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Enhanced multi-objective mountain gazelle optimization via modified adaptive weight approach for construction time-cost trade-off problems

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Abstract: This study presents an enhanced multi-objective Mountain Gazelle Optimizer integrated with a Modified Adaptive Weight Approach (MAWA) to solve construction time-cost trade-off problems. The MAWA mechanism adaptively balances exploration and exploitation, improving convergence and Pareto-front quality. The proposed MAWA-MGO is evaluated using a 19-activity construction project and compared with Multi-Objective Particle Swarm Optimization and plain MGO. Performance is assessed using hypervolume, spread, and a number of function evaluations. Results show that MAWA-MGO achieves the highest hypervolume (0.697) with substantially reduced computational effort (27 % normalized NFE), indicating superior convergence and efficiency while maintaining competitive diversity. Statistical analyses further confirm improved robustness, with lower variability in both project duration and cost. A crowding-distance-based decision-making approach is applied to identify balanced scheduling solutions, demonstrating the practical applicability of the proposed method in construction project management.

Keywords: time-cost-trade-off problems, modified adaptive weight approach, mountain gazelle algorithm, multi-criteria decision-making tool

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Introduction

In today's fast-paced construction industry, there is strong pressure to complete projects on time. Since both time and cost are important, clients and contractors aim to finish projects as scheduled while keeping costs under control. To achieve this, it is necessary to find the best combination of time and cost options, which is known in the literature as the time-cost trade-off problem (Sonmez & Bettemir, 2012).

Time-cost trade-off problem (TCTP) is an important part of managing construction projects. It is of interest to both researchers and practitioners because it is important for both academic studies and real-world projects. Therefore, there is a strong need to improve methods for solving these optimization problems (Dede, 2018).

Methods for solving time-cost trade-off problems can be divided into three main types: mathematical programming models, heuristic models, and metaheuristic global search algorithms. Mathematical programming models (Ateş et al., 2025; Kelly, 1961) often need a lot of computing power, so they are mostly suitable for small projects. Detailed explanations of heuristic methods and mathematical models can be found in Zheng et al. (2005). While these methods have advantages, they also have limits, as they do not always find the best solutions. Also, neither heuristic nor mathematical methods can handle multi-objective time-cost trade-off problems efficiently.

Metaheuristic algorithms, on the other hand, have become popular optimization tools in recent years. They are flexible, can be applied to different kinds of problems, and work well in situations where traditional methods fail. The complex relationship between project time and cost still remains a major challenge for project managers (Albayrak, 2020; Eirgash et al., 2023).

Zheng et al. (2005) examined the 18-activity project with the GA-MAWA method and created 3 different models by differentiating the mutation and selection method parameters. In this way they tried to avoid the problem of local optimization. According to the results, the proposed model was successful in eliminating the drawbacks of traditional heuristic and mathematical approaches. In addition, it was stated that the success level of the model was better when compared with the GA models previously developed.

Eirgash and Dede (2018) employed the Teaching-Learning-Based Optimization (TLBO) algorithm, which is structured around assigning different teachers to various student groups and incorporates an adaptive teaching factor. In their study, the algorithm was integrated with MAWA. When tested on projects comprising of 18 and 63 activities, the model produced successful Pareto front solutions. The results outperformed comparable studies in the literature, achieving global optimum solutions for 18-activity projects and optimal solutions for 63-activity projects.

Similarly, Toğan and Eirgash (2019) introduced the TLBO-MAWA model for optimization and evaluated its performance on projects with 7, 18, and 63 activities. Their findings indicate that the TLBO-based approach consistently delivers effective results and demonstrates notable potential for generating improved solutions. Additionally, the simplicity of the TLBO algorithm is highlighted as a key advantage of the method.

Kumar et al. (2024) formulated a TCTP model for highway projects in India using the NSGA-II algorithm to minimize project time and cost under resource and sequence constraints. The case study confirmed its effectiveness, showing that NSGA-II efficiently generates Pareto-optimal solutions and outperforms traditional methods.

Agarwal et al. (2024) applied the MOPSO algorithm to solve TCTP, demonstrating its ability to produce high-quality Pareto-optimal solutions. Comparative analysis showed MOPSO's superior performance over existing optimization techniques.

In the context of TCTPs, two commonly used solution strategies in the literature are the Non-Dominated Sorting (NDS) method and the Modified Adaptive Weight Approach (MAWA) (Deb et al., 2002; Toğan et al., 2022). Although NDS is effective at generating a diverse set of Pareto-optimal solutions, it can be computationally demanding for large-scale or high-dimensional problems. On the other hand, the MAWA approach is more efficient in terms of computation and helps guide the search toward the most promising areas of the trade-off surface.

