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Time-Cost Trade-Off Optimization with a New Initial Population Approach

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ABSTRACT

Completion of a project on time is crucial for its stakeholders when the competitive environment in all industries is considered. This favorable target is achieved by finding the optimal set of time-cost alternatives, which is known as time-cost trade-off problem (TCTP) in the literature. In this study, a new initial population approach is presented to improve the quality of the optimal set of time-cost alternatives. It employs a predefined number of solutions to the single objective TCTP into the initial population of teaching learning-based algorithm, which is an optimizer for the multi-objective optimization of TCTP. Hence, it is aimed at descending randomness on the initial population and decreasing searching effort to catch the optimal set of time-cost alternatives in the search space. The proposed methodology is tested on a series of benchmark problems and the solutions obtained are compared with those available in the technical literature. Results show that the present method can produce favorable solutions as effective as other techniques applied for simultaneous optimization of TCTPs.

Keywords: Construction project, **t**ime-cost trade-off problem, multi-objective optimization, metaheuristic algorithm.

1. INTRODUCTION

From the construction management point of view, both the client and the contractor look for the best economical scheduling subject to different parameters such as time, cost and other operational resources in a construction project. Each activity in a construction project has a normal duration and a crashed duration. Completing an activity in its forced (crashed) duration involves more direct cost and resources. On the other hand, it leads to decrease project's total duration and indirect costs (i.e. site utilities, supervisors, head-office expenses and so on). The balancing between time and cost of a project is known as the time cost trade-

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off problem (TCTP) in the literature and solving of this problem requires application of an optimization method.

The first optimization methods employed to solve TCTPs are based on mathematical solutions including the linear programming, the integer programming and the dynamic programming methods [1-5]. These were employed on relatively small test cases. On the other hand, they assume continuous relations between the all design variables of the evaluated problem. However, in practice, the execution of an activity needs operational resources such as time, cost, workmanship etc. having several options, which are discrete. Due to this feature, optimization methods based on the mathematical theory are not appropriate for problems having discrete time-cost relationships [6]. Besides, the integer programming and the dynamic programming require numerous computational efforts for solving more complex project networks or for solving projects with many different activities.

Other common methods for the solution of TCTPs are based on the heuristic algorithms [7, 8]. They apply simple rules unlike the exact algorithms as in the mathematics-based (theory based) methods. Owing to this necessity, the heuristic algorithms can be used easily for the complex problem with less effort. However, globality of the obtained solution is always questionable since they generally find the local-global solutions or the near-global ones for these algorithms. Nevertheless, the metaheuristic algorithms based on natural events were introduced as the last alternative for solving TCTPs in order to overcome the shortcomings of first two methods aforementioned.

In recent decades, various modern metaheuristic optimization methods including genetic algorithms [6, 9, 10], simulated annealing [10, 11], particle swarm optimization [10, 12-15], ant colony optimization [16-19], and shuffled frog leaping optimization [20] have been applied for solving TCTPs. In addition to these methods, differential evolution algorithm [21], Electimize algorithm [22] and Branch and Bound algorithm [23] were also utilized for optimizing the TCTPs. These algorithms numerically represent the natural events. Since the meta-heuristic algorithms improve the quality of the obtained solution iteratively, they might not stick to the local optimum due to their stochastic natures. This latter feature improves the detection chance of global optimum solution searched by the metaheuristic algorithms. As mentioned above, the algorithms into this type of optimization methods simulate the evolutionary computation and swarm intelligence. They are very useful solvers for problems that the global solutions are very difficult to obtain, as they find the near-optimal solutions instead of global ones.

To take advantage of some prominent features of each metaheuristic algorithm, some of them were hybridized to enhance the computational effort required to reach the optimal solution of the problem, and also to improve the optimality of those solutions [10, 14, 15]. All metaheuristics addressed above are the population-based algorithms, except simulated annealing. To start the iterative process of the algorithm, they need a set of possible solutions, which are randomly generated within the problem boundaries. These solutions are collected in a matrix known as the initial population. Then, they are improved through the executed subsequent iterations until reaching the predefined termination criteria. Therefore, the candidate solutions in the initial population affect the performance of the utilized optimization algorithms. Based on this observation, Aminbakhsh [14] developed a new initial population formation phase for particle swarm optimization (PSO). A certain portion of the initial population was produced by means of Siemens algorithm, and fed into the model to accelerate the searching process. Some changes were made to the original Siemens method, which is suitable for continuous problems to solve the discrete TCTPs.

