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Optimization of the Time-Cost-Quality Trade-Off in the Context of the Haftkel Dam Construction Project

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A B S T R A C T

In recent years, the increasing complexity of project implementation, the competitive nature of the business environment, and the constraints on organizational resources have heightened the importance of project management in achieving project objectives. Consequently, during the execution phases of projects, clients seek to enhance quality, reduce execution time and costs, and minimize risks, which constitute their primary goals. This study focuses on optimizing the components of the project management "survival triangle"—time, cost, and quality—in civil engineering projects, specifically through a case study of the Sartiuk Haftkel Reservoir Dam. For this purpose, a genetic algorithm was employed. Optimization was carried out in three separate scenarios, each targeting one of the elements of the survival triangle, and finally, a composite optimization was conducted that considered all three elements simultaneously. The coding related to objective functions and optimization algorithms was performed using MATLAB software. The results indicate the satisfactory performance of the genetic algorithm. Furthermore, for quality index optimization, the genetic algorithm yielded the best optimal solution, and in the composite optimization considering all indices simultaneously, it again provided the most effective result.

Keywords: *Optimization, Time, Cost, Quality, Sartiuk Haftkel Reservoir Dam*

1. Introduction

The increasing complexity of modern construction and infrastructure projects, alongside escalating competition and limited resources, has intensified the need for optimized management of key project components—namely time, cost, quality, and risk. These elements, often referred to as the "survival triangle" of project management, must be balanced strategically to ensure successful project delivery. Optimization in this context is no longer a luxury but a necessity, particularly for large-scale civil engineering projects where even marginal improvements in scheduling, budgeting, or quality assurance can lead to significant economic and operational advantages (Liu, 2024). As the demand for integrated decision-making grows, advanced computational methods, such as genetic algorithms and artificial intelligence, have emerged as powerful tools for multi-objective optimization in construction management.

The time-cost-quality-risk trade-off challenge has attracted considerable scholarly and industrial attention.

Traditional approaches often failed to address the inherent complexity and interdependency of these project parameters, especially under uncertainty. Genetic algorithms (GAs), inspired by the process of natural selection, have proven particularly effective in construction scheduling due to their capability to search large solution spaces and avoid local optima. Studies such as those by Feng et al. (Feng et al., 1997) and Hegazy (Hegazy, 1999) demonstrate the applicability of GAs in construction time-cost trade-off analysis, underscoring their adaptability in handling nonlinear, multi-constraint problems. Likewise, Que (Que, 2002) emphasized the importance of incorporating practical constraints into GA-based models, highlighting how algorithmic modifications can enhance the feasibility of real-world applications.

More recent works have extended these models by integrating intelligent systems. For example, the research by Daisy et al. (Daisy et al., 2004) introduced a multi-objective GA framework that effectively balances time and cost, serving as a precursor to later hybridized methods that incorporate neural networks and fuzzy logic. Building on this evolution, Sadeghi Askari and Soleimani Amiri (Sadeghi Askari & Soleimani Amiri, 2019) proposed an intelligent activity-based costing model, combining genetic algorithms with neural networks to increase accuracy in resource allocation. This integration aligns with broader trends in smart project management, where predictive analytics and machine learning are reshaping decision-support tools (Khalimonchuk, 2024).

Optimization is also central to supply chain and manufacturing systems, as shown in Cui et al.'s (Cui et al., 2023) cost and robust control strategy for dynamic supply chains. The relevance of these models transcends industries, indicating that optimization frameworks developed for one domain—such as supply chains—can inform methods in construction project planning. Similarly, Derpich (Derpich, 2024) explored multimodal transportation optimization with a focus on cost reduction and CO_2 emissions, suggesting the compatibility of environmental and economic objectives in large-scale infrastructure projects. These insights are valuable for dam construction and related ventures, where sustainability and operational efficiency are interwoven.

In the context of uncertainty and variability, Roth et al. (Roth et al., 2022) addressed tolerance-cost optimization by accounting for sampling-induced uncertainties—an approach with strong parallels in construction, where material variability, environmental conditions, and human factors contribute to execution risk. Their framework underscores the importance of probabilistic modeling, which is similarly advocated by Zahraie and Tavakolan (Zahraie & Tavakolan, 2009) in their study of stochastic time-cost-resource optimization using nondominated sorting genetic algorithms (NSGA) and discrete fuzzy sets. Such methods enhance the robustness of project planning by offering multiple Pareto-optimal solutions under uncertainty.