Although MAWA has previously been coupled with other metaheuristic algorithms, such as TLBO, Jaya, and GA, its application to MGO and, more importantly, to TCTPs has not been reported in the existing literature (Toğan & Eirgash, 2019; Zheng et al., 2005).

The MGO is particularly well suited for TCTPs due to its population-based search strategy, leader-follower hierarchical structure, and its natural capability to balance diversification and intensification during the optimization process. These characteristics align well with the discrete, nonlinear, and combinatorial nature of TCTPs, where multiple execution modes and precedence constraints must be simultaneously considered.

However, the standard MGO algorithm exhibits certain limitations when applied to complex multi-objective scheduling problems, including premature convergence, sensitivity to fixed weight parameters, and limited adaptability across different stages of the search process. To overcome these shortcomings, this study integrates MAWA into MGO, enabling a dynamic and self-adaptive regulation of objective weights throughout the optimization process.

Therefore, in this study, a multi-objective optimization approach is proposed by combining the MGO algorithm with the MAWA to address TCTPs. The method is applied to a 19-activity project to demonstrate the capability of the MGO algorithm in generating high-quality Pareto-optimal solutions. Several benchmark TCTP instances are evaluated to assess the optimal Pareto fronts, highlighting the effectiveness of the proposed approach.

The performance of the MAWA-MGO model is evaluated using well-established benchmark problems, with its effectiveness measured by its ability to produce approximate Pareto-optimal solutions. The results show that the MAWA-MGO algorithm is satisfactory and competitive, making it a promising tool for solving multi-objective TCTPs. The main contributions of this research are:

- Development of a new multi-objective model that integrates the MGO algorithm with MAWA to efficiently solve TCTPs.
- Use of the Critical Path Method (CPM) for project scheduling to define the time and cost objectives for optimization.

- Demonstration of the proposed algorithm's ability to generate Pareto-front solutions for complex construction planning problems, specifically validated on a 19-activity project.
- Application of Multi-Criteria Decision Making (MCDM) using the Crowding Distance Rank (CDR) mechanism to select well-distributed and non-dominated solutions from the Pareto front.
- Evaluation of the algorithm's performance using key performance metrics, including Hypervolume (HV), Spread (SP), and Number of Function Evaluations (NFE), to assess convergence, diversity, and computational efficiency.

The structure of this paper is organized as follows: Section 2 presents the mathematical formulation of the time-cost optimization problem. Section 3 explains the MAWA approach and the main characteristics of the underlying MGO framework. Section 4 details the implementation of the MAWA-MGO model on selected construction engineering cases, while Section 5 discusses the results and their implications for large-scale project optimization. Figure 1 represents the flowchart of the proposed algorithm.