In this study, a new initial population approach is proposed to enhance the convergence capability and performance of the teaching learning-based optimization (TLBO) used for the multi-objective optimization of TCTPs. The proposed approach combines the certain solutions obtained from implementing the minimum of the minimum (min-min) approach with the remaining solutions being generated randomly to compose the initial population. The min-min approach is an optimization algorithm utilized to find the acceptable solutions for the simple single objective version of TCTP. Either minimization of the project duration or the cost can be adopted as the objective function for the optimization of TCTPs having the single objective. However, for a given project cost, a single project duration can be identified in the solution space of TCTP, whereas there might be plenty of project cost values for the certain project duration. This conclusion can be observed easily from the reported results in the technical literature related to the optimization of TCTPs and also from the investigation of the solution space of the handled TCTP. Therefore, in the present study, project cost is considered as the single objective function in the optimization of TCTP by the min-min approach.

The rest of the study is organized as follows: Firstly, basic formulations for the TCTP optimization is presented and then the proposed initial population approach is detailed along with characteristics of the multi-objective teaching learning-based algorithm (MTLBO) to solve the TCTPs for construction projects. MTLBO is also integrated with the non-dominating sorting approach (NS) in order to evaluate the fitness of the possible solutions. Effect of the partial random initial population in NS-MTLBO model is exhibited by numerical simulations of benchmark TCTPs and conclusions are presented in the last section of the study.

2. TIME-COST TRADE-OFF PROBLEM (TCTP)

TCTP is a bi-objective problem, and is a balanced relationship between time and cost. During planning or in case of a delay, the project manager needs to balance the time and cost of a project to improve the overall efficiency. Therefore, TCTP is adapted to identify the set of time–cost alternatives that will provide the optimal schedule. The time of a project T can be calculated according to the following equation:

$$T = \sum_{i=1}^{k} t_i^k \, x_i^k \tag{1}$$

where k is the number of total activities of a project, t_i^k is the duration of activity i when performing the kth option, x_i^k is index variable of activity i when performing the kth option:

$$x_i^k = \begin{cases} 1 & \text{when activity } i \text{ performs the } k\text{th option} \\ & 0 \text{ else} \end{cases} \tag{2}$$

where $\sum_{i=1}^{k} x_i^k = 1$. The project duration T is calculated by using the critical path method depending on the defined activity relationships for that project. The total cost of a project consists of two parts: direct and indirect costs. The first one is determined by the sum of direct costs of all activities within a project network. The last one depends heavily upon the project duration, i.e., the longer the duration, the higher the indirect cost. The total cost of a project can be calculated by

$$C = \sum_{i=1}^{k} DC_i^k \, x_i^k + t_i ic_i^k \tag{3}$$

where C is the total cost of a project, DC_i^k is the direct cost of activity i when performing the kth option, x_i^k is index variable of activity i when performing the kth option, t_i is the duration of activity i, and ic_i^k is the indirect cost rate of a project.

3. INITIAL POPULATION APPROACH

In the past few decades, many attempts have been made for solving construction optimization problems those utilizing the various modern metaheuristic optimization methods including genetic algorithms, simulated annealing, particle swarm optimization, ant colony optimization, and shuffled frog leaping optimization. Thereby, in this study, a relatively young metaheuristic algorithm called teaching learning-based optimization (TLBO) is applied as an alternative to solving TCTPs.

It is observed that the utilized basic non-dominating sorting multi-objective teaching learning-based optimization (NS-MTLBO) algorithm is not able to achieve the optimum solutions as good as hybridized algorithms for the large scale TCTPs [24]. Therefore, in the present study, to enhance the prediction capacity of NS-MTLBO algorithm, a new approach is proposed to generate the initial population in NS-MTLBO. Apart from the simulated annealing, a set of possible solutions which are randomly generated within the problem boundaries are needed to start the iterative search process for the metaheuristic algorithms. After that, they are enhanced through the executed subsequent iterations until reaching the predefined termination criteria. Based on the numerical simulation process conducted for the solution of the optimization problem, it might be stated that the candidate solutions in the initial population affect the efficiency of the optimization algorithms used. A modified version of the Siemens method is added into the Discrete Particle Swarm Optimization (DPSO) to improve the quality of the initial swarm for improving the optimization results and for accelerating the optimization process [14].

