KARADENİZ TECHNICAL UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

CIVIL ENGINEERING DEPARTMENT

PARETO-FRONT PERFORMANCE OF MULTIOBJECTIVE TEACHING LEARNING BASED OPTIMIZATION ALGORITHM ON TIME-COST TRADE-OFF OPTIMIZATION PROBLEMS

MASTER OF SCIENCE THESIS

Mohammad Azim EIRGASH

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THESIS ETHICS DECLARATION

The study titled "Pareto-Front Performance of Multiobjective Teaching Learning Based Optimization Algorithm on Time-Cost Trade-Off Optimization Problems" which is presented as a Master of Science Thesis has been completed under the supervision of Assoc. Prof. Dr. Vedat Toğan from the beginning to the end. I declare that I have collected the data / examples myself, adequately cited and referenced the information and resources taken from the other original sources, acted in accordance with scientific research and ethical rules in the course of my work and I accept all kinds of legal consequences in case of the occurrence of the accusation. 04/01/2018.

Mohammad Azim EIRGASH

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Master Thesis

SUMMARY

PARETO-FRONT PERFORMANCE OF MULTIOBJECTIVE TEACHING LEARNING BASED OPTIMIZATION ALGORITHM ON TIME-COST TRADE OFF OPTIMIZATION PROBLEMS

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In the real world, there are plenty of problems that require finding the best solution meeting many objectives. Multiobjective optimization models are needed to obtain this solution. For this purpose, in this study, to perform such a multiobjective optimization process, an efficient Teaching Learning-Based Optimization (TLBO) algorithm has been employed. Its performance is tested on several construction projects varying from an 18-activity to 630-activity. The applied model integrates the modified adaptive weight as well as non-dominated sorting approaches to find out the Pareto front solution. Furthermore, a slight modification is made in the non-dominating sorting version of the classical sole-TLBO algorithm by adding a certain portion of pre-known solutions to the initial population of model in order to achieve an enhancement in the exploration capacity of the proposed algorithm. Thus, the Pareto front performance of the utilized model is validated re-solving the benchmark optimization problems taken from the literature. Hence, the multiobjective optimization model based on TLBO developed in this study can be preferred another alternative tool to solve time-cost trade-off problem in construction engineering and management. Thereby, the main contribution of this study can be clearly seen from the application of TLBO for the first time to solve TCTP problems in the construction management field.

Keywords: Teaching Learning-Based Optimization (TLBO), Multiobjective optimization, Metaheuristic algorithms, Time-cost trade-off problem (TCTP), Construction management.

Yüksek Lisans Tezi

ÖZET

ÖĞRETME ÖĞRENME TABANLI ÇOK AMAÇLI OPTİMİZASYON ALGORİTMASININ ZAMAN-MALİYET ÖDÜNLEŞİM PROBLEMLERİNİN PARETO-ÇÖZÜMLERİNİ BELİRLEME PERFORMANSI

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Gerçek dünyada, birçok amacı karşılayan en iyi çözümü bulmayı gerektiren birçok problem bulunmaktadır. Bu çözümü elde etmek için çok amaçlı optimizasyon modellerine ihtiyaç duyulmaktadır. Bu amaçla, bu çalışmada, böyle bir, çok amaçlı optimizasyon sürecinin gerçekleştirilmesi için Öğretme Öğrenme Tabanlı Optimizasyon (ÖÖTO) algoritması kullanılmaktadır. Oluşturulan modelin performansı 18 etkinlikten 630 etkinliğe kadar değişen çeşitli yapım projelerinde denenmektedir. Model, Pareto-çözümleri elde etmek için değiştirilmiş uyarlanabilir ağırlık ve baskın olmayan sıralama yaklaşımlarını içermektedir. Ayrıca, modelin ÖÖTO algoritmasının baskın olmayan sıralamayı içeren versiyonunda, bir iyileştirme yapabilmek için önceden bilinen çözümlerin belirli bir miktarı başlangıç popülasyonuna eklenerek model de küçük bir değişim de yapılmaktadır. Böylece, kullanılan modelin Pareto-çözümleri belirleme performansı, literatürden alınan zaman-maliyet ödünleşim optimizasyon problemlerinin tekrardan çözülmesiyle doğrulanmaktadır. Dolayısıyla, bu çalışmada geliştirilen ÖÖTO'ya dayanan çok amaçlı optimizasyon modeli, inşaat mühendisliği ve yönetiminde zaman-maliyet ödünleşim(dengeleme) problemini çözmek için alternatif bir araç olarak tercih edilebilir. Bu nedenle, bu çalışmanın ana katkısının ÖÖTO'nun inşaat yönetimi alanındaki zaman-maliyet ödünleşim(dengeleme) problemlerinin çözümünde ilk kez uygulanmasından açıkça görülebilir.

Anahtar Kelimeler: Öğretme Öğrenme Tabanlı Optimizasyon (ÖÖTO), Çok amaçlı optimizasyon, Metasezgisel algoritmalar, Zaman-maliyet Ödünleşim Problemi, Yapım yönetimi.

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LIST OF ABBREVIATIONS

TLBO	: Teaching Learning Based Optimization
NT	: Number of Teacher
T_F	: Teaching Factor
Tp	: Teacher Phase
CPM	: Critical Path Method
AoA	: Activity on Arrow
AoN	: Activity on Node
APD	: Average Percent Deviation
Avg.	: Average
CPU	: Central Processing Unit
DC	: Direct Cost
IC	: Indirect Cost
TCTP	: Time-Cost Trade-Off Problem
TCT	: Time-Cost Trade-Off
Dur.	: Duration
ES	: Early Start
EF	: Early Finish
LS	: Late Start
LF	: Late Finish
FS	: Finish-to-Start
SF	: Start-to-Finish
FF	: Finish-to-Finish
SS	: Start-to-Start
PSO	: Particle Swarm Optimization
GA	: Genetic Algorithm
HA	: Hybrid Genetic Algorithm
MOW	: Multi-Objective Weighting
GASA	: Genetic algorithm simulated annealing
MOPs	: Multiobjective Problems
PF	: Pareto-front

MAWA	**:** Modified Adaptive Weight Approach
NDS	**:** Non-dominated Sorting Approach
M-TLBO	**:** Modified Teaching Learning Based Optimization
MO-TLBO	**:** Multi-Objective Teaching Learning Based Optimization
FMOPSO	**:** Fuzzy Multi-Objective Particle Swarm Optimization
ACO	**:** Ant Colony Optimization
NP-Hard	**:** Non-Polynomial Hard
PD	**:** Percent Deviation
NFE	**:** Number of Function Evaluation
GHz	**:** Gigahertz
QSA	**:** Quantum Simulated Annealing
RAM	**:** Random Access Memory
SA	**:** Simulated Annealing
SAM	**:** Siemens Approximation Method
SFL	**:** Shuffled Frog Leaping
USD	**:** United States Dollar

1. INTRODUCTION

During the civilization of the world, people had been carried out many engineering activities to construct somethings such as home, temple, building, bridge etc. combining of these activities which can be measured and quantified forms project. In other word, project is a series of activities to be performed to construct it. Construction is a series of activities undertaken by construction companies and consultants, which produce or alter buildings and infrastructure. Construction management is to ensure the construction activities handled effectively and efficiently. Considering the competitive environment in all industries, construction management is becoming vital for both the company and project management. The development and progress of the construction industry depends upon realization of the project management integrated with an equal concentration on company management. Construction management is relatively a young field in the construction industry [1]. However, its influence has been eminently considerable. It has become a significant practice for increasing the efficiency of construction operations around the world. Competition in the construction industry has been rising due to entrance new companies into the market. Hence, project management struggles to find the efficient schedule subjected to various parameters, for example, time, cost and other operation resources. In project scheduling, finishing a project with less time and cost is a crucial factor for planning a project. However, accelerating the schedule of the project causes extra cost because of the reduction in activity duration which requires the use of additional resources. Simultaneous optimization of direct and indirect project costs is known as TCT problem. If a project is lagging behind the schedule, decision makers can carry out time–cost trade-off problems (TCTP). TCTP helps to become more acquainted with the set of time–cost choices that will guarantee the ideal schedule under specific states. Project scheduling computations are dependent on CPM (Critical Path Method). An activity is said to be critical if there is no distinction between its earliest start time and latest finish times. As soon as the duration of all the activities in a project is evaluated, the project duration can be calculated with CPM. In other words, the sum of the durations of all activities on the critical path gives the project duration.

Being in a highly competitive sector, construction project professionals are always kept on their toes to minimize the project time, cost and other resources, which affects their profitability and margins. Therefore, they try to identify the best balance between the potentially conflicting objectives. In the field of construction management, optimization is a very useful tool to meet the desired objectives under the given constraints. Through optimization, it is possible to increase the productivity of different components of project. Importance of the optimization in construction project was noticed several decades and was used for finding the ideal plan and schedules to complete a project.

Typically, activities may have different execution options (modes) that can contain possible combinations of: 1) construction methods, which denote possible construction technologies and/or materials; 2) subcontractors' quotes, which represent the proposed duration and cost of performing the activities by subcontractors, 3) crew formations, which symbolize feasible arrangements of construction labor and equipment; and 4) overtime strategies, which define the length and time of work shifts [2].

The selection of any mode of execution for each activity leads to a distinct time and cost for that activity and affects the overall duration and cost for the entire project. The combination of various possible execution modes of activities produces several project plans where each project plan has a unique duration and cost. For large projects, the enumeration of these alternative project plans is computationally hard, particularly because the number of alternatives grows exponentially with the increase in the number of activities of the project.

The purpose of this research is to employ multiobjective based TLBO algorithms to deal with the time-cost trade-off problems in construction management field. To develop a flexible time-cost trade-off (TCT) model, critical path method (CPM) scheduling in MATLAB to be used for obtaining the objective functions of project duration and total cost. The software is developed in a way capable of performing CPM scheduling for the finish to start (FS) logical relationship. To this end, multiobjective approaches of modified adaptive weight approach (MAWA) as well as non-dominating sorting (NDS) concept with the mechanism of crowding distance computation is integrated with the proposed TLBO algorithm. NDS seeks the satisfactory solution from the non-dominated solutions depending on the experience and knowledge of decision-makers. However, MAWA converts multiobjective problem to a single-objective problem, and then utilizing a single objective optimization approach to find the satisfactory solution. MAWA approach provides unique solution as no further interaction with the decision-makers is necessary. Crowding distance operator is applied to maintain the diversity and to get out of the pre-convergence solutions. Moreover, effect of partially randomly generated initial population on NDS-TLBO algorithm with the crowding distance computation is also applied to further investigate the exploration capacity of the proposed algorithm. Main logic behind of partially randomly generated initial population concept is to add a certain portion of pre-known solutions into the initial population, which was fully random, generated. This slight modification is made to the non-dominating sorting version of the classical sole-TLBO algorithm of the model. Thereby, contribution of this thesis can be clearly seen in the application of TLBO to this field and also the TLBO-based multiobjective model activated in this study provides a glamorous alternative to solving construction time–cost optimization.

1.1. Research Motivation

This research has some main motivations: the complex nature of time-cost trade-off problems; the inefficiency of traditional optimization methods for solving large-scale TCT problems; and the potential use of advanced tools and novel techniques for overcoming the limitations of traditional optimization methods. These are briefly described as follows:

1.1.1. The Complex Nature of TCT Problems

In the literature, De et al. [3] expresses that, discrete time-cost trade-off problem is classified as combinatorial NP-hard (Non-Polynomial hard) which is the category of problems with no efficient algorithm. The solution to this type of problems exhibit near optimum solution complexity and gets worse when the size of the problem grows, the computation time for solving it would grow as an exponential function of the problem size [3]. As a result, solving large combinatorial problems is very time-consuming and prohibitive. The goal in solving such type of problems typically is to find a satisfactory near optimum solution within an acceptable processing time, rather than finding the global optimum solution that may take a substantial impractical amount of time.

1.1.2. Inefficiency of Traditional Methods for Optimizing Large-Scale Problems

Many optimization models have been proposed to optimize the trade-off between time and cost in construction projects. Optimization methods based on mathematical theory like linear programming, integer programming, and dynamic programming are the first optimization method employed to solve TCT problems. The main features of these problems examined previously by using mentioned methods above are relatively small.

Linear programming is an appropriate method for solving problems with linear time-cost relationships, but fails to solve problems with discrete time-cost relationships [4]. Integer programming and dynamic programming require a lot of computational effort for solving more complex project networks or for solving projects with numerous activities. Metaheuristic optimization methods, as alternative methods of optimization were introduced to address the shortcoming of mathematical optimization methods for solving large TCT problems. In recent decades, various modern metaheuristic optimization methods including genetic algorithms, simulated annealing, particle swarm optimization, ant colony optimization, and shuffled frog leaping optimization have been applied for solving TCT problems. Although these alternative optimization methods have some advantages over the mathematical optimization methods, and they have been applied with success for optimization of many TCT problems.

1.2. Research Objectives

In this study, a multiobjective Teaching-Learning Based Optimization (TLBO) algorithm is applied to show the Pareto front performance on solving TCTP problems in construction management field. To fulfil this procedure, multiobjective approaches of modified adaptive weight (MAWA) as well as non-dominated sorting (NDS) approaches are incorporated with the proposed algorithm. In addition to this, to develop a flexible time-cost trade-off (TCT) model, critical path method (CPM) scheduling in MATLAB to be used for obtaining the objective functions of project duration and total cost. Minimization of time and cost of the project are taken into account as the objective functions. In the developed software, the finish to start (FS) logical relationship is used to perform CPM scheduling. For the purpose of fulfilling the performance evaluation criteria on the construction management optimization problems, the Pareto front performance of the basic as well as other version of NDS-TLBO algorithm is verified on the different benchmark optimization problems considering the Pareto front solutions. Hereby, the MAWA and NDS-TLBO algorithm works effectively and implies considerable performance for the optimization of time-cost problems.

1.3. Thesis Organization

The consequence of the thesis is arranged as follows:

Chapter 1 presents a short introduction about to CPM and followed by the literature review. Then the time-cost trade-off (TCT) analysis is mentioned. It discusses solution challenges, various categories, and used methods for TCTP, finally.

Chapter 2 presents the Teaching Learning Based Optimization (TLBO) algorithms, and its implementation for solution of optimization problems. Also the modified adaptive weight (MAWA) and non-dominated sorting approaches (NDS) are explained.

Chapter 3 presents TCT analyses of sample problem sets, followed by validation and empirical analyses. The results of this chapter would be a basis for chapter 4, where the results of metaheuristic methods are compared and discussed. Additionally, effect of partial random initial population on NDS-TLBO version is also elaborated in this section.

Chapter 4 includes the final remarks obtained from the calculations on the solved problems, contributions and some evaluations that can bring light on future work.

1.4. Literature Review

Some issues are addressed in this chapter to increase the intelligibility of formed multiobjective model. Firstly, critical path method (CPM) are introduced to follow a project scheduling process, then the time-cost trade-off (TCTP) problem is reviewed from the point with of literature. Finally features of Teaching Learning Based Optimization (TLBO) are explained which was proposed by [5].

1.4.1. Project Scheduling With Critical Path Method (CPM)

To complete a project all activities of project must be accomplished. Timing and order of actions affects the project finishing time. Determination of timing and order of a project's activities is known as scheduling, simply. Critical path method is one of the most common techniques used for planning and scheduling of project. Through the planning and scheduling of a project accomplished with any method developed for this purpose like Critical Path Method (CPM) the amount and time of resources such as material, equipment, workmanship etc., can be detected before the commencement of the project. Some advantages to be achieved by using CPM are indicated in [6]:

• CPM detects the critical activities. Knowing of those has vital importance to keep the project on schedule.

• CPM identifies ideal scheduling from the point of view of both time and cost in choosing methods, equipment, materials, crews, and work hours.

• CPM effectively follows in association with network the changing on the activity execution modes. Two distinct network types known as activity on arrow and activity on node are performed in CPM. As their name implies, in the first, the activities are shown on arrows connected to the nodes. However, in the second, the activities are directly represented by nodes.

In this thesis, activity on node (AoN) is used as network type for the scheduling of the construction activities. When both network types, activity on arrow (AoA) and activity on node (AoN) are compared, it can be stated that AoA needs more effort than AoN to generate of activities. Using of activity on node diagrams is more convenient way to define the logical relationships and lags.

From the discussion of arrow and node diagrams, it can be found that AoN has some substantial advantages over arrow networks:

- ✓ Easy drawing
- ✓ Absence of dummy activities used to straighten out the logic.
- ✓ Ability of taking into account the lags between activities without the addition of more activities.
- ✓ Easy applicability of three other relationships (start to start, finish to finish, and start to finish) in contrast to arrow networks.

Some terms used when planning and scheduling of a project by CPM are briefly explained as follow [7]:

- Activity**:** refers to task which are discretely defined.
- Critical Path**:** shows the sequence of activities taking the longest time, which determines the project duration.
- Duration**:** expresses the spent time for completion of an activity from the start of its.
- Early Start Date (ES): depending on the logical relationships among its predecessors, demonstrates the earliest date that an activity can start.
- Early Finish Date (EF): based on its duration, and logical relationships among its predecessors, represents the earliest date that an activity can finish.
- Late Start Date (LS): refers the latest start date allowed for an activity not to delay the project completion date.
- Late Finish (LF): refers the latest finish date allowed for an activity not to delay the project completion date.
- Total Float: demonstrates the amount of delay that an activity in the schedule without adversely affecting the critical path.
- Free Float: refers the amount of delay for an activity before it adversely affects another activity.
- Forward Pass: specifies the stage in which the early start and end dates of all activities are calculated.
- Backward Pass: specifies the stage in which the late start and end dates of all activities are calculated starting from the project end date set by the forward pass calculation.

1.4.2. Logical Relationships in CPM

In addition to traditional finish-to-start (FS) relationship which is generally adopted for activities relationships, three other relationships, start-to-start (SS), finish-to-finish (FF), and start-to-finish (SF), can be also handled in CPM to establish of networks.

a. Finish-to-start (FS) relationship: The following examples clearly express the key rationale behind the definition of FS relationship for the activities. :
The concrete cannot be placed (poured) until the formwork has been built.

b. Start-to-start (SS) relationship**:** Explanatory examples are given below for this type of relationship.

Excavation for the foundation cannot start until clearing and grubbing begins (usually with a certain lag; i.e., a certain percentage is completed).

c. Finish-to-finish (FF) relationship: Example of this type is as follows:

Backfilling a trench cannot finish until the pipe in the trench has been laid.

d. Start-to-finish (SF) relationship: Considering the construction projects, it can be noted that SF relationship is very rare and even does not exist.

1.4.3. Time-Cost Trade-off Problems (TCTP)

As it is clear that, both the contractor and the client are willing to complete the project on or ahead of the schedule. Also, completing on or under the targeted budget is another desirable accomplishment. For this reason, concurrent minimization of time and cost objectives is unavoidably favorable for both the contractor and client. Hence, the Critical Path Method (CPM) is a useful scheduling technique only when the project deadline is not fixed. To use CPM for a project with a fixed deadline or for a project which is running behind schedule, the TCT analysis is implemented to meet the project deadline. In the TCT analysis some of the activities on the critical path are substituted with their shorter modes of construction to save time. In addition, non-critical activities are relaxed to save cost [7].

Figure 1.1 indicates the relationship between the cost and time. It can be observed from this figure that with increase in project duration direct cost decreases while indirect or overhead cost increases.

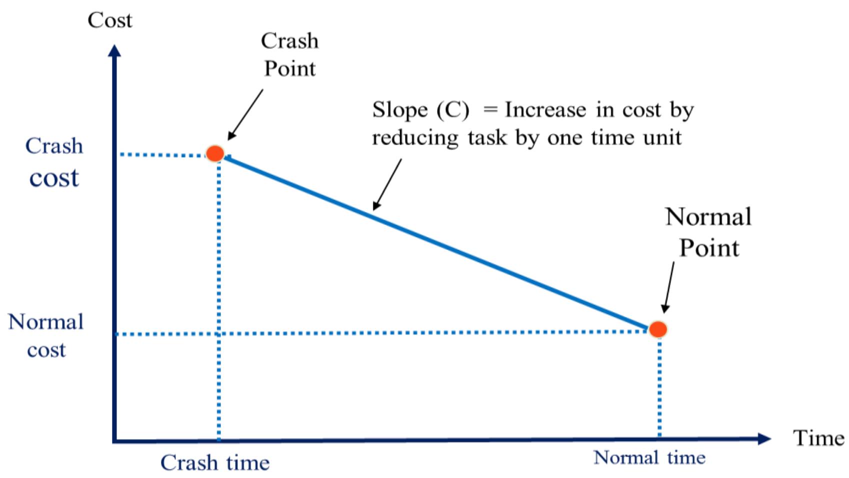

Figure 1.1. Project Time-Cost Relationship

1.4.4. TCT Optimization Challenges

Optimization is the process of trying to find the best solution to a problem that may have many possible solutions. Once the search space of the problem becomes too large for the calculating power of available computers, finding the optimal solution among all other feasible solutions to the problem may take a substantial and an impractical amount of time. Evaluating each alternative requires recalculation of the schedule using the critical path method (CPM) and reassessment of total project cost. Exhaustive enumeration is, therefore, not a feasible and practical solution even with very fast computers [8]. In fact, this process can be shortened with existing methods for optimization to find best combination of time and cost. However, although these methods were applied on solving time-cost trade-off problems of various kind of small scale projects, for the TCTP of large projects they require much more computational effort due to structures of their.

1.4.5. Optimization Methods for TCTP

To solve the TCT problem many multiobjective optimization models have been developed in the literature since finding the optimal solution of it results in very cumbersome computational effort, which requires heavier calculation. In parallel with the developing in computers and numerical methods, different optimization techniques have been applied to solve the TCTP. The common optimization algorithms methods employed for the solution of TCT problem are exact, heuristic, and metaheuristic. Exact algorithms, as the name implies, seeks the all global optimal solutions in the solution space for the defined problem. Likewise, they require huge amounts of calculations which, thus, require super personal computer (PCs) and additionally mind boggling coding techniques. Due to the ability of detecting the global optimum(s), they are preferred in order to show the optimality of the obtained results for the problem although they need more computational efforts. Linear programming, mixed-integer programming, dynamic programming, etc. are some examples for the exact algorithms to be used to solve TCTP.

Heuristic algorithms apply simple rules unlike the exact algorithms to produce solution(s) to the problems examined. Owing to this they can be used easily for the complex problem with less effort. However, for these algorithms, globality of the obtained result is always questionable since they can generally find the local global solutions or the near global ones. This methods use an algorithm to generate the feasible solution. In general, a feasible solution is not acquired over the span of the development heuristics unless the conclusion of the procedure is achieved.

Nevertheless, the algorithms called as metaheuristics and based on the nature events have been implementing to solve various problems in the distinct engineering fields. The main features of these algorithms are to numerically represent the natural events [8]. Since the metaheuristic algorithms improve the quality of the obtained solution iteratively due to stochastic nature of their, they might not stuck into the local optimum. This latter feature improves the detection chance of global optimum solution searched by the metaheuristic algorithms. Like heuristics, metaheuristic algorithms cannot guarantee the optimality of the achieved solution and requires substantial amount of computational efforts. As mentioned above, the algorithms into this type of optimization methods simulate the evolutionary computation and swarm intelligence. They are very useful tool for problems that achieving the global solutions are very difficult, as they find the near optimal solutions instead of global ones. Among others, genetic algorithms (GA), ant colony optimization (ACO), particle swarm optimization (PSO), and simulated annealing (SA) are most known metaheuristic algorithms.

1.4.5.1. Exact Methods for TCTP

Mixed-integer programming was applied for the first time to solve the TCT problem in a study carried out by Meyer and Shaffer [9]. Then, in another study, a flexible mixed-integer model was proposed to minimize the time-cost objective function [10]. Their model is able to deal different type of objective functions including linear, piecewise linear, or discrete. Moreover, this model takes the completion deadline as constraint to obtain the optimal total cost.

De et al. [3] addressed disadvantage of the models developed previously for the solution of discrete TCT problem through literature review. Two solution models based on dynamic programming, that were denoted as a centralized approach and modular decomposition approach, were implemented in [3] to identify the solution of TCT problems. Moreover, they also used parallel modules in the second solution models in their optimization process.

