Journal of Materials and Construction
ISSN 2734-9438
Website: www. jomc.vn

An advanced metaheuristic algorithm for resource leveling optimization in project management

Pham Vu Hong Son[1,2], Dau Thuy Dung[1,2*], Tran Le Anh[1,2], Nguyen Dang Nghiep Trinh[1,2]

[1]Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT)

[2]Vietnam National University Ho Chi Minh City

KEYWORDS

Construction project
Algorithm
Schedule management
Opposition-based learning
Artificial intelligence

ABSTRACT

Resource leveling is a critical method in construction project management, aimed at minimizing resource fluctuations and improving utilization efficiency across project schedules. However, addressing the complexity and high dimensionality of real-world scheduling problems remains a significant challenge. This study introduces an advanced nature-inspired metaheuristic algorithm that integrates mountain gazelle optimizer (MGO) with opposition-based learning (OBL) strategy to enhance resource leveling optimization. The novel approach leverages the demonstrated advantages of MGO and the population diversity benefits of OBL to prevent premature convergence, avoid entrapment in local optima, and improve solution quality. A case study involving two medium-sized construction projects and two resource types is conducted to evaluate the effectiveness of the approach. Experimental results over 30 independent replications show that the hybrid method outperforms all competing algorithms, achieving the best objective value and exhibiting low variability, which indicates superior solution quality and robust stability. These findings underscore the potential of the proposed framework to support efficient and reliable scheduling in construction project environments.

1. Introduction

Effective resource management is a central concern in project scheduling, especially when enterprises undertake multiple projects concurrently and must allocate different resource types across interdependent tasks. In such environments, fluctuations in resource demand frequently result in workload imbalances, idle periods, and productivity losses, all of which increase overall project costs and adversely affect performance. To mitigate these risks, the multi-resource leveling problem (MRLP) has emerged as a critical challenge, aiming to achieve balanced utilization of resources over time while ensuring adherence to project deadlines [1]. However, the combinatorial complexity of MRLP, particularly in multi-project settings, imposes significant computational burdens that surpass the capabilities of traditional scheduling techniques.

Metaheuristic optimization methods have attracted considerable attention as effective tools for addressing complex problems across diverse domains. These approaches are capable of exploring vast search spaces and generating high-quality solutions with reasonable computational effort [2, 3]. Among them, mountain gazelle optimizer (MGO), inspired by the social behavior of wild gazelles, has shown promising performance owing to its well-balanced exploration-exploitation capability [4]. Nevertheless, despite its advantages, MGO remains vulnerable to premature convergence and exhibits limited scalability when applied to high-dimensional and challenging problem settings [5, 6].

To address these limitations, this study proposes an enhanced version of MGO, termed OMGO, which integrates opposition-based learning (OBL) into the original framework. By enhancing solution diversity and reducing the likelihood of entrapment in local optima, the proposed algorithm improves global search capability and delivers more robust results in complex scheduling scenarios. The effectiveness of OMGO is validated through a case study solving MRLP in multi-project environment, thereby highlighting its practical relevance to project management applications.

2. Literature review

The escalating complexity of project environments, particularly in multi-project contexts with shared resources, has intensified the demand for advanced optimization techniques in project scheduling. A substantial body of scholarly literature has explored these challenges through diverse optimization frameworks.

Roca, Pugnaghi, and Libert [7] proposed a genetic algorithm (GA)-based solving mechanism utilizing an elitist strategy for an expanded resource leveling model. This approach effectively characterizes projects by delineating a specific work scope for each resource, with the aim of concurrently optimizing project duration and resource leveling problem (RLP) under constrained conditions. Jun and El-Rayes [8] developed a tripartite modular framework integrated

*Corresponding author: dtdung.sdh241@hcmut.edu.vn
Received 22/09/2025, Revised 07/11/2025, Accepted 10/11/2025
Link DOI: https://doi.org/10.54772/jomc.v15i02.1095

within the microsoft project environment to generate optimal trade-off solutions between project duration and resource utilization efficiency. The model introduced two novel resource leveling metrics designed to minimize resource release-rehire cycles and resource idle time, while concurrently optimizing overall completion time through the multi-objective GA optimizer.