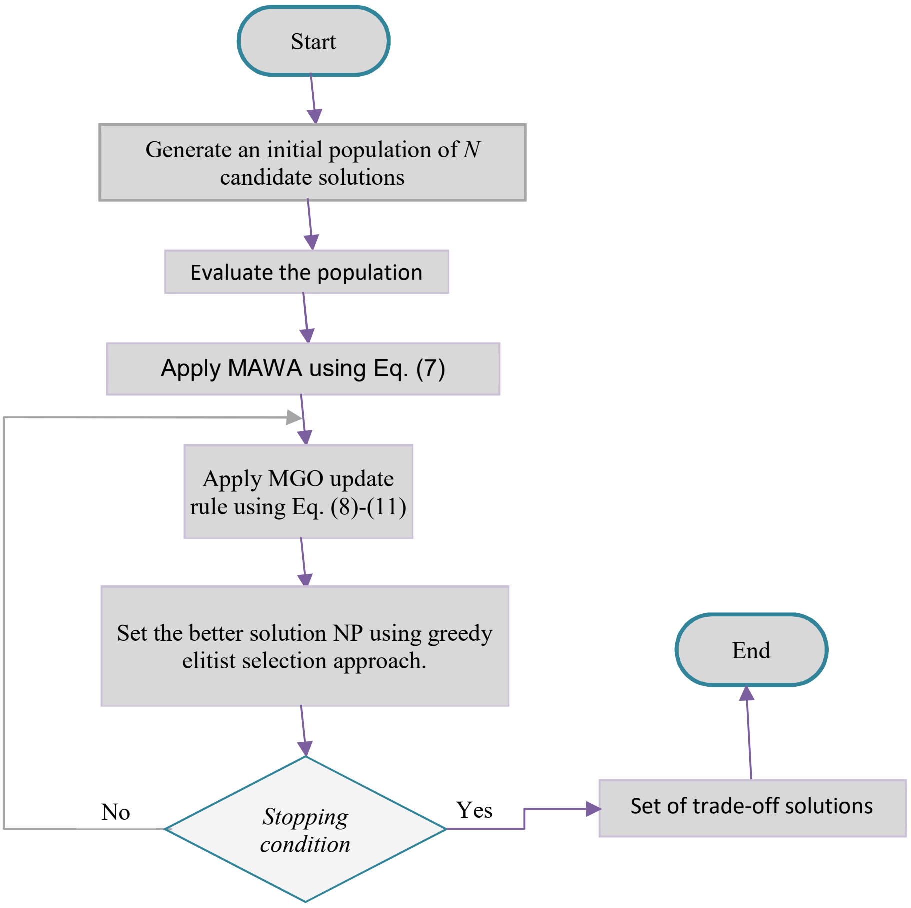

Fig. 1. Flowchart of the MAWA-MGO algorithm for TCTP (*own research*)

1. Mathematical formulation for TCTP problems

The TCTP is a multi-objective optimization model that aims to minimize both the total project duration and the overall project cost. The two objective functions are defined as follows:

Objective 1: Minimizing the project duration (PT)

The total project duration is determined by the longest (critical) path in the project network. The objective function is given by:

$$Min\ PT = (ES_i + d_i),\ \forall i \in CP \tag{1}$$

where PT denotes total project duration; CP – set of critical activity in the project duration; ES_i – earliest start time of activity i; d_i – duration of activity i; n is the total number of critical activities on a given critical path.

Objective 2: Minimizing the project cost (PC)

The total project cost is the sum of the individual activity costs based on selected execution modes:

$$Min\ PC = \sum_{i=1}^{n} cos\ cost_i \tag{2}$$

where PC represents total project cost, $cost_i$ represents the activity cost of activity i for a chosen execution mode, n – total number of activities.

2. Modified Adaptive Weight Approach (MAWA) in multi-objective optimization

The MAWA is a conceptually simple yet computationally efficient method frequently applied to multi-objective optimization problems, particularly the TCTPs often encountered in construction engineering (Eirgash & Dede, 2018). Such problems involve inherently conflicting objectives, necessitating the use of metaheuristic algorithms to effectively explore trade-offs and approximate the Pareto-optimal front. In the MAWA framework, an initial population of candidate solutions is randomly generated within predefined boundaries of the search space and then evaluated using multiple objective functions. To guide the search process and maintain a balance among conflicting objectives, MAWA integrates a dynamic weighting mechanism that adjusts based on the quality of the solutions. As described by Zheng et al. (2004), this adaptive weighting process is governed by four principal conditions, formulated as follows:

1. For $U_t^{max} \neq U_t^{min}$ and $U_c^{max} \neq U_c^{min}$

$$\begin{aligned} v_c &= U_c^{min}/U_c^{max} - U_c^{min} \\ v_t &= U_t^{min}/U_t^{max} - U_t^{min} \\ v &= v_t + v_c \\ w_t &= v_t/v \\ w_c &= v_c/v \end{aligned} \tag{3}$$

2. For $U_t^{max} = U_t^{min}$ and $U_c^{max} = U_c^{min}$

$$w_t = w_c = 0.5 \tag{4}$$

3. For $U_t^{max} = U_t^{min}$ and $U_c^{max} \neq U_c^{min}$

$$\begin{aligned} w_t &= 0.9 \\ w_c &= 0.1 \end{aligned} \tag{5}$$

4. For $U_t^{max} \neq U_t^{min}$ and $U_c^{max} = U_c^{min}$

$$\begin{aligned} w_t &= 0.1 \\ w_c &= 0.9 \end{aligned} \tag{6}$$

In each iteration, U_t^{max} and U_t^{min} denote the maximum and minimum project durations, while U_c^{min} and U_c^{max} represent the maximum and minimum total direct costs. The ratios v_t and v_c are computed as the minimum value divided by the difference between the maximum and minimum values for duration and cost, respectively. The adaptive weights w_c (time) and w_c (cost) dynamically adjust based on the population's performance. According to the MAWA, the fitness of each solution x with objectives U_t (duration) and U_c (cost) is evaluated using adaptive weights v_t and v_c, and a small random term $n \in (0,1)$ is added to prevent division by zero (Zheng et al., 2004).

