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RESEARCH ARTICLE

Utilizing arithmetic optimization algorithm for optimizing time and cost in construction project

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Abstract

The time-cost trade-off problem (TCTP) presents a significant challenge in construction management, requiring a balance between project duration and associated costs for successful completion. This study evaluates the performance of an arithmetic optimization algorithm (AOA) for solving the TCTP. AOA integrates non-dominated sorting (NDS) to generate Pareto-optimal solutions that address both time and cost objectives. The methodology involves testing the AOA on three case studies representing small- and medium-scale construction projects with 18, 29, and 63 activities. Comparative analyses with traditional metaheuristic algorithms, such as ant colony optimization, genetic algorithms, and particle optimization algorithms, reveal that NDS-AOA delivers competitive results, particularly in smaller projects, that achieve lower costs and faster computation times. However, its effectiveness decreases in medium-scale projects, indicating scalability limitations. Numerical tests suggest that while AOA is well-suited for small to medium projects, it requires further enhancements, such as hybridization with other techniques, to effectively handle larger-scale problems.

1. Introduction

Today, construction projects aim at the efficient use of resources to meet predefined objectives. Time and cost are critical parameters that significantly influence a project's overall efficiency [1]. Construction management entails the supervision of planning, execution, and completion of construction projects within specified timeframes, budgets, and resource limitations [2]. This field involves coordinating various elements of the construction process, including task scheduling, cost control, and resource allocation, such as labour, materials, and equipment [3].

In construction project planning, time-cost trade-off analysis plays a vital role in optimizing schedules by striking a balance between duration and cost. Time-cost trade-off analysis optimizes schedules by balancing project duration and cost and determining the most effective resource distribution to minimize both [4]. The critical path method (CPM) is widely used in construction projects and is primarily designed to identify the critical path of a project, which is the sequence of activities that determines the shortest possible completion time [5]. However, the presence of multiple time and cost options for each activity introduces complexity, leading to the recognition of the multi-objective Time-Cost Trade-Off Problem (TCTP). As the number of activities and options

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increases, decision makers face a more complicated search space for optimal solutions.

Extensive research has been conducted to address TCTP, employing various metaheuristic algorithms. For instance, Sönmez and Bettemir [6] formulated a hybrid strategy that integrates a genetic algorithm (GA), simulated annealing, and quantum simulated annealing techniques to address TCTP. Aminbakhsh and Sönmez [7] presented a particle swarm optimization (PSO)-based method to solve large-scale discrete TCTP, demonstrating superior solution quality and computation time, particularly for medium- and large-scale problems. Ng and Zhang [8] introduced an evolutionary algorithm with a novel ant colony optimization (ACO) algorithm inspired by ant behavior to simultaneously optimize time and cost and achieve superior performance compared to previous methods, and Afshar et al. [9] applied multi-colony ant optimization to resolve 7- and 18-activity TCTP in construction project management scenarios.

In another approach, Eirgash et al. [10] conducted a comparative study involving a Non-Dominated Sorting (NDS)-based Teaching-Learning Optimization (TLBO) algorithm for TCTP, outperforming other existing algorithms. Toğan et al. [11] introduced novel variations of the New Modified Adaptive Weight Approach (nMAWA), an optimization technique that adjusts weights dynamically to improve solution performance. They applied nMAWA using algorithms such as TLBO, Jaya, and Genetic Algorithm (GA), which showed better performance compared to the original Modified Adaptive Weight Approach (MAWA). Furthermore, Toğan et al. [12] evaluated the efficiency of TLBO and its variants, eTLBO and mTLBO, in optimizing TCTP in highway development projects, and showed considerable variations in both project duration and cost across algorithms. Yılmaz and Dede [13] incorporated the NDS approach into the RAO-1 and RAO-2 algorithms to solve TCTPs, yielding better results than several other optimization methods. Moreover, multi-objective approaches that consider additional factors, such as quality, environment, and resources, along with time and cost, have been examined in numerous studies [14-20].

Pham et al. [21] introduced a hybrid optimization model combining the Multi-Verse Optimizer (MVO) with the Sine Cosine Algorithm (SCA), aimed at solving discrete TCTP in construction project management. The model was tested on four discrete TCTP benchmark problems, including two medium-scale (63 activities) and two large-scale (630 activities) instances, revealing that the model outperformed the existing algorithms in optimizing TCTPs for large, complex construction projects. Bettemir and Birgonul [22] proposed a hybrid heuristic meta-heuristic algorithm that integrates a minimum-cost slope-based heuristic network analysis with Differential Evolution, and successfully addressed large-scale discrete TCTPs.

Albayrak [16] introduced a new hybrid algorithm that combines PSO and GA to solve the TCTP, yielding shorter project durations and more cost-effective solutions compared to standard PSO. Patil et al. [23] developed a new TCTP optimization model tailored to retrofitting projects in densely populated regions such as India. This model accounts for several project components, including electrical and structural requirements, and uses Multi-Objective Genetic Algorithms (MOGAs) to identify solutions that balance project duration and cost while meeting the necessary requirements.

While widely used algorithms such as GA, ACO, PSO, and TLBO have been applied to solve TCTP, research on the development of novel metaheuristic algorithms continues to advance. To validate the effectiveness of these algorithms, they are increasingly being tested on real-world construction problems rather than relying solely on benchmark datasets. Abualigah et al. [24] recently introduced the AOA, demonstrating its superior performance compared to eleven other widely recognized optimization algorithms in addressing complex optimization challenges. The AOA has been successfully implemented in various engineering applications, including the design of welded beams, tension/compression springs, pressure vessels, 3-bar trusses, and speed reducers, highlighting its versatility and effectiveness.

Optimization techniques are frequently enhanced by integrating methods, such as the Modified Adaptive Weight Approach (MAWA) and Non-Dominated Sorting (NDS). MAWA consolidates multiple objectives into a single one by allocating weights; however, it often becomes trapped in local optima and yields only one solution. To address this limitation, more efficient and reliable NDS approaches have gained attention, as discussed by Deb et al. [25]. NDS ranks solutions using Pareto dominance and is widely employed in TCTP because of its ability to produce multiple optimal solutions. This approach enables decision makers to select optimal solutions based on their expertise, thereby addressing the limitations of MAWA.

This study extends the AOA by incorporating the NDS method to generate effective Pareto-optimal solutions for TCTP in construction management. The primary goal is to enhance the efficiency and performance of an AOA-based multi-objective optimization framework.