Sayyadi, Esmaeeli, and Hosseinian [9] formulated a comprehensive mathematical model that embraces RLP and multi-project scheduling problem, accounting for resource unavailability during certain periods and budget constraints in real-world scenarios. The authors creatively employed vibration damping optimization (VDO) to identify homogeneous activity communities requiring common resources, thereby preventing scheduling conflicts and minimizing resource consumption. These communities were then used as input for the multi-objective gravitational search algorithm (MOGSA) to optimize the overall schedule. Irvania, Pujiraharjo, and Suharyanto [10] used symbiotic organisms search (SOS) algorithm to compare five objective functions for labor-resource leveling. The sum-of-squared-deviations objective performed best, producing a smoother labor-allocation histogram than the alternatives. Sadeghi et al. [11] introduced a fuzzy multi-objective scheduling model for agricultural water-supply projects that jointly optimizes time, cost, quality, and resource leveling under precedence and resource constraints. The model was solved on real project data using non-dominated sorting genetic algorithm-II (NSGA-II) and multi-objective particle swarm optimization (PSO), and a multi-criteria decision-making method was then applied to select the preferred schedule. The results demonstrate practical trade-off solutions aligned with stakeholder objectives and validate the model's applicability to water-supply organizations.

3. Model development

3.1. Multi-resource leveling problem

Within the multi-project MRLP framework, the central objective is to smooth resource utilization by minimizing variability over time. This is realized by decreasing the deviations between daily and average demand for each resource, with consideration given to their relative significance. The mathematical representation of this formulation is provided as follows:

$$min\, Z = \frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}[w_m(R_m(t) - \overline{R_m})^2] \quad (1)$$

where T denotes the project duration; $R_m(t)$ is the demand of resource m on day t; $\overline{R_m}$ indicates its average demand; and w_m represents the weight factor reflecting the relative importance of resource m.

The formulation is governed by the constraints below:

- Feasible scheduling interval for activities

$$ES_i \le ST_i \le LS_i \quad (2)$$

Eq. (2) ensures that each activity commences within its allowable time window, defined by the earliest start time (ES_i) and latest start time (LS_i).

- Precedence relationships:

$$max(ST_{pset_i} + D_{pset_i}) \le ST_i \le LS_i \quad (3)$$

Eq. (3) guarantees that each activity starts only after the completion of its predecessors, thereby respecting project network dependencies.

- Daily resource demand:

$$R_m(t) = \sum_{n=1}^{N}\sum_{i} R_{mt}(i)\,;\ \overline{R_m} = \frac{1}{T}\sum_{t=1}^{T} R_m(t) \quad (4)$$

$$R_m(t) = \begin{cases} R_m(t), & ST_i < t \le FT_i \\ 0, & t \le ST_i \ or\ t > FT_i \end{cases} \quad (5)$$

Eqs. (4)-(5) define the aggregation of daily demand for each resource across all N projects, where $R_{mt}(i)$ represents the demand of activity i for resource type m on day t.

3.2. Opposition-based mountain gazelle optimizer

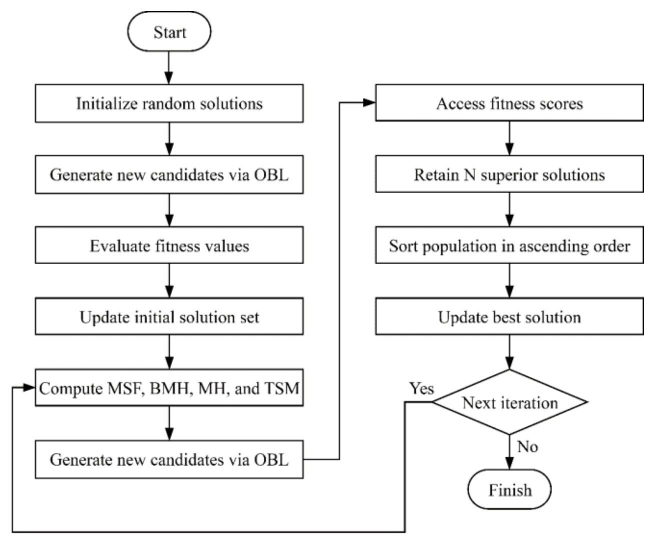

Figure 1. Process diagram of OMGO algorithm.