While many studies focus on cost and time, incorporating quality and risk into optimization frameworks remains a critical step toward holistic project evaluation. Liang Yang et al. (Liang Yang et al., 2022) presented a preventive maintenance strategy that considers energy efficiency and quality costs, reflecting how broader metrics such as system resilience and long-term performance must be included in optimization criteria. This comprehensive perspective is mirrored in Gu's (Gu, 2022) research on supply chain cost optimization in the dairy industry, where service quality plays a significant role alongside operational expenses.

Another crucial development in this field is the application of hybrid intelligent systems that combine genetic algorithms with other machine learning models. Nezamoddini et al. (Nezamoddini et al., 2020) proposed a risk-based optimization framework for integrated supply chains using genetic algorithms and artificial neural networks. Their methodology offers an adaptable architecture that can be extended to infrastructure projects where multi-criteria risk assessments are essential. Similarly, Mumali and Kałkowska (Mumali & Kałkowska, 2024) explored intelligent manufacturing process selection by merging artificial neural networks, fuzzy logic, and genetic algorithms—an approach that demonstrates the promise of combining heuristic and learning-based models in complex optimization problems.

In the realm of construction-specific AI integration, Liu (Liu, 2024) demonstrated how artificial intelligence tools, including machine learning algorithms and data-driven models, can be employed to optimize both costs and schedules in building construction. These tools facilitate real-time decision-making, enhance predictive capabilities, and allow for the dynamic adjustment of project variables. Importantly, AI models also improve the interpretability of optimization outputs, enabling project managers to make informed decisions grounded in data rather than intuition alone.

A unified insight across the literature is the increasing use of convergence performance analysis to assess the reliability and efficiency of different optimization algorithms. For example, convergence graphs comparing algorithms such as

Simulated Annealing (SA), Tabu Search (TS), and Cuckoo Optimization often reveal that genetic algorithms outperform others in both speed and precision (Daisy et al., 2004; Feng et al., 1997; Que, 2002). Moreover, the robustness of GAs is evident in multi-scenario analysis, where time, cost, quality, and risk are treated both independently and simultaneously. This capability aligns with real-world demands where trade-offs are not merely linear or isolated but interdependent and dynamic.

In light of these findings, this study adopts a multi-scenario optimization approach for the Sartiuk Haftkel Reservoir Dam construction project. Using genetic algorithms as the core technique, the study seeks to separately and jointly optimize the project's time, cost, quality, and risk factors.

2. Methods and Materials

To evaluate the designed algorithm, an actual technical case from practical projects was utilized, and risk-related data were added to it in this study. Five different scenarios were implemented for the target problem. In four of these scenarios, each of the factors—time, cost, quality, and risk—was optimized separately. In the final scenario, all four factors were considered simultaneously. The objective function value for each case is calculated as follows:

Case 1: Time Optimization

In this case, the objective function is defined as the total duration required to complete all activities. This value, which corresponds to the finish time of the last activity, is calculated considering the precedence relationships among activities and is denoted by *T*.

Case 2: Cost Optimization

In this case, the objective function is the total cost incurred for completing all activities. This value is calculated simply by summing the individual costs of each activity and is denoted by *C*.

Case 3: Quality Optimization

In this case, the objective function is the total effective quality of all activities. To compute this, the effective quality of each activity on the entire project is first calculated by multiplying the impact percentage by the quality score of the respective activity. Then, the resulting values are summed and denoted by *Q*.

Case 4: Risk Optimization

In this case (similar to Case 3), the objective function is the total effective risk of all activities. To compute this, the effective risk of each activity on the overall project is first determined by multiplying the impact percentage by the corresponding risk score of the activity. The resulting values are then summed and denoted by *R*.

Case 5: Simultaneous Optimization of Time, Cost, Quality, and Risk

In this case, the objective function is computed using Equation 1:

Equation (1):

$$F(x) = \frac{T - T_{min}}{T_{max} - T_{min}} + \frac{C - C_{min}}{C_{max} - C_{min}} + \frac{R - R_{min}}{R_{max} - R_{min}} + \frac{Q_{min} - Q}{Q_{max} - Q_{min}}$$

In the above equation, *T*, *C*, *Q*, and *R* represent the total time, cost, quality, and risk of implementing the project for a given solution or execution method. The first component represents the duration, the second component the cost, the third the quality (as a decreasing value), and the fourth the risk, all of which are used to compute the objective function value for each solution. Since the units of measurement for the survival triangle components differ, the values are normalized to range between zero and one based on the above formula, making them dimensionless and therefore comparable and summable.