This paper outlines time-cost optimization formulations, details the NDS approach and attributes of the AOA-based optimizer for solving TCTP in construction projects, and tests the performance of the NDS-AOA on benchmark problems to demonstrate its potential in real-world applications.

2. Mathematical Formulation for TCTP

TCTP is framed as a multi-objective optimization challenge, aiming to simultaneously minimize both time and cost by selecting optimal alternatives for each activity. The mathematical representation of the time calculation follows Eqs. (1)-(4).

$$ES_0 = 0 \qquad (1)$$

$$ES_j = \max_{i \epsilon p_j} \{EF_i\} \quad j = 1, \dots, n+1 \qquad (2)$$

$$EF_i = ES_i + \sum_{k=1}^{m} t_i^{(k)} \ x_i^{(k)} \quad i = 0, \dots, n+1 \qquad (3)$$

$$T = EF_{n+1} \qquad (4)$$

where T denotes the total project duration; ES_j and EF_j are the earliest start and finish times of activity j, respectively; p_j refers to the immediate predecessor(s) of activity j; $t_i^{(k)}$ is the duration of activity i for the k-th option; and $xi^{(k)}$ is the binary decision variable for activity i, where $x_i^{(k)} = 1$ if the k-th option is selected, and $x_i^{(k)} = 0$ otherwise. The two dummy activities represent the start (activity 0) and finish (activity n + 1).

The objective of the equations outlined above is to calculate project completion time by determining the longest path within the activity network, also known as the critical path. In parallel, the total cost calculation for the project includes both the direct and indirect costs. Direct costs are associated with individual activities, whereas indirect costs are calculated based on the total project duration, as expressed in Eqs. (5)-(7).

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

$$IC = T \times ICR \qquad (6)$$

$$C = DC + IC \qquad (7)$$

Here, DC refers to the total direct costs and IC represents the total direct and indirect costs of the project. C denotes the overall project cost, which combines the direct and indirect costs. The term $dc_i^{(k)} \ x_i^{(k)}$ captures the direct cost for the k-th option of activity i, whereas ICR denotes the indirect cost rate associated with the project.

This mathematical formulation allows project managers to calculate the total project duration and costs and explore various TCTPs to select the appropriate activity options. The capability of the model to optimize the trade-offs between time and cost is critical in project planning, resource allocation, and minimizing project overruns [10].

3. Multi Objective Optimization

Multi-objective optimization considers multiple competing objectives to determine the optimal solution for a given problem [26]. Unlike single-objective optimization, which focuses on one goal, multi-objective optimization aims to identify Pareto-optimal solutions that represent the best trade-offs between conflicting objectives [27]. This approach is crucial for decision-makers who must balance competing goals in real-world projects, making it an essential tool for informed decision-making. Its applications span various fields and require comprehensive understanding of multiple objectives [28]. The methodologies used range from classical mathematical programming techniques to advanced metaheuristic algorithms, facilitating the exploration of solution spaces to find NDS that offer optimal compromises [25].

3.1. NDS for multi-objective optimization

NDS is a prominent method for solving multi-objective optimization problems. In a two-objective scenario, solution A is said to dominate solution B if it performs no worse on any objective and better on at least one objective [27]. Solutions that are not dominated by any other form the first Pareto front, which is assigned a rank of one. Subsequently, the populations were ranked sequentially (i.e., 2, 3, and 4). NDS plays a crucial role in metaheuristic optimization algorithms such as NSGA and its variants [27]. These algorithms use NDS to guide the search process, ensuring that the population of solutions evolves toward Pareto-optimal solutions in subsequent iterations [29, 30]. Within each Pareto front, solutions are further differentiated using a CD metric, which measures the diversity of solutions by calculating the distance between neighboring solutions on the front. The crowding distance was calculated using Eq. (8) Yilmaz and Dede [13].

$$D_{I_j^m} = D_{I_j^m} + \frac{f_m^{I_{j+1}{}^m} - f_m^{I_{j-1}{}^m}}{f_m{}^{max} - f_m{}^{min}} \tag{8}$$

here I_j denotes the solution index of the j-th population in the sorted population for objective m, while $f_m^{I_{j+1}^m}$ and $f_m^{I_{j-1}^m}$ represent the function values of the next and previous solutions, respectively. The maximum and minimum function values for each objective were also considered when calculating CD, ensuring that the solutions were well distributed across the Pareto front. The CD values were calculated separately for the members in each rank, with the largest and smallest values of each objective in each rank treated as infinite numbers.

4. Arithmetic Optimization Algorithm (AOA)

AOA is a stochastic optimization algorithm developed by Abualigah et al. [24] that utilizes classical arithmetic operators such as addition, subtraction, division, and multiplication to determine the optimal solution for a given problem. By employing these operators within a population-based framework, the AOA initiates the optimization process by randomly generating a set of potential solutions evaluated using a specific objective function. These initial solutions are then iteratively refined through a set of rules based on optimization techniques to discover the optimal solution stochastically. This process is categorized into the exploitation and exploration phases.

4.1. Motivation

Arithmetic is a fundamental component of number theory and is integral to modern mathematics, alongside geometry, algebra, and analysis. Arithmetic operators, multiplication, division, subtraction, and addition are traditional tools used to study numbers and are employed in mathematical optimization to select the best element from a set of candidate alternatives, as demonstrated by Abualigah et al. [24]. Optimization problems are pervasive across quantitative disciplines, including engineering, economics, computer science, operations research, and industry. Continuous enhancement of solution techniques has been a long-standing focus in mathematics.

4.2. Initialization phase

According to Abualigah et al. [24], the optimization process begins with a set of candidate solutions, as shown in matrix X (Eq. 9), which is generated randomly. Thus far, the best candidate solution in each iteration has been considered the best or nearly optimal solution.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,d-1} & x_{1,d} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,d-1} & x_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{n-1,1} & x_{n-1,2} & \cdots & x_{n-1,d-1} & x_{n-1,d-1} \\ x_{n,1} & x_{n,2} & \cdots & x_{n,d-1} & x_{n,d} \end{bmatrix} \tag{9}$$

The search process of the AOA consists of two phases: exploration and exploitation. These phases are executed after defining the math optimizer accelerator (MOA) value for the current iteration, as expressed in Eq. (10).

$$MOA\ (C_{Iter}) = Min + C_{Iter} \times \left(\frac{Max - Min}{M_{Iter}}\right) \quad (10)$$

here $MOA\ (C_{Iter})$ denotes the function value at the t-th iteration, C_{Iter} denotes the current iteration (ranging from 1 to the maximum number of iterations, M_{Iter}). Min and Max denote the minimum and maximum values of the accelerated function, respectively.