$$F(x) = W_t \cdot \left(\frac{U_t - U_t^{min} + n)}{U_t^{max} - U_t^{min} + n)}\right) + W_c \cdot \left(\frac{U_c - U_c^{min} + n}{U_c^{max} - U_c^{min} + n}\right) n = 0.001 \tag{7}$$

3. Mountain Gazelle Optimizer (MGO)

Abdollahzadeh et al. (2022) introduced the MGO, a metaheuristic inspired by the hierarchical and social behavior of mountain gazelles. Combining four key mechanisms, MGO maintains a strong balance between exploration and exploitation, effectively solving diverse complex optimization problems. Figure 2 shows its initialization phase.

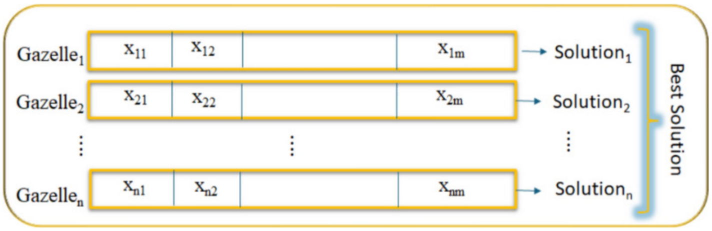

Fig. 2. Initialization of the mountain gazelle optimizer's phases (*own research*)

Similarly, Figure 3 depicts the phases of the MGO algorithm. This diagram outlines the social structure of a population, likely a species like deer or gazelle. It splits into three main groups: bachelor male herds (males living together), maternity herds (females and their young), and territorial solitary males (lone, dominant males).

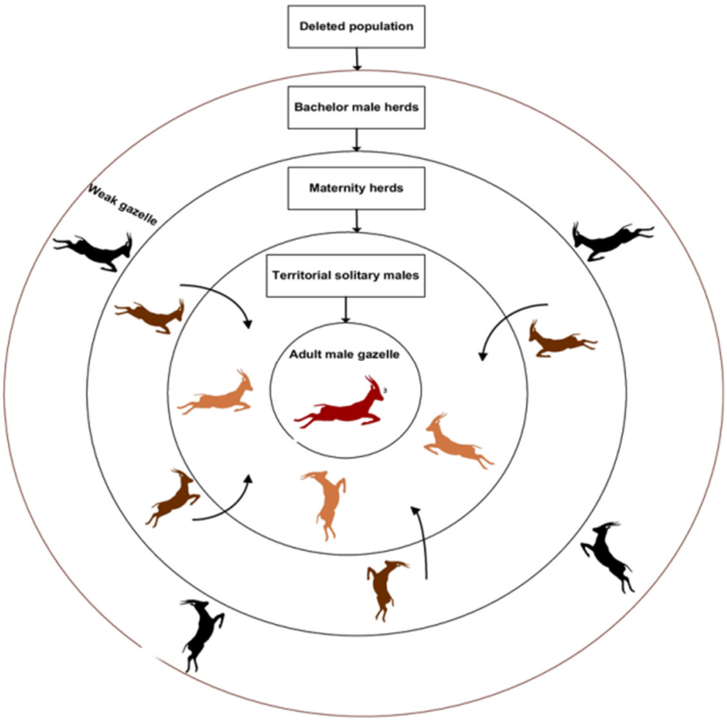

Fig. 3. Visualization of the mountain gazelle optimizer's phases (*own research*)

The paper (Abbassi et al., 2023) proposes a developed Mountain Gazelle Optimizer (MGO) to generate the best values of the unknown parameters of estimation of single- and double-diode photovoltaic cell models PV generation units.