In this study's technical case, the minimum time (T_min) and maximum time (T_max) are 478 and 745 days, respectively. The minimum cost (C_min) and maximum cost (C_max) are 531,272,672,006 IRR and 880,236,020,693 IRR, respectively. The minimum quality (Q_min) and maximum quality (Q_max) are 62 and 98, respectively. The minimum risk (R_min) and maximum risk (R_max) are 0.25 and 0.44, respectively.

3. Findings and Results

The individual objective functions were considered as the optimization of cost, time, risk, and quality in such a way that during each optimization process, only one of the above-mentioned functions was minimized or maximized. The number of optimization variables in each scenario was 23, corresponding to 23 rows from a typical bill of quantities for earth dams. Table 1 shows the optimization results for Scenario 1 (time) using various algorithms. The table also reports the percentage error or deviation relative to the best solution provided by the top-performing algorithms in this scenario, which were BOA, HHO, and GA.

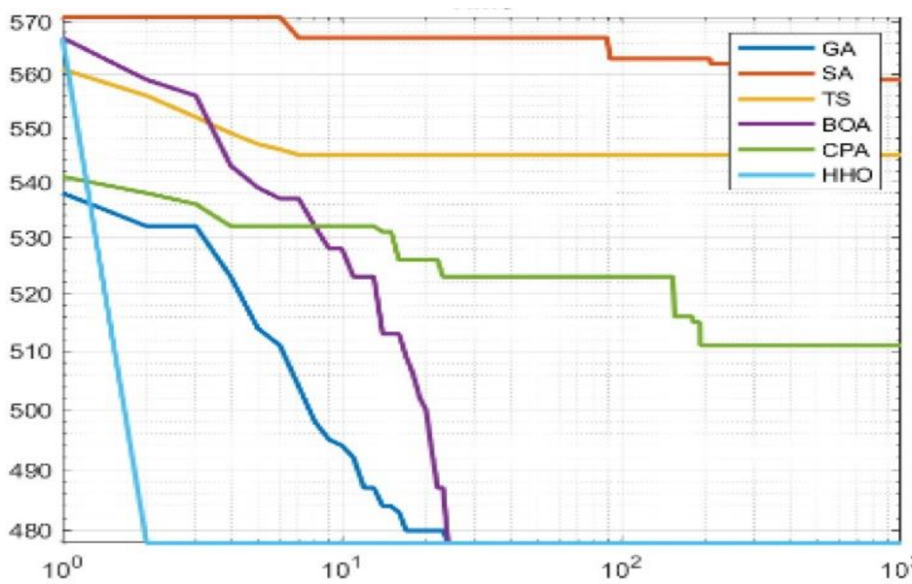
Table 1

Results of Various Algorithms for Scenario 1 (Time Optimization)

Algorithm	Time	Error (%)
GA	478	0
SA	559	0.169456
TS	545	0.140167
BOA	478	0
CPA	511	0.069038
HHO	478	0

Figure 1

Convergence Chart for Time Optimization in the Sartiuk Haftkel Reservoir Dam Project



In Figure 1, the convergence graph for Scenario 1 (time) using various algorithms is illustrated. It can be observed that BOA, HHO, and GA quickly converged to the optimal value of 478 days in the early iterations, whereas the convergence speed of other algorithms was slower. The highest error percentage belonged to the SA algorithm at 16%, while the lowest was associated with CPA at 6%.

Table 2 presents the optimization results for Scenario 2 (cost) using different algorithms. The table includes the percentage error relative to the best solution reported by the top algorithms, which in this scenario were HHO, GA, and CPA.

