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INFLUENCE OF JUMPING RATE ON OPPOSITION-BASED JAYA ALGORITHM FOR DISCRETE TIME COST TRADE-OFF OPTIMIZATION PROBLEMS

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Abstract: This paper aims to develop a new multi-objective optimization algorithm for handling construction time-cost trade-off problems (TCTPs). An intelligent strategy called opposition-based learning (OBL) is incorporated into the Jaya algorithm, resulting in the opposition-based Jaya Algorithm (OBJA). The proposed model introduces an innovative approach to opposition-based optimization by employing an iterative-based varying oppositional jumping rates. This adaptive strategy significantly contributes to increased population diversity and effective avoidance of local optima throughout both the initialization and generational phases of the optimization process. By systematically varying the opposition jumping rate, its impact on the algorithm's convergence speed, solution quality, and computational efficiency are evaluated. The experimental results demonstrate that an iterative-based varying opposition jumping rate significantly enhances OBJA's efficiency to explore and exploit the search space, leading to superior trade-off solutions. Hence, computational experiments on 9 and 19 activity problems reveal that an iterative-based varying opposition jumping rate result in high quality solution with reduced number of function evaluations. Furthermore, the OBJA model proved to be more successful than the non-dominated sorting GA (NSGA-II), multi-objective particle swarm optimzaiton (MOPSO), and plain Jaya algorithm for handling these complex TCTPs in construction project management.

Keywords: Time-cost trade-off problem, Jaya algorithm, Opposition-based learning, Iterative-based varying opposition jumping rate.

Sıçrama Oranının Ayrık Zaman Maliyeti Ödünleşim Optimizasyonu Problemleri için Karşıtlık Tabanlı JAYA Algoritması Üzerindeki Etkisi

Öz: Bu makale, inşaat sektörünün zaman-maliyet ödünleşim problemlerini (ZMÖP) çözmek için yeni bir çok amaçlı optimizasyon modeli geliştirmeyi amaçlamaktadır. Jaya algoritmasına karşıt tabanlı öğrenme (OBL) adı verilen akıllı bir strateji eklenmiş ve sonuç olarak karşıt tabanlı Jaya Algoritması (OBJA) önerilmiştir. OBL, popülasyonun daha iyi başlatılması ve popülasyonun yerel optimuma düşmemesi için nesil sıçrama oranı uygulanmaktadır. Önerilen model, iteratif tabanlı değişken karşıtlık sıçrama oranlarını kullanarak karşıt tabanlı optimizasyona yenilikçi bir yaklaşım sunmaktadır. Bu uyarlamalı strateji, optimizasyon sürecinin hem başlatma hem de nesil aşamalarında popülasyon çeşitliliğini artırmaya ve yerel optimal noktalardan etkili bir şekilde kaçınmaya önemli ölçüde katkıda bulunmaktadır. Karşıt sıçrama oranı sistematik olarak değiştirilerek algoritmanın yakınsama hızı, çözüm kalitesi ve hesaplama verimliliği üzerindeki etkisi değerlendirilmiştir. Deneysel sonuçlar, iteratif tabanlı değişken karşıt sıçrama oranının, OBJA'nın arama alanını arama ve araştırma yeteneğini önemli ölçüde artırarak üstün dengeleme çözümlerine yol açtığını göstermektedir. Bu nedenle, 9 ve 19 aktivite problemine yönelik hesaplamalı deneyler, iteratif tabanlı değişken karşıt sıçrama oranının, daha az fonksiyon değerlendirmesi ile yüksek kaliteli çözümler elde edilmesine neden olduğunu ortaya koymaktadır. Ayrıca, OBJA algoritması, bu

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karmaşık zaman-maliyet ödünleşim optimizasyon problemlerini yapı proje yönetiminde ele alırken NSGA-II, MOPSO ve basit Jaya algoritmasından daha başarılı olduğunu kanıtlamıştır.

Anahtar Kelimeler: Zaman-maliyet ödünleşim problemi, Jaya algoritması; Karşıt tabanlı öğrenme, iteratif tabanlı değişen karşıtlık sıçrama oranı.

1. INTRODUCTION

Multi-objective optimization problems involve finding solutions that balance trade-offs between multiple conflicting objectives. The solutions to the relevant problems are typically non-unique and involve compromises. That means, the simultaneous optimization of trade-off construction projects is a tough task due to the contradictory nature of the objectives. In such problems, improving one aspect, such as reducing the cost, may negatively impact the others, such as increasing the time required or reducing the quality and vice versa (El-Rayes and Kandil, 2005). Thus, the construction manager is expected to perform a trade-off analysis to identify alternatives that optimize the crucial objectives during the planning and scheduling of the project. Furthermore, the balance between project cost and project duration is a common problem in construction industry and is known as TCTPs. For instance, time is the matter of completing the project on schedule, cost is another critical factor and its control is essential for the success of the project (Panwar and Jha 2021).