When r1 > MOA, we initiate the exploration phase by implementing either M or D. The position updating equation utilized during the exploration phase is presented in Eq.(11), and $r1$ is a random number in the range (0, 1).

4.3. Exploration phase

In the exploration phase, solutions are searched randomly using division and multiplication operators and are updated using Eq. (11).

$$X_{i,j}(C_{Iter} + 1) = \begin{cases} best(x_j) \div (MOP + \varepsilon) \times \left((UB_j - LB_j) \times \mu + LB_j\right) & if\ r2 < 0.5 \\ best(x_j) \times MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right) & \text{otherwise} \end{cases} \quad (11)$$

where $X_i(C_{Iter} + 1)$ denotes the i-th solution in the next iteration, $X_{i,j}(C_{Iter})$ denotes the j-th position of the i-th solution at the current iteration, and best (x_j) is the j-th position in the best-obtained solution so far. ε is a small integer number, and UB_j and LB_j denote the upper and lower bound values of the j-th position, respectively. μ is a control parameter to adjust the search process, fixed at 0.5 in [24]. $r2$ is a random number in the arange (0, 1).

Math optimizer probability (MOP) is a coefficient calculated using Eq. (12).

$$MOP\ (C_{Iter}) = 1 - \frac{C_{Iter}^{\frac{1}{\alpha}}}{M_{Iter}^{\frac{1}{\alpha}}} \quad (12)$$

where $MOP\ (C_{Iter})$ denotes the function value at the i-th iteration, C_{Iter} indicates the current iteration, and M_{Iter} denotes the maximum number of iterations. α is a sensitive parameter that defines the exploitation accuracy over the iterations, fixed at 5 in the source paper [24].

4.4. Exploitation phase

During the exploitation phase, the solutions are further refined using subtraction and addition operators and are updated using Eq. (13).

$$X_{i,j}(C_{Iter} + 1) = \begin{cases} best(x_j) - MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right) & if\ r3 < 0.5 \\ best(x_j) + MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right) & other\ wise \end{cases} \quad (13)$$

In this equation, all notations are consistent with the previous definitions, and $r3$ is a random number in the range (0, 1).

A flowchart of the AOA based on the phases explained above is presented in Fig. 1 [24].

5. Numerical Examples

To demonstrate the effectiveness of the NDS-AOA model in obtaining Pareto front solutions for the TCTP, this study examines small- and medium-scale problems from existing technical literature. The objective is to evaluate the performance of the proposed model in solving real-world TCTP examples, highlighting its applicability and efficiency. The implemented algorithm was coded in Python and executed on a personal computer with an Intel® Core™ i3-3110M CPU (2.40 GHz) and 4GB of RAM. To ensure reliability, 10 consecutive experimental trials were conducted for each instance. The effectiveness of the developed NDS-AOA was evaluated and compared with existing methods in the literature. Assessing an algorithm's performance using the Average Percent Deviation (APD%) from the optimal solution and the Number of Function Evaluations (NFE) provides a comprehensive evaluation. NFE highlights efficiency by showing convergence speed, while APD% emphasizes accuracy by indicating proximity to the optimal solution. Considering both metrics allows the evaluation of the trade-offs between computational cost and solution quality, aiding the identification of the most suitable algorithm for specific applications.