Demeulemeester et al. [11] developed an exact solution model for discrete TCT problem in Visual C++ platform subject a time restricted scheduling. Their model is based on branch and bound optimization model improved by a horizon-varying approach. They evaluated the qualities of convex piecewise linear underestimations that was calculated for the discrete TCT curves by using two different rules they developed. The results obtained from the numerical experiments carried out with their model were confirmed through the factorial experiment, and were compared to those reported by Demeulemeester et al. [12].

Vanhoucke [14] examined the time/switch constrained discrete TCT problems handled with by Yang and Chen [13] in advance. These constraints refer the specific start time and inactive time-intervals enforced to the day, night, and weekend shifts of the activities. In the point of light of the lower bound calculation approach developed by Demeulemeester et al. [11], they offered a new variant of branch and bound algorithm. .

1.4.5.2. Heuristic Methods for TCTP

A logical systematic procedure based upon intuitive logic and analysis was developed by Siemens [7]. He named the method as Siemens Approximation Method (SAM), and denoted as a heuristic method. The model converts the convex nonlinear TCT problems to linear that approximate them with multiple curvilinear parts. SAM begins with the establishment of the project network, and then follows a series of rules to accelerate the activities having least additional cost. The results of this model show good harmony with those obtained with exact algorithms. However, Siemens [7] indicated that since the model ignores number of different paths the activities belong to, and works with the minimum cost slope considerations, it might produce an over shortened project duration beyond the intended amount.

The cost-slope method that is the other name for SAM is a simple heuristic approach for solving TCT problems. This method shortens the project duration assuming that the relationship between time and cost is linear.

According to this assumption, the cost slope of an activity is defined as the rate at which the direct cost increases when its duration is shortened by a unit of time .The detailed steps of the cost-slope method are as follows [6]:

1. Make use of normal durations and costs for all activities.
2. Construct the CPM and determine the critical path.
3. Eliminate all non-critical activities.
4. Obtain normal/crash durations and costs for all critical activities.
5. Compute and obtain the “cost-slope” of each critical activity:

$$\text{Cost Slope} = \frac{\text{Crash Cost - Normal Cost}}{\text{Crash Duration - Noraml Duration}}$$

6. Identify the critical activity with the least cost slope and possible reduction in duration.
7. Shorten the duration of the identified activity until its crash duration is achieved or the critical path changes.
8. If the network has more than one critical path, we need to shorten both of them simultaneously. This can be done by shortening a single activity that lies on all paths or by shortening one activity from each path. The option to choose is determined by comparing the cost slope of the single activity versus the sum of cost slopes for the individual activities on all critical paths.
9. Calculate the direct cost increment due to activity crashing by multiplying the cost slope by the time units crashed. Add the additional cost to the total direct cost.
10. If float times are introduced into any activity, relax them to reduce cost.

11. Plot one point (project duration versus total direct cost) on a figure.
12. Continue from Step 2 until no further crashing is possible to the project.
13. Plot indirect project costs on the same figure. Add the direct cost + indirect cost and plot the total cost curve.
14. Get the optimum TCT strategy as the one with minimum total cost. An example of a complete case study solved based on the cost-slope heuristic method.

Vanhoucke and Debels [15] search three augmentation of the discrete TCT problem; first is time / switch constraints [13], second is work continuity constraints [16], and the third one is net present value maximization [17]. They give another metaheuristic algorithm considering activity on arrow (AoA) network schedule programmed in the Visual C++. The heuristic segment of the exerted algorithm includes an emphasis on neighborhood hunt and maintain diversity attempt. The second part of their algorithms incorporates a dynamic programming which rises the time span of non-critical activities whilst, achieving the favorable finishing due date. The compared results reveals that, the proposed algorithm is applicable on net present value versions of the discrete TCT problem.

Mubarak [19] outlined 9 techniques among the others that was stated to be more than 90 [18] and that was used to shorten a project schedule.

1.4.5.3. Metaheuristic Methods for TCTP

Feng et al. [20] presenting the inadequacy of the current techniques in adapting to large-scale TCT problems, developed a more effective model depending on the rule of Holland's [21] genetic algorithm (GA). They used two chromosomes containing the information related to normal and crash options of the activities in own model. Hence, the objective function values of solutions as per their insignificant distances to the convex hull were determined.

Goldberg and Segrest [22] approve their algorithm later on improving computer program (TCGA) with an interface outlined in Microsoft Excel. The results obtained by using this algorithm indicates that it is capable of finding the optimal solutions with a high percentage for the construction project with 18-activity forming a discrete TCT problem.

The GA demonstrate proposed by Zheng et al. [23] tries to trade-off the genetic drift fact by decreasing the probability stalling out into the neighborhood optima.. Thus, Zheng et al. [23] combines a modified adaptive weight approach (MAWA) to calibrate the need of fitness value regarding the nature of the previous generation. As the generations raise, modified adaptive weight approach (MAWA) directs a diminishing formwork for the mutation rate to counteract early stopping conditions. This model outperforms the past algorithm particularly for the problems with bringing smaller overhead costs; On the other hand, it does not have the competency of applying the complete Pareto front for any of the observed conditions.

Being first introduced by Colorni et al. [24], Ng and Zhang [25] examined the multiobjective TCT problem using the ant colony optimization (ACO). They adopted the modified adaptive weight approach (MAWA) to assess the fitness function solutions. The excellence of their algorithm is tried against other explanatory strategies that were examined by Elbeltagi et al. [26] previously. The conclusion reveals that the applied ACS algorithm provides a satisfactory solution for tackling the TCT problem with substantially fewer necessities of computational assets.

Xiong and Kuang [28] made different endeavor toward integrating Zhang et al. [27] modified adaptive weight approach (MAWA) with ant colony algorithm. In this technique, two options are made to settle on conceivable choices. As per the enrolment of an arbitrary variable, the main determination is made with respect to a maximization criterion, and alternate includes a probability distribution function.

Afshar et al. [29] demonstrated the discrete TCT problem as a graph. They developed an ant colony based multiobjective optimization model. Each solution in ant colonies explored one of objective of TCT problem. Combining this information coming from an ant colony, a multi-colony non-dominated archiving ACO was formed to solve the TCT problems. Effectiveness of model was checked in terms of the results obtained by [20] and [23]. The model significantly outperformed over the compared algorithms.

A strong algorithm in considering complex major scale problems was introduced by [30]. Elbeltagi et al. [30] reviewed shuffled frog leaping (SFL) because of its adequacy in combining particle swarm optimization (PSO). In [30], a search-acceleration parametric study was carried out in order to better realize the results. Numerical problems are adopted to implement modified SFL (MSFL) utilizing Visual Basic, Microsoft project, and Microsoft Excel programs and are compared to basic SFL and GA algorithms. The results of applied MSFL indicate its efficiency to solving this type of problems.

Five forms of a simulated annealing algorithm employing activity on node (AoN) scheduling network is analyzed by [31]. Anagnostopoulos and Kotsikas [31] look for exerting an inquiry strategy practically equivalent to annealing procedure of dissolved materials. Moreover, they use analysis of difference (ANOVA) and Duncan Multiple Range Test (DMRT) to gauge quality and effectiveness of the solutions presented by many problem factors. Test instance sets are produced randomly utilizing the RanGen2 program for the SA algorithms coded in the Visual Basic programming language. In the end, they rank the SA variations as per the results of the Duncan test and predict certainty interval of the optimum solution for the generally advantageous and the most noticeably bad algorithms.

The application of PSO algorithm to investigate crashing options of the cost and deadline TCT problems is analyzed by [32]. The purposed Yang‘s [32] model is to produce Pareto front solution, in order to help decision makers in running further “what if” analysis. The coding of this model is performed in MATLAB optimization engine and is implemented into a numerical simulation, also a real-life highway restoration project. The study involves a numerical example of an 8-activty network, and the case-study including 28-activity. Average percent deviation (APD) per ten runs along with adopting suitable parameters is taken into account to measure the performance of the proposed algorithm. Eventually, the efficiency of PSO algorithm is approved satisfying a negligible percentage deviation.

In a novel approach, a Fuzzy-based PSO for solving time-cost-quality trade-off problems with nondeterministic input data are presented by [33]. Zhang and Xing [33] unraveled the numerical example of fuzzy multi-attribute useful technique derived from [34]. The model is installed in the restricted fuzzy arithmetic operations to improve the PSO algorithm by creating solutions that ensure maximum quality whilst calling for minimum time and cost. Assuming time, cost, and quality of the options as triangular fuzzy numbers, coding of utilized PSO algorithm is performed in Visual C++. For each mode combining, fuzzy multiobjective particle swarm optimization (FMOPSO) utilizes fuzzy feature beneficial for producing composite fuzzy useful values. The proposed PSO algorithm combines the mean integration representation (GMIR), in order to find the solution with the substantial composite fuzzy benefit. The algorithm is investigated on a three modal 13-activity network, and the compared results to fuzzy-GA algorithm illustrate the effectiveness of the FMOPSO.

Meyer and Sheffer [35] had unraveled time-cost trade-off problem taking into account both linear and discrete relationship between time and cost, by utilizing mixed integer programming. On the other hand, integer programming needs lot of process time when the numbers of options to finish activity rises.

In addition to trade-off between the time and cost for a project planning, it is also possible to adopt another criterion such as quality. Adding the quality into the TCT problem as a new target introduces a new problem known as the time cost-quality trade-off. Zhang and Xing [33], Babu and Suresh [36], Khang and Myint [37], Tareghian and Taheri [38], Kim et al. [39], Mungle et al. [40], Tavana et al. [41], and Monghasemi et al. [42] examined this type of trade-off problem via their models. Furthermore, keeping the availability of resources in mind, Hegazy [8], Liu and Wang [43], Ghoddousiet al. [44], Afruzi et al. [45] and Rostami et al. [46] solved TCT with restricted resource.

Sonmez and Bettemir [47] studied about hybrid methods for discrete time-cost trade-off problem (DTCTP) analysis. They utilized different methods for DTCTP problem like genetic algorithm (GA), hybrid metaheuristic (HMH), simulated annealing (SA), quantum simulated annealing (QSA) and Hybrid algorithm (HA). Hybrid Algorithm (HA) was utilized to ten benchmark optimization problems ranging from 18 to 630 activities. They compared the results obtained by different methods and found that use of SA and QSA advances the convergence of GA while HA enriches the DTCTP performance.

Aminbakhsh and Sönmez [48] introduce an efficient method based on particle swarm optimization (PSO) for the solution of large-scale discrete time–cost trade-off problem (DTCTP). In this study, Siemens method is initially used to produce a certain portion of initial population and incorporated with PSO model to accelerate the searching process. Numerical simulation results demonstrated that the introduced new model is able to produce much better results in point of view of the quality of solution obtained, and the time spent required to detect him as compared to the previous models, particularly for medium and large-scale TCTP problems.

Bettemir and Birgönül [49] adopted minimum cost-slope method for solving the discrete TCT problem. They addressed that for the discrete TCT problem, since crashing modes are also discrete; they disrupt the linearity in the cost function. Due to this, the application of the minimum cost slope method becomes not suitable for the discrete TCT problem.

Abdel Raheem and Khalafallah [50] have presented the development of a new evolutionary algorithm, named “Electimize,” that is based on the simulation of the flow of electric current in the branches of an electric circuit. The main motive in their research is to provide the construction industry with a robust optimization tool that overcomes some of the shortcomings of existing evolutionary algorithms.

Ahmet-Baykal Hafizoğlu [51] first considered the deadline problem for the discrete time/cost alternatives. Branch and Bound Algorithm and several heuristic procedures has been proposed. All procedures are based on the Linear Programming Relaxations of the problem. The properties of the Linear Programming Relaxation are defined and used them in designing the proposed algorithms. Afterwards, a Discrete Time/Cost Curve Problem is taken into account. This approach uses the successive solutions of the Deadline Problem.

Aminbakhsh [52] generated a hybrid-PSO model integrating the benefits of the modified-SAM method with PSO algorithm. Integration process of the required algorithms was managed via C++ programming language through the Microsoft Visual Studio 2010. To validate the potency of the PSO optimizer, benchmark optimization problems taken from the literature were resolved using the proposed algorithm and a comparison was also presented for the results obtained with the previous models. Moreover, mixed integer programming using the AIMMS optimization software is applied to discover all the optimal solutions of the example problems to assess the performance. To measure the quality of the acquired solutions, optimal solutions and the average deviations are evaluated for multiple experimental runs. The results indicate that the proposed algorithms outperform the previously proposed models.

De et al. [56] demonstrate that any exact solution algorithm for the discrete TCT problem would quite often show an exponential poor scenario adversity; in that, the computational time would go up in an exponential way as the number of the problem gets increased. It has been inferred that exact algorithms are inclined to get into stuck in neighborhood optima in non-convex solution spaces [56, 20, 57, and 29]. Besides, the researchers using heuristic algorithms recognize that they are similar to exact procedures, however, can't deal with large-scale problems effectively [7]. Eventually, the main shortcomings of the current metaheuristic algorithms are seen as the probability of stagnated into local optima [23, 47].

2. OPTIMIZATION ALGORITHMS

This chapter is devoted to multiobjective teaching learning based optimizer (TLBO). Initially, theoretical properties of contemporary TLBO algorithm is presented for solution of time-cost trade-off benchmark optimization problems, contributing specific emphasis on time-cost extension of these analyses. To develop a flexible time-cost trade-off (TCT) model, critical path method (CPM) scheduling in MATLAB to be used for obtaining the objective functions of project duration and total cost. Summation of all the activities on the critical path is equal to the total project duration. The software is utilized to perform CPM scheduling for the finish to start (FS) logical relationship to obtain the project duration objective function. To this end, the purpose of this research is to employ multiobjective TLBO algorithm to handle the time–cost trade-off problems. It also includes the application of modified adaptive weight approach (MAWA) as well as non-dominating sorting (NDS) concept with the mechanism of crowding distance computation. As it is clear that, optimization techniques being used for single objective optimization for several years. Afterwards, the unification of more than one objective in the fitness function has finally become popular in the research studies. This unification of more than one objective in the fitness function is called multiobjective function. In the present work, minimization of time and total cost of the project is taken into account as bi / multiobjective functions. For fulfilling time-cost trade-off optimization, a multiobjective optimization approach is in need. Therefore, initially, a classic modified adaptive weight approach (MAWA) is utilized to unravel the various benchmark optimization TCTP problems. In spite of being the most simplistic approach, MAWA can achieve near optimum solutions as no further interaction with the decision-makers is required. This approach simply assigns weights to each objective function and combines them into a single objective function. However, the performance of the modified weighting approach becomes worst and is not capable of exploring the global optima whenever applied to more complex medium as well as large scale problems. Hence, in this thesis, to overcome this deficiency of MAWA, an effective and more promising non-dominating sorting (NDS) concept and the mechanism of crowding distance computation is also adopted. As it is obvious, nowadays, instead of MAWA approach, the NDS superior approach is broadly being acknowledged in solving the mentioned TCTP problems. In contrast to MAWA approach, there is no unique solution provided by NDS approach, but Pareto front solutions are produced and selected by comparing two solutions to each other. This NDS approach seeks the satisfactory solution from the non-dominated solutions depending on the experience and knowledge of decision-makers. The employed multiobjective TLBO algorithm can find out the Pareto front solution which provides flexibility to planners and decision makers in making efficient time-cost decisions. The concept of the Pareto front solution is the commonly accepted tool for comparing two solutions in multiobjective optimization that have no unified criterion with respect to optima. Considering the number of activities and selecting options for each of the activities, usually the selection has not one unique solution, but it consists of a set of solutions that are not preferred to each other and are known as Pareto solutions. In addition to this, to develop a flexible time-cost trade-off (TCT) model, critical path method (CPM) scheduling in MATLAB to be used for applying multiobjective TLBO optimization engine. Thereby, contribution of this thesis can be clearly seen in TLBO application on the construction management filed and also the development of the TLBO-based multiobjective approach in this study secures superiority to solving construction time–cost optimization. The Pareto front performance of MAWA-TLBO and NDS-TLBO are compared to those previously presented models with regard to the average percent deviation (APD) and optimality of the obtained solutions. The results reveal that NDS-TLBO is more effective as compared to the original MAWA-TLBO and other state-of-the-art algorithms. Furthermore, the effect of partial random initial population on NDS-TLBO for time-cost trade-off optimization problems is investigated to demonstrate the variation on exploration capacity of the proposed algorithm. This new approach is implemented on the non-dominated sorting version of the classical core-TLBO algorithm.

2.1. Teaching-Learning Based Optimization (TLBO)

Like other metaheuristic algorithms, TLBO [60] was also proposed as a population-based algorithm. "Teaching" phase, which is the first mode of TLBO, creates randomly requested solutions of focuses called learners inside the inquiry space. Afterward, a learner being the most qualified is taken into account as the teacher. He / she offers his or her insight to the learners, in this way the others get huge information from the teacher. The learners also learn by interacting among them. After various successive Teaching-Learning cycles, where the teacher passes on information among the learners and raises their insight near her or his level, the dispersion of the arbitrariness inside the hunting space winds up plainly smaller and smaller stretching around a point embraced as the teacher. Convergence over a solution implies that the knowledge level of the entire class indicates smoothness.

TLBO that was proposed by Rao et al. [60] and also Rao and Savsani [61] simulates the influence of a teacher on the output of learners in a class. It has emerged as one of the simple and efficient techniques for solving single-objective benchmark problems and real life application problems in which it has been empirically shown to perform well on many optimization problems [62-65]. These are precisely the characteristics of TLBO that make it attractive to extend it to solve multiobjective problems (MOPs) [63, 64, 66-68].

TLBO algorithm has already been effectively exerted to numerous engineering optimization problems. Among them, TLBO algorithm has been utilized in electric power generators under various targets, for example, energy cost, emission, electrical energy misfortunes, voltage deviations, and so forth [67, 69, and 70]. Cooling limit and efficiency coefficient of cooler is taken as destinations to improve thermoelectric cooler by Rao and Patel [71]. Optimization for some structural engineering problems, i.e., truss frameworks, I-beams, grillage structures are done underweight obeying stress, deflection and frequency constraints [65, 72-74].

TLBO algorithm proceeds with two basic modes; (i) teacher phase and (ii) learner phase. In the former phase, the class learns through the teacher. However, in the latter, learning is carried out with the interaction among the students in the class. Analogously, all students (learners) represent the population for an optimization algorithm; the subjects to be taught are considered as the design variables of the optimization problem; exam result of the learners gives the 'fitness' value for that corresponding subject to be taught.

2.2. Time-Cost Trade-Off Optimization

The main goal of a discrete TCT optimization problem is to determine a set of time-cost alternatives which provide an optimal balance between the time and cost for project scheduling under the specific conditions. The TCT analysis is implemented to meet the project deadline for a project with a fixed deadline or for a project which is running behind schedule. As mentioned above, TCTP mainly concentrates on selecting appropriate options for every activity to obtain the objective of time and cost of a project. The objective of time of a project can be calculated according to Eqns. (1)–(4).

$$ES_0 = 0 \text{ (the subscript 0 represent zero)} \tag{1}$$

$$ES_j = \max_{i \in p_j} \{EF_i\} \qquad j = 1, \cdots, n+1 \tag{2}$$

$$EF_i = ES_i + t_i^{(k)} x_i^{(k)} \qquad i = 0, \cdots, n+1 \tag{3}$$

$$T = EF_{n+1} \tag{4}$$

Where, T is the total time duration of the project and maximization of which is one of the objectives of TCTP. It represents the complete time of critical activities placed on the critical path of the project activity network. ES_j and EF_j are earliest start time and earliest finish time, respectively; p_j is immediate predecessor of activity j; $t_i^{(k)}$ is duration of activity i for the kth option; and $x_i^{(k)}$ is index variable of activity i. If $x_i^{(k)} = 1$, then activity i performs the kth option, while $x_i^{(k)} = 0$ means not. The sum of index variables of all options should be equal to 1. Activity 0 (n+1) is the only dummy activity.

The total cost of a project composes of direct cost and indirect cost. Sum of direct cost of all activities within a project network gives the direct cost. Besides, indirect cost depends on the project duration. Thus, indirect cost increases as the finishing date of a project is getting longer. Afterwards, Eqns. (5)–(7) are applied to calculate the total cost of a project.

$$DC = \sum_{i=0}^{n+1} dc_i^{(k)} x_i^{(k)} \tag{5}$$

$$IC = T \times ICR \tag{6}$$

$$C = DC + IC \tag{7}$$

where DC and IC, respectively, are the total direct and indirect costs of a project; C is the total cost of a project; $dc_i^{(k)} x_i^{(k)}$ shows the direct cost of activity i under the kth option; and ICR is the indirect cost rate of a project.

2.3. Optimum Solution of TCTP via MAWA-TLBO

The solution of TCTP employing TLBO process is summarized in five steps as follows:

Step I: Define the number of learners (population size) in the class and the maximum number of iterations (stopping criteria) to initialize the TLBO algorithm.

Step II: Fill the initial matrix (class; *CL*) with *pn* (student or population size) number of solution vectors that contains *dn* number of randomly generated design variables (X_i) between the upper (X_i^{max}) and lower (X_i^{min}) limit of the solution range (Eq. (8)).

$$X_i^{min} \le X_i \le X_i^{max} \qquad i = 1, \cdots, dn \tag{8}$$

Thus, initial matrix (*CL*) can be written as:

$$CL = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,dn} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,dn} \\ \vdots & \vdots & \vdots & \vdots \\ X_{pn-1,1} & X_{pn-1,2} & \cdots & X_{pn-1,dn} \\ X_{pn,1} & X_{pn,2} & \cdots & X_{pn,dn} \end{bmatrix} \tag{9}$$

In which each row of the matrix is a candidate solution of TCTP problem that is corresponded two objective function values associated with time (f_t (**X**)) and cost ((f_c (**X**))).

$$f(\mathbf{X}) = \begin{bmatrix} f_t(\mathbf{X}_1), \ f_c(\mathbf{X}_1) \\ f_t(\mathbf{X}_2), \ f_c(\mathbf{X}_2) \\ \vdots \\ f_t(\mathbf{X}_{pn-1}), \ f_c(\mathbf{X}_{pn-1}) \\ f_t(\mathbf{X}_{pn}), \ f_c(\mathbf{X}_{pn}) \end{bmatrix} \tag{10}$$

Step III: Apply "teacher phase (t_p)" of the TLBO algorithm. Due to teacher has the best knowledge, the variables with minimum objective function is assigned as a teacher

($\mathbf{X}_{teacher}$) of the class. Because of the fact that TCTP problem is a multiobjective, to determine the teacher, Eq. (19) is taken into consideration.

$$\mathbf{X}_{teacher} = f_{\min}(\mathbf{X}) \tag{11}$$

Then, knowledge of the teacher is used to increase the capacity of the whole class. The main aim is to increase of the mean ($\mathbf{X}_{mean}$) of the class. For that reason the equation of new students is found, according to teacher and mean of the class as seen in Eq. (12).

$$\mathbf{X}^{tp}_{new,\, i} = \mathbf{X}_{old,\, i} + \text{rand}\ (0, 1).\ (\mathbf{X}_{teacher} - T_{\mathrm{F}}.\ \mathbf{X}_{mean}) \tag{12}$$

where T_{F} represents teaching factor defined as

$$T_{\mathrm{F}} = \text{round}\ [1 + \text{rand}\ (0.1)] \ \ \rightarrow \{1\text{- }2\} \tag{13}$$

and it takes a value 1 or 2 depending on the uniformly distributed random numbers that are within the range [0, 1]. If the new solution ($\mathbf{X}^{tp}_{new,\, i}$) is better than the old one in point of the objective function (Eq. (19)), the new solution is accepted.

Step IV: Proceed with the "learner phase (l_p)" of the TLBO algorithm. As it stated above, students also have an important role in the learning process by communication, interaction, investigation, etc. This interaction can be expressed as follows:

$$\mathbf{X}^{l_p}_{new,i} = \begin{cases} \mathbf{X}_{old,i} + \text{rand}(0,1)\left(\mathbf{X}_i - \mathbf{X}_j\right) & \text{for} \quad f(\mathbf{X}_i) > f(\mathbf{X}_j) \\ \mathbf{X}_{old,i} + \text{rand}(0,1)\left(\mathbf{X}_j - \mathbf{X}_i\right) & \text{for} \quad f(\mathbf{X}_i) < f(\mathbf{X}_j) \end{cases} \tag{14}$$

where $\mathbf{X}_i$ and X_j are randomly selected learners that are different each other. If the new solution ($\mathbf{X}^{lp}_{new,\, i}$) is better, it is replaced with old one.