In this study, to improve the quality of the solutions obtained at the end of the optimization process conducted with NS-MTLBO and to accelerate the search carried out within the solution space, a new initial population creation concept is proposed. The main principle behind this concept is based on the separation of the candidate solutions of the initial population as pre-known and randomly generated. A specific number of solutions for the initial population named as pre-known are picked up automatically among those obtained from the solution of optimization problem with single objective by TLBO method. The proposed model takes advantages of the min-min approach which is based on performing the straightforward single objective optimization. The min-min approach is available in the optimization engines placing in some software. For example, MATLAB offers an optimization library including mathematical and metaheuristic algorithms. Use of this library does not requires knowledge of coding in implementing the algorithms proposed. In the min-min approach, all the possible set of solutions are ordered according to the quality of the objective functions of time and cost within a small computational effort. The aim is to find the solution that gives the least total project cost subjected to the least project duration. The objective functions are either minimization of the project duration or cost. For performing this approach, in the present study, the project cost is initially considered as the objective function. However, there are plenty of solutions in the solution pool, which indicate the same project duration with different cost. The minimum duration for the particular minimum cost is taken as the optimum solution in each iteration and stored in an external archive. This process continues until the stopping criteria is met, and is called min-min approach. Then, the predefined number of solutions are picked up among those that are kept in the external archive, and thus pre-known solutions are defined for the initial population. The remaining possible solutions to be needed to complete the initial population are generated randomly to preserve diversity. The graphical demonstration of the proposed new initial population concept denoted as partial random initial population is illustrated in Fig. 1.

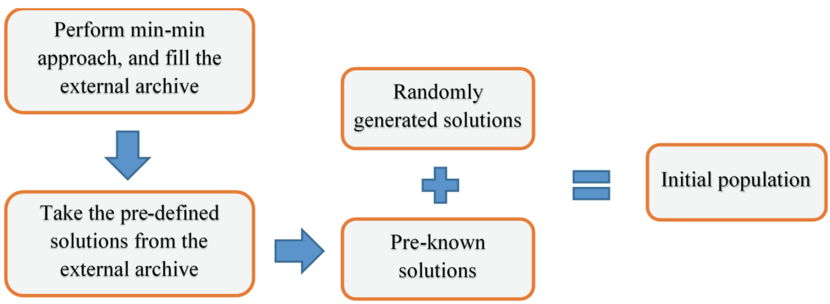


Fig. 1 - Partial random initial population in NDS-MTLBO model

Table 1 - Alternative percentages of pre-known and randomly generated solutions for the initial population

Indices	Percentage of pre-known solutions in the initial population	Percentage of randomly generated solutions in the initial population
O_1	60	40
O_2	40	60
O_3	30	70
O_4	50	50

To determine the proper percentages of pre-known and randomly generated solutions in the initial population, a set of percentage alternatives are defined in Table 1. Each of these alternatives is tested to further verify the effect of partial random initial population on the NS-MTLBO algorithm. For simplicity, an index is identified for each combination considered in Table 1. For example, in the case of the population size being 100, the initial population consist of 60 (100×60%) pre-known solutions and 40 (100×40%) randomly generated solutions, for index of O_1.

4. NON-DOMINATED SORTING TLBO ALGORITHM FOR MULTI-OBJECTIVE OPTIMIZATION

Minimization of time and total cost of the project at the same time requires the implementation of multi-objective optimization, and in contrast to optimization with the single objective, there is no unique global optimum solution for the multi-objective optimization. Instead, a set of solutions known as Pareto optimal is identified at the end of the multi-objective optimization process. Any solution in Pareto optimal is not preferred to another. The multi-objective optimization models developed for the solutions of TCTPs are generally based on the modified adaptive weight approach (MAWA) and non-dominating sorting (NS) approach. However, instead of MAWA approach, NS as a superior approach along with the mechanism of crowding distance computation has been broadly utilized in solving the mentioned TCTP problems, recently.

NS-MTLBO algorithm proposed in the current work comprises remarkable features of NS approach and TLBO algorithm to solve multi-objective optimization problems and to find out a bunch of diverse solutions. NS approach and crowding distance computation mechanism proposed by Deb et al. [25] are responsible for handling the objectives effectively and efficiently in NS-MTLBO model. Besides, the teacher and learner phases of TLBO guarantee the exploration and exploitation of the solution space searched.

The initial population including predefined P number of students is arranged with the non-dominance concept. Application of NS approach assigns a rank value to the solution. The higher rank implies higher superiority in accordance with the non-dominance concept. However, it cannot be said anything about the dominance of the solutions which are in the same rank. To describe the superiority of these solutions, the crowding distance metric is utilized. Ultimately, all solutions are kept up in the external archive.