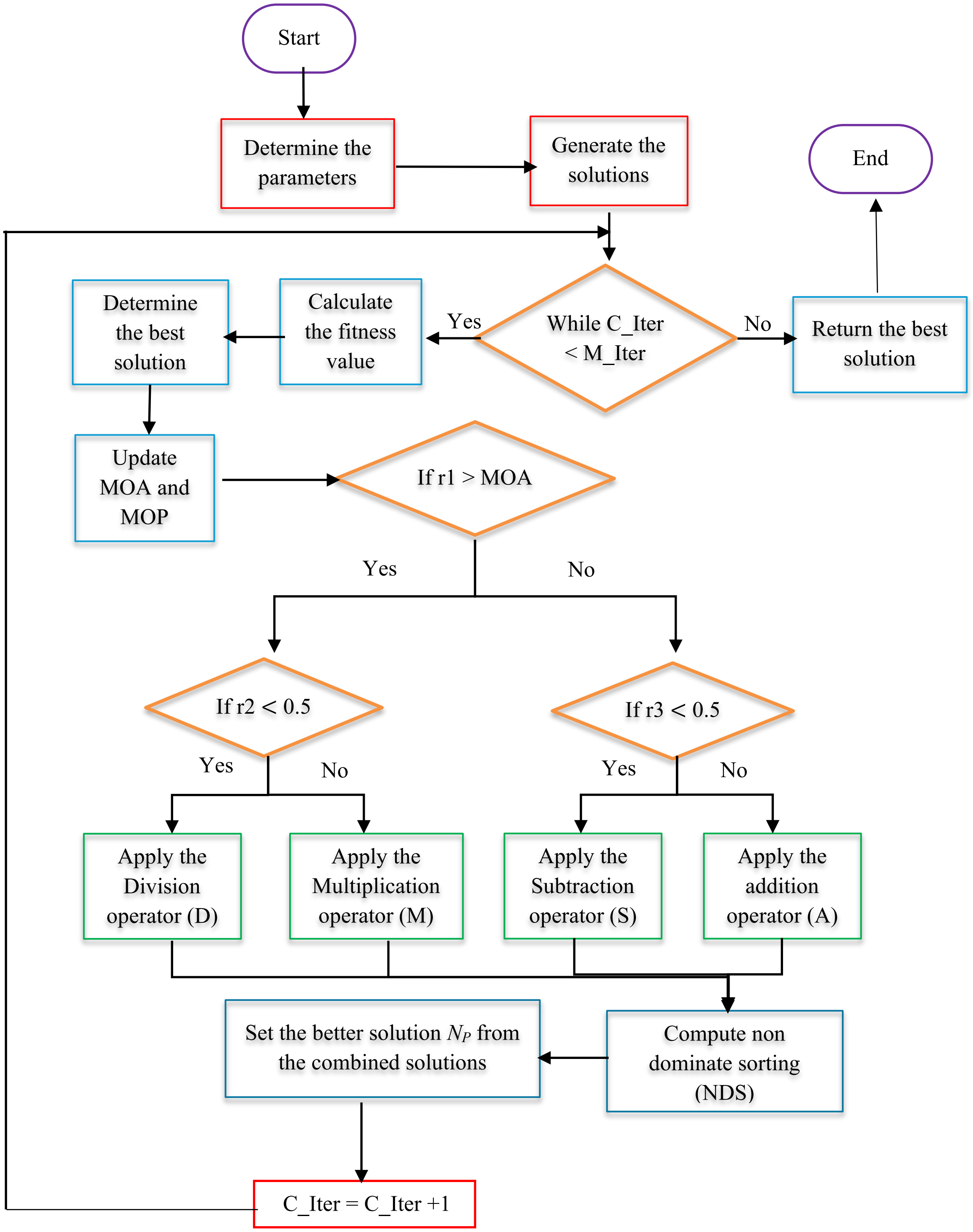

Fig. 1. The flowchart of AOA

5.1. Case study of 18-activity project

This 18-activity example was originally introduced by Feng et al. [31] and incorporates the time-cost alternatives specified by Hegazy [32]. The project includes various construction modes (options) for its activities, with relationships detailed in Table 1 alongside corresponding construction time and cost values. An indirect cost rate of $1,500 per day was adopted. The project comprises one activity with two modes, eleven activities with three modes, two activities with four modes, and five activities with five modes, resulting in a total of 5.90×10^9 possible schedules.

Table 2 summarizes the results obtained from the AOA alongside the performance of six previous metaheuristic algorithms for the 18-activity problem. For a duration of 110 days, the ACS-TCO of Ng and Zhang [8] and ACS of Zhang and Ng [18] provided solutions with higher costs compared to the proposed AOA results. The Pareto front solutions reported for NA-ACO by Afshar et al. [9], PSO by Aminbakhsh and Sönmez [7], TLBO by Eirgash et al. [10], and RAO-2 by Yılmaz and Dede [13] are identical to those obtained by the NDS-AOA method. Notably, the proposed algorithm explores only a small fraction ($3,220/5.90\times10^9$ $=0.0000005\%$) of the solution space, demonstrating a remarkable reduction in the Number of Function Evaluations (NFE) compared to N-ACO by Afshar et al. [9], Aminbakhsh and Sönmez [7], TLBO by Eirgash et al. [10], and RAO-2 by Yılmaz and Dede [13]. This indicates the proposed algorithm's success. Comparing AOA with contemporary methods reveals that NDS-AOA is among the most effective algorithms for Pareto front optimization of complex small-scale TCTPs. Table 3 illustrates the Pareto front along with the selected durations for the corresponding 18 activities, and Fig. 2 shows the Pareto optimal front solution.

Table 1. Options for 18-activities project with five modes

Description		Option 1		Option 2		Option 3		Option 4		Option 5	
Tasks	Precedent activity	Dur (days)	Cost $	Dur	Cost	Dur	Cost	Dur	Cost	Dur	Cost
1	-	14	2,400	15	2,150	16	1,900	21	1,500	24	1,200
2	-	15	3,000	18	2,400	20	1,800	23	1,500	25	1,000
3	-	15	4,500	22	4,000	33	3,200	-	-	-	-
4	-	12	45,000	16	35,000	20	30,000	-	-	-	-
5	1	22	20,000	24	17,500	28	15,000	30	10,000	-	-
6	1	14	40,000	18	32,000	24	18,000	-	-	-	-
7	5	9	30,000	15	24,000	18	22,000	-	-	-	-
8	6	14	220	15	215	16	200	21	208	24	120
9	6	15	300	18	240	20	180	23	150	25	100
10	2, 6	15	450	22	400	33	320	-	-	-	-
11	7, 8	12	450	16	350	20	300	-	-	-	-
12	5, 9, 10	22	2,000	24	1,750	28	1,500	30	1,000	-	-
13	3	14	4,000	18	3,200	24	1,800	-	-	-	-
14	4, 10	9	3,000	15	2,400	18	2,200	-	-	-	-
15	12	12	4,500	16	3,500	-	-	-	-	-	-
16	13, 14	20	3,000	22	2,000	24	1,750	28	1,500	30	1,000
17	11, 14, 15	14	4,000	18	3,200	24	1,800	-	-	-	-
18	16, 17	9	3,000	15	2,400	18	2,200	-	-	-	-

Table 2. Comparison between different algorithms for 18-activity projects

Dur (days)	TCO[8]	ACO[9]	ACS[18]	PSO[7]	TLBO[10]	RAO-2[13]	This study
100	283,320	283,320	285,400	283,320	283,320	283,320	283,320
101	279,820	279,820	282,508	279,820	279,820	279,820	279,820
104	276,320	276,320	277,200	276,320	276,320	276,320	276,320
110	271,320	271,270	273,165	271,270	271,270	271,270	271,270
Pop. Size	10	50	10	80	40	60	20
Number of iterations	200	300	200	100	100	100	80
NFE	2,000	15,000	2,000	8,000	8,040	6,060	3,220
No of runs	1	1	1	10	10	10	10
APD %	0.018	0.000	0.018	0.000	0.000	0.000	0.000

Table 3. Selected options and solutions generated for 18-activity TCTP problems

PF Sol	Time (day)	Cost ($)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	100	283,320	1	5	3	3	3	1	3	5	1	1	2	1	3	3	1	5	1	1
2	101	279,820	1	5	3	3	4	1	3	5	1	1	2	1	3	3	1	5	1	1
3	104	276,320	1	5	3	3	4	2	3	5	1	1	2	1	3	3	1	5	1	1
4	110	271,270	1	5	3	3	4	3	3	5	1	1	3	1	3	3	1	5	1	1