Step V: Check the stopping criterion. This criterion usually is defined as the maximum iteration number. If the stopping criterion is satisfied, the optimization process is terminated, otherwise the iteration process continues from the step III.

2.4. Modified Adaptive Weight Approach (MAWA) in Multiobjective Optimization

This approach simply assigns weights to each objective function and combines them into a single objective function. It is the approach which has got the simplest formulation and easy to be implemented. In spite of being simple one, is able to achieve optimum or near optimum solutions as no further interaction with the decision-makers is needed. Modified adaptive weight approach (MAWA) proposed by Zheng et al. [27] is utilized in this study to solve the multiobjective problem. To identify adaptive weight for each objective, MAWA benefits the information from the existing set of solutions. For MAWA, the formulations are expressed through the following four conditions [4]:

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

$$v_c = Z_c^{min} / Z_c^{max} - Z_c^{min}$$

$$v_t = Z_t^{min} / Z_t^{max} - Z_t^{min}$$

$$v = v_t + v_c \tag{15}$$

$$w_t = v_t / v$$

$$w_c = v_c / v$$

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

$$w_t = w_c = 0.5 \tag{16}$$

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

$$w_t = 0.9$$

$$w_c = 0.1 \tag{17}$$

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

$$w_t = 0.1$$
$$w_c = 0.9 \tag{18}$$

where $Z_t^{\max}$ and $Z_t^{\min}$ are maximum and minimum values for the objective of project duration, respectively, in the current iteration. Similarly, $Z_c^{\max}$ and $Z_c^{\min}$ are maximum and minimum values for the objective of total direct cost, respectively, in the current iteration. v_t and v_c are ratio between the minimum value and difference between maximum and minimum points for the objective project duration and total direct cost, respectively. w_c is weight for the objective of total direct cost, and w_t is weight for the objective of time. These weights adjust itself with adaptive manner. It means that their values changes depending on the performance of the current population. According to MAWA, the following equation is evaluated to assign fitness to each solution:

$$f(x) = w_t \frac{Z_t - Z_t^{\min} + r}{Z_t^{\max} - Z_t^{\min} + r} + w_c \frac{Z_c - Z_c^{\min} + r}{Z_c^{\max} - Z_c^{\min} + r} \tag{19}$$

where x shows any candidate solution in the current generation; $f(x)$ is the fitness of that solution; Z_c and Z_t represent the total cost and the time of the xth solution, respectively. r is a small positive random number between 0 and 1; w_c, and w_t are the adaptive weights for cost and time. To avoid a case of $Z_c^{max} = Z_c^{min}$ or $Z_t^{\max} = Z_t^{min}$, r is added in Eq. (19) [27]. The flowchart of the process can be seen in Figure. 2.1.

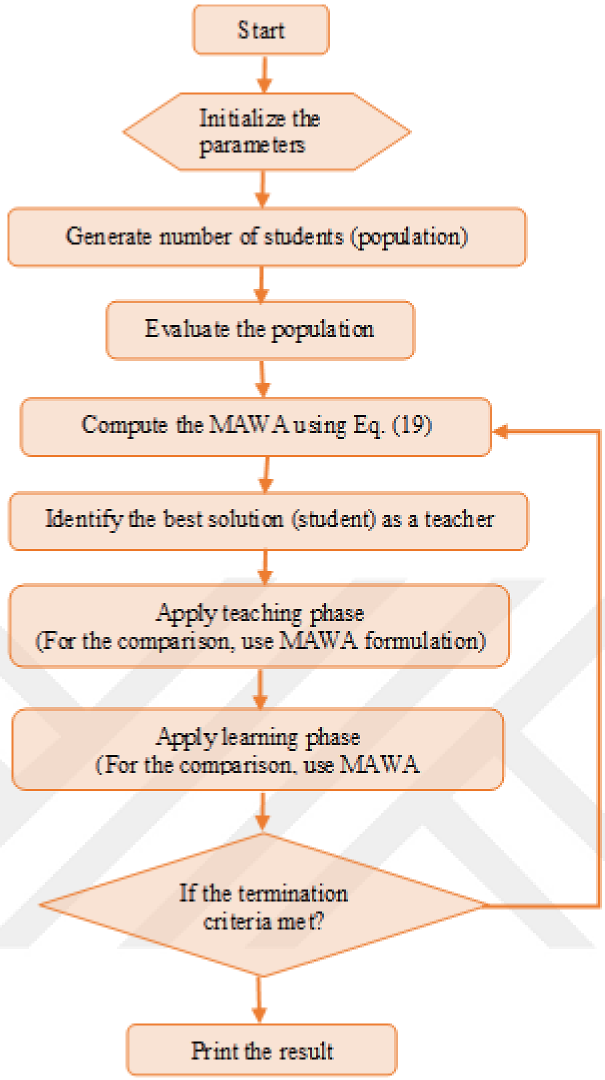

Figure. 2.1. Flowchart of the MAWA-TLBO algorithm for TCTP

2.5. Non-dominated Sorting TLBO Algorithm for Multiobjective Optimization

As it is obvious, nowadays, instead of modified adaptive weight approach (MAWA) approach, this non-dominating sorting (NDS) superior approach is extensively being acknowledged in unraveling the different benchmark optimization TCTP problems. In contrast to MAWA approach, there is no unique solution provided by NDS approach, but Pareto front solutions are produced and selected by comparing two solutions to each other. This NDS approach seeks the satisfactory solution from the non-dominated solutions depending on the experience and knowledge of decision-makers. The domination concept defined as: design A dominates design B if it is better in at least one criterion and not worse in all other objectives Deb et al. [75]. The process of sorting designs variables based on dominance is called non-dominated sorting (NDS). At any phase in an optimization run, a population or repository of "current" designs is kept up. At each progression, every feasible design that is not dominated by some other designs in the population (or archive) is given the rank of 1. These are the just non-dominated designs in the population. At that point, these designs are adroitly expelled from the repository, and the rest of the designs are judged for domination. Those that are not dominated by any of the rest of the designs are given the rank of 2. The method is repeated, re-positioning the rest of the designs after eliminating non-dominated designs, to build up ranks 3, 4, and so on. As the run progresses, new designs will dominate and replace other designs on a series of local Pareto fronts. The final result will regularly be a combination of variables that are not overwhelmed by any other designs and converge towards the Pareto front. From this bunch of designs, one can pick up the design that best suits the present requirements or those that move towards hunting.

NDS-TLBO algorithm comprises remarkable features of NDS approach and TLBO algorithm to unravel multiobjective optimization problems and to find out a bunch of diverse solutions. NDS approach and crowding distance computation mechanism proposed by Deb et al. [75] are responsible to handle objectives effective and efficiently in NDS-TLBO model. Besides, the teacher and learner phases of TLBO guarantee the exploration and exploitation of the searched solution space.

The initial population including predefined *P* number of students is arranged with the non-dominance concept. Application of NDS approach assigns a rank value to the each solution. The higher rank implies the higher superiority in accordance with the non-dominance concept. However, it cannot be stated anything about the dominance among the solutions which are into the same rank. To describe the excellency of these solutions crowding distance metric is utilized. Ultimately, all solutions are kept up in the external archive and the learner with the highest value of rank and crowding distance is adopted as the teacher of the class. Once the teacher is chosen the process continues according to the teacher phase of the TLBO algorithm. At the end of the teacher phase process of TLBO *P* updated solutions are created. Combining these updated solutions with *P* solutions in the external produces *2P* solutions. To go on the learning phase of TLBO, *P* numbers of best learners are chosen from the *2P* solutions according to the non-dominating sorting concept and the crowding distance metric. Then, these learners are further updated depending on the learner phase of the TLBO algorithm. These steps are continuously repeated until satisfying a pre-defined criterion.

2.5.1. Optimum Solution of TCTP via NDS-TLBO Algorithm

The solution of TCTP employing NDS-TLBO process detailed in above is summarized in five main steps as follows:

Step I: Define the number of learners (population size) in the class and the maximum number of iterations (stopping criteria) to initialize the TLBO algorithm.

Step II: Fill the initial matrix (class; *CL*) with *pn* (student or population size) number of solution vectors that contains *dn* number of randomly generated design variables (X_i) between the upper ($X_i^{\max}$) and lower ($X_i^{\min}$) limit of the solution range (Eq. (20)).

$$X_i^{\min} \le X_i \le X_i^{\max} \qquad i = 1, \cdots, dn \tag{20}$$

Thus, initial matrix (*CL*) can be written as:

$$CL = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,dn} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,dn} \\ \vdots & \vdots & \vdots & \vdots \\ X_{pn-1,1} & X_{pn-1,2} & \cdots & X_{pn-1,dn} \\ X_{pn,1} & X_{pn,2} & \cdots & X_{pn,dn} \end{bmatrix} \tag{21}$$

In which each row of the matrix is a candidate solution of TCTP problem that is corresponded two objective function values associated with time (f_t ($\mathbf{X}$)) and cost ((f_c ($\mathbf{X}$))).

$$f(\mathbf{X}) = \begin{bmatrix} f_t(\mathbf{X}_1), \;\; f_c(\mathbf{X}_1) \\ f_t(\mathbf{X}_2), \;\; f_c(\mathbf{X}_2) \\ \vdots \\ f_t(\mathbf{X}_{pn-1}), \;\; f_c(\mathbf{X}_{pn-1}) \\ f_t(\mathbf{X}_{pn}), \;\; f_c(\mathbf{X}_{pn}) \end{bmatrix} \tag{22}$$

Perform a non-dominated sorting on *CL*. Then calculate the crowded distance values of solutions in the front(s) and sort them. Keep the sorted solution in an external archive.

Step III: Apply "teaching phase (t_p)" of the TLBO algorithm. Due to the fact that teacher has the best knowledge, the best learner in the class is assigned as a teacher ($\mathbf{X}_{teacher}$) of the class based on non-dominated sorting and crowding distance metric.

$$\mathbf{X}_{teacher} = \mathbf{X}_\mathrm{i} \mid \text{in front 1 and max. crowded distance} \tag{23}$$

Then, knowledge of the teacher is used to increase the capacity of the whole class. The main aim is to increase of the mean ($\mathbf{X}_{mean}$) of the class. For that reason the equation of new students is found, according to teacher and mean of the class as seen in Eq. (24).

$$\mathbf{X}^{tp}_{new,\,i} = \mathbf{X}_{old,\,i} + \text{rand}\,(0,\,1).\,(\mathbf{X}_{teacher} - T_\mathrm{F}.\,\mathbf{X}_{mean}) \tag{24}$$

where T_F represents teaching factor defined as

$$T_\mathrm{F} = \text{round}\,[1 + \text{rand}\,(0.1)] \;\rightarrow \{1\text{-}\,2\} \tag{25}$$

And it takes a value 1 or 2 based on the uniformly distributed random numbers that are within the range [0, 1]. If the new solution ($\mathbf{X}^{tp}_{new,\,i}$) is better than the old one in point of the objective function, the new solution is accepted.

After employing the teaching phase, combine the current population with the archived one. Perform a non-dominated sorting on the combined population. Then calculate the crowded distance values of solutions in the front(s) and sort them. Select *N* individual from it.

Step IV: Proceed with the "learning phase (l_p)" of the TLBO algorithm. As it stated above, students also have an important role in the learning process by communication, interaction, investigation, etc. This interaction can be expressed as follows:

$$\mathbf{X}^{l_p}_{new,i} = \begin{cases} \mathbf{X}_{old,i} + \text{rand}(0,1)\left(\mathbf{X}_i - \mathbf{X}_j\right) & \text{if } \mathbf{X}_i \text{ lies on a better non-dominated front than } \mathbf{X}_j \\ \mathbf{X}_{old,i} + \text{rand}(0,1)\left(\mathbf{X}_j - \mathbf{X}_i\right) & \text{if } \mathbf{X}_j \text{ lies on a better non-dominated front than } \mathbf{X}_i \end{cases} \tag{26}$$

where $\mathbf{X}_i$ and $\boldsymbol{X}_j$ are randomly selected learners that are different each other. If the new solution ($\mathbf{X}^{lp}_{new,\, i}$) is better, it is replaced with old one.

Combine the current population with the one that is used at the starting of the phase. Perform a non-dominated sorting on the combined population. Then calculate the crowded distance values of solutions in the front(s) and sort them. Select N individual from it.

Step V: Check the stopping criterion. This criterion usually is defined as the maximum iteration number. If the stopping is satisfied, the optimization process is terminated, otherwise the iteration process continues from the step III. The flowchart of the process can be seen in Figure 2.2.

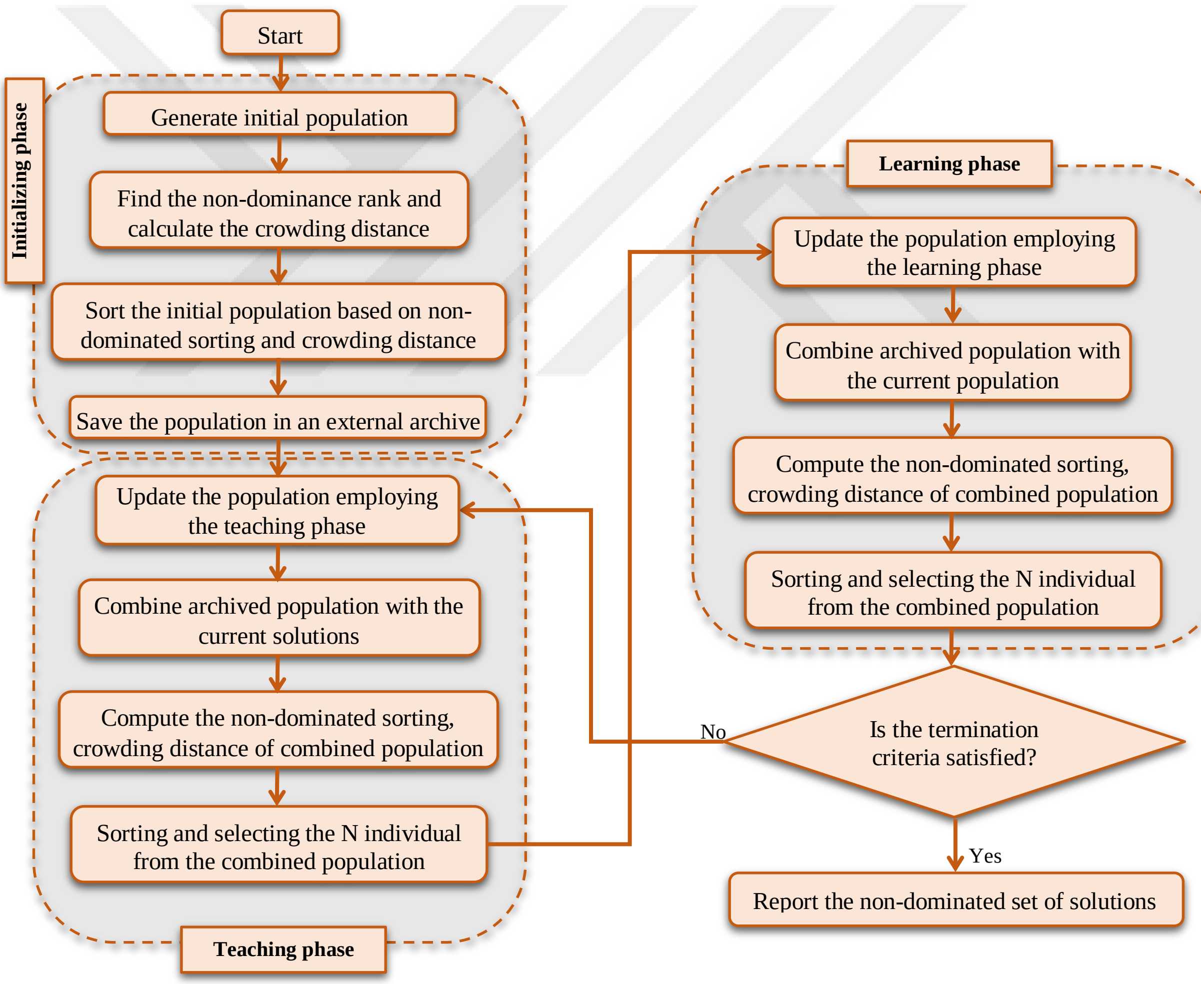

Figure 2.2. Flowchart of the NDS-TLBO algorithm for TCTP

2.5.2. Crowding Distance Computation

This function sorts the current population based on non-domination concept. All the individuals in the first front are given a rank of 1, the second front individuals are assigned rank 2 and so on. After assigning the rank the crowding in each front is computed. The crowding measure is a secondary measure used to favor an even distribution of points along the Pareto front. The crowding distance computation needs sorting the population according to each objective function value in ascending order of magnitude Deb et al. [75]. Thereafter, an infinite distance value is assigned to the solutions being at the top and the bottom places for each objective function. For all others, a distance value equal to the absolute normalized difference in the function values of two adjacent solutions is assigned. Crowding distance value is the sum of individual distance values calculated for each objective that was normalized. Crowed comparison assist in achieving more diversely distributed solutions. If the algorithm is already able to locate diverse solutions along the front, so no need to use a diversifier.

2.5.3. External Archive

In NDS-TLBO process, the best solutions obtained until that moment are kept in a place called external archive. At the beginning of the process of NDS-TLBO, all individuals, NP, in the initial population are put into the external archive. As NDS-TLBO progresses NP new solutions are obtained. These are, as well, kept into the external archive. Then, depending on the non-domination rank and crowding distance rank NP solutions are picked up from the external archive that includes 2NP solutions to go on next process of NDS-TLBO. This operation continues until obtaining a convergence or reaching a termination criterion.

3. NUMERICAL EXAMPLES FOR TCTP

In this chapter, validation and performance measurement of the TLBO algorithm are demonstrated on the examples examined. The instances to be studied to validate the proposed model are previously solved from many researchers. A small and more complex medium scale as well as a large scale instances are adopted in order to show the performance evaluation of the utilized model based on TLBO.

3.1. Validating the Algorithms

In this thesis, two approaches are proposed combining with TLBO algorithm. Firstly, MAWA-TLBO performance is investigated. This approach converts the multiobjective problem to a single-objective problem, and then utilizing a single-objective optimization approach to find the satisfactory solution which is known as modified adaptive weighted approach. Second approach investigated is NDS-TLBO. This approach seeks the satisfactory solution from the non-inferior solutions based on the experiences and knowledge of decision makers, whereas the determination of the non-dominating solution is a bit more sophisticated and complicated. The utilized multiobjective algorithms can ascertain the Pareto front solution which provides flexibility to planners and decision makers in making efficient time-cost decisions. Thereby, contribution of this thesis can be clearly seen in TLBO application on this field.

Four examples of construction projects taken from the technical literature ranging from 7 to 630 activities are investigated to show the performance of the MAWA-TLBO. The MAWA-TLBO model is initially tested against the model developed by Zhang et al. [23], Afshar et al. [29] and Ng and Zhang. [25]. To this end, an 18-activity TCT problem is adopted to solve time-cost trade-off problem, treating various overhead cost values. Application of MAWA-TLBO in solution of 63-activity problem derived from Bettemir [79] is experimented. Since 63-activity problem has not been solved with the application of MAWA, the results obtained in this study by utilizing MAWA-TLBO are compared with the solutions acquired through NDS-GA, NDS-ACO, and NDS-PSO models of Bettemir [79]. The results prove that, MAWA-TLBO model developed in this study produces satisfactory results. It is also observed that the quality of the obtained solutions for 18-activity with five modes and large example problem of 63-activity slightly deteriorate as they are prone to smaller daily indirect costs as well as with mode increments. More specifically, the diversity in population can't be preserved and staging to local optima because of the MAWA's drawback. The reason of this can be also explained by the complexity of the problem and the premature stopping condition. Moreover, the utilized model requires the decision-makers to determine the final best solution. Therefore, to overcome this issue an effective and more promising approach, called non-dominating sorting approach is adopted combining with TLBO algorithm.

Throughout the validation process, ten experimental runs are implemented for analysis of any of the example problems. The average percent deviations from the optima, obtained using exact procedure, are evaluated accordingly. Details of all the implemented TCT problems, selected parameter values, and the results of the numerical simulations for MAWA-TLBO as well as NDS-TLBO algorithms are presented in the ongoing section.

3.2. Application of Teaching Learning Based Optimization for Time-Cost Trade-off Problems in Construction Projects

In this study, to find a set of Pareto front solutions, a multiobjective optimization model which is based on the teaching learning based optimization (TLBO) incorporated with the modified adaptive weight approach (MAWA) is proposed. Four examples of construction projects taken from the technical literature ranging from 7 to 63 activities are investigated to show the performance of the MAWA-TLBO. The results are compared with those obtained using previously proposed models considering the optimal or near optimal solutions. It was found that, the MAWA-TLBO algorithm works effectively for the TCTP problems in construction engineering and management field.

The well-known problems taken from the literature are ranging from 18 to 63 activity projects. The larger part of the preceding DTCTP research [4, 8, 25, 27, 29, 30, 32, 33, 57, 59, 76] utilized small example problems involving up to 18-activity to assess the efficiency of the suggested metaheuristics. However, 63-activity projects have been practiced by [47, 48]. This MAWA-TLBO algorithm is also tested on the solution of a more complex problem to minimize trade-off between time and cost. Hence, the example problem of 63-activity project derived from Bettemir [79] is also resolved with the model proposed in this study. The obtained results demonstrate the potency of the proposed algorithm comparing the solutions reported by the previous metaheuristic algorithms.

3.3. Numerical Examples of MAWA-TLBO

To demonstrate the performance of the utilized MAWA-TLBO model for obtaining Pareto front solutions of the TCTP, small and medium scale problems taken from the technical literature are investigated. The utilized algorithm was coded in MATLAB and runs were executed from a personal computer having Intel (R) Core (TM) i3 CPU 2.40 GHz and 3GB RAM. Consecutive experimental run number is adopted as 10 for the entire instances.

3.3.1. Empirical Example of 7-Activity Project

The network introduced by Feng et al [4] and shown in Figure 3.1 contains 7 activities with logical relationship of Finish to Start (FS) with 3 to 5 possible options (alternatives). Possible activity options are presented in Table 3.1 in association with the corresponding durations and costs. The problem complexity will be [3^5 x 4^1 x 5^1] = 4860 possible solutions with a daily indirect cost of $1500.

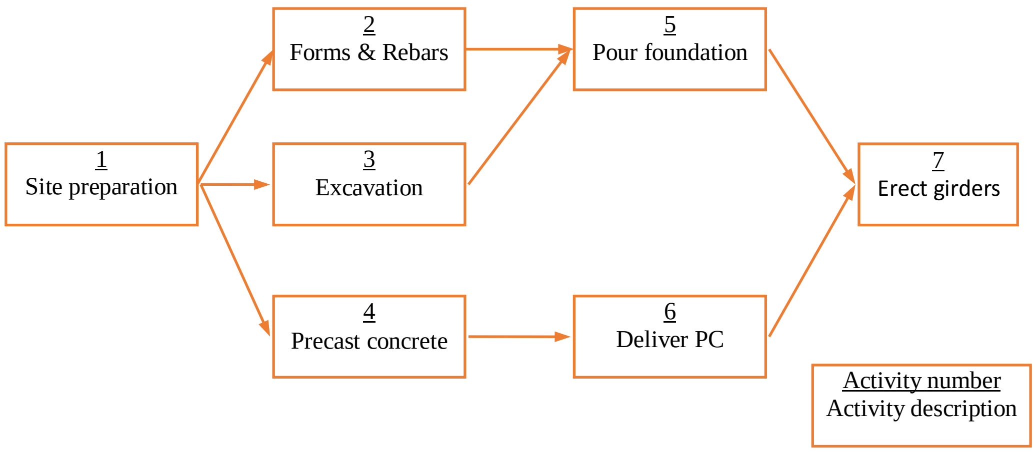

Figure 3.1. Network configuration of 7-activity test example

Table 3.1. Options for 7- activity project

Activity Description	Activity number	Precedent activity	Option / Mode	Duration (days)	Direct cost ($)
Site Preparation	1	-	1 2 3	14 20 24	23000 18000 12000
Forms and rebar	2	1	1 2 3 4 5	15 18 20 23 25	3000 2400 1800 1500 1000
Excavation	3	1	1 2 3	15 22 33	4500 4000 3200
Precast concrete girder	4	1	1 2 3	12 16 20	45000 35000 30000
Pour foundation and piers	5	2,3	1 2 3 4	22 24 28 30	20000 17500 15000 10000
Deliver PC girders	6	4	1 2 3	14 18 24	40000 32000 18000
Erect girders	7	5,6	1 2 3	9 15 18	30000 24000 22000

The complete solution space of the 4860 solution acquired for assumed indirect cost of $1500/day is illustrated in Figure 3.2. In addition, all the minimum cost versus minimum duration of complete solution space for the current problem is presented in Figure 3.3.

