excavation	1	1	15	4,500
		2	22	4,000
		3	33	3,200
Pre-cast concrete girders	1	1	12	45,000
		2	16	35,000
		3	20	30,000
pour foundation and piers	2,3	1	22	20,000
		2	24	17,500
		3	28	15,000
		4	30	10,000
Deliver pre-cast girder	4	1	14	40,000
		2	18	32,000
		3	24	18,000
Erect girders	5,6	1	9	30,000
		2	15	24,000
		3	18	22,000

[Source: Rajesh, Shweta, and Dubey. (2012, 197)]

The test project with detailed information presented in Table 4.6 is used as a case study which was originally introduced by Feng et al. 1992 and then the same used by Zheng et al.2005 for stochastic construction time-cost-risk trade-off analysis and other researchers use it in their study using different algorithms.

To understand the project more clearly, the activity-on-node network of this case project is shown in Figure 4.6. The path in bold is the critical path for this project. The project duration is 105 days and the total cost is $253,700 if the indirect cost is fixed at $1,500/day.

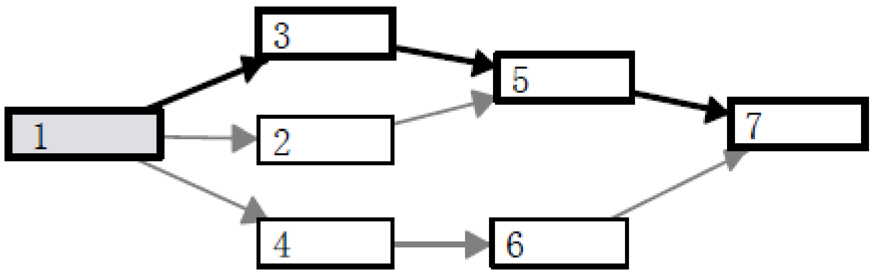


Figure 4.6: Network for the project case

The project consists of seven activities and 3-5 alternative time-cost options for the completion of each activity. For instance, in the 3rd activity – excavation, there are 3 options to complete this activity with different durations and direct costs due to different resources utilization. Table 4.6 includes the related data on different resource utilizations and their corresponding time and cost is based on from Feng et al. 1992.

Project crashing is a complex project which consists of many stages and the management, which requires deep knowledge regarding the project's activity, parameters considered and using the best crashing algorithm.

A lot of work has to be done before executing the first expediting activity of a project, one of them is crashing algorithm selection which may relatively low cost than the crisis of implementing inappropriate algorithm especially for a project with a large number of activities. Contractors and project managers are encouraged to participate in this process in order to meet targeted milestones imposed by owners. In many instances, several alternatives or models are analyzed. The models considered in this study are multi-objective ant colony optimization (MOACO), modified adaptive weight approach (MAWA), fuzzy logic model and multi objective optimization model (MOOM). However, in all these methods, crashing is still reduced to some form of analysis, where crashing is performed based on limited factors only and all these methods obtain different optimal solution to a single project. Table 4.7, shows the optimal solutions obtained using these methods to the project in table 4.6.

Table 4.7: optimal solutions obtained using these methods

Model	Crash Time (days)	Crash Cost (dollar)	Risk factor	Quality %	Resource options 1 2 3 4 5 6 7
MOACO	60	155,500	X	92	1 1 1 2 1 1 1
MAWA	60	173,000	0.1492	X	1 2 1 1 2 1 1
MOOM	60	165,500	0.136	X	1 1 1 1 1 1 1
Fuzzy logic	60	173,500	X	X	1 1 2 1 2 1 1

Where, X = is a parameter which is not quantified in the specified algorithm

Two dimensional graphic comparisons of the optimal solutions is shown in figure 4.7 since it is impossible to compare in three or four dimension at this time i.e. before quantifying risk and quality to all models.

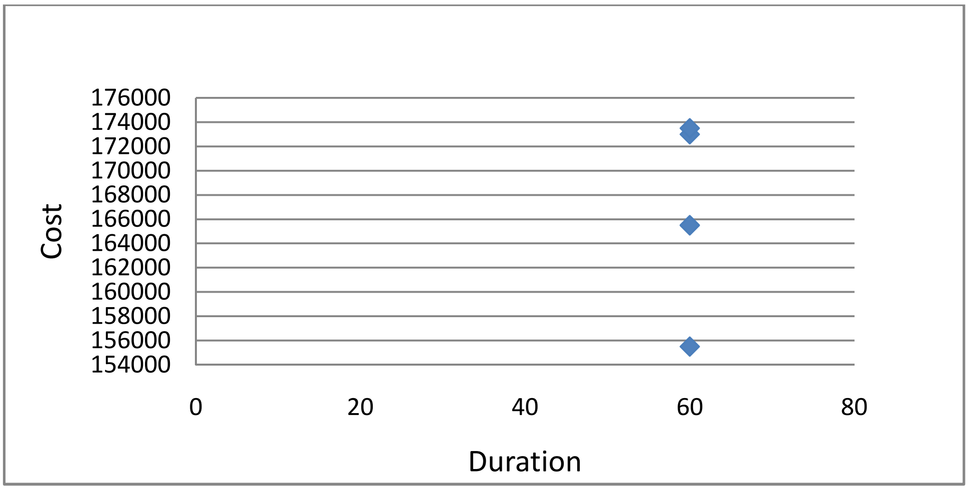


Figure 4.7: two dimensional optimal solution comparisons

On other hand, researches reveal that other factors such as resource availability, logistics, complexity and others will be of essence and gain more important in setting priorities for activity crashing. To show how to satisfy this need a numerical example is considered and analysed as below using TOPSIS method.