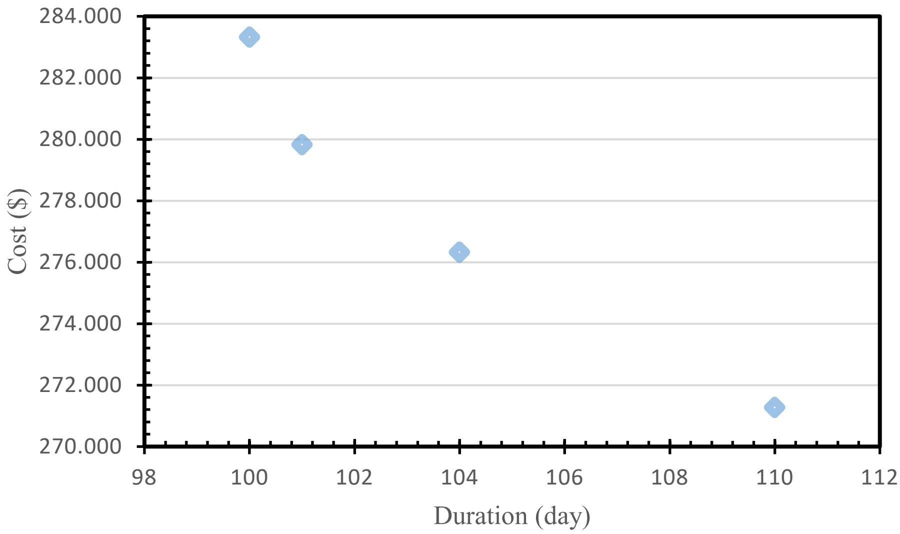

Fig. 2. Pareto fronts optimal solutions of 18-activity problem

5.2. Case study of 29 activity projects

The problem under consideration was originally proposed by Sakellaropoulos and Chassiakos [33] and involves optimizing a highway development project consisting of 29 activities with generalized activity relationships. The project includes six activities with a single option, six with two options, and seventeen with three options, resulting in 8.3×10^9 possible combinations and making the problem highly complex. Toğan et al. [12] addressed this problem using TLBO and its two variants, eTLBO and mTLBO, to account for finish-to-start relationships. In this study, we followed a similar approach to Toğan et al. [12], presenting the logical precedence relationships among activities in Table 4. An indirect cost of $150 per day aligns with prior research assumptions.

As shown in Table 5, we compared the performance of NDS-AOA with TLBO, eTLBO, and mTLBO. The NDS-AOA demonstrated remarkable efficiency by producing a global optimal solution in just one second across 10 generations, using a population size of 20 and 30 iterations.

Table 4. Options for 29-activities project with three modes

	Description		Option 1		Option 2		Option 3	
Act.	Activity description	Preced activity	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)
1	Road excavation	-	5	2,030	4	2,300	-	-
2	Embankment construction	1	8	1,020	7	1,280	6	1,510
3	Subbase and base layers	1, 2	8	1,700	7	1,850	6	2,090
4	Asphalt layer	3	4	590	3	730	-	-
5	Temporary marking and signing	4	2	90		-	-	-
6	Earth and semi-rock excavation	1	4	910	3	1,100	-	-
7	Embankment construction	2, 6	2	250	-	-	-	-
8	Subbase and base layers	7, 3	7	1,490	6	1,650	5	1,830
9	Asphalt layer	4, 8	4	520	3	750	-	-
10	Temporary marking and signing	5, 9	2	90	--	-	-	-
11	Traffic diversion	5, 10	1	50	-	-	-	-
12	Rock excavation	11	8	3,260	7	3,580	6	3,710
13	Main Road, Earth, and semi rock excavation - existing pavement removal	12	5	1,140	4	1,400	3	1,720
14	Main Road, Subgrade stabilization, retaining wall/culvert construction	13	4	300	3	450	-	-
15	Embankment construction	12, 14	8	1,020	6	1,300	5	1,430
16	Drainage layer	15	9	790	8	900	6	1,180
17	Drainage pipe construction	15	13	3,340	12	3,750	11	4,060
18	Electrical ins. at roadway verges	15	9	470	8	650	7	830
19	Planting at roadway verges	15	6	460	5	600	4	810
20	Ditches	17	6	1,280	5	1,430	-	-
21	Subbase layer	20	14	1,090	12	1,320	10	1,560
22	Base layer	21	14	900	11	1,140	9	1,400
23	Median Island (New Jersey)	22	14	2,220	12	2,510	11	2,690
24	Electrical ins. at median island	23	3	230	-	-	-	-
25	Asphalt layer No. 1	23	6	1,590	5	1,790	4	1,990
26	Asphalt layer No. 2	25	10	2,630	9	2930	8	3240
27	Friction course overlay	26	8	2,060	7	2450	6	2660
28	Final marking and signing	27	10	320	9	440	8	610
29	Traffic restoration	28	1	50	-	-	-	-

Table 5. Analysis results of 29-activity TCTP problems (daily indirect cost of $150)

Toğan et al. [12]						This study (AOA)	
TLBO		eTLBO		mTLBO			
Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)	Dur (days)	Cost ($)
135	57,270	132	57,640	133	55,070	133	54,530
144	56,990	143	56,700	138	54,910	138	54,290
145	56,530	145	56,460	141	54,840	139	54,260
148	56,300	149	55,650			143	54,280
Pop. Size		40				20	
Num. of iterations		50				30	
NFE		4,040				1,220	

In contrast, the TLBO model by Toğan et al. [12] utilized larger population sizes of 40 and 50 iterations, resulting in longer computational times. Based on this comparison, NDS-AOA proved to be more efficient and potentially more effective, achieving lower project costs with project durations comparable to those obtained by Toğan et al. [12]. Notably, the NFE in AOA was significantly lower than those reported in previous studies, indicating superior performance in terms of both duration and cost. This reduction in function evaluations implies that AOA requires fewer iterations and computational resources to reach optimal solutions. The Pareto fronts optimal solutions generated by AOA for this case study are presented in Table 6, while Fig. 3 illustrates the Pareto optimal front solutions.