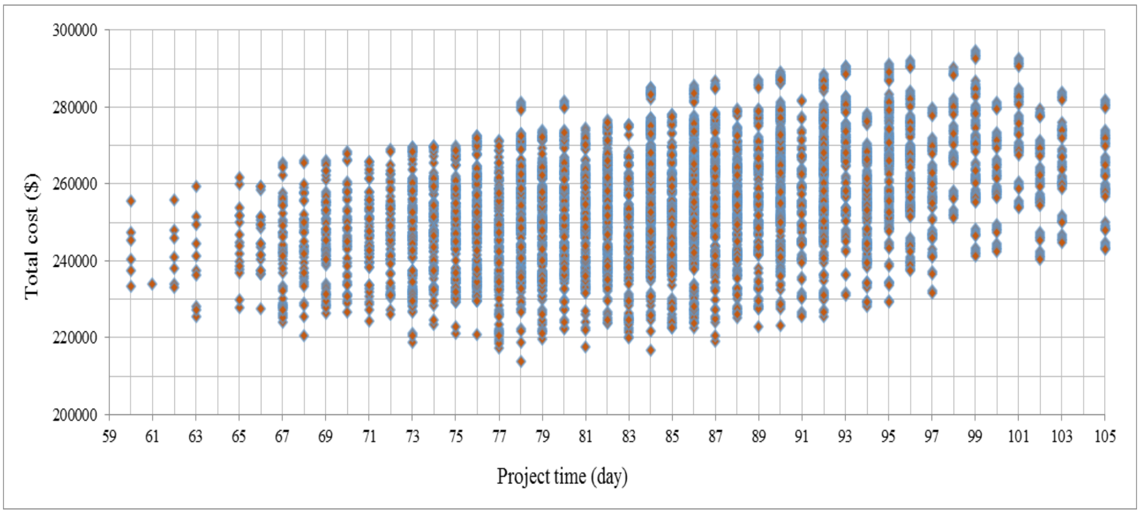

Figure 3.2. Complete solution space (4860 solution) of 7-activity problem

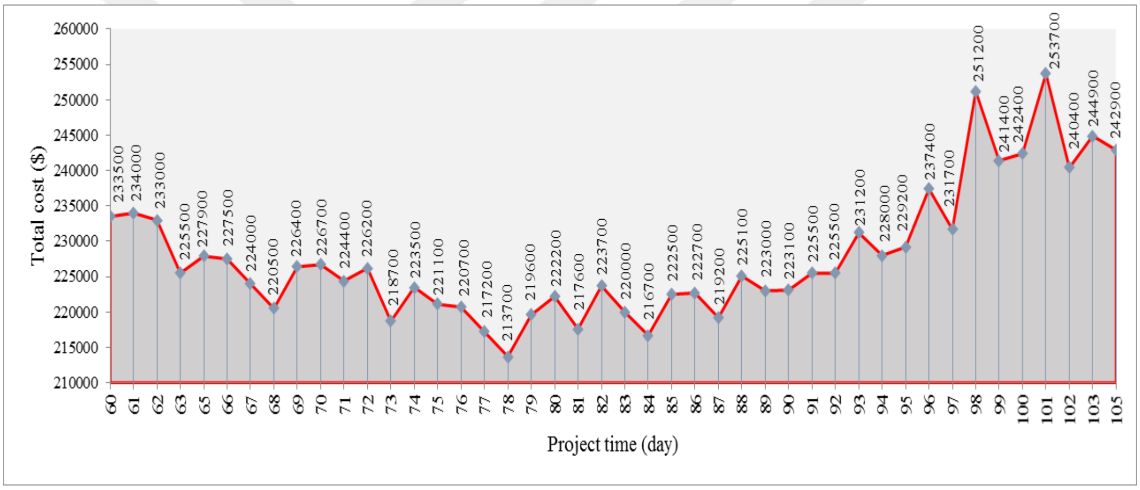

Figure 3.3. The entire minimum cost versus minimum duration of solution space for 7-activity problem

Table 3.2 summarizes the results of the TLBO along with the performance of four previous metaheuristics for the 7-activity problem. Solutions obtained by Gen and Cheng [76], Zheng et al. [23] and Magalhães-Mendes [54] are not better than those achieved by TLBO and did not propose any Pareto front. MAWA-TLBO's results offer less cost 0.9% to 1.55% than that obtained by MAWA-GA's. The Pareto front solutions reported for the MAWA of Xiong et al. [77], Surajit and Sultana [55] and Azeez [58] are same with the results obtained by the MAWA-TLBO method. The comparison of TLBO with the previous methods reveals that utilized TLBO works well or as good as the previously proposed algorithms for the small-scale TCTPs. Additionally, it can also be stated that the

MAWA-TLBO algorithm produces high-quality solutions quickly once needed only 1 seconds to complete 10 generations.

Table 3.2. Comparison of Pareto fronts located for small-scale 7-activity problem

Authors	**Best generation number**	**Criteria**		**Calculation Time**
		Time (Day)	**Cost ($)**	
Gen and Cheng [76], MAWA-GA	5	79	256400	Not reported
Zheng et al. [27], MAWA-GA	5	66	236500	Not reported
Magalhães-Mendes [54], MAWA-GA	2	63	225500	5 seconds for 50 generations
Xiong et al. [77], MAWA-ACO Surajit and Sultana [55], MAWA-GA Azeez [58], MAWA-ACS	Not reported	60	233500	Not reported
		62	233000	
		63	225500	
		67	224000	
		68	220500	
This paper (MAWA-TLBO)	2	60	233500	1 second for 10 generations
		62	233000	
		63	225500	
		66	227500	
		67	224000	
		68	220500	
	Pop size: 5			
	Generation Number: 10			
	f-count (NFE): 105			

The graphical representation of the results (Pareto front solutions) obtained by employing MAWA-TLBO is illustrated in Figure 3.4 while Table 3.3 presents details for the associated solutions.

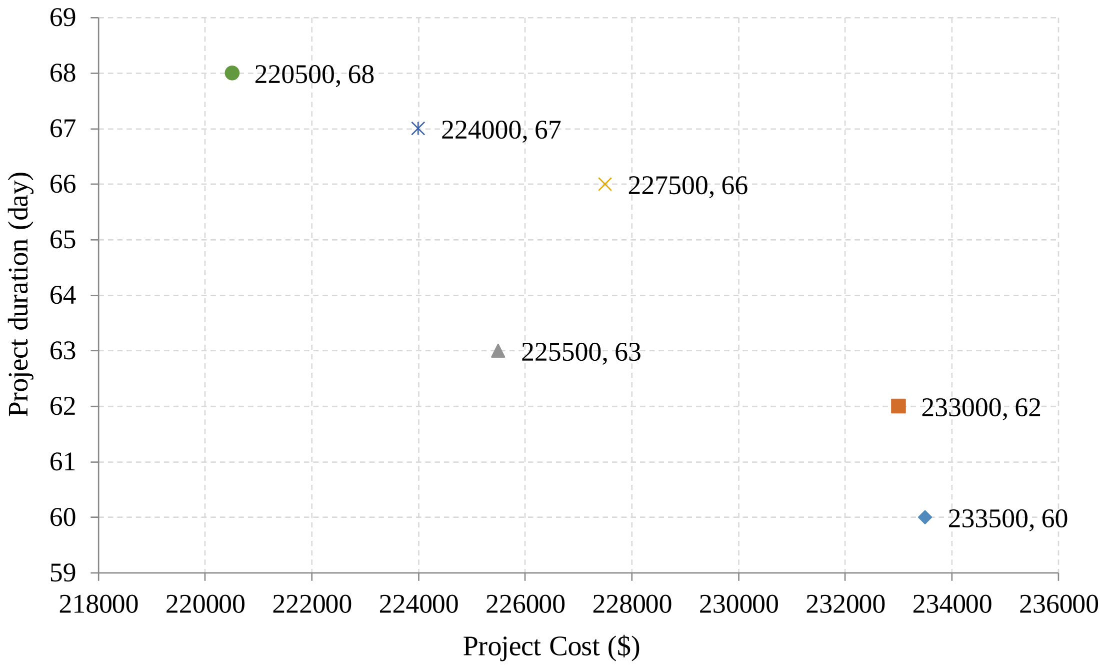

Figure 3.4. Pareto optimal solutions of 7-activity problem obtained by MAWA-TLBO

Table 3.3. Solution obtained for 7-activity TCTP problem using MAWA-TLBO along with selected options

Pareto-front solutions	**Project time (days)**	**Project total cost ($)**	**Options selected by the mode to execute the corresponding activity**						
			1	2	3	4	5	6	7
1	60	233500	1	1	1	1	1	3	1
2	62	233000	1	1	1	2	1	3	1
3	63	225500	1	1	1	2	2	2	1
4	66	227500	1	1	1	2	3	3	1
5	67	224000	1	1	1	3	3	3	1
6	68	220500	1	1	1	3	4	3	1

The convergence history of the solved problem is presented in Figure3.5. The figure implies that the considered generations are a bit more and it is redundantly cycling after the 5th iteration which is optimum value. Therefore, both population and number of generation values can be taken as 5 for the current TCT problem.

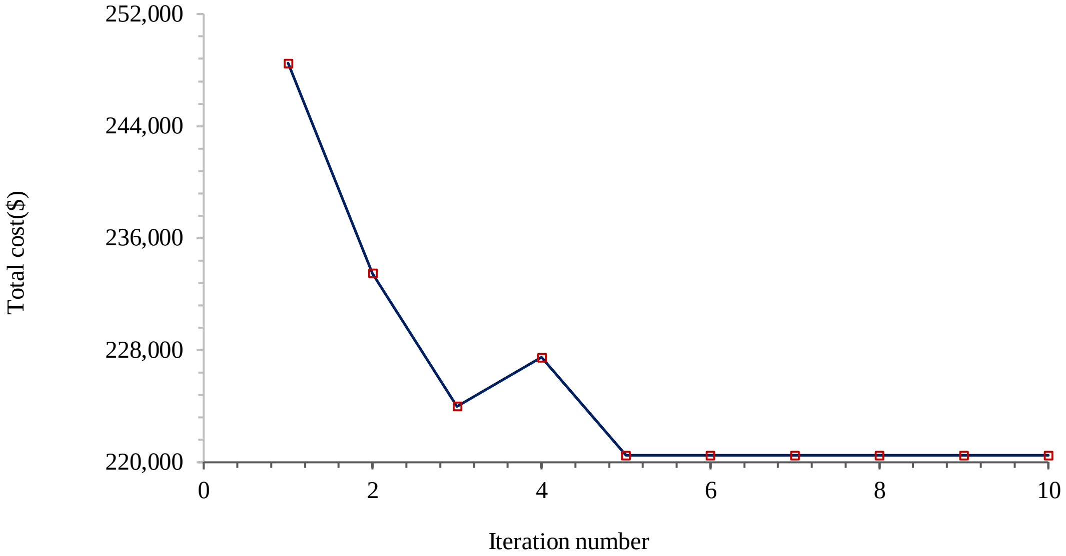

Figure 3.5. Convergence history of 7-activity TCTP problem using MAWA-TLBO

Time-cost optimization have a great effect on lowering the time and cost of construction project and overcome the delays and cost excess that could take place during the execution of any construction project. The project critical path calculated first using forward planning to find the normal duration and for that the options selected were the normal time/normal cost, and the project time was 105 days, and $253700. After using TCO model the highest value of time was 68 days, and the cost was $220500. From the total cost 15%, and 54.4% of the project time were saved by using optimized values. This is achieved by using the saved the indirect cost to allocate the more resources and increase the number of the crews or labors in the construction works or any different construction method used. The MAWA-TLBO searched 105 (= 10 x 5 x 2 + 5) possible different schedules, only searching a small portion of 2.17% of the solution space (105/4860) could generate the global optimal solutions where number of population and iteration are 5 and 10, respectively. Therefore, the number of function evaluations can be taken as 105 (f-count = 10x5x2+5).

3.3.2. Empirical Example of 18-Activity Project with Five Modes

A case of study is a project of eighteen activities originally introduced by Feng et al. [20]. The network with logical relationship of FS is shown in Figure 3.6. The activity relationships for the model project, the five modes of construction for each activity and their associated time and cost are presented in Table 3.4. Indirect cost rate adopted in this problem is $1500/day.

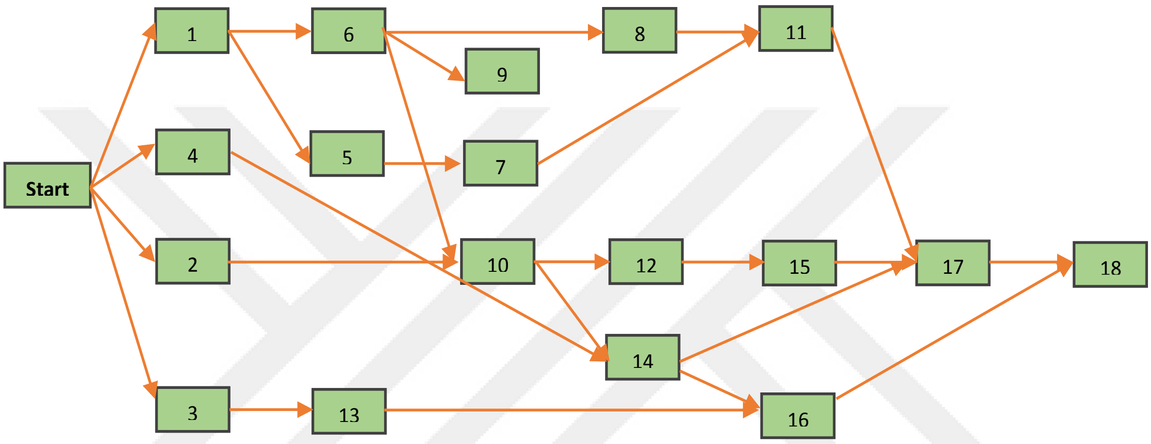

Figure 3.6. Activity relationships for the model project of 18-activity

Table 3.4 Options for 18- activity project with five modes

Description		Mode1		Mode2		Mode3		Mode4		Mode5	
Activity Number	Precedent Activity	Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)
1	-	14	2400	15	2150	16	2400	21	1500	24	1200
2	-	15	300	18	2400	20	1900	23	1500	25	1000
3	-	15	4500	22	4000	33	1800				
4	-	12	45000	16	35000	20	3200				
5	1	22	20000	24	17500	28	30000	30	10000		
6	1	14	40000	18	32000	24	15000				
7	5	9	30000	15	24000	18	18000				
8	6	14	220	15	21	16	22000	21		24	
9	6	15	300	18	240	20	200	23	208	25	120
10	2 , 6	15	450	22	400	33	180		150		100
11	7 , 8	12	450	16	350	20	320				
12	5 , 9 , 10	22	2000	24	1750	28	1500	30			
13	3	14	4000	18	3200	24	1800				
14	4 , 10	9	3000	15	2400	18	2200				
15	12	12	4500	16	3500						
16	13 , 14	20	3000	22	2000	24	1750	28	1500	30	1000
17	11,14,15	14	4000	18	3200	24	1800				1200
18	16,17	9	3000	15	2400	18	2200				1000

A comparison amongst the MAWA-TLBO algorithm, MAWA-GA based TCO model Zheng et al. [23], MAWA-AS Afshar et al. [29] and also MAWA- SGPU algorithm Ng and Zhang [25] utilizing the same project is shown in Table 3.5 and Figure 3.7. It can be seen from Table 3.5, MAWA-TLBO based model is executed with less size of population and number of iteration than those of the MAWA-GA and MAWA-AS models. Besides, examining the time and cost results for the case project, it can be noticed that the MAWA-TLBO based model offers a more optimal cost value with the same project completion time. For example, for 100 days, the cost of solution obtained by the MAWA-TLBO is $283420 while MAWA-GA model cost is to $287720. This results in a saving of $4300 which is equivalent to 1.50% of the total cost. In the situation of ACS-SGPU and AS-MAWA model the total cost is $285400, $286670 which is in between the MAWA-GA and MAWA-TLBO models. However, the iterations of ACS-SGPU and MAWA-TLBO are less than that of MAWA-GA and MAWA-AS. Even though the quality of solutions generated by ACS-SGPU is not as good as MAWA-TLBO, it is superior to the MAWA-GA and MAWA-AS models and can generate better Pareto front solutions.

The Pareto fronts as well as selected duration of corresponding activity for 18-activity with five modes problem is given in Table 3.6. The convergence history representation of the current solved problem is presented in Figure 3.8. As in this case of the MAWA-TLBO, convergence history graphs demonstrates that the applied MAWA-TLBO converges to optimal or near optimal solutions after 55th iterations. Therefore, population and generation number can be taken as 40 and 60, respectively.

Table 3.5. Comparison between different algorithms of 18-activity project with five modes using MAWA-TLBO

Description	**MAWA–GA Zhang et al. [27]**		**MAWA-ACS-SGPU Ng and Zhang et al. [25]**		**MAWA-AS Afshar et al. [29]**		**MAWA-TLBO (this study)**	
	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)
Best results obtained from the models (with indirect cost =$1500)	100	287720	100	285400	100	286670	100	283420
	101	284020	101	282508	101	281300	101	281200
	104	280020	104	277200	104	277265	104	277170
	110	273720	110	273165	110	272265	110	273470
Pop. Size	50		10		50		40	
Num. of iterations	500		200		400		70	
NFE	25000		2000		20000		5640	

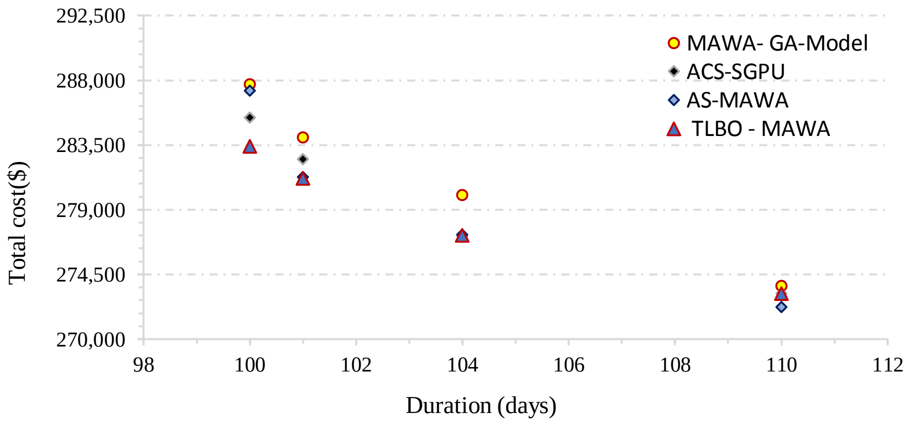

Figure 3.7. Comparison of Pareto front between different algorithms for 18-activity TCTP

Table 3.6. Options selected and solution generated for 18-activity TCTP problem using MAWA-TLBO

P-F Sol.	**Project time (days)**	**Project total cost ($)**	**selected duration of the corresponding activity (days)**																	
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	100	283420	14	25	33	20	28	14	18	24	15	15	12	22	24	18	12	28	14	9
2	101	281200	14	23	22	20	30	14	18	16	15	15	16	22	24	18	12	30	14	9
3	104	277170	14	25	33	20	30	24	18	24	15	15	12	22	24	18	12	24	14	9
4	110	273470	14	20	33	20	30	24	18	24	15	15	20	22	18	18	12	30	14	9

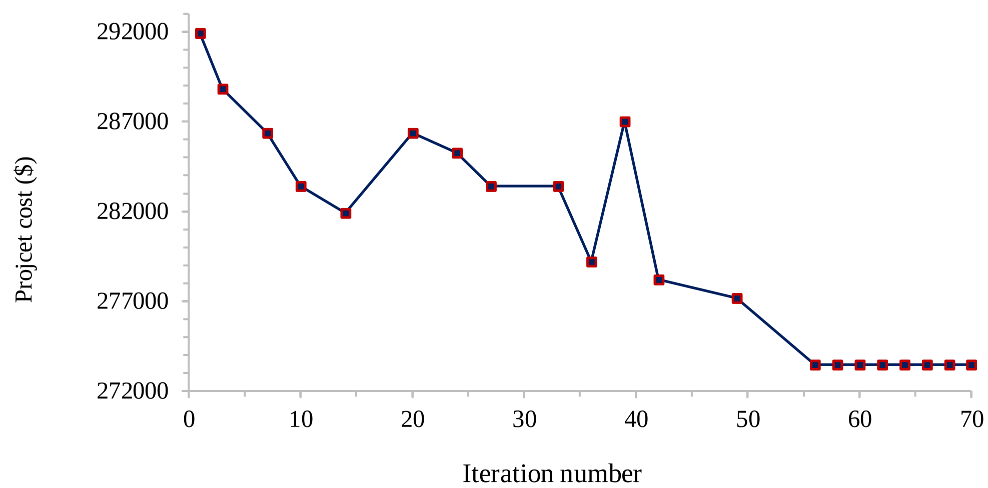

Figure3.8. Convergence history of 18-activity TCTP problem with five modes

3.3.3. Empirical Example of 18-Activity Project with Three Modes

This example problem was initially presented by Feng et al. [4]. Table 3.7 shows the detail of the model project such as the activity relationships, modes of construction for each activity and their associated time and cost. In addition, cost rate for indirect cost is $1000/day.

Table 3.7 Options for 18-activity project with three modes

Activity Number	Precedent Activity	Option /Mode1		Option /Mode2		Option /Mode3	
		Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)	Dur. (day)	Direct Cost ($)
1	-	14	2400	24	1200	21	1500
2	-	15	3000	25	1000	23	1500
3	-	15	4500	33	3200	33	3200
4	-	12	45000	20	30000	20	30000
5	1	22	20000	30	10000	30	10000
6	1	14	40000	24	18000	24	18000
7	5	9	30000	18	22000	18	22000
8	6	14	220	24	120	21	208
9	6	15	300	25	100	23	150
10	2 , 6	15	450	33	320	33	320
11	7 , 8	12	450	20	300	20	300
12	5 , 9 , 10	22	2000	30	1000	30	1000
13	3	14	4000	24	1800	24	1800
14	4 , 10	9	3000	18	2200	18	2200
15	12 , 14	12	4500	16	3500	16	3500
16	13 , 14	20	3000	30	1000	28	1500
17	11,17,15	14	4000	24	1800	24	1800
18	16	9	2400	18	1200	18	2200

Table 3.8 demonstrates the results for comparison of several mathematical and evolutionary-based methods with meta-heuristic MAWA-TLBO. The proposed MAWA-TLBO algorithm confirms better and identical optimal solution as good as the other GA-based RKV-TCO and Constraint Programming (CP) using optimization engines. Furthermore, the algorithm TLBO reaches the optimal solution quickly, i.e., in 63 sec. This utilized algorithm implies its efficiency and accuracy by searching only a small fraction of the total search space. In this example, there are 4.72×10^{9} possible schedules. The MAWA-TLBO searched 5640(= 40x70x2+40) possible different schedules, only a small portion (0.00012%) of the solution space where number of population is 40, iteration number is 70.

Therefore, number of function evaluation is 5640 (f-count =70x40x2+40) which reveals a remarkable reduction in iteration comparing Feng et al. [4] model.