Example considered in this paper gets along well with the algorithm selection analysis regarding project crashing. It is not expanded as its main aim is to develop an optimization algorithm. In the analysis of the example the most commonly used four parameters/factors are taken into consideration:

- ✓ f1 – crash duration (days)
- ✓ f2 – crash cost (in dollar)
- ✓ f3 – risk (0< f3<1),
- ✓ f4 – quality (%).

A research conducted has determined and quantified the risk factors for the optimal solutions of the models shown in table 4.7 during its study on Optimization of Multi-objective Time-cost Trade off Problem with Various Risk Zones as shown in Table 4.8.

Table 4.8: Comparison between the different models considering different parameters

solution	1	2	3	4
Time (days)	60	60	60	60
Cost (dollar)	165,500	155,500	173,500	173,000
Risk	0.136	0.1835	0.1542	0.1492
Resource options	1 1 1 1 1 1 1	1 1 1 2 1 1 1	1 1 2 1 2 1 1	1 2 1 1 2 1 1
Model	MOOM	MOACO	Fuzzy logic	MAWA

[Source: S. Singh, G.C. Dubey, and R. Shrivastava. (2012, 65)]

Using the conversion method, Interconvert ability of Quality and Risk Parameters, and rearranging the decision matrix can determined as shown in table 4.9.

Step 1: Obtain the decision matrix

Table 4.9: Decision matrix

	f_1	f_2	f_3	f_4
a_1	60	165,500	0.1360	96.02
a_2	60	155,500	0.1835	92.00
a_3	60	173,500	0.1542	95.01
a_4	60	173,000	0.1492	95.29

Where, a_1 = MOOM model

a_2 = MOACO model

a_3 = Fuzzy Logic model

a_4 = MAWA model

Step 2: Obtain the normalized decision matrix

Table 4.10: Normalized decision matrix

	f_1	f_2	f_3	f_4
a_1	0.50	0.6607	0.4340	0.5075
a_2	0.50	0.6208	0.5856	0.4863
a_3	0.50	0.6926	0.4921	0.5022
a_4	0.50	0.6906	0.4761	0.5037

Step 3: Obtain the weighted decision matrix v by multiplying each column of R by corresponding weight

Table 4.11: weighted decision matrix

Weight	W_1 = 0.30	W_2 = 0.30	W_3 = 0.20	W_4 = 0.20
	f_1	f_2	f_3	f_4
a_1	0.15	0.1982	**0.0868**	**0.1015**
a_2	0.15	**0.1862**	0.1171	0.0973
a_3	0.15	0.2078	0.0984	0.1004
a_4	0.15	0.2072	0.0952	0.1007

Step 4: Obtain the Ideal (A*) and the Negative Ideal (A^-) solutions from the weighted decision matrix V.

Table 4.12: Ideal (A*) and negative ideal (A^-) solution

A*	**0.15**	**0.1862**	**0.0868**	**0.1015**
A^-	0.15	0.2078	0.1171	0.0973

Step 5: Compute the separation measures from the Ideal (S_i*) and the Negative Ideal (S_i^-) solutions for all alternatives:

Ideal solution (S_i*) Negative ideal solution (S_i^-)

S_1* = 0.0120 S_1^- = 0.0320

$S_2^* = 0.0306$ $S_2^- = 0.0216$

$S_3^* = 0.0245$ $S_3^- = 0.0190$

$S_4^* = 0.0226$ $S_4^- = 0.0222$

Step 6: For each alternatives determine the relative closeness values to the ideal solution:

$C_1^* = 0.7273$

$C_2^* = 0.4138$

$C_3^* = 0.4368$

$C_4^* = 0.4955$

Notice that the closeness rating is a number between 0 and 1, with 0 being the worst possible solution and 1 the best possible solution.

Step 7: Determine the preference order by arranging the alternatives in the descending order of C_i^*, i = 1….m:

Thus the ranks for the alternatives in the project crashing algorithm selection problem using the TOPSIS in the descending order emerge as:

A_1 (MOOM model), A_4 (MAWA model), A_3 (Fuzzy Logic model), A_2 (MOACO model)

5. CONCLUSION AND RECOMMENDATION

In this paper a new project crashing algorithm selection method was introduced to choose alternatives based on the interest and preferences of the decision maker(s). The method is capable of avoiding financial and other related crisis due to irrelevant algorithm selection.

In order to solve this problem the Technique for Order of Preference using Similarity to Ideal Solution (**TOPSIS**) method was used. The validity of the proposed method is verified by an example which confirms the capability of method.

Some extensions of this research as a future study might be of interest. While in this paper **TOPSIS** is considered as a problem solving method, other Multi-Objective Decision Making methods or other tools can also be used. Another extension of this research could be to develop a single and dependable algorithm considering various parameters at time to satisfy decision maker(s) interest.

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