Upon the literature, it is clear that the solution to trade-off problems have been long lasting challenge to the researchers, despite the advancement of various optimization methods and strategies in other fields aimed at addressing these problems (Tran et al. 2018). Three different approaches are utilized to solve the trade-off problems.

Initially, trade-off problems were addressed employing a combination of analytical and heuristic methods. However, the performance of activities requires the allocation of operational resources such as time and cost along with a variety of discrete alternatives (Vanhoucke and Debels, 2007). Heuristic algorithms, in contrast to mathematical approaches, are frequently applied to sophisticated trade-off problems because of their simplicity and less computational requirements. Nevertheless, the quality of the solutions generated by these algorithms is often uncertain. To overcome these shortcomings, meta-heuristic algorithms (MHAs) have emerged as the preferred methods to tackle the TCTPs more effectively (Panwar and Jha 2021). To evaluate the balance between project duration and project cost in construction project management, numerous research studies using different meta-heuristic techniques have been carried out. For instance, Zheng et al. (2004) introduced the genetic algorithm (GA) to efficiently manage TCTP, showcasing its advantages over earlier models proposed by Feng et al. (1997).

Toğan and Eirgash (2019) introduced the teaching learning based modified adaptive wieght approach (TLBO-MAWA) model for optimization and evaluated its effectiveness on projects with 7, 18, and 63 activities. The model's performance was evaluated on projects with 7, 18, and 63 activities, and the results consistently demonstrated its ability to generate high-quality solutions. One of the notable advantages of the teaching-learning-based optimization (TLBO) algorithm is its simplicity, which contributes to its ease of use and implementation.

Eirgash et al. (2023) presented a new optimization algorithm called modified dynamic oppositional TLBO (MDOLTLBO), which incorporates a modified dynamic oppositional learning strategy with plain TLBO. This algorithm was applied to solve generalized TCTP problems with varying complexities, ranging from 29 to 290 activities. The empirical results demonstrated that MDOLTLBO outperformed both the dynamic oppositional TLBO (DOLTLBO) and plain TLBO algorithms, highlighting its effectiveness in tackling TCTP problems. Pham et al. (2024) proposed a new optimization algorithm called improved multi-verse optimizer (iMVO) for solving TCTP problems in construction projects. This algorithm links multi-verse optimizer with OBL strategy. The effectiveness of iMVO was evaluated on projects with different numbers of activities, ranging from 18 to 290. The results showed that iMVO outperformed previous algorithms in finding high-quality solutions while also being computationally efficient, making it a promising approach for solving TCTP problems.

The application of metaheuristic algorithms to tackle TCTPs has gained significant interest in recent years, offering a promising avenue for more effective problem-solving. These algorithms, including Genetic algorithm (GA, Deb et al. 2002), TLBO (Rao et al., 2011), and Arithmetic optimization algorithm (AOA, Abualigah et al., 2021) which offer suitable solutions for detecting the complex search space. Metaheuristics provide a more flexible approach to solving complicated optimization problems, particularly when dealing with real-world construction projects.

One such algorithm is the Jaya algorithm, which is a metaheuristic optimization technique presented by (Rao, 2016), employs a population-based approach to search for optimal solutions. The Jaya algorithm, despite its simplicity, is a remarkably effective optimization technique capable of addressing both constrained and unconstrained optimization problems (Rao, 2016). However, Jaya's performance can be further enhanced by incorporating additional mechanisms to improve its convergence speed and solution quality.

The Jaya algorithm has been broadly utilized across numerous domains, such as engineering design optimization, manufacturing process optimization, and scheduling problems, owing to its simplicity and efficiency in identifying optimal or near-optimal solutions. Notable applications include structural engineering optimization problems (Sheikholeslami et al., 2017), solving multi-objective engineering design tasks (Kaveh & Dadras, 2017), and manufacturing system optimization (Bhoi et al., 2019). Its versatility makes it a preferred method in both academic research and industrial practices.