3.1. Mathematical formulation

Let $X(t) = [x_1(t), x_2(t), \dots, x_N(t)]$ represent a population of N gazelles at iteration t, each gazelle corresponding to a candidate solution in a D-dimensional search space. The initial population is randomly generated within the given search boundaries:

$$x_{i,j}(0) = b_l + r_j \cdot (b_u - b_l)$$

Here, b_l and b_u represent the lower and upper bounds of the search space, respectively, while $r_j \in [0,1]$ is a uniformly distributed random variable. This modification significantly influences the update strategies territorial solitary males (TSM), maternity herds (MH), and bachelor male herds (BMH), which are reformulated in equations (8)-(10) to incorporate the variability introduced by chaos-based dynamics. The migration to search for food (MSF) mechanism, however, remains the same as in the original MGO, as shown in equations (11).

$$TSM = male_{gazelle} - \left|\left(ri_1 \cdot BH - ri_2 \cdot X(t)\right) \cdot F\right| \tag{8}$$

$$MH = (BH) + \left(ri_3 \cdot male_{gazelle} - ri_4 \cdot X_{rand}\right) \tag{9}$$

$$BMH = (X(t) - D) + \left(ri_5 \cdot male_{gazelle} - ri_6 \cdot BH\right) \tag{10}$$

$$MSF = (b_u - b_l) \cdot r_7 + b_l \tag{11}$$

4. Numerical example

This study demonstrates the flexibility, efficiency, and effectiveness of the proposed MAWA-MGO model through its application to a real-world case study involving the construction of a three-story building in Delhi, India, as summarized in Table 1. The project comprises 19 activities, each with three alternative execution methods associated with different resource allocations, resulting in varying durations and costs. Table 1 presents the project time (T), measured in **days**, and project cost (C), expressed in **Indian Rupees**, for each alternative prior to construction. The MAWA-MGO-based scheduling model is employed to generate Pareto-optimal solutions for this case study.

Table 2 compares the performance of MOPSO (Agarwal et al., 2024), plain MGO, and the proposed MAWA-MGO on a 19-activity project.

The metrics include project completion time (PCT) and project completion cost (PCC). MAWA-MGO consistently achieves lower or comparable PCT and competitive PCC values, demonstrating its ability to effectively balance both time and cost objectives. Despite using a smaller population size (40) and fewer iterations (130) than MOPSO, MAWA-MGO attains high-quality solutions with significantly fewer function evaluations (5,440 vs. 20,000), highlighting its computational efficiency. These results confirm that integrating the MAWA strategy into MGO improves both the quality and efficiency of project scheduling optimization.

Table 1. Options for 19 activity projects with three modes (*own research*)

Description		Mode 1		Mode 2		Mode 3	
Act. No	Predecessor Act.	T	C	T	C	T	C
1	–	3	1326324	5	1032641	8	923634
2	1	5	1026756	9	914737	9	849627
3	1	14	118404	15	107573	15	103734
4	2, 3	10	1626972	13	1472345	14	1391235
5	1	16	1026756	19	962438	20	923593
6	3, 5	13	117144	14	102312	14	101231
7	5	10	1626972	14	1531267	16	1492451
8	4, 6	7	118404	8	109212	14	92101
9	7, 8	5	1200036	9	1026384	14	885738
10	9	6	1626972	8	1512438	9	1442733
11	9	9	759780	11	683412	12	652846
12	10, 11	20	815964	25	753578	25	713580
13	10, 11	4	180744	5	162358	8	136489
14	12	12	783984	13	732678	15	697896
15	13	18	180744	20	114678	20	101569
16	13, 14	10	783984	12	735675	20	634568
17	16	8	180744	9	163848	12	136385
18	15, 16	11	674952	13	643782	13	618904
19	17, 18	4	66060	5	63321	6	61456

Table 2. Pareto-front solutions of 19 activity TCTP problem (*own research*)

Sol. No	Agarwal et al. (2024)		This study			
	MOPSO		Plain MGO		MAWA-MGO	
	PCT	PCC	PCT	PCC	PCT	PCC
1	124	13653118	114	12858804	110	13131802
2	128	13440491	119	12634927	111	12995830
3	130	13044162	139	12731970	124	13156641
4	132	12976175	123	13391744	128	13043361
5	133	12885800	120	12608784	125	12868925
6	134	12858263	147	12012051	138	12589462
7	136	12842530	120	12608784	116	12782002
8	138	12801272	110	13238207	119	12633846
9	139	12761554	111	13054246	137	12717131
10	141	12539569	113	12926509	136	12963368
NOP	100		40		40	
NOI	200		130		130	
NFE	20000		5440		5440	
NOP – number of populations, NOI – number of iterations, NFE – number of function evaluation						

Figure 4 presents the performance of MOPSO, Plain MGO, and MAWA-MGO over ten runs in terms of Project Completion Time (PCT) and Project Completion Cost (PCC). MOPSO showed a consistent trend, with PCT increasing from 124 to 140 days while PCC decreased from $1.34 \cdot 10^7$ INR to $1.22 \cdot 10^7$ INR, indicating a stable trade-off between time and cost. Plain MGO exhibited high variability, reaching a maximum PCT of 146 days and minimum PCC of $1.20 \cdot 10^7$ INR in Run 6, but a very low PCT of 110 days in Run 8. MAWA-MGO achieved the fastest project time with a minimum PCT of 110 days in Run 1, although its cost performance was less predictable. These results suggest that MAWA-MGO is preferable for minimizing time, Plain MGO can achieve the lowest cost but is unstable, and MOPSO provides the most balanced and reliable trade-off.