MGO has recently been proposed as a promising metaheuristic for global optimization, inspired by the social hierarchy and behavioral patterns of wild gazelles. Its underlying mathematical model captures essential natural phenomena and has demonstrated strong performance across diverse benchmark functions [4]. Nevertheless, as with many population-based algorithms, MGO is prone to premature convergence during early iterations, particularly when applied to high-dimensional search spaces. This premature convergence often reduces solution diversity, thereby limiting the likelihood of escaping local optima and delaying the discovery of superior solutions.

An improved variant of MGO is introduced by incorporating OBL mechanism. The core idea of OBL is to simultaneously evaluate candidate solutions and their corresponding opposites, thereby broadening the exploration space and increasing the likelihood of identifying high-quality solutions. This integration enables the algorithm to avoid stagnation around local optima while maintaining an effective convergence rate. In addition, the adoption of OBL enhances population diversity and strengthens the robustness of the algorithm. A flowchart illustrating the operational steps of OMGO is provided in Figure 1.

4. Computational experiment

The effectiveness of the proposed approach is examined through a case study of two medium-sized construction projects conducted simultaneously and characterized by complex precedence relationships, with data referenced from the research work of Tran et al. [1]. Each activity requires two types of resources (R1 and R2) along with fixed durations. To reflect their relative importance, weights are assigned to the two resources, with $w_1 = 0.7$ for R1 and $w_2 = 0.3$ for R2. Table 1 summarizes the activity data applied in this case study, in which activities 2-21 correspond to Project 1, activities 22-36 correspond to Project 2, and activity 1 serves as a dummy node linking the two independent projects into a unified project network.

Resource leveling model is employed as a primary optimization strategy to balance resource utilization and reduce excessive demand in construction projects. By rescheduling tasks within their allowable float times, the approach enhances resource allocation while ensuring compliance with project deadlines. The optimized start times of non-critical activities are reported in Table 2, while Figure 2 provides a visual comparison of resource utilization before and after leveling. As shown, the maximum daily demand for R1 is reduced from 48 to 34 workers, and for R2 it decreases from 32 to 23 units, thus mitigating peak requirements and promoting a more balanced allocation across the project duration. Collectively, these results highlight the effectiveness of OMGO algorithm in achieving a smoother and more uniform distribution of resources, thereby underscoring its practical value for multi-resource planning in complex multi-project settings.

Through 30 independent runs, the results in Table 3 confirm that OMGO consistently outperforms other advanced algorithms. It attains a best objective value of 24.894 and a mean of 25.598, both surpassing competing methods, while maintaining a relatively small variation across runs. In addition, its worst-case performance is also highly competitive with the best results achieved by alternative approaches. Overall, these outcomes emphasize OMGO's ability to provide high-quality solutions with notable stability and robustness, thereby reinforcing its reliability for tackling complex RLPs.

Table 1. Project information.

Activity	Duration	Predecessors	R1	R2	ES	LS
1	0	-	0	0	0	0
2	3	1	3	3	0	20
3	5	2	3	4	3	23
4	4	3	8	6	8	28
5	2	4	9	5	12	32
6	6	1	2	5	0	0
7	6	6	12	3	6	6
8	5	7	12	4	12	12
9	8	8, 14	12	2	17	17
10	9	9, 15, 19	2	5	25	25
11	10	5, 10	12	5	34	34
12	6	11, 21	8	3	44	44
13	4	6	8	4	6	7
14	6	13	7	4	10	11
15	3	8, 14	4	8	17	22
16	4	9, 15, 19	10	2	25	39
17	4	16	12	3	29	43
18	3	17	6	3	33	47
19	5	8, 14	6	2	17	20
20	6	19	15	2	22	35
21	3	20	8	5	28	41
22	6	1	3	5	0	3