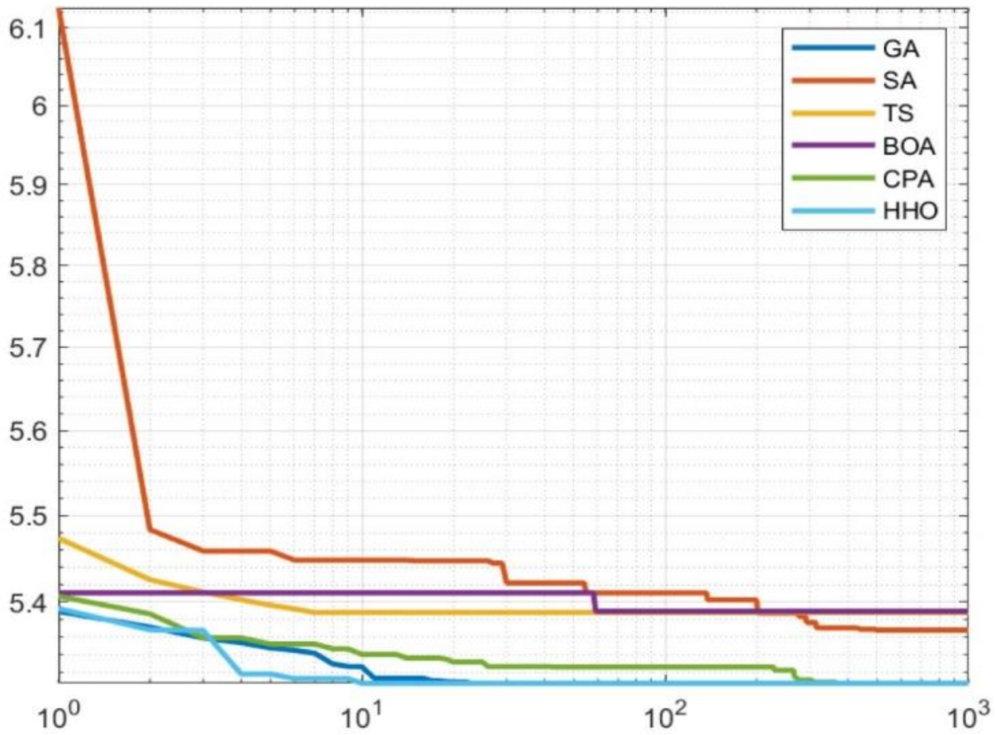
Table 2

Results of Various Algorithms for Scenario 2 (Cost Optimization)

Algorithm	Cost (IRR)	Error (%)
GA	530,773,130,016.25	0
SA	536,788,583,955.35	0.011333
TS	538,797,077,389.35	0.015117
BOA	538,940,274,531.55	0.015387
CPA	530,773,130,016.25	0
HHO	530,773,130,016.25	0

Figure 2

Convergence Chart for Cost Optimization in the Sartiuk Haftkel Reservoir Dam Project



In Figure 2, the convergence graph for Scenario 2 (cost) using various algorithms is shown. GA, HHO, and CPA algorithms quickly converged to the optimal value in the early iterations, while others were slower. The highest error was recorded for the TS algorithm at 1.5%, and the lowest for the SA algorithm at 1.1%.

The optimization results for Scenario 3 (quality) using various algorithms are presented in the following table. The percentage error compared to the best solution reported by the best algorithm (GA) is also included.