Teaching learning-based optimization (TLBO)

TLBO algorithm proposed by Rao et al. [26] simulates the teacher and students of a classroom. This algorithm proceeds with two basic phases; (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 interaction among the students in the class. Analogously, all students (learners) represent the population for an optimization algorithm; the subjects taught are considered as the design variables of the optimization problem; the exam result of the learners gives the 'fitness' value for the corresponding subject taught. TLBO has emerged as one of the simple and efficient techniques for solving single-objective benchmark and real-life application problems, in which it has been empirically shown to perform well on many optimization problems [27-30].

In NS-MTLBO model, the learner with the highest value of rank and the 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 continue the learning phase of TLBO, P numbers of the 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.

Optimum solution of TCTP via NS-MTLBO algorithm

The solution of TCTP employing NS-MTLBO process including the partial random initial population newly proposed in this study is summarized as follows:

Step I: Perform an optimization process through the min-min approach detailed above and collect the solutions which have the minimum project cost corresponding to the minimum project duration into an external archive. In that process, the total cost of the project is taken as a sole objective function, and is used TLBO algorithm.

Step II: Convey a pre-defined number of solutions from the external archive into the initial population and fill the initial population with the randomly generated solutions. It (initial population; CL) contains *pn* (student or population size) number of solution vectors and *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. In addition, to initialize the TLBO algorithm, define the maximum number of iterations (stopping criteria).

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

$$CL = \begin{bmatrix} X_{1,1} & \cdots & X_{1,dn} \\ \vdots & \ddots & \vdots \\ X_{pn,1} & \cdots & X_{pn,dn} \end{bmatrix} \tag{4}$$

Evaluate the matrix and determine the corresponding two objective function values associated with the project duration ($f_t(\mathbf{X})$) and the total project cost ($f_c(\mathbf{X})$) by

$$f(\mathbf{X}) = \begin{bmatrix} f_t(\mathbf{X}_1), f_c(\mathbf{X}_1) \\ \vdots \\ f_t(\mathbf{X}_{pn}), f_c(\mathbf{X}_{pn}) \end{bmatrix} \tag{5}$$

Perform a non-dominated sorting concept on the solutions. Then, calculate the crowded distance values of solutions in the front(s) and sort them. Keep the sorted solutions 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 ($\mathbf{X}_{\text{teacher}}$) of the class based on non-dominated sorting and crowding distance metric.

$$\mathbf{X}_{teacher} = \mathbf{X}_i | \text{ in front 1 and having max. crowded distance} \tag{6}$$

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

$$\mathbf{X}^{tp}_{new,\boldsymbol{i}} = \mathbf{X}_{old,i} + rand(0,1)\ (\mathbf{X}_{teacher} - T_F\ \mathbf{X}_{mean}) \tag{7}$$