Activity	Duration	Predecessors	R1	R2	ES	LS
23	2	22, 31	2	4	6	29
24	5	23	2	4	8	31
25	4	24	3	4	13	36
26	5	24	4	2	13	45
27	9	22, 31	6	4	6	9
28	12	27	2	6	15	18
29	10	28, 33	2	8	27	30
30	10	25, 29	6	2	37	40
31	5	1	2	6	0	4
32	7	22, 31	4	6	6	17
33	6	32	3	4	13	24
34	5	31	2	4	5	34
35	7	34	4	4	10	39
36	4	35	4	8	17	46

Table 2. Optimal start times for non-critical activities obtained by OMGO.

Activity	2	3	4	5	13	14	15	16	17	18	19	20
ST_i	0	3	28	32	6	10	17	31	43	47	20	25
Activity	21	23	24	25	26	31	32	33	34	35	36	
ST_i	35	12	22	34	38	0	16	23	5	38	46	

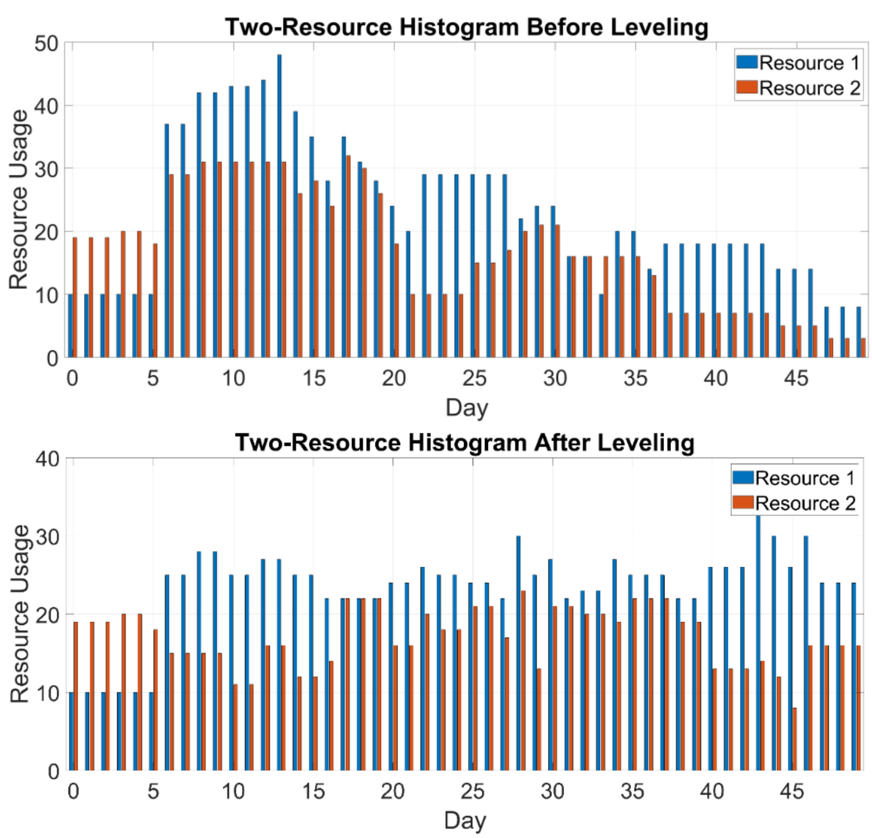

Figure 2. Resource utilization before and after leveling using OMGO.

Table 3. Comparative performance of different algorithms.