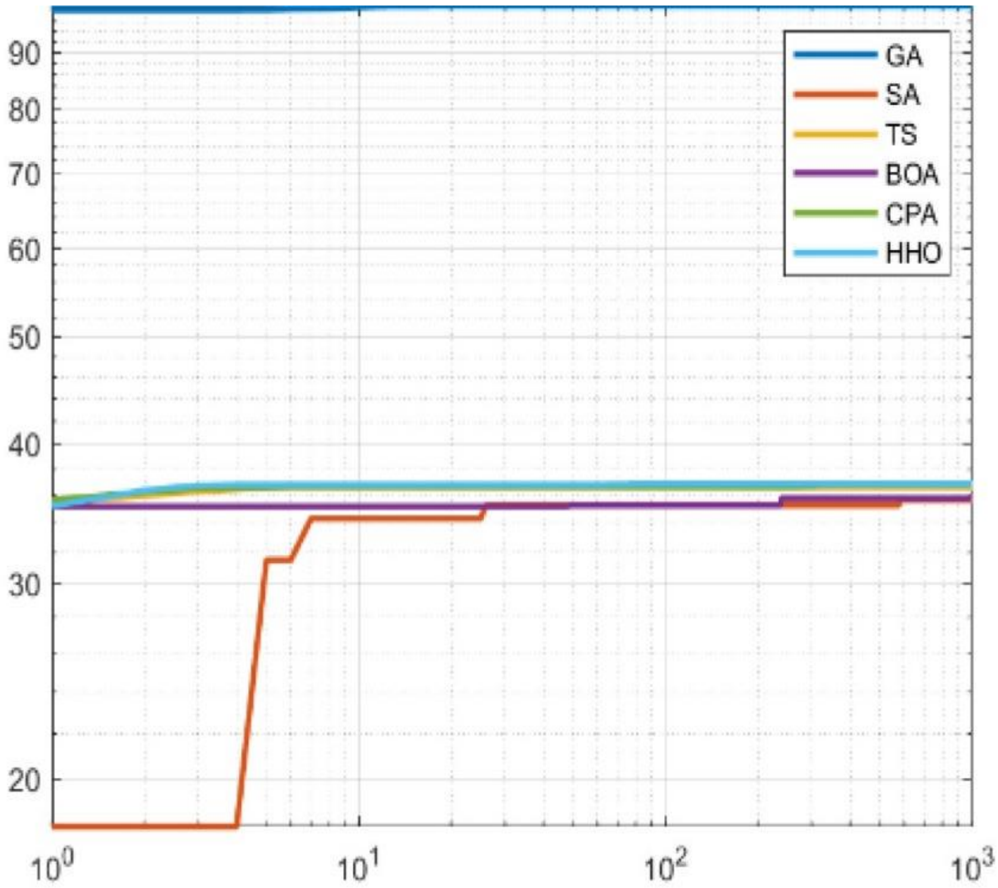
Table 3

Results of Various Algorithms for Scenario 3 (Quality Optimization)

Algorithm	Quality	Error (%)
GA	99.1063	0
SA	35.6934	0.639847
TS	36.6334	0.630363
BOA	35.8923	0.637840
CPA	36.8308	0.628371
HHO	36.8736	0.627939

Figure 3

Convergence Chart for Quality Optimization in the Sartiuk Haftkel Reservoir Dam Project



In Figure 3, the convergence graph for Scenario 3 (quality) using different algorithms is shown. It is evident that the GA algorithm rapidly converged to the optimal value during early iterations, whereas the convergence of other algorithms was significantly slower. The highest error was observed in the SA algorithm at 64%, while the lowest error was found in the HHO algorithm at 62%.

Table 4 shows the optimization results for Scenario 4 (risk) using various algorithms. The percentage error relative to the best results achieved by the GA and HHO algorithms is also reported.