Meta-heuristic algorithms are frequently integrated with optimization methods like modified adaptive weight approach (MAWA) and non-dominated sorting (NDS) to improve the outcomes of optimization problems in various domains. MAWA, a traditional approach, combines multiple objective functions into a single one by assigning specific weights to each objective. Nevertheless, its effectiveness diminishes, especially in complex or large-scale problems, as it struggles to efficiently explore the global optimum. To overcome this shortfall, the more robust and efficient NDS approach has become increasingly popular (Deb et al., 2002).

In above-mentioned studies, the generation of the initial population relies purely on randomness. The design variables are then evaluated as per their fitness value and proceed to the next iteration phases. However, due to the random distribution, even individuals with low fitness contribute to the computation, which slows down the process and is undesirable. In contrast, beginning the evolution with high-fitness individuals can accelerate the search for the optimal solution and improve the convergence rate of the algorithms, as noted by (Mahdavi, 2018). To perform this process, strategies like opposite-based learning (OBL) have been proposed (Tizhoosh, 2005). OBL strategically evaluates both the candidate solution and its opposite, recognizing that the opposite solution is presumably nearer to the global optimum compared to a solution produced randomly (Rahnamayan et al., 2007). Motivated by the aforementioned advantages of the OBL, the present study aims to improve the efficiency of solving TCTPs by refining the plain Jaya algorithm. This enhanced approach incorporates an iterative-based varying opposition jumping rate and merges opposition numbers with the Jaya algorithm. By introducing the opposition jumping rate, the algorithm prevents premature convergence to local optima and ensuring a more accurate detection of the search space. As a result, it promotes faster convergence and greater accuracy in locating global optima, particularly in challenging optimization problems.

The primary objective of this study is to fill the current gap in solving multi-objective TCTPs by presenting an optimization algorithm named the opposition-based Jaya Algorithm (OBJA). This algorithm intends to obtain Pareto front solutions with lower NFE values for solving 9 and 19 activity projects. The proposed OBJA algorithm's performance is evaluated against several algorithms available in the literature, including plain Jaya, multi-objective particle swarm optimization (MOPSO, Agarwal et al. 2024), and NSGA-II (Kumar et al. 2024). The experimental results imply that the suggested OBJA algorithm surpasses the comparison algorithms evaluating the scheduling calculations needed. Table 1 summarizes the previous records related to TCTP problems with the year of the relevant problems.

Table 1. An overview of recent trade-off problems application

	Category	Authors, Years	Category	Authors, Years
Authors , Years	TCTPs	*Ghoddousi et al. 2013*	TCTPs	*Elbeltagi et al. 2016*
	TCTPs	*Albayrak, 2020*	TCTPs	*Aminbakhsh and Sonmez, 2016*
	TCTPs	*Eirgash et al., 2023*	TCTPs	*Bettemir and Yücel , 2023*
	TCTPs	*Agarwal et al, 2024*	TCTPs	*Kumar et al., 2024*
	TCQTs	*Sheikh, Kumar, 2020*	TCQTs	*Eirgash et al., 2022*
	TCQTs	*Mahdavi and Mousavi, 2022*	TCQTs	*Tran & Tarigan, 2022*
	TCETs	*Ozcan-Deniz et al., 2012*	TCETs	*Tiwari et al, 2020*
	TCETs	*Banihashemi et al., 2020*	TCETs	*Eirgash et al., 2023*
	TCQETs	*Zheng, 2016*	TCQETs	*Banihashemi and Khalilzadeh, 2020*
	TCQETs	*Huynh et al., 2020*	TCQETs	*Eirgash and Toğan, 2024*
Legend		*Time Cost Trade-off Problems (TCTPs)* *Time Cost Quality Trade-off Problems (TCQTs)* *Time Cost Environmental Impacts Trade-off Problems (TCETs)* *Time-Cost Quality Environmental Impacts Trade-off Problems (TCQETs)*		

The highlights of this study are summarized as follows:

1. OBJA is suggested by augmenting plain Jaya with an iterative-based varying opposition jumping rate to effectively expand the search space.
2. The efficiency of the suggested OBJA is evaluated using 9 and 19 activity construction engineering projects.
3. The project's total duration and its corresponding objectives are obtained using the critical path method (CPM).
4. Number of function evaluations (NFE) is taken into account to evaluate the effectiveness of OBJA against plain Jaya, MOPSO, and NSGA-II algorithms.

The demonstration of this study begins with a presentation of the fundamental formulations for time-cost optimization. Afterward, the opposition jumping rate phase of opposition-based learning technique along with attributes of the employed plain Jaya-based optimizers to solve the TCTP for construction projects is described. To show the efficiency of oppositional Jaya in solving the example problems, construction engineering TCTPs are then evaluated, and eventually, numerical results and conclusions are provided with comparisons.