Measure	GA [1]	PSO [1]	SOS [1]	FFBI [1]	MCO	OMGO
Best	33.983	33.651	33.299	33.299	27.650	24.894
Mean	35.006	34.886	34.390	33.502	28.111	25.598
Worst	38.355	38.355	35.471	34.159	29.234	26.070
Std.	1.411	1.279	0.559	0.249	0.236	0.233

5. Conclusion

This study introduces an enhanced metaheuristic algorithm that integrates OBL into the baseline MGO to solve the MRLP in multi-project environments. By broadening the search space and improving population diversity, OMGO effectively mitigates premature convergence and enhances solution quality. The case study results demonstrate its effectiveness in reducing peak resource demands, achieving smoother allocation, and outperforming established metaheuristics in terms of accuracy, stability, and convergence. Overall, the findings underscore OMGO's practical value as a reliable and efficient optimization tool for complex scheduling tasks in construction project management.

Despite these positive results, the study's scope is narrow in terms of portfolio size and resource diversity, which limits its external validity for larger and more heterogeneous settings. The scheduling dataset assumes fixed activity durations and a single objective that minimizes squared day-to-day deviations. Therefore, the model does not represent uncertainty in activity durations, explicit cost components, or multi-objective trade-offs. Future research will extend the evaluation to larger multi-project portfolios with richer resource taxonomies and more varied precedence structures. It will also incorporate stochastic activity durations through uncertainty-aware formulations, embed explicit cost and workforce policies to reflect budget constraints, and develop multi-objective variants that explore Pareto trade-offs among leveling quality, time, and cost.

Acknowledgements

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

References

[1]. Tran, D.H., Le, H.Q.P., Nguyen, N.T., Le, T.T. (2024). Robust forensic-based investigation algorithm for resource leveling in multiple projects. *Scientia Iranica*, 31(7): 603-618.

[2]. Bianchi, L., Dorigo, M., Gambardella, L.M., Gutjahr, W.J. (2009). A survey on metaheuristics for stochastic combinatorial optimization. *Natural Computing*, 8(2): 239-287.

[3]. Harita, M., Wong, A., Suppi, R., Rexachs, D., Luque, E. (2024). A metaheuristic search algorithm based on sampling and clustering. *IEEE Access*, 12: 15493-15508.

[4]. Abdollahzadeh, B., Gharehchopogh, F.S., Khodadadi, N., Mirjalili, S. (2022). Mountain Gazelle Optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems. *Advances in Engineering Software*, 174: 103282.

[5]. Sarangi, P., Mohapatra, P. (2023). Evolved opposition-based mountain gazelle optimizer to solve optimization problems. *Journal of King Saud University-Computer and Information Sciences*, 35(10): 101812.

[6]. Pham, V.H.S., Nguyen Dang, N.T., Nguyen, V.N. (2025). Optimizing constrained engineering optimization problems using improved mountain gazelle optimizer. *Applied Computational Intelligence and Soft Computing*, 2025(1): 1922567.

[7]. Roca, J., Pugnaghi, E., Libert, G. (2008). Solving an extended resource leveling problem with multi-objective evolutionary algorithms. *International Journal of Computational Intelligence*, 4(4): 289-300.

[8]. Jun, D.H., El-Rayes, K. (2011). Multiobjective optimization of resource leveling and allocation during construction scheduling. *Journal of construction engineering and management*, 137(12): 1080-1088.

[9]. Sayyadi, A., Esmaeeli, H., Hosseinian, A.H. (2022). A community detection approach for the resource leveling problem in a multi-project scheduling environment. *Computers & Industrial Engineering*, 169: 108202.

[10]. Irvania, A., Pujiraharjo, A., Suharyanto, A. (2024). Resource leveling optimization using different objective functions on building project. *ASTONJADRO*, 13(1): 182-191.

[11]. Sadeghi, R., Heidari, A., Zahedi, F., Khordehbinan, M.W., Khalilzadeh, M. (2023). Application of NSGA-II and fuzzy TOPSIS to time-cost-quality trade-off resource leveling for scheduling an agricultural water supply project. *International Journal of Environmental Science and Technology*, 20(10): 10633-10660.