Table 3.8. Comparison between different algorithms of 18-activity project with three modes

<table>
<tr><th rowspan="2">Approaches</th><th rowspan="2">Deviation ***</th><th colspan="2">Criteria</th><th rowspan="2">Calculation Time</th></tr>
<tr><th>Time (days)</th><th>Cost ($)</th></tr>
<tr><td>Optimal Solution</td><td>0%</td><td>110</td><td>216270</td><td>-</td></tr>
<tr><td>Excel Solver*</td><td>18%</td><td>110</td><td>254620</td><td>2 minutes</td></tr>
<tr><td>Risk Solver Platform Standard SLGRG Nonlinear*</td><td>0%</td><td>110</td><td>216270</td><td>1.5 minutes</td></tr>
<tr><td>Risk Solver Platform Standard Largescale GRG Solver*</td><td>0%</td><td>110</td><td>216270</td><td>1.5 minutes</td></tr>
<tr><td>TCT Optimization Using Evolver (includes an evolutionary engine)*</td><td>10%</td><td>110</td><td>238070</td><td>30 minutes</td></tr>
<tr><td>Risk Solver Platform Standard Evolutionary Solver*</td><td>27%</td><td>110</td><td>275320</td><td>18 minutes</td></tr>
<tr><td>Optimization Results using CPLEX CP Optimizer*</td><td>0%</td><td>110</td><td>216270</td><td>9 minutes</td></tr>
<tr><td>IBM ILOG Optimization Studio*</td><td>0%</td><td>110</td><td>216270</td><td>9 minutes</td></tr>
<tr><td>Random Key Variant for Time-Cost Optimization (RKV-TCO)**</td><td>0%</td><td>110</td><td>216270</td><td>5 (five) Seconds for 50 generations</td></tr>
<tr><td rowspan="4">Feng et al. [4] model</td><td rowspan="4">0%</td><td>110</td><td>216270</td><td rowspan="4">Not reported</td></tr>
<tr><td colspan="2">Pop size: 400</td></tr>
<tr><td colspan="2">Generation Number: 50</td></tr>
<tr><td colspan="2">f-count (NFE): 20000</td></tr>
<tr><td rowspan="4">This paper (MAWA-TLBO)</td><td rowspan="4">0%</td><td>110</td><td>216270</td><td rowspan="4">1 minute for 50 generations</td></tr>
<tr><td colspan="2">Pop size: 40</td></tr>
<tr><td colspan="2">Generation Number: 70</td></tr>
<tr><td colspan="2">f-count (NFE): 5640</td></tr>
<tr><td colspan="5">*Reported by Behrooz Golzarpoor [53] **Reported by Jorge Magalhães-Mendes [54]
***Percentage of deviation of the result from optimal solution</td></tr>
</table>

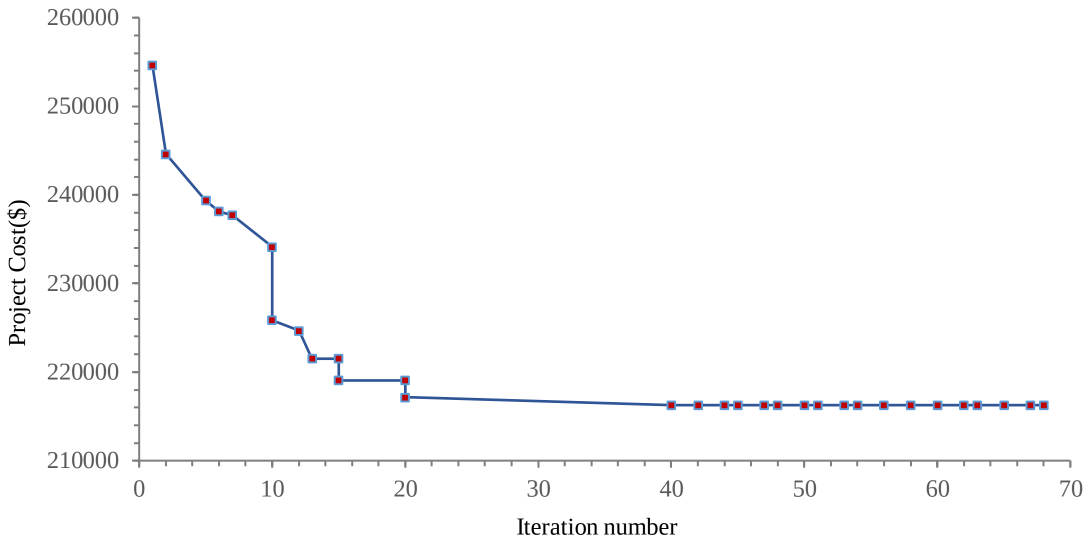

Figure 3.9. Convergence history of 18-activity TCTP problem with three modes

The convergence history of the optimization engine used in this study is presented in Figure 3.9. It shows that the considered generations are a bit large and it is unnecessarily running after the 48th iteration which is optimum value and prolonged the searching computational time. So for the present TCT problem population and number of generations can be adopted as 40 and 50, respectively. Therefore, the fast convergence rate of MAWA-TLBO seems to demonstrate its efficiency and stability in handling this type of small scale TCTP optimization problems.

3.3.4. Empirical Example of 63-Activity Project

Based on the literature findings the well-practiced 7 and 18 activities problems are also unraveled to validate the performance of the employed algorithm. These problems have been practiced in wide-spread studies using various meta-heuristic algorithms incorporating with non-dominating sorting (NDS) and modified adaptive weighting (MAW) approaches. It is firmly believed that MAWA is inferior compared to non-dominated sorting approach. However, it has not been encountered any project in the literature involving more activities that is examined with MAWA. To exhibit the performance of sole TLBO integrated with modified adaptive weighting approach on a construction project consisting more than 18-activity, in this study, a project with 63-activity taken from Bettemir [79] is reinvestigated by MAWA-TLBO.

The activity-on-node diagram for the project is presented in Figure 3.10, and time–cost optional modes are given in Table 3.9. The costs in Table 3.9 are given in US Dollars, and the durations are given in days.

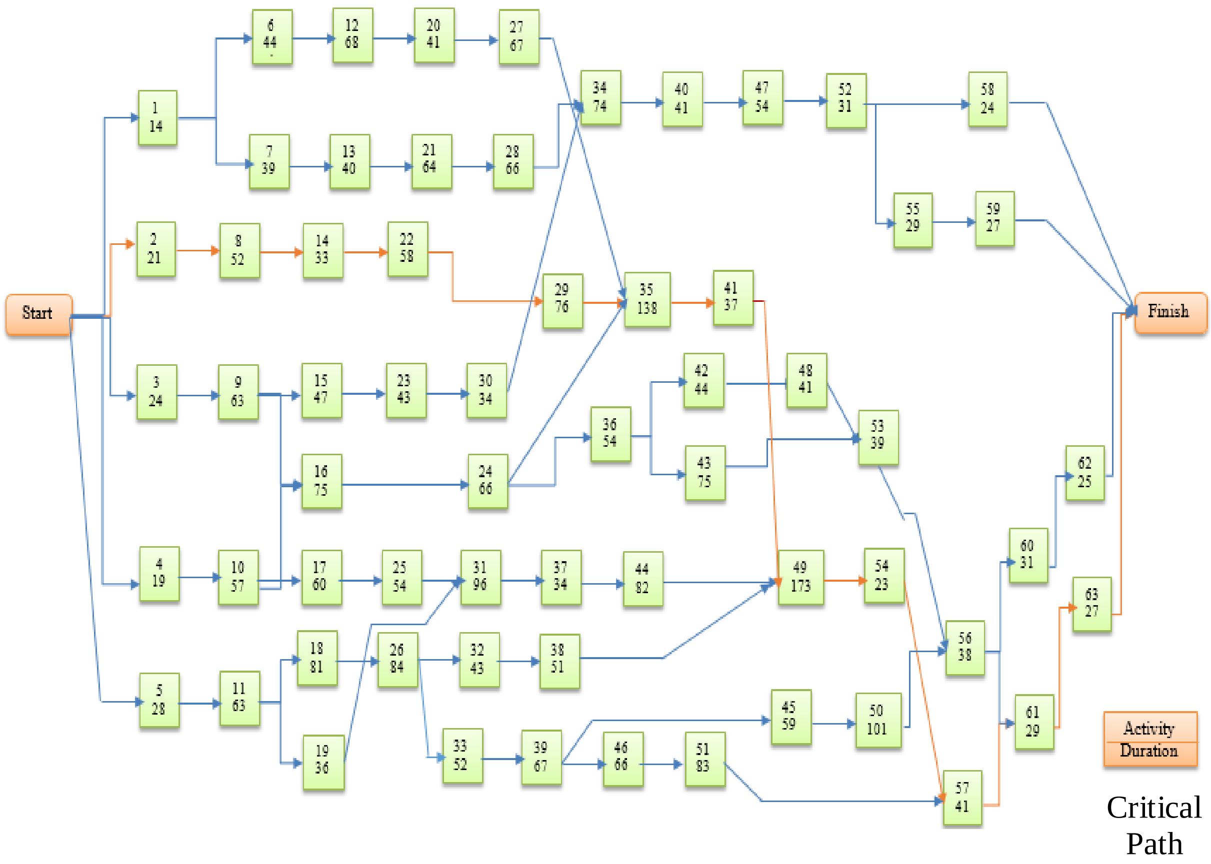

Figure 3.10. Network representation of the 63-activity network

Table 3.9. Data for the 63-activity TCT problem

Activity Number	Precedent Activity	Mode 1		Mode 2		Mode 3		Mode 4		Mode 5	
		Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)
1	-	14	3700	12	4250	10	5400	9	6250		
2	-	21	11250	18	14800	17	16200	15	19650		
3	-	24	22450	22	24900	19	27950	17	31650		
4	-	19	17800	17	19400	15	21600	-			
5	-	28	31180	26	34200	23	38250	21	41400		
6	1	44	54260	42	58450	38	63225	35	68150		
7	1	39	47600	36	50750	33	54800	30	59750		
8	2	52	62140	47	69700	44	72600	39	81750		
9	3	63	72750	59	79450	55	86250	51	91500	49	99500
10	4	57	66500	53	70250	50	75800	46	80750	41	86450
11	5	63	83100	59	89450	55	97800	50	104250	45	112400
12	6	68	75500	62	82000	58	87500	53	91800	49	96550
13	7	40	34250	37	38500	33	43950	31	48750		
14	8	33	52750	30	58450	27	63400	25	66250		
15	9	47	38140	40	41500	35	47650	32	54100		
16	9 , 10	75	94600	70	101250	66	112750	61	124500	57	132850
17	10	60	78450	55	84500	49	91250	47	94640		
18	10, 11	81	127150	73	143250	66	154600	47	161900		
19	11	36	82500	34	94800	30	101700	-			
20	12	41	48350	37	53250	34	59450	32	66800		
21	13	64	85250	60	92600	57	99800	53	107500	49	113750
22	14	58	74250	53	79100	50	86700	47	91500	42	97400
23	15	43	66450	41	69800	37	75800	33	81400	30	88450
24	16	66	72500	62	78500	58	83700	53	89350	49	96400
25	17	54	66650	50	70100	47	74800	43	79500	40	86800
26	18	84	93500	79	102500	73	111250	68	119750	62	128500
27	20	67	78500	60	86450	57	89100	56	91500	53	94750
28	21	66	85000	63	89750	60	92500	58	96800	54	100500

Table 3.9. Continued

Activity Number	Precedent Activity	Mode 1		Mode 2		Mode 3		Mode 4		Mode 5	
		Dur (days)	**Cost ($)**	**Dur (days)**	**Cost ($)**	**Dur (days)**	**Cost ($)**	**Dur (days)**	**Cost ($)**	**Dur (days)**	**Cost ($)**
29	22	76	92700	71	98500	67	104600	64	109900	60	115600
30	23	34	27500	32	29800	29	31750	27	33800	26	36200
31	19, 25	96	145000	89	154800	83	168650	77	179500	72	189100
32	26	43	43150	40	48300	37	51450	35	54600	33	61450
33	26	52	61250	49	64350	44	68750	41	74500	38	79500
34	28, 30	74	89250	71	93800	66	99750	62	105100	57	114250
35	24, 27, 29	138	183000	126	201500	115	238000	103	283750	98	297500
36	24	54	47500	49	50750	42	56800	38	62750	33	68250
37	31	34	22500	32	24100	29	26750	27	29800	24	31600
38	32	51	61250	47	65800	44	71250	41	76500	38	80400
39	33	67	81150	61	87600	57	92100	52	97450	49	102800
40	34	41	45250	39	48400	36	51200	33	54700	31	58200
41	35	37	17500	31	21200	27	26850	23	32300		
42	36	44	36400	41	39750	38	42800	32	48300	30	50250
43	36	75	66800	69	71200	63	76400	59	81300	54	86200
44	37	82	102750	76	109500	70	127000	66	136800	63	146000
45	39	59	847500	55	91400	51	101300	47	126500	43	142750
46	39	66	94250	63	99500	59	108250	55	118500	50	136000
47	40	54	73500	51	78500	47	83600	44	88700	41	93400
48	42	41	36750	39	39800	37	43800	34	48500	31	53950
49	38, 41, 44	173	267500	159	289700	147	312000	138	352500	121	397750
50	45	101	47800	74	61300	63	76800	49	91500		
51	46	83	84600	77	93650	72	98500	65	104600	61	113200
52	47	31	23150	28	27600	26	29800	24	32750	21	35200
53	43, 48	39	31500	36	34250	33	37800	29	41250	26	44600
54	49	23	16500	22	17800	21	19750	20	21200	18	24300
55	52, 53	29	23400	27	25250	26	26900	24	29400	22	32500
56	50, 53	38	41250	35	44650	33	47800	31	51400	29	55450

Table 3.9. Continued

Activity Number	Precedent Activity	Mode 1		Mode 2		Mode 3		Mode 4		Mode 5	
		Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)
57	51, 54	41	37800	38	41250	35	45600	32	49750	30	53400
58	52	24	12500	22	13600	20	15250	18	16800	16	19450
59	55	27	34600	24	37500	22	41250	19	46750	17	50750
60	56	31	28500	29	30500	27	33250	25	38000	21	43800
61	56, 57	29	22500	27	24750	25	27250	22	29800	20	33500
62	60	25	38750	23	41200	21	44750	19	49800	17	51100
63	61	27	9500	26	9700	25	10100	24	10800	22	12700

The project includes two activities consist of three modes, 15 activities have four modes, and 46 activities have five modes. The number of total possible time–cost alternatives for the project is 1.4E+42. The project was investigated under the two cases: in the first case (63a), the indirect cost is taken as $2300/day, while it is adopted as $3500/day in the second case (63b). The optimal solutions of 630days, $5,421,120 for 63a and 621days, $6,176,170 for 63b had been originally provided by Bettemir [79] using integer programming. Bettemir [79] utilized eight metaheuristic algorithms out of which three core algorithms and five hybrid algorithms incorporating with the non-dominating sorting approach to solve the mentioned TCTP problem.

As previously mentioned, since 63-activity problem has not been solved with the application of MAWA, the results obtained in this study by utilizing MAWA-TLBO are compared with the solutions acquired through NDS-GA, NDS-ACO, and NDS-PSO models of Bettemir [79]. The compared results of 63a and 63b activity problems are tabulated in Table 3.10 and 3.11, respectively. In addition, Table 3.12 illustrates Pareto front results of ten consecutive experimental runs with corresponding average percent deviations (%APD) from the optima. Graphical representations of the Pareto front solutions of the current solved problems are given in Figure 3.11 and 3.12.

Table 3.10. Analysis results of 63-Activity project for the Case 1 (IC= $2300) using MAWA-TLBO

Sr.No	**Bettemir [79]**						**MAWA-TLBO**	
	NDS-GA		**NDS-ACO**		**NDS-PSO**			
	Dur	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**
1	641	5704200	635	5490120	637	5421620	629	5613820
2	661	5712485	653	5494410	644	5428920	614	5644640
3	650	5722260	638	5491180	651	5439620	630	5600190
4	653	5713450	657	5491620	634	5422920	616	5623260
5	645	5699650	644	5494920	651	5440570	630	5642405
6	639	5684295	626	5486630	633	5421320	637	5637290
7	640	5695655	664	5495080	633	5421320	639	5503940
8	621	5707600	661	5490350	633	5421620	630	5696820
9	641	5693015	643	5490680	633	5421320	627	5588485
10	623	5690790	635	5492210	633	5421320	632	5625310
Pop. size		-					180	
Num. of Iteration		-					450	
NFE		250000					162180	
Note: Dur = Duration								

The MAWA-TLBO searched 162180 (= 180 x 450 x 2 + 180) possible different schedules, only searching a negligible portion of the solution space [162180/1.4E+42] could generate the Pareto front solutions where population and number of iterations are 180 and 450, respectively.

Table 3.11. Analysis results of 63-Activity project for the Case 2 (IC= $3500) using MAWA-TLBO

Sr.No	Bettemir [79]						MAWA-TLBO	
	NDS-GA		NDS-ACO		NDS-PSO			
	Dur	Cost	Dur	Cost	Dur	Cost	Dur	Cost
1	617	6462580	631	6219220	644	6201720	630	6291540
2	651	6411540	632	6205850	629	6217470	628	6264970
3	647	6442440	626	6234520	644	6210170	630	6280170
4	639	6420500	640	6223830	648	6218170	637	6262570
5	648	6447900	617	6231440	649	6216020	625	6292850
6	627	6433810	627	6197070	647	6207870	613	6261820
7	618	6439240	604	6247850	651	6216220	624	6289790
8	623	6449790	635	6231860	649	6215420	622	6280170
9	630	6443805	623	6198650	645	6208920	636	6280750
10	629	6450065	651	6262830	642	6198520	634	6263980
Pop. size		-					180	
Num. of Iteration		-					450	
NFE		250000					162180	

Therefore, number of function evaluation is 162180, and the APD values are %3.528 and %1.172 respectively. It can be stated that the proposed MAWA-TLBO model requires less the size of population and number of iteration than those of the Bettemirs' [79] models.

Even though it is known that, generally the model utilizing NDS outperforms the model employing the MAWA, considering this phenomenon it can be concluded that the proposed MAWA-TLBO model in this study produces satisfactory results for both 63a and 63b Cases. Depending up on this output, and referring on Tables 11-13, it might be stated that MAWA-TLBO could achieve better solutions than NDS-GA, however, the proposed model find the slightly better solutions having less project duration and more cost than NDS-ACO and NDS-PSO for 63a. However, for 63b, MAWA-TLBO model produces alternatives Pareto front solutions as good as Bettemirs' [79] models although they have been incorporated with non-dominating sorting approach.

Table 3.12. Average deviations from the optimal for problems 63a and 63b using MAWA-TLBO

Algorithms	63a	APD (%)	63b	APD (%)
	No of Runs		No of Runs	
GA, Bettemir [79]	10	5.86	10	5.16
ACO, Bettemir [79]	10	1.2	10	0.7
PSO, Bettemir [79]	10	0.152	10	0.2
MAWA-TLBO	10	3.528	10	1.172

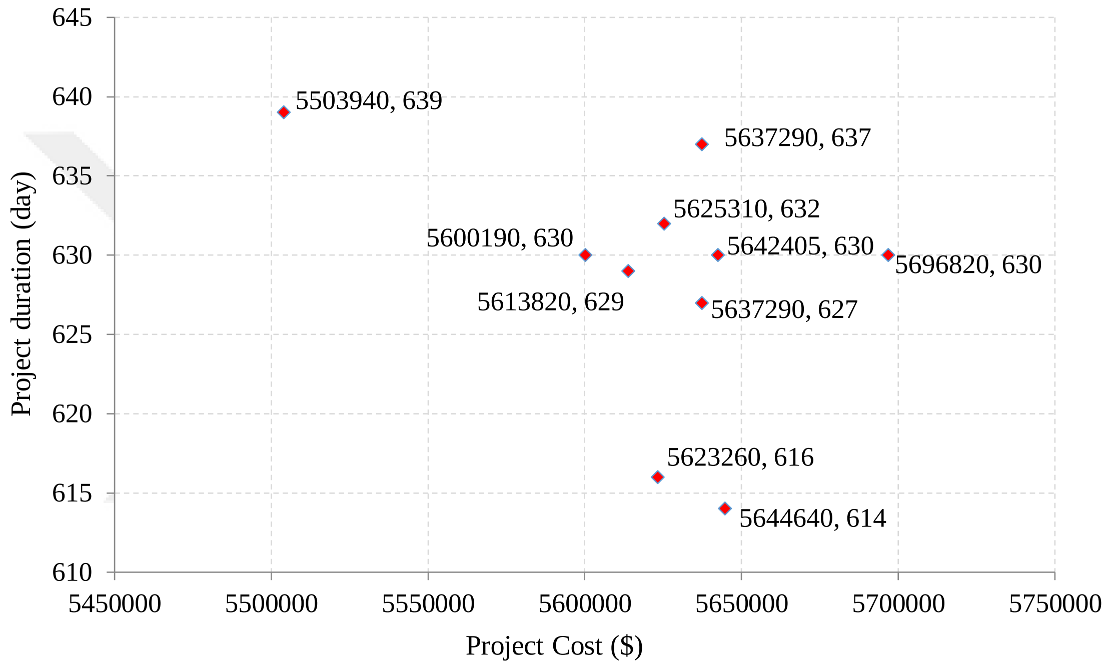

Figure 3.11. Pareto solutions of 63a-activity problem obtained by MAWA-TLBO

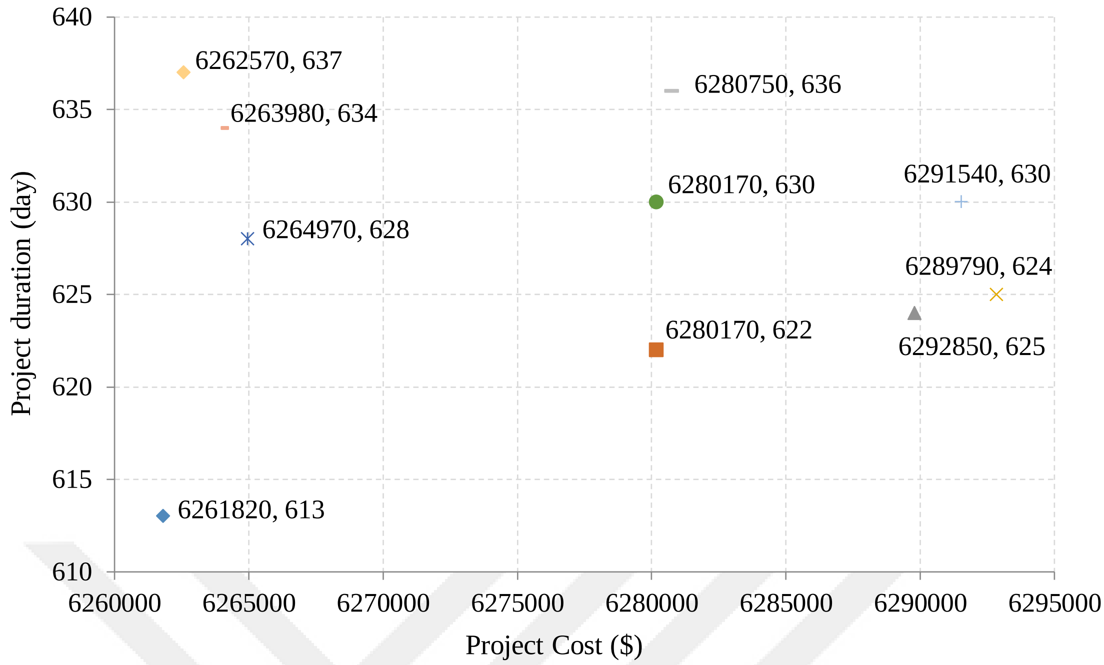

Figure 3.12. Pareto solutions of 63b-activity problem obtained by MAWA-TLBO

In the current study, a multiobjective optimization model called as MAWA-TLBO has been proposed to handle the discrete time-cost trade off problems, in order to optimize the total project duration and total cost concurrently. The largest model project examined with using metaheuristic algorithms and MAWA approach was the project with 18-activity. In addition, a more complex TCTP problem including 63-activity is also solved to validate the performance of the proposed MAWA-TLBO algorithm. From the results, it is clear that the applied MAWA-TLBO algorithm is proficient of finding optimum or near-optimum solutions for the small 7-activity and 18-activity with three and five modes problems. Furthermore, it was demonstrated that this algorithm exploits computational effort by searching just small fraction of the search space. On the other hand, it is observed that the quality of the obtained solutions for 18-activity with five modes and large example problem of 63 activities slightly deteriorate as they are prone to smaller daily indirect costs as well as with the mode increments. More specifically, the diversity in population can’t be preserved. The reason of this can be also explained by the complexity of the problem and smoothness of the solution space. In case of solving this type of TCT problems, main shortcoming of the current modified method is realized as the probability of stagnating into local optima, due to the MAWA‘s drawback. Also that can avoid losing some solutions with better performance because of premature convergence of the search. Furthermore, it is observed that further refinements are necessary to ensure a steady performance of the model when applying to large-scale projects.