2. MATERIALS AND METHODS

2.1. Time Cost Trade-off Problems (TCTP)

The trade-off optimization process in construction projects seeks to optimize both project duration and project cost while identifying the optimal solutions that are applicable to all project activities.

2.2. Mathematical formulation for TCTP problems

The minimum total project duration can be expressed as follows in Eq. (1):

$$\textit{Project completion time} = PCT = \sum_{A \in CP} ACT_A \tag{1}$$

Where:

- *PCT* is the activity completion time (*ACT*) in the critical path
- ACT_A is the completion time of the critical path activity (*A*)
- Critical Path (*CP*)

The minimum project cost can be expressed as follows in Eq. (2):

$$\textit{Project completion cost} = PCC = \sum_{A} D.C + I.C \; per\, day \times PCT \; in\, days \tag{2}$$

+ Where:

- *PCC* is the total individual activity completion cost (*ACC*) of the project
- *ACC* includes direct and indirect costs of an activity
- *D.C.* is direct costs (including labor, materials, and equipment costs)
- *I.C* is indirect cost (including overhead and losses)
- $\sum_{A} D.C$ total direct costs of individual project activities

2.3. Jaya Optimization Algorithm

The Jaya is a straightforward but powerful optimization algorithm suggested by (Rao, 2016). The algorithm's name "Jaya" comes from a Sanskrit word meaning "victory" emphasizing the algorithm's objective to always move towards the optimal solution without needing algorithm-specific parameters like crossover or mutation rates used in other evolutionary algorithms. Key characteristics of applied algorithm as follow:

1. Parameter-free: The Jaya algorithm does not require specific algorithmic parameters such as crossover rates or mutation probabilities.
2. Population-based: It uses a population of solutions to detect the search space.
3. Guided by best and worst solutions: In each iteration of the Jaya algorithm, solutions are updated to be closer to the best solution and farther from the worst solution in the current population.

Steps of the Jaya Algorithm

1. Initialization: Randomly create an initial set of potential solutions to start the optimization process.
2. Evaluation: Calculate the objective function value for each candidate solution to determine its fitness.
3. Update Solutions:

- For each candidate solution, solutions are updated to be closer to the best solution and farther from the worst solution within the current population.
- Use the following update formula

$$X_{i,j}^{new} = X_{i,j} + r_1 * (X_{best,j} - |X_{i,j}|) - r_2 * (X_{worst,j} - |X_{i,j}|) \quad (3)$$

where $X_{i,j}$ is the j-th dimension of the i-th candidate solution, $X_{best,j}$ is the j-th dimension of the best solution, $X_{worst,j}$ is the j-th dimension of the worst solution, and $r1$and $r2$ take random values between 0 and 1. $X_{best,j}$ represents the best solution found so far in the population. The purpose of X_{best} is to guide the search process toward better solutions. $X_{worst,j}$ represents the worst solution in the current population. The aim of X_{worst} is to keep solutions away from poor-performing areas in the search space.

4. Selection**:** Evaluate the new solution against the current one and retain the more favorable solution.
5. Termination**:** Continue to repeat steps 2-4 until a stopping criterion is satisfied.

2.4. Oppsition-Based Learning (OBL) for Optimization

Opposition-based learning (OBL, Tizhoosh, 2005) is a type of machine learning technique that aims to accelerate the search process by considering not only the current solution but also its opposite. The principle behind OBL is that the opposite solution often lies in a different region of the search space, potentially leading to faster exploration and discovery of new, promising areas. OBL promotes a wider exploration of the search space by considering alternative solutions, thereby decreasing the chance of converging to suboptimal solutions. The opposite number in the D-dimensional space is depicted in Figure 1: Let us assume $X= (X_1, X_2 \ldots X_D)$ represents a point in an n-dimensional space, where $X_1, X_2 \ldots X_D \in [a_j, b_j]$, and it is expressed as follows:

$$X_j^o = a_j + b_j - X_j, \quad j = 1, \cdots, D \quad (4)$$

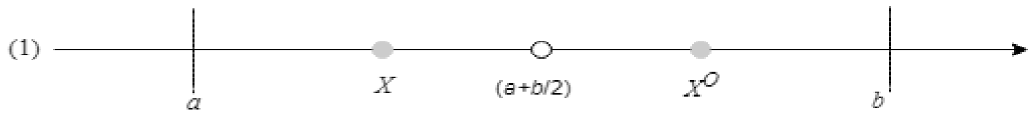


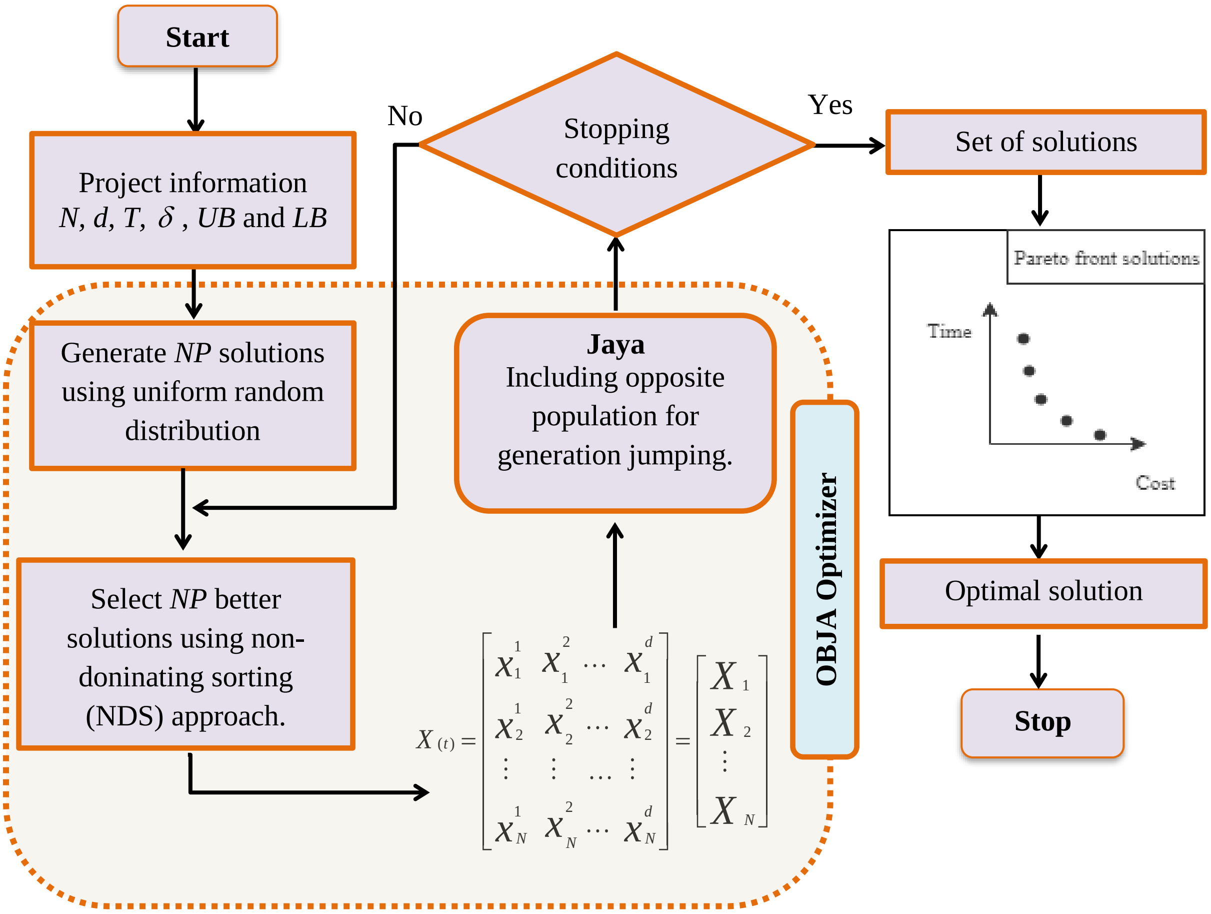
Figure 1:
The original OBL scheme (1D space)

2.4.1. Opposition Based Jumping Rate

When the jumping condition *Jr* is met, the current population is substituted with its opposite solutions. The *Jr* value was set at 0.3 by Rahnamayan et al. (2007), the *Jr* for OBJA algorithm is not set at 0.3. Furthermore, experimental records show that a fixed *Jr* diminishes overall performance; to put it simply, a higher *Jr* value can accelerate convergence to the optimal solution while preserving diverse population (Zhao et al., 2013). Thus, it is beneficial to employ to use a gradually increasing varying opposition *Jr* as the iterations progress. i.e., $Rand\,() \leq -(t/T)^2 + 2(t/T)$.