Table 6. Selected options and solutions generated for 29-activity TCTP problem

PF Sol	Dur (days)	Cost ($)	Obtained solution vector
1	133	54,530	2 1 1 3 1 1 1 3 2 1 1 1 1 2 3 1 1 1 1 2 3 3 3 1 1 1 1 3 1
2	138	54,290	1 1 1 3 1 1 1 1 1 1 1 1 1 2 3 1 1 1 1 1 3 3 3 1 1 1 1 3 1
3	139	54,260	1 1 1 3 1 1 1 1 1 1 1 1 1 2 3 1 1 1 1 1 3 3 2 1 1 1 1 3 1
4	143	54,280	1 1 1 3 1 1 1 1 1 1 1 1 1 1 3 1 1 1 1 2 3 3 1 1 1 1 1 1 1

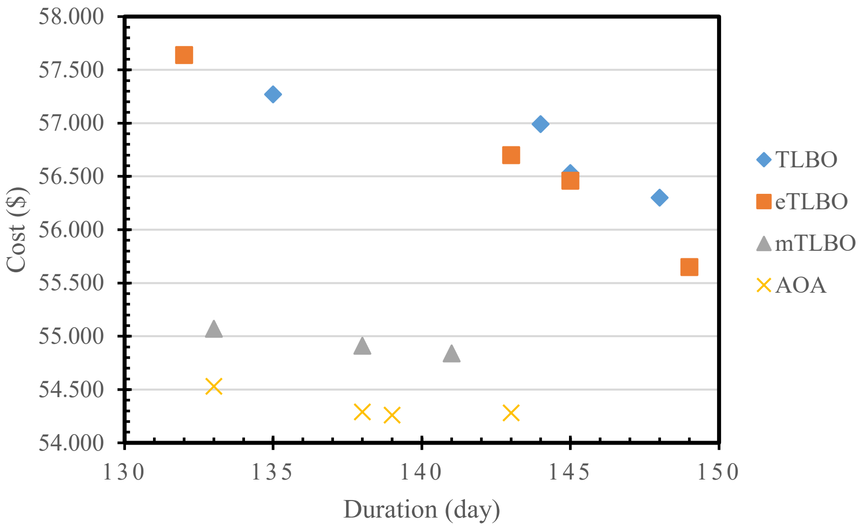

Fig. 3. Pareto optimal solutions of 29-activity problems

5.3. Case study of 63 activity project

A medium-scale construction project comprising 63 activities with five options, proposed by Bettemir [34], was evaluated using the AOA. The time-cost alternatives for this problem are detailed in Table 7. The project includes two activities with three modes, fifteen activities with four modes, and forty-six activities with five modes, resulting in an astonishing 1.4×10^{42} possible time-cost alternatives. Two scenarios were tested: case (63a) with an indirect cost of $2,300 per day, and case (63b) with an indirect cost of $3,500 per day. Bettemir [34] identified the optimal solutions for these scenarios using integer programming, finding that the optimal time and cost for case (63a) were 630 days and $5,421,120, respectively, while for case (63b), the optimal time and cost were 621 days and $6,176,170.

Previous studies have addressed this problem using various metaheuristic approaches. Bettemir [34] applied eight different metaheuristic algorithms, five of which were hybrid models. Aminbakhsh and Sönmez [7] reported Pareto front solutions using the PSO method. Eirgash et al. [10] employed an NDS-based TLBO algorithm to solve the problem, and Yilmaz and Dede [13] utilized RAO algorithms. In this study, we applied the NDS-AOA to both cases (63a) and (63b) and compared the results with those from previous studies using GA, PSO, ACO, TLBO, and RAO-2 algorithms. Each algorithm was tested with ten different runs to ensure a robust comparison. The comparisons for cases (63a) and (63b) are presented in Tables 8 and 9, respectively.

The NDS-AOA approach tested in this study was designed to efficiently explore a limited portion of the solution space. Specifically, AOA searched 65,250 possible different schedules (65,250=250×130×2+250), representing only a minuscule fraction of the total solution space ($65,250/1.4\times10^{42}$). The population size and number of iterations were set to 250 and 130, respectively. The number of function evaluations was limited to 65,250, significantly fewer than in previous studies, resulting in APD values of 0.39% and 0.60% for cases (63a) and (63b), respectively.

As shown in Table 8, the AOA outperformed previous optimization methods, including GA, ACO, PSO [34], TLBO [10], and RAO-2 [13], in terms of the Number of Function Evaluations (NFE). However, the APD values for AOA were slightly higher than those achieved by PSO, TLBO, and RAO-2, indicating that while AOA's solution accuracy remains competitive, it was not the highest for this medium-scale project.

Table 7. Options for 63- activities project with five modes

	Description	Option 1		Option 2		Option 3		Option 4		Option 5	
No	Precedent	Dur (days)	Cost ($)	Dur	Cost ($)	Dur	Cost ($)	Dur	Cost ($)	Dur	Cost ($)
1	-	14	3,700	12	4,250	10	5,400	9	6,250	-	-
2	-	21	11,250	18	14,800	17	16,200	15	19,650	-	-
3	-	24	22,450	22	24,900	19	27,950	17	31,650	-	-
4	-	19	17,800	17	19,400	15	21,600	-	-	-	-
5	-	28	31,180	26	34,200	23	38,250	21	41,400	-	-
6	1	44	54,260	42	58,450	38	63,225	35	68,150	-	-
7	1	39	47,600	36	50,750	33	54,800	30	59,750	-	-
8	2	52	62,140	47	69,700	44	72,600	39	81,750	-	-
9	3	63	72,750	59	79,450	55	86,250	51	91,500	49	99,500
10	4	57	66,500	53	70,250	50	75,800	46	80,750	41	86,450
11	5	63	83,100	59	89,450	55	97,800	50	104,250	45	112,400
12	6	68	75,500	62	82,000	58	87,500	53	91,800	49	965,500
13	7	40	34,250	37	38,500	33	43,950	31	48,750	-	-
14	8	33	52,750	30	58,450	27	63,400	25	66,250	-	-