Consequently, optimization results clearly reveal the applicability and efficiency of the TLBO application for the first time on solving TCTP Problems in construction management field. The results also indicate that the TLBO has a great potential for solving simultaneous optimization of large TCTP problems e.g. 63-activity project.

3.4. Time-Cost Trade-off Optimization Using Non-Dominated Sorting TLBO Algorithm

In a project schedule, it is possible to reduce the time required to complete a project by assigning extra resources to critical activities. However, accelerating a project causes additional expense. This issue is addressed by finding optimal set of time-cost alternatives and is known as time-cost trade-off problem in the literature. Another aim of this study is to determine the optimal set of time-cost alternatives using a multiobjective teaching-learning-based optimization (TLBO) algorithm integrated with the non-dominated sorting concept and the mechanism of crowding distance. This algorithm is applied to successfully optimize the projects ranging from a small to medium large projects. Numerical simulations indicates that the utilized model search and identify optimal / near optimal trade-offs between project time and cost in construction engineering and management. Therefore, it is concluded that the developed TLBO-based multiobjective approach offers satisfactorily solutions for time–cost trade-off optimization problems.

By reviewing the recent models, it can be recognized that many researchers have investigated various benchmark time-cost trade-off (TCT) optimization problems using different metaheuristic algorithms incorporated with modified adaptive weighting (MAWA) approach. This approach is converting multiobjective problem to a single-objective problem, and then utilizing a single-objective optimization approach to find the satisfactory solution. However, the performance of the modified weighting approach becomes worst and is not able to explore the global optima whenever utilized to more complex medium scale problems. Hence, in this study, to overcome this drawback of MAWA, NDS concept and the mechanism of crowding distance are incorporated with TLBO algorithm. As it is obvious, today instead of MAWA approach, this superior approach (NDS and crowding distance metric) is broadly being acknowledged in solving the mentioned TCTP problems.

3.5. Numerical Examples of NDS-TLBO

To demonstrate the performance of the utilized NDS-TLBO model for obtaining Pareto front solutions of the TCTP, medium and large scale problems taken from the technical literature are investigated. The utilized algorithm was executed in MATLAB environment and implemented on a personal computer having Intel (R) Core (TM) i3 CPU 2.40 GHz and 3GB RAM. Consecutive experimental run number is adopted as 10 for the entire instances.

3.5.1. Empirical Example of 18-Activity Project

The first problem includes the 18-activity network. Details of network were given in Feng et al. [4] using the time-cost options presented in Hegazy [8]. Most of the previous studies [27, 25, 29, 59 and 78] utilized this test problem to assess the efficiency of the proposed multiobjective metaheuristics. This problem with a total of $4.72\text{x}10^{\mathbf{9}}$ possible schedules is examined with a daily indirect cost of $1500. The network with logical relationship of FS as well as time–cost optional modes detailing of the problem is given in section 3.3.2.

Table 3.13 presents the results of the TLBO along with those reported by other five previous metaheuristics for the 18-activity problem. Solutions obtained by Zheng et al. [27] are of poor quality compared to the results of TLBO. For 110 D days, ACS-TCO of Ng and Zhang [25] and ACS of Zhang and Ng [78] provide a solution which costs more than the proposed TLBO's result. The Pareto front solutions reported for NA-ACO of Afshar et al. [29] as well as NDS- PSO of Aminbakhsh [48] are identical to the results acquired by the TLBO method. However, the utilized algorithm exhibit its competency and accuracy by exploring a tiny bit portion [$5640/4.72\text{x}10^{\mathbf{9}}$ =0.00012%] of the solution space. This reveals a remarkable reduction in number of function evaluations of administered algorithm comparing NA-ACO of Afshar et al. [29] and NDS- PSO of Aminbakhsh [48].

Furthermore, the fast convergence rate of NDS-TLBO seems to demonstrate its efficiency and stability in solving of the time-cost trade-off optimization problems. So, these findings strictly confirm the applicability of the proposed NDS-TLBO model in the field of construction management.

Table 3.13. Comparison of Pareto fronts located for 18-activity problem using NDS-TLBO

Duration (days)	**Zhang et al. [27]**	**Ng and Zhang [25]**	**Afshar et al. [29]**	**Zhang and Ng [78]**	**Aminbakhsh and Sonmez [48]**	**NDS-TLBO (This paper)**
100	287720	283320	283320	285400	283320	283320
101	284020	279820	279820	282508	279820	279820
104	280020	276320	276320	277200	276320	276320
110	273720	271320	271270	273165	271270	271270
Pop. size	50	10	50	10	80	40
Num. of iterations	500	200	300	200	100	100
NFE	25000	2000	15000	2000	8000	8040

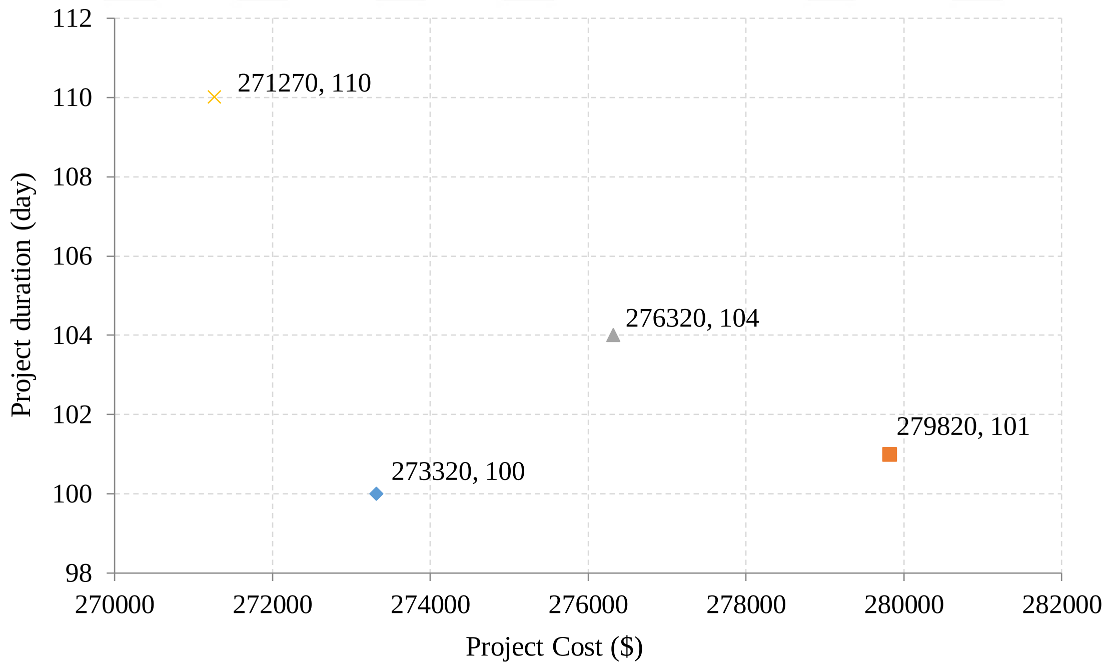

Figure 3.13. Pareto optimal solutions of 18-activity problem obtained by NDS-TLBO

Table 3.14. Options selected and solution generated for 18-activity TCTP problem using NDS TLBO

PF Sol	**Time (day)**	**Cost($)**	**selected duration of the corresponding activity (days)**																	
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	100	283320	14	25	33	20	28	14	18	24	15	15	16	22	24	18	12	30	14	9
2	101	279820	14	25	33	20	30	14	18	24	15	15	16	22	24	18	12	30	14	9
3	104	276320	14	25	33	20	30	18	18	24	15	15	16	22	24	18	12	30	14	9
4	110	271270	14	25	33	20	30	24	18	24	15	15	20	22	24	18	12	30	14	9

Pareto front graphical representations of the current examined problem are given in Figure 3.13 and 3.14. From the Figure 3.14, it is clear that the global optimum solutions are achieved in the 1st run analysis and could explore 100 days, \$283320 six times, 101days, \$279820 five times, 104 day, \$276320 four times and 110 days, \$271270 three times. This can be considered as strong potency of the applied algorithm. The comparison of TLBO with the contemporary methods discloses that proposed NDS-TLBO is among the most fitting algorithms for Pareto front optimization of the more complex small-scale TCTPs. The Pareto front along with selected duration of corresponding activity for 18-activity is illustrated in Table 3.14.

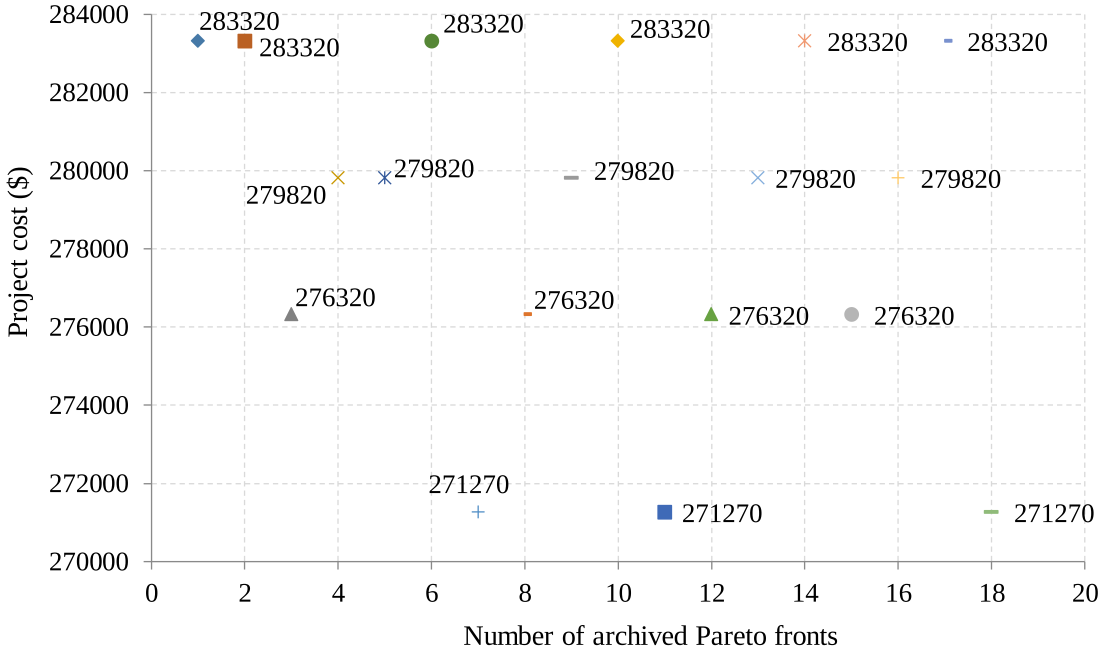

Figure 3.14. Graphical representation of first run analysis of 18-activity TCTP problem with 0.3 Pareto fraction

3.5.2. Medium-Scale Test Problem

To further exhibit the performance of sole TLBO integrated with non-dominating sorting concept and crowding distance computation on a project with 63-activity taken from Bettemir [79] is reinvestigated by the proposed algorithm. The activity-on-node diagram for the project and time–cost optional modes detailing of the problem is illustrated in section 3.3.4. The project was tested under the two cases: in the first case (63a), the indirect cost is taken as $2300/day, whereas it is adopted as $3500/day in the second case (63b). The optimal solutions of 630 days with $5,421,120 as cost for 63a and 621 days with $6,176,170 as cost for 63b had been originally provided by Bettemir [79] using integer programming. Bettemir [79] utilized eight meta-heuristic algorithms out of which three core algorithms and five hybrid algorithms incorporating with the non-dominating sorting approach to solve the mentioned TCTP problem. Aminbakhsh [48] has also reported best Pareto front solutions of the same 63-activity problem applying the modified discrete particle swarm optimization method.

As previously mentioned, since 63-activity problem has not been practiced more by the researchers, the results obtained in this study by utilizing NDS-TLBO are compared with the solutions acquired through core NDS-GA, NDS-ACO, and NDS-PSO models of Bettemir [79] only. The results are not compared with Aminbakhsh's [48] model although; Aminbakhsh [48] has also reported the best Pareto front solutions of the same 63-activity problem. Because, Aminbakhsh [48] has applied the hybrid discrete particle swarm optimization algorithms. Moreover, a certain portion of initial population is fed into models to accelerate the searching process.

The compared results of 63a and 63b activity problems are tabulated in Tables 3.15 and 3.17, respectively. In addition Table 3.18 illustrates Pareto front results of ten consecutive experimental runs with corresponding average percent deviations (%APD) from the optima. Graphical representations of the Pareto front solution of the current solved problems are given in Figure 3.15 and 3.16. The selected duration of corresponding activities is given in Table 3.16.

Table 3.15. Analysis results of 63-Activity project for the Case 1 (IC= $2300) using NDS-TLBO

Sr. No	Bettemir [79]						(This paper)	
	NDS-GA		NDS-ACO		NDS-PSO		NDS-TLBO	
	Dur	Cost	Dur	Cost	Dur	Cost	Dur	Cost
1	641	5704200	635	5490120	637	5421620	630	5428870
2	661	5712485	653	5494410	644	5428920	630	5428120
3	650	5722260	638	5491180	651	5439620	630	5427770
4	653	5713450	657	5491620	634	5422920	630	5428120
5	645	5699650	644	5494920	651	5440570	630	5428920
6	639	5684295	626	5486630	633	5421320	637	5428220
7	640	5695655	664	5495080	633	5421320	633	5428870
8	621	5707600	661	5490350	633	5421620	628	5428170
9	641	5693015	643	5490680	633	5421320	633	5428470
10	623	5690790	635	5492210	633	5421320	633	5428720
Pop. size		-	-		-		180	
Num. of iterations		-	-		-		450	
NFE		250000	250000		250000		162180	

Table 3.16. Options selected and solution generated for 63-activity TCTP problem of NDS approach (IC=$2300/day)

P-F Sol.	Project time (days)	Project total cost ($)	Selected duration of the corresponding activity (days)															
			1	2	3	4	5	6	-------------------				57	58	59	60	61	63
1	630	6427770	12	18	24	19	28	44	39	52	63	57	63	68	40	33	47	75
			60	81	36	41	64	53	43	66	50	84	67	66	76	34	96	43
			52	74	138	54	29	51	67	41	23	44	75	82	55	66	54	41
			147	101	83	31	39	18	29	38	30	24	27	31	20	25	22	
The underlined activities show the critical path activities for the current solution																		

The NDS-TLBO searched 162180 (= 180 x 450 x 2 + 180) possible different schedules, only searching a negligible portion of the solution space [162180/1.4E+42]. Population and number of iterations are adopted as 180 and 450, respectively.

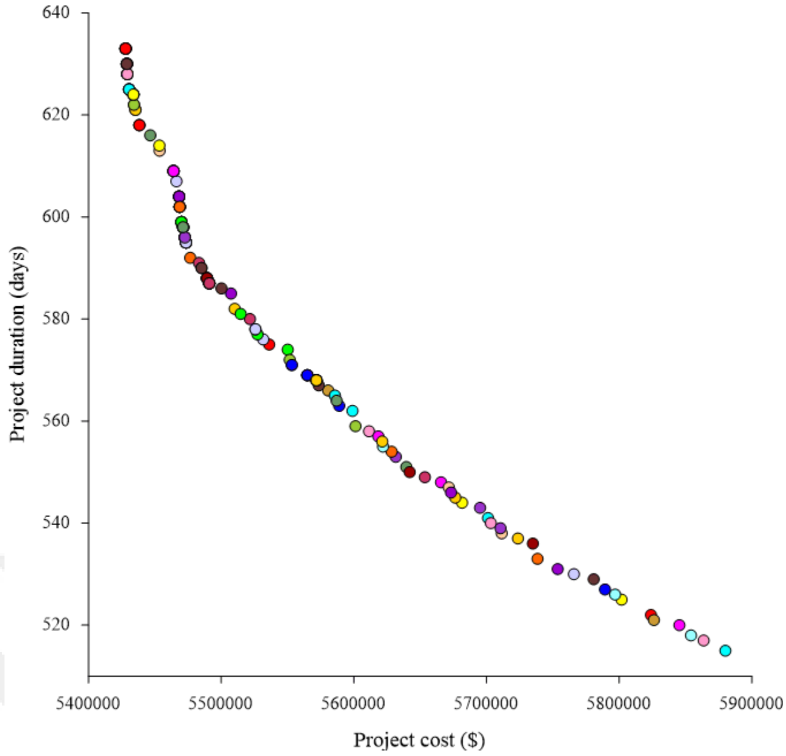

Figure 3.15. Pareto front solution of 63a-activity problem using NDS-TLBO

Table 3.17. Analysis results of 63b-Activity project for the Case 2 (IC=$3500) using NDS-TLBO

Sr. No	**Bettemir [79]**						**(This paper)**	
	NDS-GA		**NDS-ACO**		**NDS-PSO**		**NDS-TLBO**	
	Dur	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**
1	617	6462580	631	6219220	644	6201720	612	6192140
2	651	6411540	632	6205850	629	6217470	617	6184820
3	647	6442440	626	6234520	644	6210170	590	6188690
4	639	6420500	640	6223830	648	6218170	588	6195910
5	648	6447900	617	6231440	649	6216020	591	6191490
6	627	6433810	627	6197070	647	6207870	586	6196840
7	618	6439240	604	6247850	651	6216220	592	6189140
8	623	6449790	635	6231860	649	6215420	589	6199870
9	630	6443805	623	6198650	645	6208920	617	6187390
10	629	6450065	651	6262830	642	6198520	616	6190570
Pop. size	-		-		-		180	
Num. of iterations	-		-		-		450	
NFE	250000		250000		250000		162180	

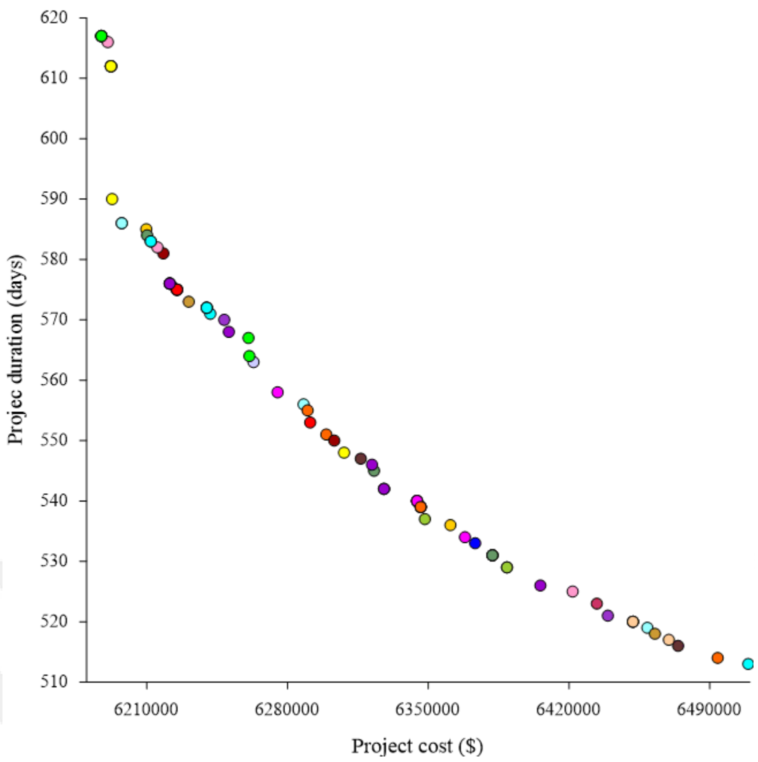

Figure 3.16. Pareto front solution of 63b-activity problem using NDS-TLBO

Table 3.18. Average deviations from the optima for problems 63a and 63b using NDS-TLBO

Algorithms	**63a**	**APD (%)**	**63b**	**APD (%)**
	No of Runs		**No of Runs**	
GA, Bettemir [79]	10	5.86	10	5.16
ACO, Bettemir [79]	10	1.2	10	0.7
PSO, Bettemir [79]	10	0.152	10	0.2
NDS-TLBO (This paper)	10	0.128	10	0.14

The APD values are %0.128 and %0.14 respectively. This implies that both the number of function evaluation as well as average percent deviation of the NDS-TLBO based model are less than those of the Bettemir s' [79] models. Thereby, it was found that, the proposed algorithm has more exploration capability and more promising in solving medium scale time-cost trade-off problems as compared previous model.

3.5.3. Large-Scale Test Problems

To investigate the efficiency of core TLBO integrated with non-dominating sorting approach on a large-scale project with 630-activity is also resolved by the proposed algorithm. The model project was formed by duplicating the 63-Activity project 9 times [79]. The project model includes two example cases: Case 1 with $2300 and Case 2 with $3500 daily indirect costs are solved. Global optimums obtained by Bettemir [79] using mixed integer programming for Case1 and Case 2 are $54.211.200 and $61.761.700, respectively.

As mentioned before, ten consecutive experimental runs are conducted for this project also. Best results of ten runs are presented in Table 3.19 and 3.20 for Case 1 and Case 2 with corresponding average percent deviations (%APD) from the optima. Also corresponding rank and crowding distance of the best results are provided in Table 3.19. Graphical representations of the Pareto front solution obtained by the proposed NDS-TLBO are demonstrated in Figure 17 and 18.