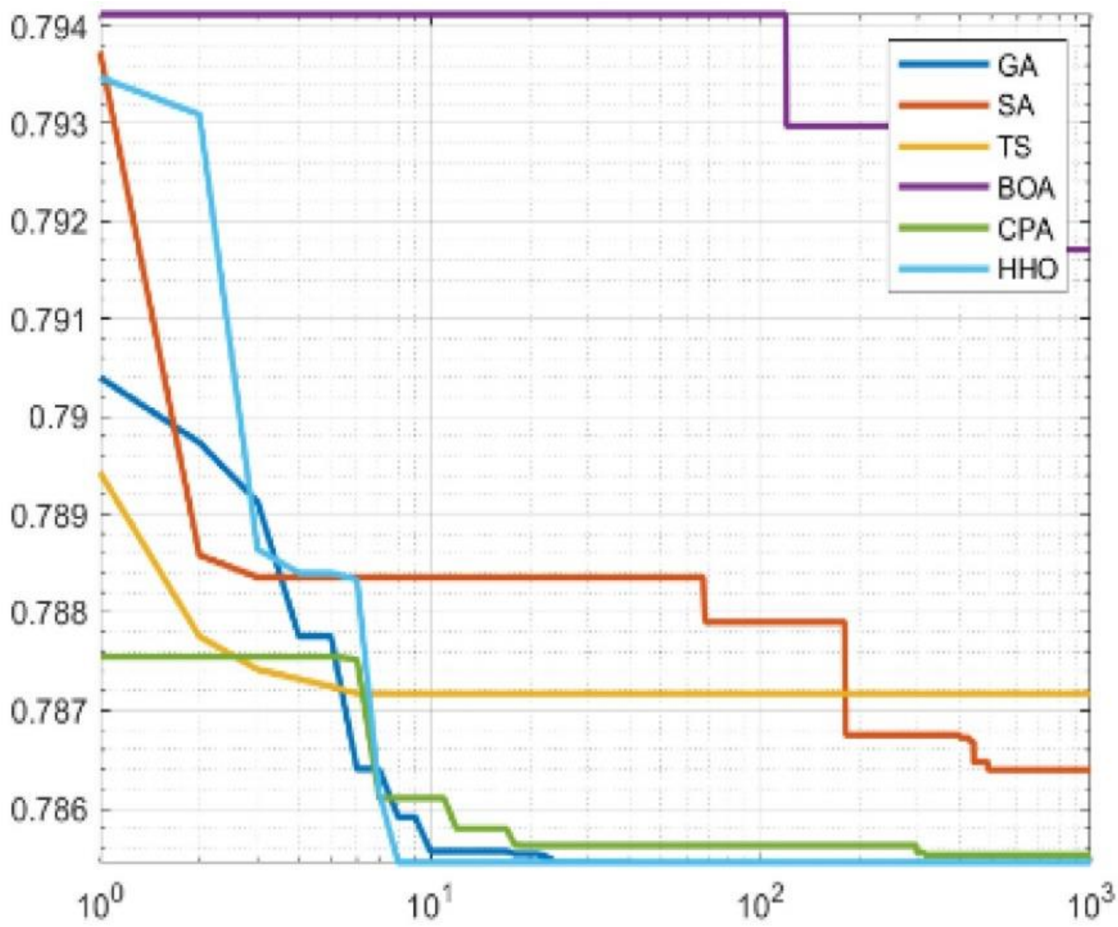
Table 4

Results of Various Algorithms for Scenario 4 (Risk Optimization)

Algorithm	Risk	Error (%)
GA	0.785451	0
SA	0.786394	0.001201
TS	0.787170	0.002189
BOA	0.791712	0.007971
CPA	0.785531	0.000102
HHO	0.785451	0

Figure 4

Convergence Chart for Risk Optimization in the Sartiuk Haftkel Reservoir Dam Project



In Figure 4, the convergence graph for Scenario 4 (risk) using different algorithms is shown. GA and HHO rapidly reached the optimal value in early iterations, whereas other algorithms showed slower convergence. The highest error was reported for the BOA algorithm at 0.7%, and the lowest for CPA at 0.01%.

Table 5 presents the results for Scenario 5 (overall optimization) using various algorithms. The percentage deviation relative to the best outcomes achieved by GA and HHO algorithms is also included.

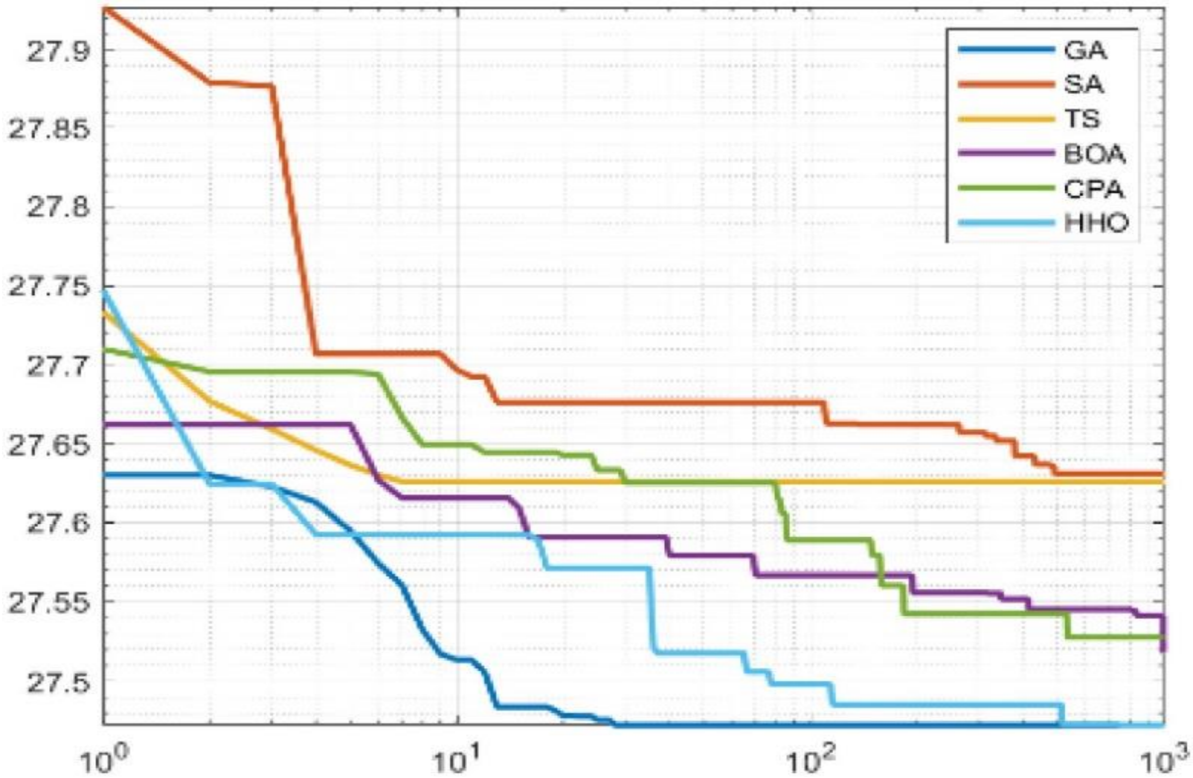
Table 5

Results of Various Algorithms for Scenario 5 (Overall Optimization)