2.4.2. Using the OBJA to Optimize TCTP Project

This section offers an overview of the OBJA optimizer. The Jaya serves as the core optimization technique within the time-cost optimization model. The NDS approach is employed to choose the top-performing solutions from the combined population. The flowchart illustrating the OBJA algorithm is depicted in Figure 2.



$$X_{(t)} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \cdots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^d \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix}$$

Figure 2:
The overall process of the suggested algorithm (OBJA)

3. NUMERICAL SIMULATIONS APPLICATION

This study considers the distinct trade-off problems of 9 and 19 activity construction projects. More specifically, 9 and 19 activity projects are solved considering time-cost trade-off (TCTP) alternatives with basic FS relationships. The OBJA algorithm was developed using MATLAB (R2024b) and tested on a computer with an Intel (R) Core (TM) i3 CPU operating at 2.40 GHz and 3GB of RAM. The number of iteration is used as the termination condition.

3.1 Empirical example of 9 acitivity project

The project consists of 9 activities, each of which can be executed in one of three modes with a total f 3^9 distinct methods to complete the project. The project is a real case study of highway construction project in Indian context. Table 2 provides a detailed breakdown of each activity, including immediate predecessor, execution modes, activity durations, and costs. Selecting the optimal combination is crucial to meeting project objectives. Furthermore, the project's indirect costs, which represent overheads, are set at 50.000 INR per day, accumulating throughout the project duration.

Table 2. Options for 9 activity project with three modes

Description		Opt 1		Opt 2		Opt 3	
Act.	Predecessor Act.	T	C	T	C	T	C
1	-	6	4543455	8	3994833	10	3745356
2	1	8	489638	10	582245	12	678364
3	2	6	318934	8	415534	9	464321
4	3	26	1501323	30	1682498	35	1923492
5	4	7	482578	10	615853	12	704678
6	5	4	445678	5	475963	8	604568
7	6	5	573940	6	596298	9	718364
8	7	8	23528474	10	22097743	13	19784335
9	8	5	3773844	7	3615342	9	3415836

The performance of OBJA has been evaluated against NSGA-II (Kumar et al., 2024) and the plain Jaya on a 9 activity project, with the simulation outcomes shown in Table 3. OBJA explored 1530 possible schedules (calculated as 30×50+30=1530), which represents only a small portion of the overall search space compared to the comparision algorithm. The lower NFE values demonstrate the performance of the suggested algorithm.

Table 3. Pareto-front solutions for 9 activity TCTPs

Sr. No	Kumar et al. (2024)		(This study)			
	NSGA-II		Plain Jaya		OBJA	
	PCT	PCC	PCT	PCC	PCT	PCC
1	79	35821424	79	34073511	79	33678511
2	82	31365103	82	31775103	82	31365103
3	84	33904393	75	35657864	84	31115626
4	85	33938863	80	32313725	79	33678511
5	86	35863278	82	31365103	86	30957124
6	87	31321566	77	34612133	80	30757618
7	88	33736718	88	31197618	88	31197618
8	89	33554321	77	34612133	77	34227133
9	90	33792950	80	32313725	80	31913725
10	91	32366209	75	36032864	75	35657864
NOP	100		40		30	
NOI	150		50		50	
NFE	15000		2000		1500	
Note: PCT – Project completion time, PCC – Project completion cost, NOP – Number of populations, NOI – Number of iterations						

The visual representation of the Pareto optimal solutions of the comparison algorithms for 9 activity project is demonstrated in Figure 3. It is obvious that the OBJA algorithm provides better Pareto-optimal solutions than NSGA-II and plain Jaya.

The selected option and the solution sorted by project cost for the 9 activity are provided in Table 4. In particular, solution 2 illustrates a more favorable choice if the project manager gives higher priority to the project schedule.

Table 4. Option chosen and solution sorted by project duration and cost for 9 activity

Pareto-front solutions	PCT	PCC	Resource allocation for the associated activity.								
			1	2	3	4	5	6	7	8	9
1	86	30957124	3	1	1	1	1	1	1	3	3
2	75	35657864	1	1	1	1	1	1	1	1	1