Table 3.19. Best results for 630-activity project (Case 1: daily indirect cost of $2300)

This paper		%PD	Rank	Crowding Distance
NDS-TLBO				
Dur	Cost ($)			
6373	54611340	0.74	1	0.0423
6387	54775880	1.04	1	0.0397
6383	54805960	1.09	1	0.0154
6364	54829460	1.14	1	0.0250
6360	54856620	1.19	1	0.0126
6302	54943070	1.35	1	0.0119
6377	54692200	0.88	1	0.0451
6388	54705310	0.91	1	0.0416
6346	54849940	1.17	1	0.0119
6300	54992260	1.44	3	0.0137
Pop. size	250	%APD =1.10		
Num. of iterations	450			
NFE	225250			
NFE= Number of Function Evaluations				

Table 3.20. Best results for 630-Activity project (Case 2: daily indirect cost of $3500)

This paper		%PD	Rank	Crowding Distance
NDS-TLBO				
Dur	Cost ($)			
6212	62793865	1.67	1	0.0649
6220	62750580	1.60	1	0.0621
6204	62591490	1.34	1	0.1022
6232	62692340	1.50	1	Inf (∞)
6236	62741130	1.58	1	Inf (∞)
6225	62586260	1.33	1	Inf (∞)
6201	62744310	1.59	1	0.0418
6127	62650570	1.43	1	0.0876
6190	62699400	1.51	1	Inf (∞)
6279	62734550	1.57	1	Inf (∞)
Pop. size	250	%APD =1.51		
Num. of iterations	450			
NFE	225250			
NFE= Number of Function Evaluations				

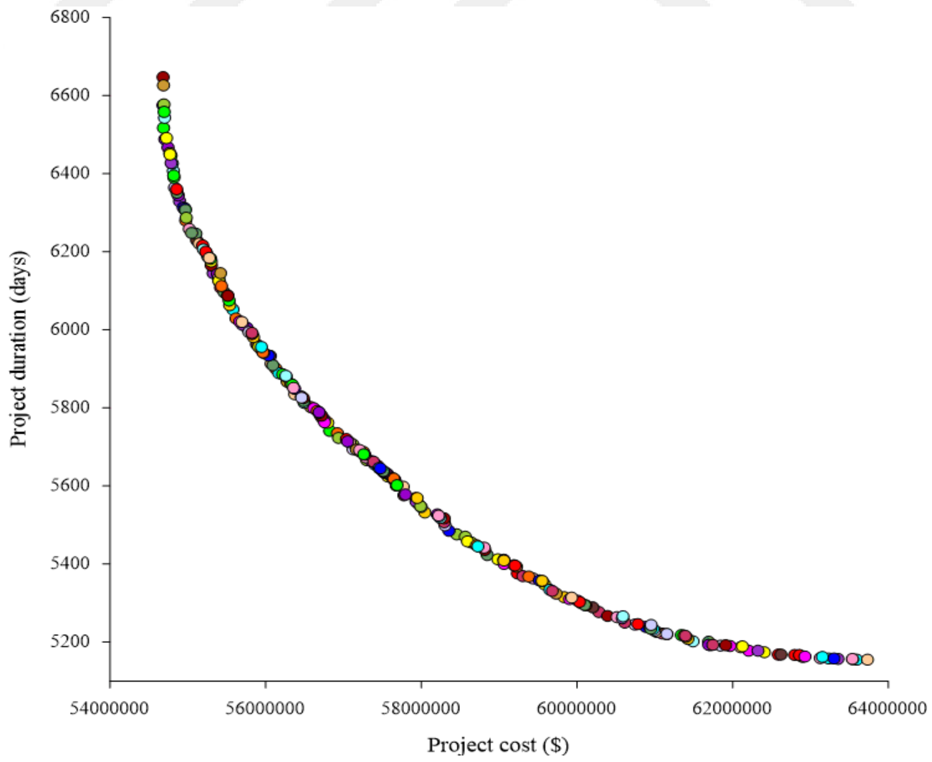

Figure 3.17. Pareto front solutions of 630 activity problem obtained by NDS-TLBO algorithm for Case 1

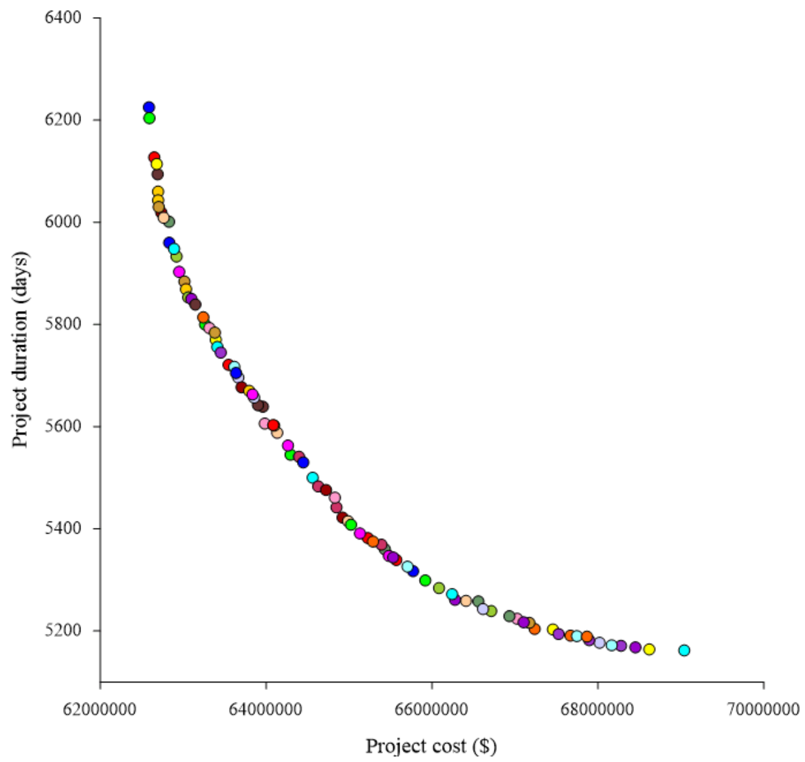

Figure 3.18. Pareto front solutions of 630-activity problem obtained by NDS-TLBO algorithm for Case 2

The compared mean values of ten runs for Case 1 and Case 2 are presented in Tables 3.21 and 3.22, respectively. In addition, Table 3.23 shows the compared %APD of Case 1 and Case 2 with the previous models.

Table 3.21. Comparison of mean values of 10 runs for Case 1 (daily indirect cost=$2300)

Descriptions	**Bettemir [79]**			**This paper**
	NDS-GA	**NDS-ACO**	**NDS-PSO**	**NDS-TLBO**
Mean value	58983147	56703583	54815790	54806204
Pop. size	-	-	-	250
Num. of iterations	-	-	-	450
NFE	250000	250000	250000	225250
NFE = Number of Function Evaluations				

Table 3.22. Comparison of mean values of 10 runs for Case 2 (daily indirect cost=$3500)

Desrciptions	Bettemir [79]			This paper
	NDS-GA	NDS-ACO	NDS-PSO	NDS-TLBO
Mean value	66395840	64574989	63121500	62698449
Pop. size	-	-	-	250
Num. of iterations	-	-	-	450
NFE	250000	250000	250000	225250
NFE= Number of Function Evaluations				

Table 3.23. Average deviations of 630- activity problem from the optimal solutions for the models obtained by NDS-TLBO

Algorithms	Case 1		Case 2	
	No of Runs	APD (%)	No of Runs	APD (%)
GA, Bettemir [47]	10	8.83	10	7.5
ACO, Bettemir [47]	10	4.59	10	4.55
PSO, Bettemir [47]	10	1.11	10	2.21
NDS-TLBO (This paper)	10	1.10	10	1.51

The APD values of NDS-TLBO for two cases are 1.10 and 1.51 and these values are smaller than the APD values of NDS-GA, NDS-ACO and NDS-PSO models proposed by Sonmez and Bettemir [47]. Considering Tables 9-13, the results of NDS-TLBO for large networks indicate that NDS-TLBO as a rule provides adequate optimal and near-optimal solutions for the TCTP problems. Hence, NDS-TLBO model is among the top performing algorithms, providing a powerful alternative for the time-cost trade-off problems.

Time-cost trade-off optimization problems encountered in the construction management field cannot be solved by linear programming or other analytical methods. Therefore, different metaheuristic optimization algorithms have been applied to optimize those problems. This study describes a newly developed Pareto-based NDS-TLBO algorithm and mechanism of crowding distance computation to confirm the suitability of the proposed model for solving multiobjective optimization problems. The Pareto front of the solutions is guided by the teacher which is the best learner and the mean of learners achieved so far. Validation of NDS-TLBO algorithm is tested on a small test project consisting of 18-activity, medium-scale project with 63-activity and more complex large-scale problem with 630-activity. Based on the numerical results, it can be indicated that NDS-TLBO based model produces alternative Pareto front solution with less both the total number of function evaluations and average percent deviation than those of the previously proposed models. Consequently, optimization results clearly demonstrate the applicability and efficiency of the TLBO application for the first time on solving TCTP problems in construction management field. The results also indicate that the TLBO has a great potential for solving simultaneous optimization of large TCTP problems e.g. 630-activity project. Moreover, the simplicity can be taken into account as strength point of existing method.

3.6. Effect of Partial Random Initial Population on NDS-TLBO

By reviewing the recent models, it can be stated that many researchers have investigated various benchmark time-cost trade-off (TCT) optimization problems using new concepts such as initial population, niche formation and acceleration approaches. And also, in order to enhance the convergence capability of the algorithms, hybrid metaheuristic algorithms were developed in the previous studies. Aminbakhsh [48] has applied the hybrid discrete particle swarm optimization algorithm. Additionally, produces a certain portion of initial population by means of Siemens algorithm and fed into models to accelerate the searching process. In the Siemens algorithm as a rule, activities with the least costs are identified and crashed with the minimum cost slope considerations. Sonmez and Bettemir [47] have used hybrid genetic algorithm (HA) to unravel the eight well-known benchmark TCTP problems.

As in the previous sections it is observed that the proposed sole TLBO algorithms are a bit weak to compete with the hybrid algorithms. Thereby, to assess the overall efficiency of competitive algorithm, in the present study, effect of partial random initial population on NDS-TLBO algorithm for TCTP problems is also applied to further investigate the exploration capacity of the proposed algorithm. Inspiring the initial population concept of Aminbakhsh‘s [48] model, slight modification is made to the non-dominating sorting version of the classical sole-TLBO algorithm by introducing a definite portion of initial population. To this end, instead of Siemens algorithm which requires additional efforts, the proposed model combines complementary strengths of the min-min (minimum of the minimum) approach which is the single objective version of TLBO algorithm. To increase the quality a superior portion of the initial population is generated by means of the single objective TLBO method, with the remaining initial seeds being generated randomly. This min-min approach is the simplest algorithm having bi-objective functions. The objective functions are either minimization of project duration or cost. And this approach, in place of Pareto front provides a unique solution. For performing of this approach, in the present study, initially, project cost is taken into account as the objective function and obtain the unique optimum solution. However, there are plenty of solutions based on the project duration for the corresponding single project cost in the solution pool. Astonishingly, in the solution space, there is such a duration which is the minimum of the minimum solutions based on the duration for the particular cost. So, this minimum of the minimum duration for the particular cost is taken as the optimum solution in each iteration. This process continues until the stopping criteria met and is called min-min approach. Therefore, numerical simulations of medium and large scale projects are presented to demonstrate the Pareto front performance of the proposed algorithm. In order to further verify the effect of partial random initial population on the NDS-TLBO algorithm, alternative initial populations are taken as in Table 3.24.

In the ongoing sections, the applied algorithm, as wells as various adopted initial populations and graphical representations are elaborated.

Table 3.24. Alternative percentages of pre-known and randomly generated solutions for the population

Indices	Percentage of pre-known solutions in the population (%)	Percentage of randomly generated solutions in the population (%)
E_1	60	40
E_2	40	60
E_3	30	70
E_4	50	50

3.6.1. Medium-Scale Test Instances

To investigate the Pareto front performance of the proposed algorithm on projects with 63-activity taken from the literature is re-solved. The project was tested under the two cases: in the first case (63a), the indirect cost is adopted as $2300/day, whereas it is taken as $3500/day in the second case (63b). The optimal solutions of 630 days with $5.421.120

as cost for 63a and 621 days with $6.176.170 as cost for 63b has been originally provided by Sonmez and Bettemir [47] using integer programming. The detailing of the problem is given in section 3.3.4.

In this method, with this new improvement, ten consecutive experimental runs are also conducted for this project. Pareto front solutions of 63-activity TCTP problem with E_1 to E_4 indices for both Cases are illustrated in Tables 3.25-3.28. In addition to this, to clearly observe the distinct performance of the proposed algorithm, best results of superior initial population are presented in Table 3.29 and 3.30 for Case 1 and Case 2 with corresponding average percent deviations (%APD) from the optima. Table 3.29 and 3.30 demonstrate the results for comparison of hybrid optimization-based methods with partial random initial population based NDS-TLBO algorithm. The selected duration of corresponding activities for the optimal solution of Case 2 is given in Table 3.31. In addition, Table 3.32 shows the compared %APD of Case 1 and Case 2 with the previous models.

Table 3.25. Pareto front solutions of 63-activity TCTP problem with E_1 index for both the Cases

Partial Random Initial population based NDS- TLBO			
Case 1 (Indirect cost = 2300 $/day)		**Case 2 (Indirect cost = 3500 $/day)**	
Dur	**Cost ($)**	**Dur**	**Cost ($)**
633	5427920	621	6179720
634	5448920	622	6183820
635	5430670	623	6188920
636	5438370	624	6184220
637	5428220	625	6181020
638	5432270	626	6186070
639	5431570	627	6193420
640	5441670	628	6197070
641	5430070	629	6192260
642	5436520	630	6198570
Pop. size	100		
Num. of iterations	250		
NFE	50000		
NFE = Number of Function Evaluations			

Table 3.26. Pareto front solutions of 63-activity TCTP problem with E_2 index for both the Cases

Partial Random Initial population based NDS- TLBO			
Case 1 (Indirect cost = 2300 $/day)		**Case 2 (Indirect cost = 3500 $/day)**	
Dur	**Cost ($)**	**Dur**	**Cost ($)**
633	5427920	621	6180020
628	5428170	621	6179720
637	5428220	621	6181820
630	5427770	621	6182640
633	5427920	622	6179470
630	5427770	625	6180070
628	5428170	621	6179720
630	5428870	618	6182020
630	5427770	621	6182640
630	5428120	623	6182070
Pop. size	100		
Num. of iterations	250		
NFE	50000		

Table 3.27. Pareto front solutions of 63-activity TCTP problem with E_3 index both the Cases

Partial Random Initial population based NDS- TLBO			
Case 1 (Indirect cost = 2300 $/day)		**Case 2 (Indirect cost = 3500 $/day)**	
Dur	**Cost ($)**	**Dur**	**Cost ($)**
630	5428170	626	6186070
631	5433170	629	6192260
634	5428220	627	6193420
637	5436520	621	6179720
638	5428970	612	6192270
639	5429920	623	6191170
640	5434770	620	6196270
641	5431420	622	6183820
644	5438220	625	6181020
645	5438720	624	6184220
Pop. size	100		
Num. of iterations	250		
NFE	50000		
NFE = Number of Function Evaluations			

Table 3.28. Pareto front solutions of 63-activity TCTP problem with E_4 index both the Cases

Partial Random Initial population based NDS- TLBO			
Case 1 (Indirect cost = 2300 $/day)		**Case 2 (Indirect cost = 3500 $/day)**	
Dur	**Cost ($)**	**Dur**	**Cost ($)**
630	5427770	621	6180020
639	5429920	625	6190070
634	5428070	627	6189770
642	5436520	624	6188170
633	5427920	628	6197070
631	5433170	631	6210010
638	5428970	630	6198570
635	5442370	629	6188670
637	5428220	626	6186070
640	5430570	632	6212020
Pop. size	100		
Num. of iterations	250		
NFE	50000		

Table 3.29. Best results for 63-Activity project (Case 1: daily indirect cost of $2300) using partial random initial population based NDS-TLBO

Sr. No	**Sonmez and Bettemir [47]**		**Aminbakhsh [48]**		**(This paper)**		**%PD**
	GASA		**D-PSO**		**TLBO**		
	Dur	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**	
1	633	5421320	630	5421120	633	5427920	0.125
2	633	5421320	630	5422420	628	5428170	0.130
3	633	5421620	630	5421120	637	5428220	0.130
4	633	5421320	630	5421120	630	5427770	0.122
5	633	5421620	633	5421320	633	5427920	0.125
6	633	5421620	636	5422970	630	5427770	0.122
7	633	5421620	631	5424420	628	5428170	0.130
8	633	5421620	633	5421320	630	5428870	0.142
9	633	5421620	633	5421320	630	5427770	0.122
10	629	6450065	629	5423270	630	5428120	0.142
Pop. size		200	200		100		APD% = 0.128
Num. of iterations		250	250		250		
NFE		50000	50000		50000		
NFE = Number of Function Evaluations							

Table 3.30. Best results for 63-Activity project (Case 2: daily indirect cost of $3500) using partial random initial population based NDS-TLBO

Sr. No	**Sonmez and Bettemir** [47]		**Aminbakhsh** [48]		**(This paper)**		**%PD**
	GASA		**D-PSO**		**TLBO**		
	Dur	**Cost**	**Dur**	**Cost**	**Dur**	**Cost**	
1	629	6181270	616	6177820	621	6180020	0.062
2	630	6177570	626	6177370	621	6179720	0.057
3	633	6184670	621	6176220	621	6181820	0.062
4	631	6183320	621	6178020	621	6182640	0.104
5	618	6180420	629	6177270	622	6179470	0.053
6	629	6180520	621	6177120	625	6180070	0.061
7	629	6179870	621	6176170	621	6179720	0.057
8	621	6180620	618	6177570	618	6182020	0.094
9	629	6177270	618	6177670	621	6182640	0.104
10	630	6182020	618	6177570	623	6182070	0.095
Pop. size	200		200		100		APD% = 0.075
Num. of iterations	250		250		250		
NFE	50000		50000		50000		
NFE = Number of Function Evaluations							

Table 3.31. Options selected and solution generated for 63-activity TCTP problem obtained by partial random initial population based NDS-TLBO approach (IC=$3500/day)

P-F Sol.	**Project time (days)**	**Project total cost ($)**	**Selected duration of the corresponding activity (days)**															
			1	**2**	**3**	**4**	**5**	**6**	-------------------				**57**	**58**	**59**	**60**	**61**	**63**
1	630	6427770	12	18	24	19	28	44	39	52	63	57	63	68	40	33	47	75
			60	81	36	41	64	53	43	66	50	84	67	66	76	34	96	43
			52	74	138	54	29	51	67	41	23	44	75	82	55	66	54	41
			147	101	83	31	39	18	29	38	30	24	27	31	20	25	22	
The red colored bars show the critical path activities for the current solution.																		

Table 3.32. Average deviations of 63-activity problem from the optimal solutions for the models obtained by partial random initial population based NDS-TLBO

Algorithms	**Case 1**		**Case 2**	
	No of Runs	**APD (%)**	**No of Runs**	**APD (%)**
GA, Sonmez and Bettemir [47]	10	5.86	10	5.16
HA, Sonmez and Bettemir [47]	10	2.61	10	2.50
DPSO, Aminbakhsh and Bettemir [48]	10	0.02	10	0.05
NDS-TLBO	10	0.128	10	0.14
Partial random initial population based NDS-TLBO (This study)	10	0.128	10	0.075

Considering Tables 3.25-3.32, the results of partial random initial population based NDS-TLBO for medium networks indicate that the proposed algorithm normally provides adequate optimal and near-optimal solutions for the TCTP problems.

Also, the effect of partial random initial population on the convergence of the NDS-TLBO algorithm with E_2 (40% pre-known + 60% randomly generated solutions in the initial population) which is providing better solution and the smoothened convergence history of the same is demonstrated in Figure 3.19 and 3.20 for Case 1 and Case 2. These figures illustrate that the implemented generation converges after the 150th iteration which is the optimum value for Case 1. Similarly, it converges the optimum solution after the 120th iteration for Case 2. Therefore, for both cases, population and number of iterations can be adopted as 100 and 150, respectively.

In this manner, the convergence history of the proposed algorithm with E_1 (60% pre-known + 40% randomly generated solutions in the initial population) is presented in Figure 3.21 and 3.22.

At the same time, Figure 3.23 and 3.24 display the convergence history of 63-activity TCTP problem with E_4 (50% pre-known + 50% randomly generated solutions in the initial population) for Case 1 and Case 2. Furthermore, Figure 3.25 and 3.26 indicate the convergence history of 63-activity TCTP problem with E_3 (30% pre-known + 70% randomly generated solutions in the initial population) for Case 1 and Case 2. Thereby, convergence histories graphs indicate that the utilized NDS-TLBO converges much faster than the original TLBO and converges to better solutions.

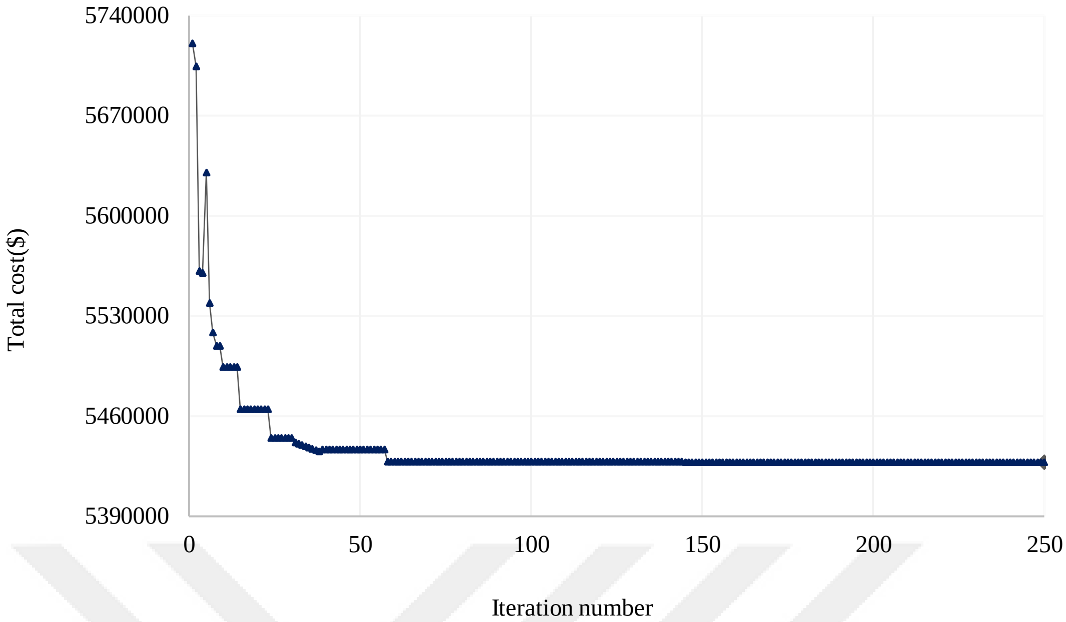

Figure 3.19. Convergence history of 63-activity TCTP problem with E_2 (40% pre-known + 60% randomly generated solutions in the initial population) for Case 1

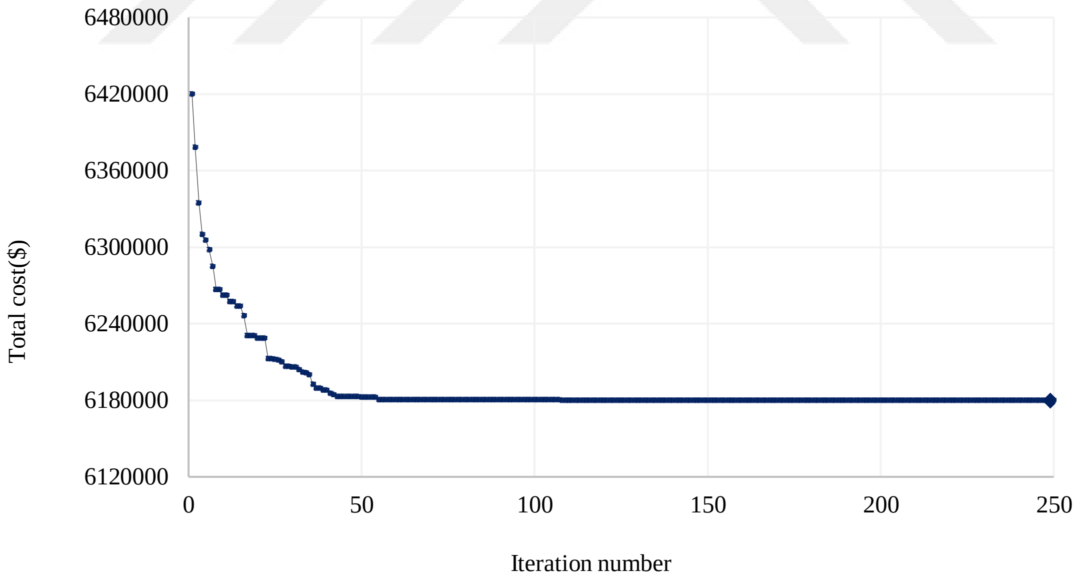

Figure 3.20. Convergence history of 63-activity TCTP problem with E_2 (40% pre-known + 60% randomly generated solutions in the initial population) for Case 2

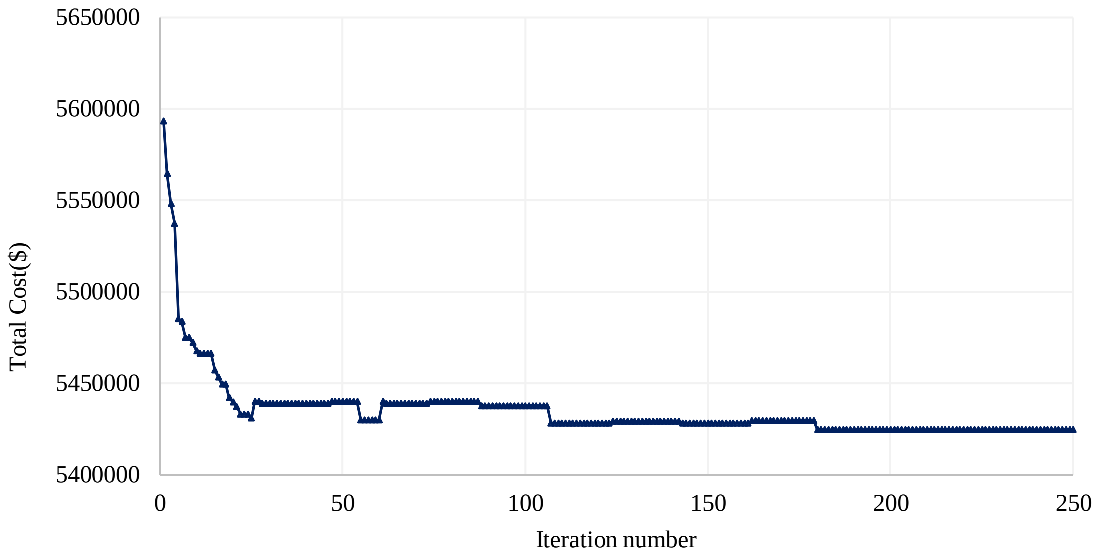

Figure 3.21. Convergence history of 63-activity TCTP problem with E_1 (60% pre-known + 40% randomly generated solutions in the initial population) for Case 1