Algorithm	Overall	Error (%)
GA	27.4727	0
SA	27.6311	0.005766
TS	27.6259	0.005576
BOA	27.5185	0.001667
CPA	27.5277	0.002002
HHO	27.4727	0

Figure 5

Convergence Chart for Overall Multi-Objective Optimization in the Sartiuk Haftkel Reservoir Dam Project



In Figure 5, the convergence behavior for Scenario 5 (overall optimization) is illustrated using different algorithms. GA and HHO quickly converged to the optimal value during early iterations, while other algorithms exhibited slower convergence rates. The highest error was associated with the SA algorithm at 0.57%, and the lowest error belonged to the BOA algorithm at 0.16%.

4. Discussion and Conclusion

The results of this study, focused on the optimization of time, cost, quality, and risk components in the Sartiuk Haftkel Reservoir Dam construction project using various metaheuristic algorithms, confirmed the superior performance of Genetic Algorithms (GA) and several hybridized models across all scenarios. In the first scenario, which involved time optimization, GA, BOA, and HHO achieved the optimal completion duration of 478 days with a zero error percentage, while other algorithms such as SA and TS displayed slower convergence and higher error margins. This finding aligns with earlier studies demonstrating the capability of genetic algorithms to efficiently handle the time-cost trade-off problem in construction planning (Feng et al., 1997; Hegazy, 1999). Similarly, the rapid convergence observed in GA echoes the outcomes reported by Daisy et al. (Daisy et al., 2004), who emphasized the strength of GA in identifying optimal project schedules in early iterations, thus saving considerable computational time.

The second scenario, focused on cost optimization, further highlighted the robustness of GA and HHO, both producing identical cost outputs with zero error. The consistency of GA in cost-related optimization is well documented in the literature. For example, Cui et al. (Cui et al., 2023) demonstrated that GA-based strategies perform well in complex supply chain systems, especially when optimizing cost functions under dynamic conditions. Similarly, the integration of hybrid models, such as those using artificial neural networks, has been shown to enhance the predictive accuracy of cost estimates in uncertain environments (Nezamoddini et al., 2020). These findings are also supported by Khalimonchuk (Khalimonchuk, 2024), who showed that machine learning and intelligent algorithms can significantly reduce cost variability and improve financial outcomes in technological enterprises. Thus, the performance of GA in this study further reinforces its cross-disciplinary applicability and computational efficiency.

In the third scenario, concerning quality optimization, GA once again outperformed all other algorithms, converging to the highest effective quality score of 99.1. Other algorithms, such as SA and TS, demonstrated considerably higher error rates exceeding 60%. This outcome can be attributed to GA's capacity for effective exploration and exploitation in multi-objective spaces, particularly when the objective function incorporates qualitative factors. The findings resonate with the work of Liang Yang et al. (Liang Yang et al., 2022), who optimized quality and energy efficiency in preventive maintenance systems, showing that multi-criteria GAs can address both tangible and intangible objectives simultaneously. Moreover, the capability of GA to model quality as a critical project success factor aligns with the broader argument made by Gu (Gu, 2022), who stressed the importance of incorporating service and product quality into optimization frameworks for industrial networks.

Scenario four, addressing risk optimization, illustrated that both GA and HHO delivered optimal values with minimal error rates, followed closely by CPA. The effectiveness of GA in risk-based scenarios is well supported in prior work. For instance, Nezamoddini et al. (Nezamoddini et al., 2020) utilized a risk-based optimization framework combining genetic algorithms and neural networks to improve supply chain resilience, emphasizing GA's capacity to account for risk propagation in complex systems. Likewise, Roth et al. (Roth et al., 2022) demonstrated that optimization models that accommodate uncertainty and stochastic variation—particularly through sampling-induced error handling—can enhance decision-making in environments characterized by fluctuating risk profiles. This further substantiates the relevance of GA in scenarios where project variability and exposure are high, such as large-scale construction and infrastructure development.