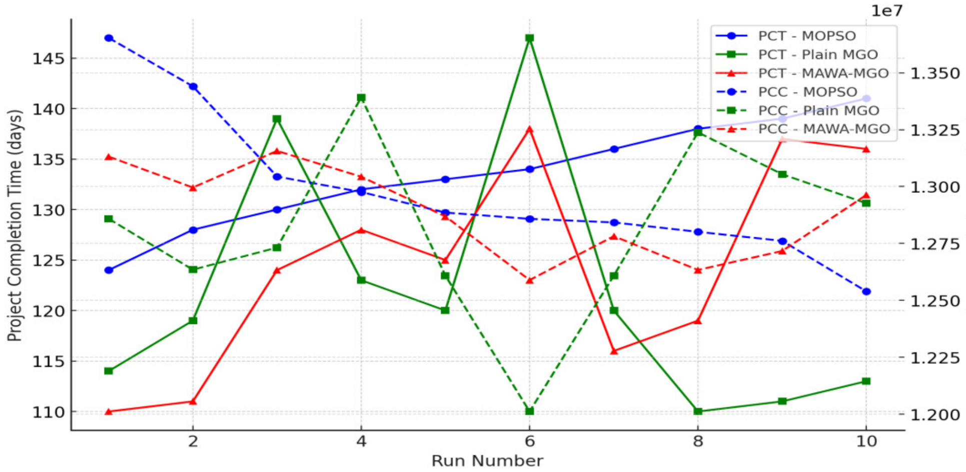

Fig. 4. Represents the comparison of the obtained solutions (*own research*)

4.1. Performance metrics for TCTP problems

In the literature, there is no standardized performance indicator metric to evaluate the performance of multi-objective optimization algorithms. Moreover, evaluating the performance of multi-objective optimization problems is more complex than evaluating single-objective optimization problems. Many quality indicators have been proposed to evaluate the convergence and diversity of these algorithms (Habibi et al., 2017). Therefore, in this study, the Number of Function Evaluations (NFE), Spread (Sp), and Hypervolume (HV) performance indicator metrics were calculated. The performance indicators that each metric indicates are given below:

- Hyper volume (HV): Measures the area covered by Pareto-optimal solutions, higher HV values represent better solutions.
- Spread (Sp): Evaluates the distribution of Pareto-optimal solutions, lower Sp values indicate better solution diversity.
- Number of function evaluations (NFE): Indicates the total number of function evaluations the optimization algorithm was run. A lower NFE value indicates that the result was obtained with fewer searches.

For instance, the graphical depiction in Table 3 and Figure 5 illustrates the performance metrics derived from the 10 Pareto-optimal sets for the 19-activity project using the plain MGO, MAWA-MGO, and MOPSO algorithms. In this scenario, the HV value of 0.697, calculated for MAWA-MGO, indicates that it encompasses a larger portion of the Pareto front solutions compared to the other algorithms. These findings suggest that the MAWA-MGO algorithm offers better distribution and solution diversity for TCTP problems. This enhanced performance can be attributed to the significant influence of the MAWA strategy integrated into the base MGO algorithm.

Table 3. Performance comparison of the proposed models and plain MGO, MAWA-MGO and MOPSO algorithms for the 19 activity project (*own research*)

Algorithms	NPFs	NFE	Sp	HV
MOPSO (Agarwal et al., 2024)	10	1^*	0.912	0.621
MAWA-MGO (this study)	10	0.27	0.778	0.697
Plain MGO (this study)	10	0.27	0.891	0.630
* Normalized values of function evaluation number (NFE)				