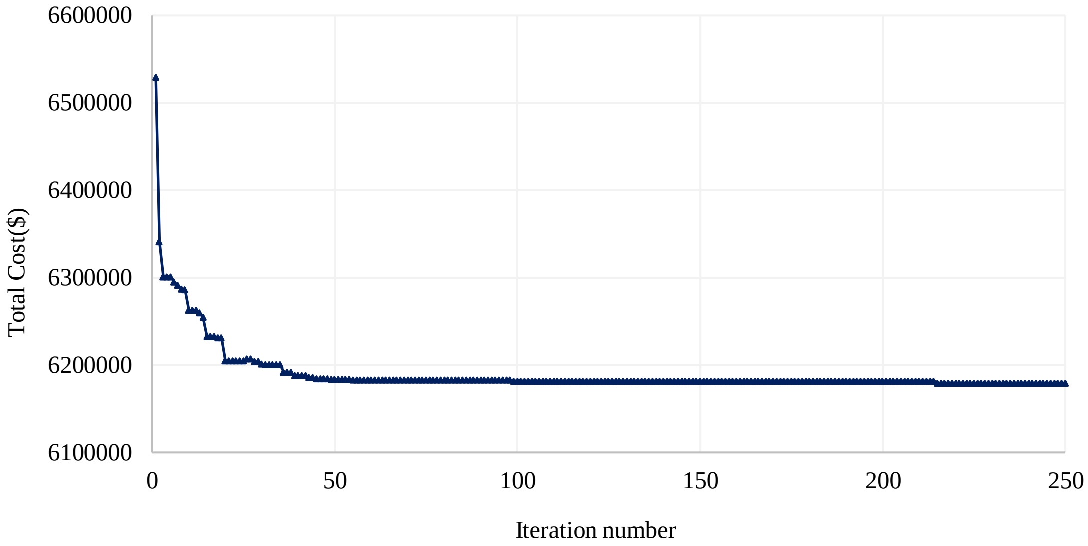

Figure 3.22. Convergence history of 63-activity TCTP problem with E_1 (60% pre-known + 40% randomly generated solutions in the initial population) for Case 2

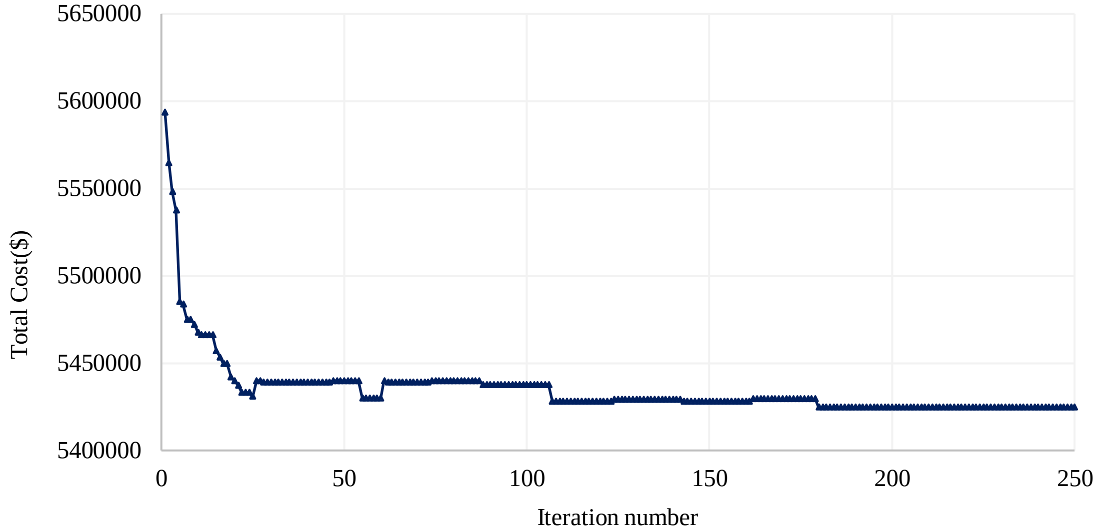

Figure 3.23. Convergence history of 63-activity TCTP problem with E_4 (50% pre-known + 50% randomly generated solutions in the initial population) for Case 1

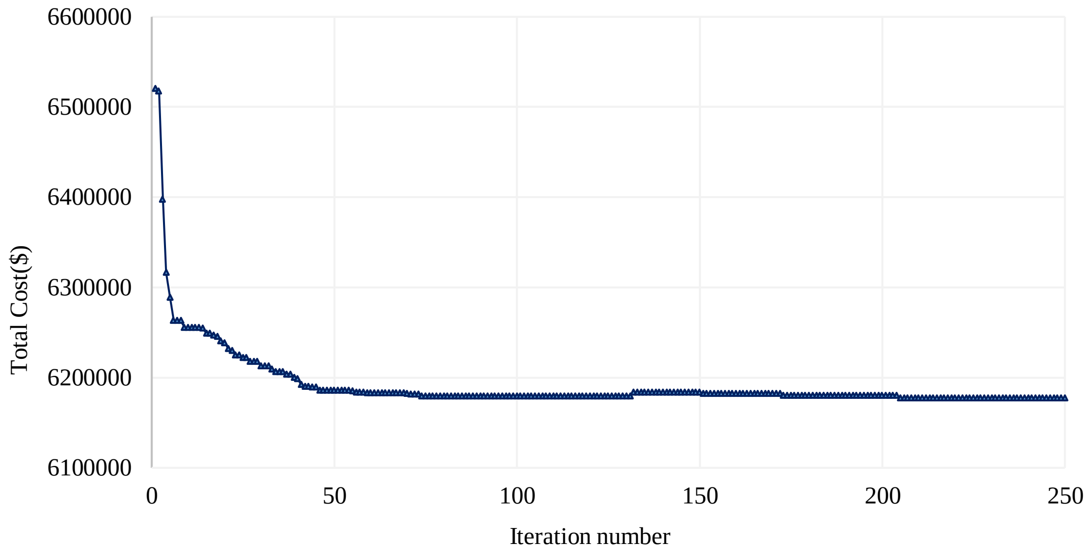

Figure 3.24. Convergence history of 63-activity TCTP problem with E_4 (50% pre-known + 50% randomly generated solutions in the initial population) for Case 2

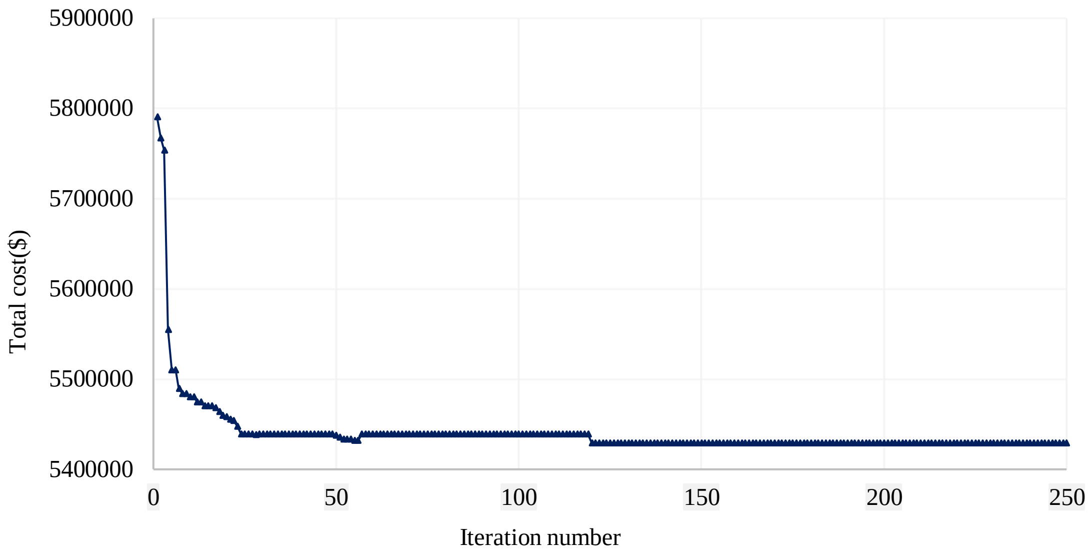

Figure 3.25. Convergence history of 63-activity TCTP problem with E_3 (30% pre-known + 70% randomly generated solutions in the initial population) for Case 1

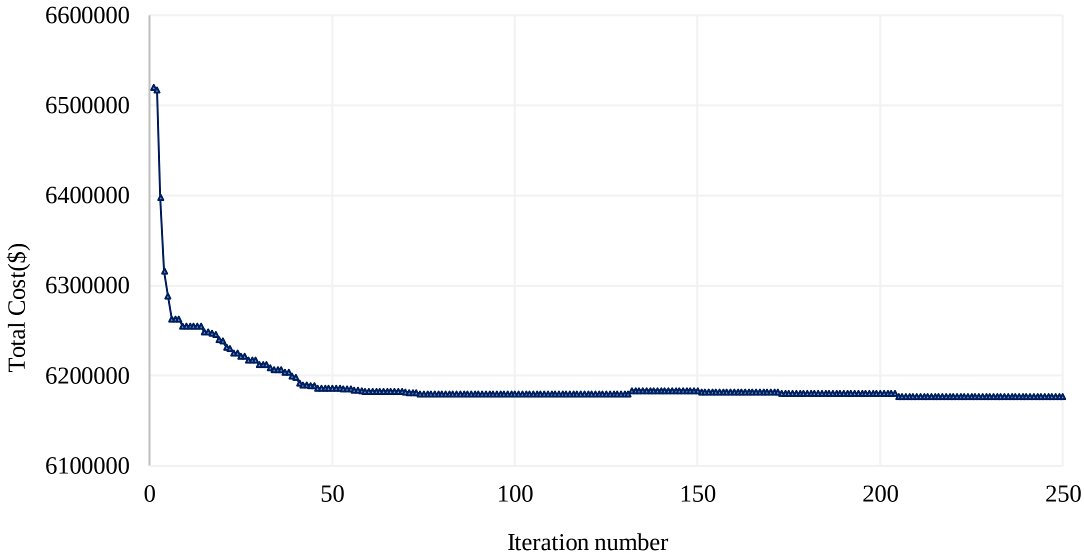

Figure 3.26. Convergence history of 63-activity TCTP problem with E_3 (30% pre-known + 70% randomly generated solutions in the initial population) for Case 2

Performance of the partial random initial population based NDS-TLBO algorithm was compared with the performance of the Pareto front solutions reported for genetic algorithm simulated annealing (GASA), Sonmez and Bettemir [47] as well as discrete particle swarm optimization (D-PSO) of Aminbakhsh [48]. As 50.000 schedules (objective function evaluations) are used as the stopping criteria in all of the experiments [47, 48]. The results acquired by the proposed TLBO method indicate better solutions as compared to the Sonmez and Bettemir [47].

On the other hand, it is apparent from the results that the applied algorithm could evolve potential improvement when exposed to large daily indirect cost. In contrast, it could achieve identical solution as exposed to smaller daily indirect cost. Therefore, this can easily be programmed by utilizing levy flight (a random walk) model and can systematically surf through the search space to avoid local minimum. However, being simple as well as relatively young algorithm, the proposed algorithm could achieve almost identical solution as compared to the Aminbakhsh‘s [48] model with the half of objective function evaluations of the previous models. That means, the applied algorithm reaches the optimality within the 25000 schedules. This reveals a remarkable reduction in number of function evaluations of the proposed algorithm as compared to the previous models. Even though, the applied meta-heuristic algorithm (TLBO) could not obtain global optima in any of the trials. However, by searching merely 25,000 solutions out of 1.37×10^{42} potential solutions, proposed algorithm was able to determine very high quality solutions that are either optimal or very close to the optimal. The reason of not achieving the global optima can be referred to the complex nature of the problem and the early stopping condition. Therefore, the initial population based NDS-TLBO provides a user-friendly and efficient concept to support time-cost optimization of medium scale problems.

3.6.2. Large-Scale Test Instances

As it is obvious that, the study concentrating on generation of large-scale complex TCTP problems that involves more activities and modes, would enable a better understanding of the performance of heuristic and meta-heuristic methods for real world projects. To this end, in this section, to investigate further the performance of the proposed algorithm on a large scale 630-activity project adopted from the literature is unraveled. In this project two overhead costs are taken into account in two cases: The overhead costs for Case 1 (630a) and Case 2 (630b) are 2300$/day and 3500$/day, respectively. The optimal solutions of 6300 days with $54.211.200 as cost for 630a and 6210 days with $61.761.700 as cost for 630b had been originally provided by Sonmez and Bettemir [47] using integer programming. The detailing of the problem is given in section 3.5.3. To solve the current problem, it is found out that, the best combination of partial random initial population (E_2) produces effective solution for the medium scale problem. Therefore, this suitable combination is adopted to unravel the large scale problem as well. To obtain the best Pareto front solutions ten consecutive experimental runs are implemented on this project. Best results of ten runs are demonstrated in Table 3.33 and 3.34 for Case 1 and Case 2 along with corresponding average percent deviations (%APD) from the optima and also rank and crowding distances are provided.

Table 3.33. Best results for 630-Activity project (Case 1: IC=$2300/day) using partial random initial population based NDS-TLBO

This paper		**%PD**	**Rank**	**Crowding Distance**
NDS-TLBO				
Dur	**Cost ($)**			
6387	54775880	0.01	1	0.0640
6447	54682080	0.86	1	0.0498
6480	54684970	0.87	1	0.0486
6417	54687510	0.87	1	0.0434
6458	54695920	0.89	1	0.0416
6433	54697060	0.89	1	0.0354
6473	54697450	0.89	1	0.0352
6424	54702050	0.90	2	0.0349
6475	54711350	0.92	1	0.0345
6342	54720110	0.93	1	0.0336
Pop. size	100	%APD =0.911		
Num. of iterations	250			
NFE	50000			

Table 3.34. Best results for 630-Activity project (Case 2: IC=$3500/day) partial random using initial population based NDS-TLBO

This paper		**%PD**	**Rank**	**Crowding Distance**
NDS-TLBO				
Dur	Cost ($)			
6204	62591490	1.34	1	0.0857
6127	62650570	1.43	1	0.0834
6114	62680270	1.48	1	0.0786
6094	62691570	1.50	1	0.0742
6060	62696280	1.51	2	0.0316
6043	62697220	1.51	1	0.0315
6137	62702240	1.52	1	0.0312
6030	62704580	1.52	1	0.0301
6159	62711150	1.53	1	0.0300
6130	62723120	1.56	3	0.0294
Pop. size	100	%APD =1.49		
Num. of iterations	250			
NFE	50000			

The compared mean values of ten runs for Case 1 and Case 2 are presented in Tables 3.35 and 3.36, respectively. In addition, Table 3.37 represents the compared %APD of Case 1 and Case 2 with the previous and basic TLBO algorithms.

Table 3.35. Comparison of mean values of 10 runs for Case 1 (IC=$2300/day) using partial random initial population based NDS-TLBO

Descriptions	**Bettemir [79]**			**This paper**
	NDS-GA	**NDS-ACO**	**NDS-PSO**	**NDS-TLBO**
Mean value	58983147	56703583	54815790	54705438
Pop. size	-	-	-	100
Num. of iterations	-	-	-	250
NFE	250000	250000	250000	50000
NFE = number of function evaluations				

Table 3.36. Comparison of mean values of 10 runs for Case 2 (daily indirect cost=$3500) using initial population based NDS-TLBO

Descriptions	Bettemir [79]			This paper
	NDS-GA	NDS-ACO	NDS-PSO	NDS-TLBO
Mean value	66395840	64574989	63121500	62684849
Pop. size	-	-	-	100
Num. of iterations	-	-	-	250
NFE	50000	50000	50000	50000

Table 3.37. Average deviations from the optimal solutions for the models obtained using initial population based NDS-TLBO

Algorithms	Case 1		Case 2	
	No of Runs	APD (%)	No of Runs	APD (%)
GA, Sonmez and Bettemir [47]	10	8.83	10	7.50
HA, Sonmez and Bettemir [47]	10	2.41	10	2.47
DPSO, Aminbakhsh and Bettemir [48]	10	0.33	10	0.34
Core NDS-TLBO	10	1.10	10	1.51
Partial random initial population based NDS-TLBO (This paper)	10	0.91	10	1.49

Partial random initial population based NDS-TLBO algorithm achieved very successful results and outperformed the hybrid genetic algorithm (HA) Sonmez and Bettemir, [47] as well as basic TLBO algorithms for large-scale instances. The acquired APD values for instances 630a and 630b are 0.91% and 1.49 %, respectively. By searching only 50.000 solutions out of 2.38 $\times 10^{42}$ potential solutions, partial random initial population based NDS-TLBO was able to obtain high quality solutions for the largescale problems. Hybrid algorithm of Sonmez and Bettemir [47] was able to achieve APD values of 2.41% and 2.47% within 50.000 schedules. Therefore, it can be seen from the result summary that performance of TLBO has improved due to the partial random initial population based modification. It is mentionable that, in this study also, the applied metaheuristic algorithm (TLBO) could not obtain global optima in any of the trials. However, by searching merely 25.000 solutions out of 1.37×10^{42} potential solutions, proposed algorithm was able to detect the solutions very close to the optimal. The reason of not achieving the global optima can be referred to the complex nature of the problem and premature convergence condition. Therefore, the partial random initial population based NDS-TLBO provides a user-friendly and efficient concept to support time-cost optimization of medium scale problems. Importantly, the simplicity of the proposed TLBO algorithm can be taken into account as strength point of it.

4. CONCLUSIONS

In this thesis, significance of sufficient schedules for construction projects has been discussed to validate and assess the proposed algorithms. Well-known 7, 18, 63 and 630-activity benchmark problems have been solved to validate the performance of the TLBO algorithm. The adequate values required to operate the algorithms have been assumed after series of trial and error, with regard to the solutions given for these examples within the literature. The robustness and potency of the applied algorithms have been investigated through the results obtained from these studies. The discrete basic-TLBO algorithm presented in this thesis has been established in the classical version proposed by the [5]. However, a minor change has been made to the NDS-TLBO algorithm to enhance the efficiency of the search process by introducing the partial random initial population based concept.

In this research, the computational result is with up to about 630-activity and 5 modes have revealed the satisfactory behavior of the teaching learning based optimization algorithm used to solve the TCT Problem. It is observed that the efficiency of the algorithm is affected by the number of activities and the tightness of the indirect cost value. This metaheuristic procedure generates solutions that deviate from the optimal solutions by no more than ten percent on average.

It has been seen that the solutions produced via NDS phase of the model have reasonably good fit compared to the MAWA phase of the model, furthermore, it is resulted that the partial random initial population based version of NDS-TLBO algorithm outperforms the both non-dominating sorting approach as well as modified adaptive weight approach of the current research. However, it has been observed that the quality of the acquired solutions have been somehow deteriorated for test problems with smaller daily indirect costs. Robustness of this model in regards to its proficiency in locating the non-dominated front for the medium-sized problems has been confirmed. Consequently, the utilized algorithm has been proven to outperform the results of the previous studies reported in the literature. Because of the strong convergence capabilities of the applied algorithm in locating the Pareto fronts of the represented TCTP problems, it would be taken into account as a surpassing technique in the construction management field.

Consequently, partial random initial population based NDS-TLBO presents better results than the other sole TLBO algorithms, so it is the most suitable algorithm for time-cost trade-off optimization problem.

4.1. Contributions

This research contributes considerably to improve the limitations of solving large-scale discrete time-cost trade-off (DTCT) problems. While the solution methods for solving DTCT problems in the literature are limited to 63-activity [48], using the proposed algorithm, the number of activities increases to 630-activity without compromising the quality of solution, within an acceptable range of less than 7% deviation from the global optimum.

The following are a summary of contributions of the research:

- Developed a flexible time-cost trade-off (TCT) model in MATLAB environment to be used for applying multiobjective TLBO for the first time on solving TCTP Problems in construction management field of civil engineering.
- Investigated various multiobjective optimization approaches such modified adaptive weight (MAWA), non-dominating sorting (NDS) and partial random initial population version of NDS-TLBO for solving large-scale TCT optimization problems. Suitable methods for modeling and solving TCT problems were chosen and their efficiency in solving large size problems was examined.
- The developed partial random initial population NDS-TLBO based TCT model proved its ability to solve very large-scale TCT problems. The solutions are satisfactory near optimum (mostly with less than 7% deviation from the optimal solution) with an acceptable processing time.
- Concluded on the superiority of the applied multiobjective TLBO approaches comparing to the previous optimization methods.

4.2. Future Research

In spite of the significant improvements on the time and cost optimization of large-scale construction projects presented in this research, various other enhancements are offered for the future extensions of the current research, including:

- Investigating the performance of other optimization packages for optimization of time and cost in construction projects which have the integer programming using the AIMMS optimization software.
- Extending the number of objective functions of problems to more than two such as quality, productivity, safety, and environmental effects etc., will also be an investigation area that deserves further devotion. Consequently, the model would turn into a more complicated combinatorial optimization problem which would be harder and more time consuming to solve.
- Expanding the optimization model to include resource allocation and resource leveling constraints, in order to perform resource utilization while optimizing time and cost. This would provide a more complete optimization strategy for construction projects.
- Applying modified version of TLBO by introducing concept of number teachers (NT) and adaptive teaching factor.
- Providing an interface to project management software such as Primavera packages and Microsoft Project in order to import and export model data to/from project management software directly.

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Education	M.Sc.
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Working Experience	3 Years
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Educational Background

Master of Science 09.2014 – 12.2017	**Karadeniz Technical University** Faculty of Engineering, Civil Engineering	3, 79 /4
Undergraduate (India) 07.2010- 04.2014	**National Institute of Technology Warangal** Faculty of Engineering, Civil Engineering	7, 48 /10
High School 01.2007 – 03.2010	**Abu Muslim High School** Class topper	9, 97/10

Working Experience

January 2018 – Present
English Teacher at Teol Yabancı Dil Okulu in Trabzon Branch

September 2013 – March2014 (1 Semester), Hyderabad, India

Coordinator

NITW (National institute of Technology Warangal)

- To conduct a workshop on Bridge Design organized by the Civil Engineering Association.
- Submitted the Monthly Report to the Chairman of the Civil Engineering Association.

July 20 – March 2013

Proficiency to work on project management program “Oracle Primavera P6 “

ECC (Engineering CADD Center), Hyderabad – 500028-Telangana, India

Jun 2008(1year, 7 Months) | Andkhoi, Afghanistan

Finance Accountant

VUSAF-i-Germany (Andkhoi Ziba Magazine**)**

- Typing, Editing and proofreading the topics intended to be printed.
- Accepting the advertisements for the marketing to subsidize the magazine.

Jan 2007 **-** Feb 2009 (3years) | Andkhoi, Afghanistan

Head’s Assistant

Nawayee High Educational Center.

- Taught primary to intermediate English IRC Levels.
- Organized the several academic gatherings to motivate the students.

Language Skill:

	Understanding				**Speaking**				**Writing**	
English Language	Listening		Reading		Spoken interaction		Spoken production			
	C1	Proficient	C1	Proficient	C1	Proficient	C1	Proficient	C1	Proficient
Turkish Language	Listening		Reading		Spoken interaction		Spoken production			
	C1	Proficient	C1	Proficient	C1	Proficient	C1	Excellent	C1	Proficient
Persian Language	Listening		Reading		Spoken interaction		Spoken production			
	C1	Proficient	C1	Proficient	C1	Proficient	C1	Proficient	C1	Proficient
Pashto Language	Listening		Reading		Spoken interaction		Spoken production			
	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge
Hindi (Urdu) Language	Listening		Reading		Spoken interaction		Spoken production			
	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge	B1	Working Knowledge
Uzbek Language	Listening		Reading		Spoken interaction		Spoken production			
	C1	Native	C1	Native	C1	Native	C1	Native	C1	Native

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7. Eirgash, M. A., Toğan, V., and Dede, T. 2017. “Application of Teaching Learning Based Optimization For Time-Cost Trade-Off Problems In Construction Projects.” Submitted on KSCE Journal of Civil Engineering.

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