where T_F represents teaching factor defined as

$$T_F\ = round\ [1 + rand(0,1)] \rightarrow \{1, 2\} \tag{8}$$

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

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

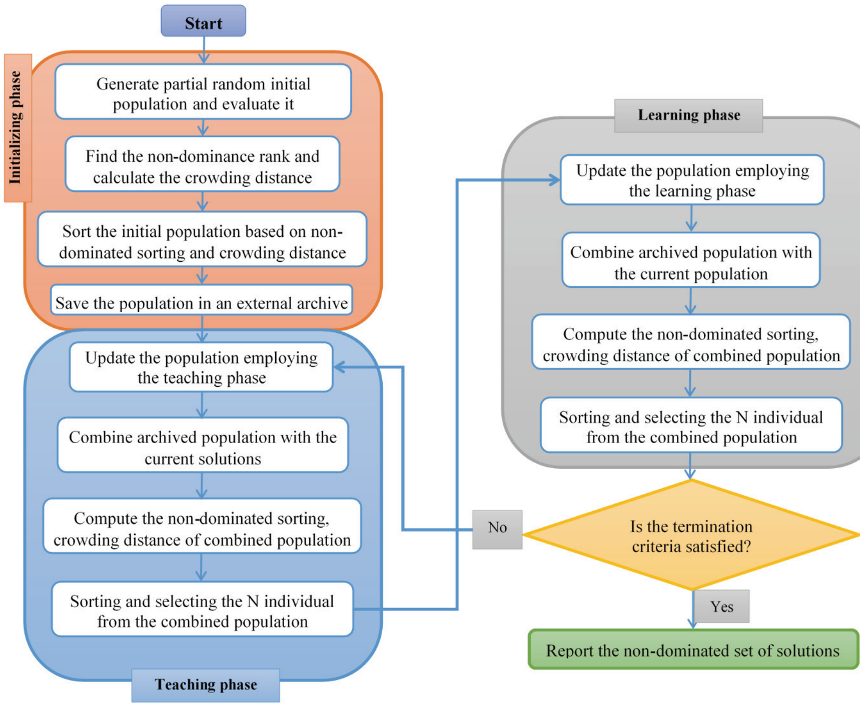


Fig. 2 - Flowchart of the NS-MTLBO algorithm for the solution of TCTP

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

$$\mathbf{X}_{new,i}^{lp} = \begin{cases} \mathbf{X}_{old,i} + rand(0,1)\left(\mathbf{X}_i - \mathbf{X}_j\right) \rightarrow \text{if } \mathbf{X}_i \text{ lies on a better non-dominated front than } \mathbf{X}_j \\ \mathbf{X}_{old,i} + rand(0,1)\left(\mathbf{X}_j - \mathbf{X}_i\right) \rightarrow \text{if } \mathbf{X}_j \text{ lies on a better non-dominated front than } \mathbf{X}_i \end{cases} \quad (9)$$

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

Combine the current population with that 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 *P* individual from it.

Step V: Check the stopping criterion. This criterion is usually 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. The flowchart of the process can be seen in Fig. 2.

5. NUMERICAL EXAMPLES

For performance evaluation of the NS-MTLBO method, a medium-scale problem and a large-scale problem are evaluated. The algorithm is implemented in MATLAB (R2015a), and runs are executed on a personal computer having Intel (R) Core (TM) i3 CPU 2.40 GHz and 3GB RAM. Total number of objective function evaluations is adopted as terminating criteria for the multi-objective optimization process. Due to stochastic nature of TLBO, 10 consecutive experimental runs are conducted for the entire instances.

Medium-scale test problem

A medium-scale project with 63 activities taken from Bettemir [31] is examined as the first test project to exhibit the performance of the proposed NS-TLBO. The activity-on-node diagram for the project is presented in Fig. 3. The project involves two activities with three modes, 15 activities with four modes, and 46 activities with five modes. The number of total possible time–cost alternatives for the project is 1.4E+42. The project is tested over two cases. The indirect cost is taken to be \$2300/day in the first case (63a), whereas \$3500/day in the second case (63b).

Ten consecutive experimental runs are conducted with the proposed initial population concept in NS-MTLBO for this project. Experimental runs are repeated for each predefined percentage alternatives given in Table 1. Pareto front solutions obtained from these investigations for both cases are illustrated in Tables 2 to 5, respectively.

In Tables 2-5, it can be observed that the proposed algorithm works well with the O_2 index (40% pre-defined solutions +60% randomly generated solutions). Therefore, Pareto front solutions obtained with O_2 index are used to compare the results with the others to clearly demonstrate the performance of the proposed new initial population approach in NS-MTLBO algorithm. Tables 6 and 7 compare the best results of obtained in the present study and the other studies for Case 1 and Case 2 with corresponding average percent deviations (%APD) from the optima. The optimal solutions obtained using the integer programming for both cases were reported in Bettemir [31] as 630 days with \$5.421.120 for 63a (Case 1) and 621 days with $6.176.170 for 63b (Case 2). In addition, Table 8 shows %APD comparison of Case 1 and Case 2 for the proposed model and previous ones.