15	9	47	38,140	40	41,500	35	47,650	32	54,100	-	-
16	9, 10	75	94,600	70	101,250	66	112,750	61	124,500	57	132,850
17	10	60	78,450	55	84,500	49	91,250	47	94,640	-	-
18	10, 11	81	127,150	73	143,250	66	154,600	47	161,900	-	-
19	11	36	82,500	34	94,800	30	101,700	-	-	-	-
20	12	41	48,350	37	53,250	34	59,450	32	66,800	-	-
21	13	64	85,250	60	92,600	57	99,800	53	107,500	49	113,750
22	14	58	74,250	53	79,100	50	86,700	47	91,500	42	97,400
23	15	43	66,450	41	69,800	37	75,800	33	81,400	30	88,450
24	16	66	72,500	62	78,500	58	83,700	53	89,350	49	96,400
25	17	54	66,650	50	70,100	47	74,800	43	79,500	40	86,800
26	18	84	93,500	79	102,500	73	111,250	68	119,750	62	128,500
27	20	67	78,500	60	86,450	57	89,100	56	91,500	53	94,750
28	21	66	85,000	63	89,750	60	92,500	58	96,800	54	100,500
29	22	76	92,700	71	98,500	67	104,600	64	109,900	60	115,600
30	23	34	27,500	32	29,800	29	31,750	27	33,800	26	36,200
31	19, 25	96	145,000	89	154,800	83	168,650	77	179,500	72	189,100
32	26	43	43,150	40	48,300	37	51,450	35	54,600	33	61,450
33	26	52	61,250	49	64,350	44	68,750	41	74,500	38	79,500
34	28, 30	74	89,250	71	93,800	66	99,750	62	105,100	57	114,250
35	24, 27, 29	138	183,000	126	201,500	115	238,000	103	283,750	98	297,500
36	24	54	47,500	49	50,750	42	56,800	38	62,750	33	68,250
37	31	34	22,500	32	24,100	29	26,750	27	29,800	24	31,600
38	32	51	61,250	47	65,800	44	71,250	41	76,500	38	80,400
39	33	67	81,150	61	87,600	57	92,100	52	97,450	49	102,800
40	34	41	45,250	39	48,400	36	51,200	33	54,700	31	58,200
41	35	37	17,500	31	21,200	27	26,850	23	32,300	-	-
42	36	44	36,400	41	39,750	38	42,800	32	48,300	30	50,250
43	36	75	66,800	69	71,200	63	76,400	59	81,300	54	86,200
44	37	82	102,750	76	109,500	70	127,000	66	136,800	63	146,000
45	39	59	847,500	55	91,400	51	101,300	47	126,500	43	142,750
46	39	66	94,250	63	99,500	59	108,250	55	118,500	50	136,000
47	40	54	73,500	51	78,500	47	83,600	44	88,700	41	9,400
48	42	41	36,750	39	39,800	37	43,800	34	48,500	31	53,950
49	38, 41, 44	173	267,500	159	289,700	147	312,000	138	352,500	121	397,750
50	45	101	47,800	74	61,300	63	76,800	49	91,500	-	-
51	46	83	84,600	77	93,650	72	98,500	65	104,600	61	113,200
52	47	31	23,150	28	27,600	26	29,800	24	32,750	21	35,200
53	43, 48	39	31,500	36	34,250	33	37,800	29	41,250	26	44,600
54	49	23	16,500	22	17,800	21	19,750	20	21,200	18	24,300
55	52, 53	29	23,400	27	25,250	26	26,900	24	29,400	22	32,500
56	50, 53	38	41,250	35	44,650	33	47,800	31	51,400	29	55,450
57	51, 54	41	37,800	38	41,250	35	45,600	32	49,750	30	53,400
58	52	24	12,500	22	13,600	20	15,250	18	16,800	16	19,450
59	55	27	34,600	24	37,500	22	41,250	19	46,750	17	50,750
60	56	31	28,500	29	30,500	27	33,250	25	38,000	21	43,800
61	56, 57	29	22,500	27	24,750	25	27,250	22	29,800	20	33,500
62	60	25	38,750	23	41,200	21	44,750	19	49,800	17	51,100
63	61	27	9,500	26	9,700	25	10,100	24	10,800	22	12,700

Table 8. Analysis results of 63a-activity project (daily indirect cost of $2,300)

Sr No	Bettemir [34]						Eirgash et al [10]		Yilmaz and Dede [13]		This study	
	GA		ACO		PSO		TLBO		RAO-2		AOA	
	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)
1	641	5,704,200	635	5,490,120	637	5,421,620	630	5,428,870	633	5,425,370	629	5,445,770
2	661	5,712,485	653	5,494,410	644	5,428,920	630	5,428,120	630	5,426,210	638	5,445,020
3	650	5,722,260	638	5,491,180	651	5,439,620	630	5,427,770	629	5,424,570	648	5,440,170
4	653	5,713,450	657	5,491,620	634	5,422,920	630	5,428,120	633	5,423,020	632	5,443,370
5	645	5,699,650	644	5,494,920	651	5,440,570	630	5,428,920	629	5,423,370	637	5,450,870
6	639	5,684,295	626	5,486,630	633	5,421,320	637	5,428,220	630	5,426,520	652	5,444,660
7	640	5,695,655	664	5,495,080	633	5,421,320	633	5,428,870	630	5,427,020	643	5,437,370
8	621	5,707,600	661	5,490,350	633	5,421,620	628	5,428,170	633	5,422,620	666	5,446,720
9	641	5,693,015	643	5,490,680	633	5,421,320	633	5,428,470	630	5,423,720	658	5,455,720
10	623	5,690,790	635	5,492,210	633	5,421,320	633	5,428,720	632	5,427,730	639	5,418,320
Pop Size		500	500		500		180		200		250	
Num of Iteration		500	500		500		450		700		130	
NFE		250,000	250,000		250,000		162, 180		140,200		65,250	
APD (%)		5.18	1.2		0.09		0.13		0.07		0.39	

Table 9. Analysis results of 63b-activity project (daily indirect cost of $3,500)

Sr No	Bettemir [34]						Eirgash et al [10]		Yilmaz and Dede [13]		This study	
	GA		ACO		PSO		TLBO		RAO-2		AOA	
	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)	Time (day)	Cost ($)
1	617	6,462,580	631	6,219,220	644	6,201,720	612	6,192,140	602	6,185,520	611	6,224,390
2	651	6,411,540	632	6,205,850	629	6,217,470	617	6,184,820	591	6,189,120	627	6,206,270
3	647	6,442,440	626	6,234,520	644	6,210,170	590	6,188,690	589	6,192,880	596	6,215,060
4	639	6,420,500	640	6,223,830	648	6,218,170	588	6,195,910	592	6,185,770	600	6,220,470
5	648	6,447,900	617	6,231,440	649	6,216,020	591	6,191,490	595	6,188,090	618	6,204,360
6	627	6,433,810	627	6,197,070	647	6,207,870	586	6,196,840	621	6,182,220	612	6,221,520
7	618	6,439,240	604	6,247,850	651	6,216,220	592	6,189,140	592	6,185,170	606	6,226,470
8	623	6,449,790	635	6,231,860	649	6,215,420	589	6,199,870	617	6,183,620	631	6,221,970
9	630	6,443,805	623	6,198,650	645	6,208,920	617	6,187,390	616	6,202,590	611	6,225,870
10	629	6,450,065	651	6,262,830	642	6,198,520	616	6,190,570	595	6,195,790	633	6,216,610
Pop Size		500	500		500		180		200		250	
Num of Iteration		500	500		500		450		700		130	
NFE		250,000	250,000		250,000		162, 180		140,200		65,250	
APD (%)		4.1	0.7		0.18		0.14		0.12		0.60	