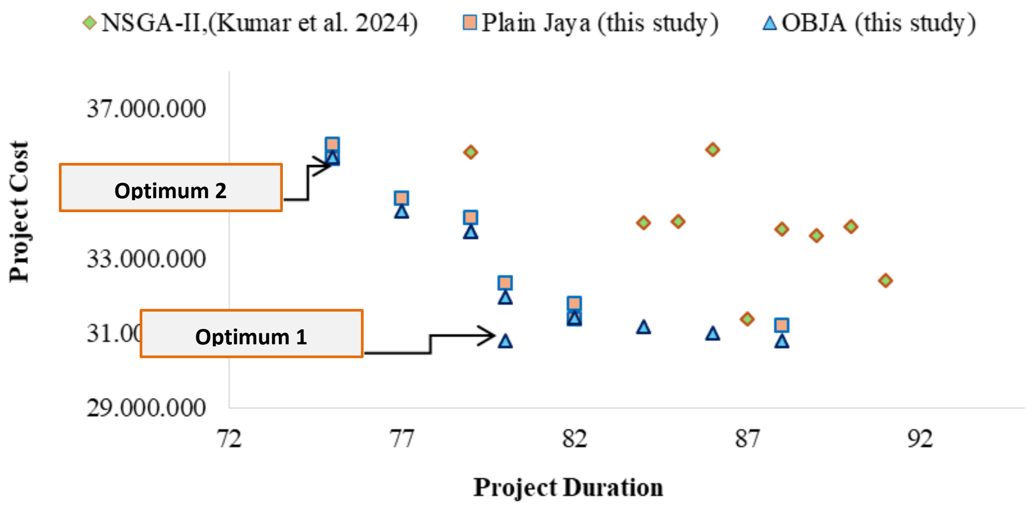


Figure 3:
Pareto front solutions of the comparison algorithms for 9 activity project

According to figure 3, the OBJA optimizer ensures more optimal project duraion and cost values compared to the NSGA-II and the NFE is 1/10th (1500/15000) of the search effort used in NSGA-II algorithm. Morover, 0.076 indicates the exact ratio of the schedule evaluation/search domain. That means, it indicates the flexibility and superiority of the algorithm utilized in the study. This indicates that incorporating the iterative-based varying opposition jumping rate strategy with Jaya algorithm significantly enhances the quality of the solutions produced.

3.2 Empirical example of 19 activity project

The 19 activity project is taken from Agarwal et al. (2024). The case study conducted on a construction project in Delhi, India, illustrates the practical application. and each activity involves three alternative execution methods associated with different resource requirements, durations, and costs. Table 5 provides the initial project time (T) and cost (C) values for each option and activity before construction. Given the 3^{19} potential combinations of task execution methods, a new optimization algorithm is essential for determining the optimal solutions. The OBJA-based scheduling model is employed to obtain Pareto front solutions during the scheduling phase of this particular project.

Table 5. Options for 19 activity project with three modes

Description		Opt 1		Opt 2		Opt 3	
Act. No	Predecessor Activity	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

The performance of OBJA has been evaluated against MOPSO (Agarwal et al., 2024) and the plan Jaya on a 19 activity project, with the simulation outcomes shown in Table 6. An iteration number of 50 and a population size of 40 are considered. Morover, 0.00000172 indicates the exact ratio of the schedule evaluation/search domain. OBJA explored 2040 possible schedules (calculated as 40×50+40=2040), which represents only a small portion of the overall search space compared to the other algorithms. The lower NFE values indicate the effectiveness of the OBJA algorithm. These findings suggest that incorporating the iterative-based varying opposition jumping rate strategy into the Jaya algorithm substantially improves the quality of the generated solutions.

Table 6. Pareto front solutions of 19 activity TCTP problem (ICR = INR 0).

Sr. No	Agarwal et al. (2024)		(This study)			
	MOPSO		Plain Jaya		OBJA	
	PCT	PCC	PCT	PCC	PCT	PCC
1	124	13653118	108	13528648	108	13425485
2	128	13440491	109	13329543	109	13289513
3	130	13044162	110	13238207	110	13131802
4	132	12976175	111	13054246	111	12995830
5	133	12885800	113	12926509	113	12891009
6	134	12858263	114	12858804	114	12859885
7	136	12842530	119	12634927	115	12808579
8	138	12801272	120	12608784	116	12782002
9	139	12761554	147	12012051	119	12633846
10	141	12539569	152	12009610	154	11965455

NOP	100	50	40
NOI	200	50	50
NFE	20000	2500	2000

The visual depiction of the Pareto optimal solutions of the comparison algorithms for 19 activity project is demonstrated in Figure 4. It is obvious that the OBJA with time varying opposition jumping rate algorithm provides the better Pareto-optimal solutions than MOPSO and plain Jaya.