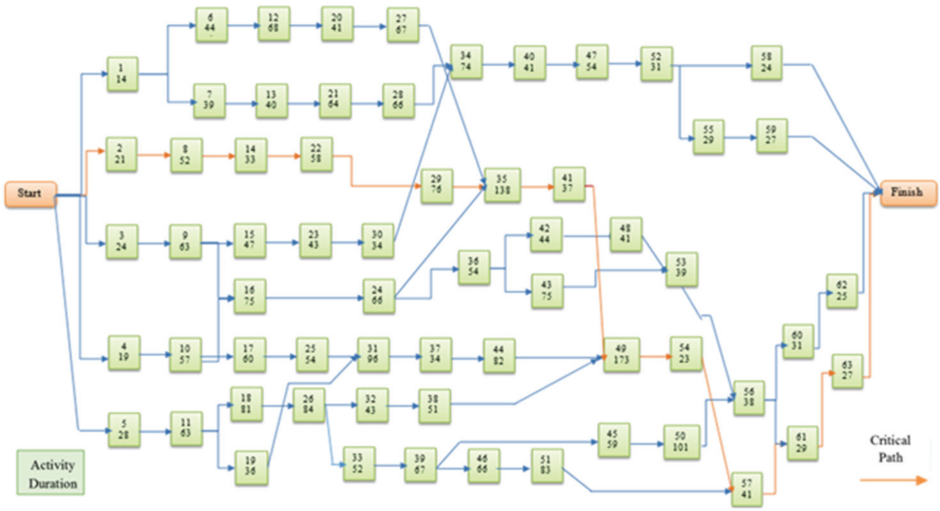


Fig. 3 - Network representation of the 63 activities project

Table 2 - Pareto front solutions of 63-activity project with O_1 *index for both cases*

Partial Random Initial population-based NS- MTLBO			
Case 1 (ic=2300 $/day)		Case 2 (ic=3500 $/day)	
Duration (days)	Total cost ($)	Duration (days)	Total 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
NFE	50000	50000	

ic: indirect cost, NFE: number of objective function evaluations with 100 population size and 250 number of iteration

Table 3 - Pareto front solutions of 63-activity project with O_2 *index for both cases*

Partial Random Initial population based NS- MTLBO			
Case 1 (ic=2300 \$/day)		Case 2 (ic=3500 \$/day)	
Duration (days)	Total cost (\$)	Duration (days)	Total 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
NFE	50000	50000	

Table 4 - Pareto front solutions of 63-activity project with O_3 *index for both cases*

Partial Random Initial population based NS- MTLBO			
Case 1 (ic=2300 \$/day)		Case 2 (ic=3500 \$/day)	
Duration (days)	Total cost (\$)	Duration (days)	Total 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
NFE	50000	50000	

Table 5 - Pareto front solutions of 63-activity project with O_4 *index for both cases*

Partial Random Initial population based NS- MTLBO			
Case 1 (ic=2300 $/day)		Case 2 (ic=3500 $/day)	
Duration (days)	Total cost ($)	Duration (days)	Total 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
NFE	50000	50000	

*Table 6 - The best results for 63-Activity project (*Case 1*: daily indirect cost of* $2300*)*

Run no	Sönmez and Bettemir [10]		Aminbakhsh [14]		This study		%PD
	GASA		DPSO		TLBO		
	Dur. (days)	Cost ($)	Dur. (days)	Cost ($)	Dur. (days)	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		
Num of iter.	250		250		250		%APD=0.128
NFE	50000		50000		50000		

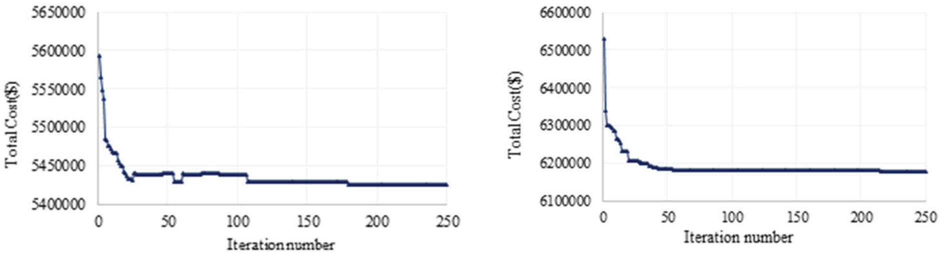
*Table 7 - The best results for 63-Activity project (*Case 2*: daily indirect cost of* $3500*)*

Run no	Sönmez and Bettemir [10]		Aminbakhsh [14]		This study		%PD
	GASA		DPSO		TLBO		
	Dur. (days)	Cost ($)	Dur. (days)	Cost ($)	Dur. (days)	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 iter.	250		250		250		
NFE	50000		50000		50000		

Table 8 -Average deviations of 63-activity problem from the optimal solution for the models

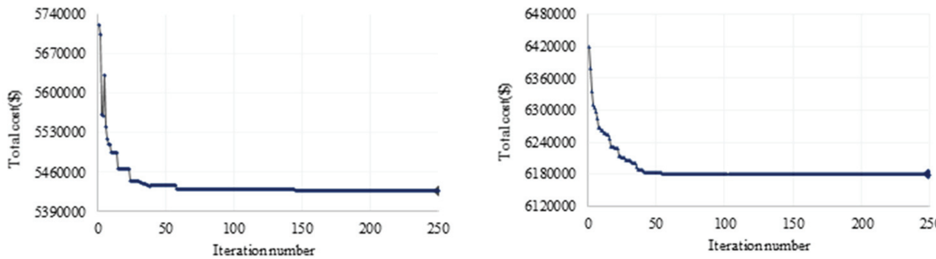
Algorithms	Case 1		Case 2	
	Runs	%APD	Runs	%APD
GA, [10]	10	5.86	10	5.16
HA, [10]	10	2.61	10	2.50
DPSO, [15]	10	0.02	10	0.05
NS-TLBO, [24]	10	0.128	10	0.14
This study	10	0.128	10	0.075