Figures 4 and 5 provide a graphical representation of the Pareto front solutions, further illustrating AOA's capability to balance the time and cost objectives. The performance of AOA tends to decrease as project size increases, particularly when addressing larger-scale TCTPs. This decline in efficiency is attributed to the increased complexity of the search space as the number of activities and modes grows. Nevertheless, the AOA model demonstrated satisfactory performance for the medium-sized 63-activity problem. Both scenarios (63a) and (63b) confirmed that AOA could efficiently generate Pareto-optimal solutions with competitive results in terms of cost minimization and project duration.

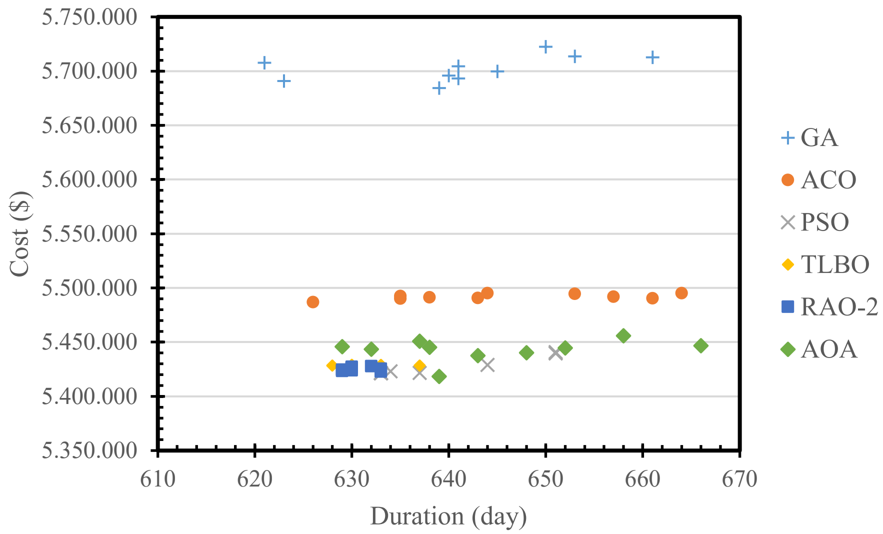

Fig. 4. Pareto front solutions of the 63a problem

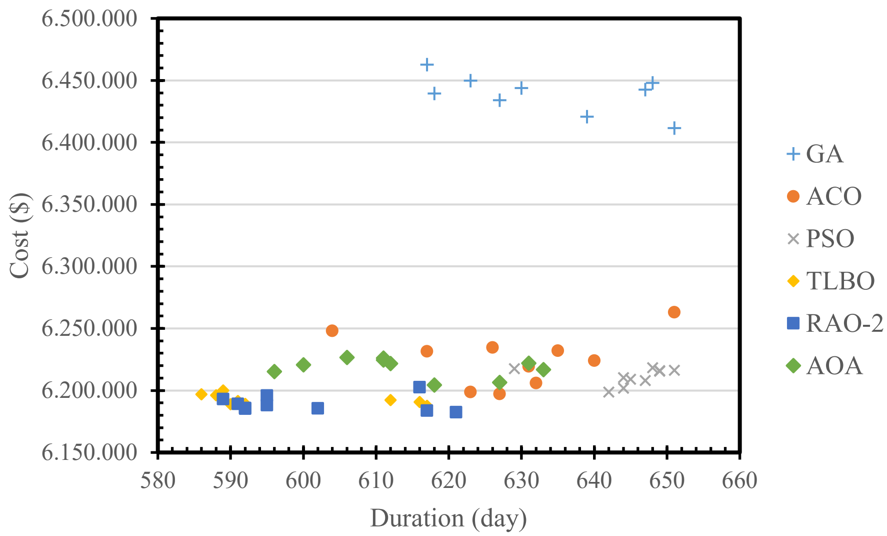

Fig. 5. Pareto front solutions of 63b problem

6. Conclusion

In construction management, optimizing the TCTP is critical for maintaining a competitive advantage in the highly competitive construction sector. Efficiently balancing project duration and cost is essential to meet tight deadlines, reduce overruns, and maximize profitability. This study explored the potential of the newly developed AOA for solving multi-objective optimization problems, specifically focusing on the TCTP. The AOA model was tested across different project scales—comprising 18, 29, and 63 activities—and demonstrated its efficiency in generating Pareto-optimal solutions with fewer function evaluations than many established metaheuristic algorithms.

The results confirmed that AOA is particularly effective in small-scale problems, generating high-quality Pareto front solutions with fewer total function evaluations and lower APD compared to GA, ACO, TLBO, and RAO-2 algorithms. In smaller projects, AOA consistently outperformed these models in terms of both solution quality and computational efficiency. However, as the problem size increased, AOA's performance began to decline, especially in medium-scale projects with 63 activities. In the case of the 63-activity project, AOA was outperformed by more advanced algorithms such as PSO, TLBO, and RAO-2 in terms of Pareto optimality.

This study marks the first successful application of AOA for solving the TCTP in construction management. The results underscore the feasibility and potential of AOA as a viable alternative to other metaheuristic approaches in small-scale projects. Therefore, future research should focus on refining the algorithm's structure and testing its applicability to medium- and large-scale TCTPs. To overcome current limitations, methods such as hybridization with other algorithms, adaptive parameter tuning, improving the exploration-exploitation balance, multi-swarm approaches, problem decomposition, and leveraging parallel computing should be investigated. Incorporating these enhancements is expected to improve the robustness and scalability of AOA for solving TCTPs.

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Author Contributions

A.S. Sulub: Methodology, Investigation, Software, Visualization, Writing - Original draft preparation; F. Mostofi: Methodology, Software, Validation, Writing- Reviewing and Editing; V. Toğan: Conceptualization, Supervision, Validation, Writing- Reviewing and Editing.

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Data Availability Statement

No new data were created or analyzed in this study.

Ethics Committee Permission

Not applicable.

Conflict of Interests

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