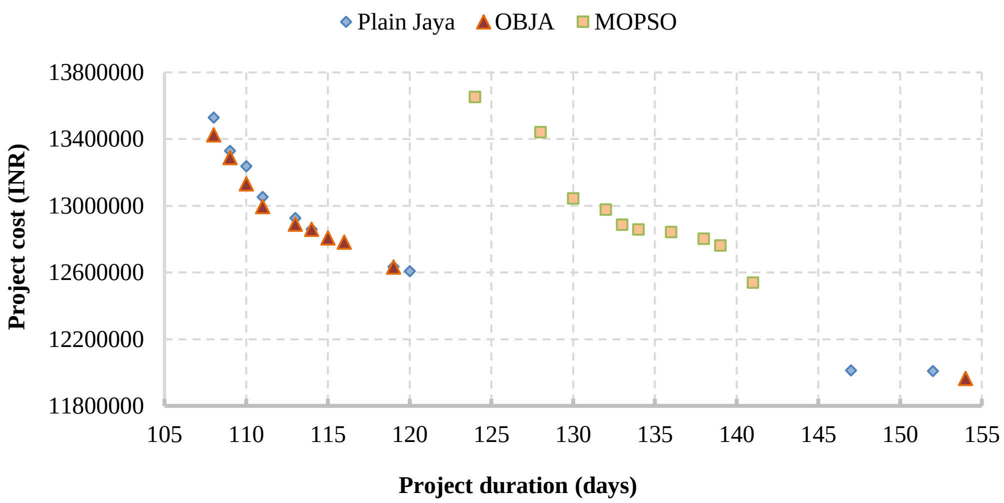


Figure 4:
Pareto front solutions of the comparison algorithms for 19 activity project

4. DISCUSSION

The results demonstrate that the OBJA algorithm effectively finds optimal solutions for both a 9-activity highway construction project and a 19-activity project involving a three-story building in Delhi, India. In the case of the 9-activity highway project, OBJA achieves better project duration and cost values compared to NSGA-II, while requiring only one-tenth of the search effort (NFE of 1500 versus 15000 for NSGA-II). Additionally, the ratio of the schedule evaluation to the search domain is precisely 0.076. Likewise, in the 19-activity building project, OBJA explored 2040 potential schedules (calculated as 40×50+40=2040), covering only a small fraction of the total search domain relative to other benchmark algorithms. This results in fewer objective function evaluations (NFE), demonstrating the computational efficiency of the OBJA algorithm. Overall, the comparison highlights OBJA's capability to achieve superior cost and time outcomes compared to MOPSO, NSGA-II, and plain Jaya. The effectiveness of OBJA is largely due to its iterative-based varying oppositional jumping rate strategy, which incorporates opposite solutions to broaden the search space and prevent the algorithm from getting trapped in suboptimal regions.

5. CONCLUSION

Time cost trade-off optimization problems (TCTPs) are essential in project management, allowing decision-makers to efficiently balance project duration with their related costs. These problems are inherently complex and combinatorial, especially in large-scale projects where numerous activities and modes must be accounted for simultaneously. This innovative multi-objective optimization algorithm leverages the oppositional Jaya algorithm to enhance population initialization, significantly improving diversity and generating high-quality candidate solutions with strong fitness while eliminating less fit solutions. Additionally, OBJA is applied during the generation jumping process to maintain a balance between diversity and convergence.

The projects, comprising 9 and 19 activity construction project with multiple options for each, present a substantial scheduling challenge. Nevertheless, the OBJA optimizer effectively analyzes the various combinations of activity options, taking into account their durations and costs. Consequently, it identifies Pareto optimal solutions that reveal the equilibrium between project duration and project cost, offering decision-makers a wide range of viable options to consider.

A comparison of the NFE is fulfilled to assess the performance of OBJA relative to plain Jaya. Moreover, OBJA demonstrated superior diversity, generated more satisfactory solutions, and outperformed multi-objective evolutionary algorithms like MOPSO, NSGA-II, and plain Jaya in terms of overall satisfaction. The iterative-based varrying opposition jumping rate strategy is responsible for the enhanced performance, which empowers OBJA to discover superior trade-off solutions.

However, the use of OBJA has certain limitations that require attention. This study recognizes that the model's applicability may be limited to specific contexts and suggests the need for broader validation across different types of infrastructure and geographic regions. Future studies should focus on expanding validation efforts through a range of diverse case studies. Furthermore, the paper suggests exploring alternative learning strategies (e.g., reinforcemenet learning) as a potential approach for solving highly complex TCTPs.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

AUTHOR CONTRIBUTION

Mohammad Azim Eirgash: Analysis, interpretation, editing, determining and implementing the modeling process, literature review and writing the article.

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