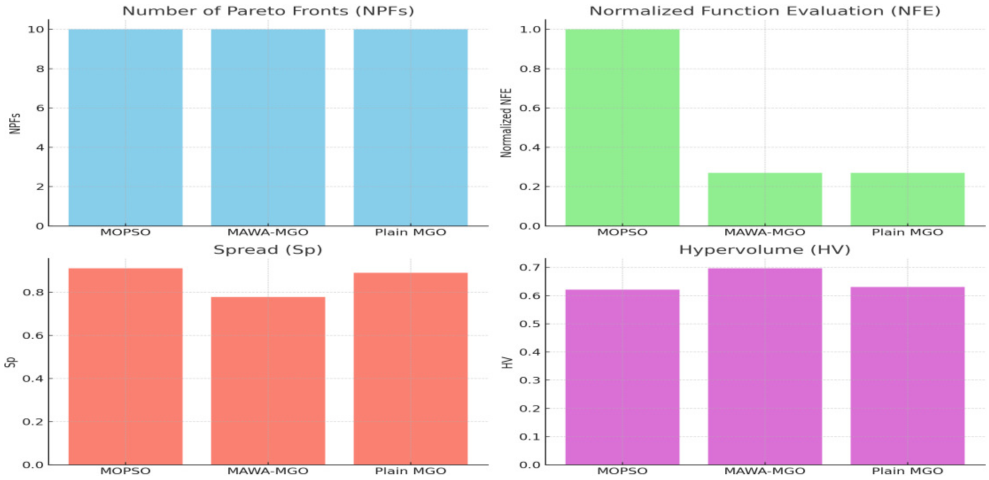

Fig. 5. Graphical representation of the performance metric comparisons for the proposed algorithm with other algorithms for the 19 activity project (*own research*)

Figure 5 presents the comparative performance of MOPSO (Agarwal et al., 2024), Plain MGO, and MAWA-MGO across four metrics: number of Pareto fronts (NPFs), normalized NFE, Sp, and HV. All algorithms produced the same number of Pareto fronts (10). In terms of computational cost, MOPSO required the highest function evaluations (normalized to 100%), whereas both Plain MGO and MAWA-MGO needed only 27% of MOPSO's evaluations, demonstrating significantly higher efficiency. Regarding diversity, MOPSO achieved the largest spread (0.912), while MAWA-MGO had the smallest (0.778). Conversely, MAWA-MGO attained the highest HV (0.697), indicating superior convergence, followed by Plain MGO (0.630) and MOPSO (0.621). Overall, MAWA-MGO achieves a favorable balance between convergence and diversity with substantially reduced computational effort, while MOPSO prioritizes diversity at the expense of computational efficiency.

4.2. Multi-criteria decision making (MCDM)

Table 4 presents three high-performing solutions for the 19-activity project using the Crowding Distance Rank (CDR) mechanism, which preserves diversity along the Pareto front by measuring solution spacing. Higher CDR values indicate less crowded regions. The solution with PCT = 110 days and PCC = 13,131,802 has an infinite CDR, representing a boundary solution, while the next two solutions (PCT = 111, PCC = 12,995,830; PCT = 138, PCC = 12,589,462) have CDR values of 0.971 and 0.897. CDR ranking ensures well-distributed, non-dominated solutions that balance convergence and diversity, effectively capturing the trade-off between project time and cost.

Table 4. Three high-performing solutions for the 19 activity project using CDR mechanism (*own research*)

MAWA-MGO		Crowding distance rank (CDR)	CDR order
PCT	PCC		
110	13,131,802	`Inf (∞)`	1
111	12,995,830	0.971	2
138	12,589,462	0.897	3

4.3. Correlation analysis between PCT and PCC

Table 5 presents the PCT and PCC for the MAWA-MGO algorithm over ten project runs. The results indicate that PCT values range from 110 to 138 days, while PCC values vary between 12,589,462 and 13,156,641 INR. The calculated Pearson correlation coefficient between PCT and PCC is approximately −0.27, suggesting a weak negative correlation. However, the corresponding *p-value* of 0.447 indicates that this correlation is not statistically significant. Overall, these findings imply that, for the MAWA-MGO algorithm, there is no meaningful linear relationship between project duration and cost.

Table 5. Correlation between PCT and PCC (*own research*)

Variable 1	Variable 2	Pearson Correlation Coefficient (r)	*p*-value
PCT	PCC	–0.27, a weak negative correlation, not statistically significant	0.447

4.4. Statistical analysis of the comparison algorithms

Table 6 presents the statistical performance of the compared algorithms for the PCT objective. MAWA-MGO demonstrates **improved stability and robustness** compared to the plain MGO, as indicated by a lower standard deviation and a more consistent median value. Although MOPSO exhibits the highest mean PCT value, it also shows limited competitiveness in terms of overall solution quality. The results confirm that the MAWA mechanism enhances the reliability of the MGO by reducing performance variability while maintaining competitive PCT outcomes.