The fifth and final scenario, which examined the simultaneous optimization of time, cost, quality, and risk, offered the most integrative insight. Once again, GA and HHO achieved optimal objective function values with zero error, indicating their suitability for multi-objective and composite optimization problems. This result demonstrates the practicality of using GAs in comprehensive project planning models, a claim echoed by studies such as that of Zahraie and Tavakolan (Zahraie & Tavakolan, 2009), who used nondominated sorting genetic algorithms (NSGA) and fuzzy sets to handle stochastic trade-offs in time-cost-resource optimization. Furthermore, Derpich (Derpich, 2024) explored multimodal transportation optimization and found that intelligent algorithms like GA can successfully manage multiple conflicting objectives, including cost and environmental impact. These studies collectively affirm that GA is not only efficient in individual component optimization but also capable of producing high-quality solutions in holistic project models.

The comparative convergence analysis conducted in this study further validates the effectiveness of GA, BOA, and HHO. Figures across all scenarios illustrated that these algorithms converged significantly faster to optimal solutions than SA and TS. This corroborates the findings of earlier researchers such as Daisy et al. (Daisy et al., 2004) and Que (Que, 2002), who documented GA's advantage in convergence rate and solution stability. In particular, the combination of fast convergence and low error in multi-objective settings suggests a critical advantage for project managers needing real-time or near-real-time optimization tools. Liu (Liu, 2024) reinforced this by demonstrating how artificial intelligence techniques integrated with construction management systems can dramatically enhance responsiveness and agility in planning and scheduling tasks.

In addition, the modular adaptability of GA observed in this study reflects the algorithm's compatibility with hybrid intelligent systems. Research by Mumali and Kałkowska (Mumali & Kałkowska, 2024) highlighted how genetic algorithms can be combined with fuzzy logic and neural networks for intelligent manufacturing process selection, a technique highly translatable to construction environments where uncertainty, resource variability, and performance metrics are intertwined. The flexibility of GA to accommodate various parameters and weightings also aligns with the research of Sadeghi Askari (Sadeghi Askari & Soleimani Amiri, 2019), who used a GA-neural hybrid model for intelligent cost estimation in the banking sector, revealing its broader utility across industries.

From a methodological perspective, the comprehensive modeling of the four project dimensions—time, cost, quality, and risk—using real-world data and optimization techniques enhances the external validity of the findings. The formulation of the fifth scenario, in particular, which normalized and aggregated all indicators into a unified objective function, demonstrates the model's capacity to support integrated decision-making. Such multi-scenario evaluations resonate with Cui et al.'s (Cui et al., 2023) dynamic supply chain models and provide a foundation for extending optimization beyond construction to other domains such as transportation, logistics, and public utilities.

Despite the robust findings, this study has several limitations. First, the optimization model was applied to a single case study—the Sartiuk Haftkel Reservoir Dam—which may limit the generalizability of results to other types of construction projects with different scopes, constraints, and stakeholder requirements. Second, while multiple optimization algorithms were tested, not all modern metaheuristic approaches (e.g., Ant Colony Optimization, Particle Swarm Optimization) were included in the comparison, possibly omitting some competitive alternatives. Third, although the model considered four critical dimensions, the potential influence of other project factors such as stakeholder satisfaction, environmental compliance, or social impact was not examined. Finally, while algorithmic performance was evaluated primarily through convergence speed and error rate, other important metrics like robustness under dynamic conditions or sensitivity to parameter tuning were not extensively analyzed.

Future research should explore the extension of this optimization framework to a broader range of projects across different sectors and geographical regions. Comparative studies involving additional intelligent algorithms, including deep learning models or evolutionary strategies, may also yield deeper insights into performance trade-offs. Furthermore, future work can incorporate real-time data streams and digital twin models to dynamically update optimization parameters during project execution. Integrating behavioral and socio-environmental variables into the optimization framework could also make the model more reflective of real-world complexities. Moreover, investigating the scalability of the model for mega-projects with hundreds of interdependent activities could help validate the approach for national or transnational infrastructure initiatives. Finally, applying reinforcement learning techniques to adjust parameter weights over time may enhance the adaptability and predictive accuracy of multi-objective optimization tools.

For practitioners, the findings of this study suggest that integrating genetic algorithms into construction project planning can significantly improve efficiency across critical dimensions. Project managers should consider adopting hybrid optimization tools that balance time, cost, quality, and risk, especially in large-scale or resource-constrained environments. Tools and platforms that visualize convergence performance in real time can aid in monitoring algorithm efficiency and identifying potential performance bottlenecks. Moreover, using intelligent systems for decision support allows teams to simulate multiple scenarios, enabling better strategic planning and risk mitigation. Finally, organizations should invest in training and capacity-building initiatives to enhance the technical competencies required to implement and interpret multi-objective optimization models effectively.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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