Considering Tables 6-8, the results of the partial random initial population based NS-MTLBO for medium networks indicate that the proposed algorithm normally provides the adequate optimal and near-optimal solutions for the TCTP. Convergence histories of the proposed algorithm for O_1-O_4 indices are illustrated in Figs. 4-7, respectively. Thereby, convergence history graphs indicate that the NS-MTLBO algorithm together with the proposed new initial population concept converges to better solutions much faster than the original TLBO. Also, the convergence of the NS-MTLBO algorithm with O_2 index (40% pre-known +60% randomly generated solutions in the initial population) provides the better solution and a smoothed convergence history (see Fig. 5) for Case 1 and Case 2. The figure illustrates that the implemented generation converges after 150th iteration, which is the optimum value for Case 1. Similarly, it converges the optimum solution after 120th iteration for Case 2.



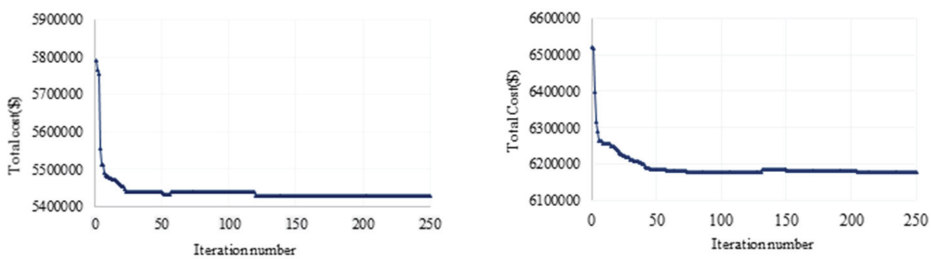
a. Case 1 *b. Case 2*

Fig. 4 - Convergence history of 63-activity TCTP problem with O_1 *index for Case 1 and Case 2*



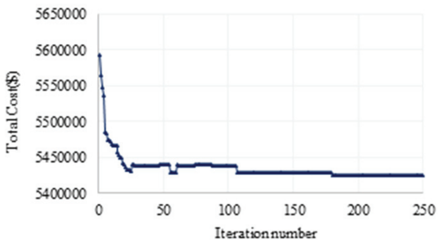
a. Case 1 *b. Case 2*

Fig. 5 - Convergence history of 63-activity TCTP problem with O_2 *index for Case 1 and Case 2*

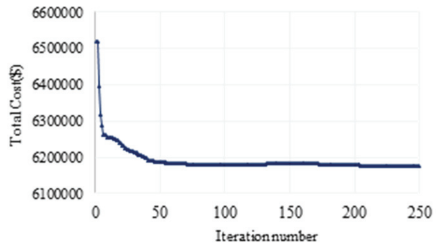


a. Case 1 *b. Case 2*

Fig. 6 - Convergence history of 63-activity TCTP problem with O_3 *index for Case 1 and Case 2*



a. Case 1



b. Case 2

Fig. 7 - Convergence history of 63-activity TCTP problem with O_4 *index for Case 1 and Case 2*

Large-scale test problem

As it is obvious that the study concentrating on the generation of large-scale complex TCTPs involving more activities and modes, would enable a better understanding of the performance of heuristic and metaheuristic methods for real-world projects. To this end, in this section, to further investigate the performance of the proposed algorithm on a large scale 630-activity project adopted from the literature is examined. The model project was formed by duplicating the 63-activity project nine times [31]. In this project, two overhead costs are considered 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 the cost for 630a and 6210 days with $61.761.700 as the cost for 630b were originally provided by Sönmez and Bettemir [10] using the integer programming.

To solve the current problem, it is found out that the best combination of the partial random initial population (O_2) produces an effective solution for the medium scale problem. Therefore, this suitable combination is adopted to solve the large-scale problem as well. To obtain the best Pareto front solutions, ten consecutive experimental runs are implemented on this project. The best results of 10 runs are demonstrated in Tables 11 and 12 for Case 1 and Case 2 along with corresponding %APD from the optima.