Table 6. Statistical analysis for PCT (*own research*)

Algorithm	Mean	Std Dev	Min	Median	Max
MOPSO	133.50	5.25	124.00	133.50	141
Plain MGO	121.60	12.20	110.00	119.50	147
MAWA-MGO	124.40	10.43	110.00	124.50	138

Table 7 indicates that the MAWA-MGO achieves more stable and reliable PCC results compared to the competing algorithms, as evidenced by the lowest standard deviation and the close agreement between the mean and median values. This reduced variability demonstrates that the MAWA mechanism effectively improves the robustness and consistency of the MGO, leading to more dependable cost optimization performance across independent runs.

Table 7. Statistical analysis for PCC (*own research*)

Algorithm	Mean	Std Dev	Min	Median	Max
MOPSO	12,980,293	330,908	12,539,569	12,872,031	13,653,118
Plain MGO	12,806,603	387,545	12,012,051	12,795,387	13,391,744
MAWA-MGO	12,888,236	202,091	12,589,462	12,916,146	13,156,641

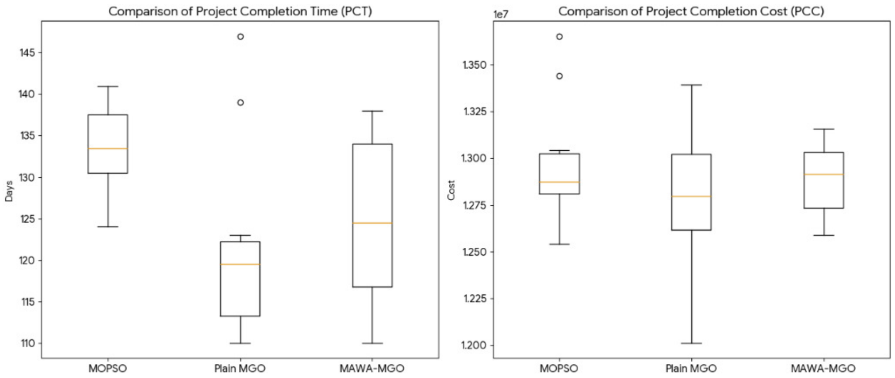

Fig. 6. Box plot for the comparison algorithms (*own research*)

Figure 6 illustrates the box plots of PCT and PCC for MOPSO, The Plain MGO, and MAWA-MGO. MAWA-MGO exhibits a more compact interquartile range for both objectives, indicating greater stability and robustness across runs. While the Plain MGO occasionally achieves lower extreme values, it shows higher variability. The MOPSO demonstrates higher dispersion, particularly in PCT. Overall, MAWA-MGO provides a balanced trade-off between solution quality and consistency for both time and cost objectives.

Conclusion

This study investigated the effectiveness of the proposed MAWA-MGO algorithm for solving construction time-cost trade-off problems. Application to a 19-activity real-world construction project demonstrated that MAWA-MGO consistently generates high-quality Pareto-optimal solutions with a balanced compromise between project completion time and cost. Quantitative results show that MAWA-MGO achieves the highest hypervolume value (0.697), indicating superior convergence, while maintaining competitive diversity ($Sp = 0.778$). In terms of computational efficiency, the proposed approach required only 5,440 function evaluations, corresponding to a 72.8 % reduction compared to MOPSO.

Crowding Distance Rank (CDR) analysis not only ensures well-distributed non--dominated solutions but also serves as an effective decision-making tool by prioritizing solutions based on diversity and spacing. Correlation analysis shows a weak, non-significant relationship between project time and cost, highlighting the algorithm’s multi-objective capability. Overall, MAWA-MGO is an important advancement in construction project scheduling, providing a robust, reliable, and computationally efficient approach while facilitating informed decision-making through CDR.

Despite these promising results, this study has certain limitations. The validation was conducted using a single case study with a limited number of activities, which may restrict the generalizability of the findings. In addition, only time and cost objectives were considered, while other important construction criteria such as resource leveling, quality, environmental impact, and risk were not incorporated. Furthermore, the performance evaluation was limited to a finite number of independent runs and deterministic project data.

Future research should address these limitations by testing the proposed framework on larger and more complex projects, incorporating additional criteria such as quality, environmental impact, risk, and resource utilization, thereby enhancing its applicability to real-world construction project scheduling.

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