Table 9 - The best results for 630-activity project for Case 1 *(indirect cost=$2300/day)*

This study		%PD	Rank	Crowding distance
NS-MTLBO				
Dur. (days)	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

Table 9 - The best results for 630-activity project for Case 1 *(indirect cost=$2300/day) (continue)*

This study		%PD	Rank	Crowding distance
NS-MTLBO				
Dur. (days)	Cost ($)			
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			
Num. of iterations	250	%APD=0.911		
NFE	50000			

Table 10 - The best results for 630-activity project for Case 2 *(indirect cost=$3500/day)*

This study		%PD	Rank	Crowding distance
NS-MTLBO				
Dur. (days)	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			
Num. of iterations	250	%APD=1.49		
NFE	50000			

Comparison of mean values of 10 runs for Case 1 and Case 2 for the previously developed models and the proposed model in this study are presented in Tables 11 and 12, respectively. In addition, Table 13 represents the compared %APD of Case 1 and Case 2 with the previous and basic TLBO algorithms.

Table 11 - Comparison of mean values of 10 runs for Case 1 (: indirect cost =$2300/day)

Results	Bettemir [13]			This study
	NS-GA	NS-ACO	NS-PSO	NS-MTLBO
Mean value	58983147	56703583	54815790	54705438
Pop. size	-	-	-	100
Num. of iteration	-	-	-	250
NFE	250000	250000	250000	50000

Table 12 - Comparison of mean values of 10 runs for Case 2 (: indirect cost =$3500/day)

Results	Bettemir [13]			This study
	NS-GA	NS-ACO	NS-PSO	NS-MTLBO
Mean value	66395840	64574989	63121500	62684849
Pop. size	-	-	-	100
Num. of iteration	-	-	-	250
NFE	250000	250000	250000	50000

Table 13 - Average deviations from the optimal solutions for the cases of 630-activity project

Algorithms	Case 1		Case 2	
	Runs	%APD	Runs	%APD
GA, Bettemir [31]	10	8.83	10	7.50
HA, Sönmez and Bettemir [10]	10	2.41	10	2.47
DPSO, Aminbakhsh [14]	10	0.33	10	0.34
NS-TLBO, Eirgash [24]	10	1.10	10	1.51
This study	10	0.91	10	1.49

Partial random initial population based NS-TLBO algorithm achieved very successful results and outperformed the hybrid genetic algorithm (HA) by Sönmez and Bettemir [10] 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 2.38×10^{42} potential solutions, partial random initial population based NS-MTLBO is able to obtain high quality solutions for the large scale problems. The hybrid algorithm of Sönmez and Bettemir [10] is able to achieve %APD values of 2.41 and 2.47% within 50,000 schedules (number of objective function evaluation).

Performance of TLBO has improved due to the partial random initial population-based modification as observed from the results. It can be commented that applied metaheuristic algorithm (TLBO) could not obtain the global optima in any of trials. However, by searching merely 25,000 solutions out of 1.37×10^{42} potential solutions, proposed algorithm is able to find solutions very close to the optima. The reason for not achieving the global optima can be explained by the complex nature of the problem and premature convergence condition. Therefore, the partial random initial population based NS-MTLBO provides a user-friendly and efficient approach to support the time-cost optimization of medium scale problems. It is worth mentioning that the simplicity of the proposed TLBO algorithm is its most important feature.

6. CONCLUSIONS

Since the previously proposed core NS-MTLBO model was insufficient in solving the large-scale TCTP problems, a new initial population creation approach in NS-MTLBO is developed to further improve the exploration capacity of the core NS-MTLBO model for the TCTPs in this study. If the proposed approach is compared with its former version, the developed model can accelerate the optimization process with a less searching process and enhance the results obtained. However, beside some improvements in the multi-objective optimization process, the proposed model cannot detect the global optima. In contrast, it can identify the satisfactory solutions near-optimum (mostly with less than 7% deviation from the optimal solution) without compromising the quality of the solution. It can be stated that different approaches may be added to the model in order to increase the possibility of catching the global optimum. For further research, some certain recommendations may be done, such as the integration of Levy flight (a random walk) model with the proposed model to systematically surf through the search space to avoid the local minimum. In conclusion, the results obtained from the numerical experiments indicate that the proposed multi-objective model based on NS-MTLBO algorithm including the partial random initial population concept can be preferred as an alternative model in solution of TCTPs.

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