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Advanced metaheuristic optimization for reducing time and cost while enhancing quality in major projects

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Abstract:
The management of large and complex construction projects, particularly the optimization of project completion time, cost, quality, and coordinated resource allocation, remains a critical challenge. This challenge becomes increasingly pronounced in projects characterized by numerous activities, strong temporal dependencies, and limited resources. The growing number of concurrent projects has intensified implementation delays, leading to increased construction costs, reduced quality, and, in extreme cases, economic infeasibility. This study proposes an efficient hybrid framework to investigate the factors influencing delay time, project cost, and quality. The results of reliability analysis showed a Cronbach's alpha value of 0,80 for the design and engineering phase (10 factors), 0,76 for the procurement phase (15 factors), and 0,59 for the construction phase (23 factors), confirming acceptable data reliability. A comparative analysis between the quantitative index method and a metaheuristic approach, namely an enhanced harmony search (HS) algorithm, was then conducted. The results demonstrate that the HS algorithm effectively balances the time-cost-quality trade-off, achieving notable reductions in project duration and total cost while maintaining the desired quality level. The proposed framework exhibits higher convergence stability and adaptability than conventional methods, highlighting its potential as a practical decision-support tool for data-driven and sustainable management of large-scale construction projects.

Keywords:
performance metrics; artificial intelligence optimization algorithms; smart scheduling systems; project cost efficiency; performance enhancement

1 Introduction

Modern construction projects encounter rising challenges owing to growing complexity, uncertainty, and limited resources, requiring project managers to balance conflicting objectives such as time, cost, and quality objectives. Therefore, effective project management is critical, as timely and cost-efficient delivery strongly influences project success and client satisfaction. Time management focuses on achieving scheduled completion, whereas cost performance is closely linked to construction duration. Consequently, integrated planning encompasses scope definition, resource allocation, and budgeting, which are essential for optimising the overall project performance. In construction projects, project time, cost, and quality are inherently interdependent, rendering simultaneous optimization a complex task. Time-cost trade-off (TCT) analysis is employed to minimise project duration and total cost through appropriate resource allocation while considering both direct and indirect costs.

The critical path method (CPM) is widely used to determine project duration and identify critical activities. However, traditional CPM-based deterministic approaches and commercial software often struggle to capture the nonlinear interactions and uncertainty inherent in large-scale construction projects. Recent research has increasingly focused on improving the integration of time, cost, and quality objectives using advanced optimization techniques. Studies indicate that combining metaheuristic algorithms with artificial intelligence methods, such as neural networks and machine learning models, substantially enhances optimization accuracy and robustness [1].

Hybrid approaches, including NSGA-II combined with AHP, have demonstrated strong performance in balancing conflicting objectives in complex construction environments [2]. These developments have contributed to improved modelling capabilities for large-scale construction projects, enabling a more accurate representation of time–cost–quality interactions. Hence, the TCT optimization problem, which aims to minimise project duration and cost simultaneously, has become a critical task in project scheduling and planning [3,4]. Accelerating the project duration generally results in increased costs, whereas reducing costs often leads to longer project durations, highlighting the competitive need for construction firms to manage both objectives effectively [5]. The time-cost-quality trade-off problem (TCQTP) extends the traditional TCT analysis by incorporating quality as a key performance criterion. In repetitive construction projects that involve repeated activities across multiple units and dominate the construction industry, TCQTP is used to develop schedules that balance time, cost, and quality objectives across all alternatives [6].

Heuristic methods are widely applied owing to their simplicity and computational efficiency; however, they often assume linear time-cost relationships, do not guarantee optimal solutions, and provide limited capability for scenario analysis and what-if evaluations [7,8,9]. Metaheuristic algorithms address many of these limitations by maintaining population diversity and effectively exploring nonlinear and complex search spaces [10]. Given these capabilities, recent studies have focused on enhancing metaheuristic frameworks to address the interdependent and uncertain nature of construction project objectives. Pham and Huynh [11] proposed a bio-inspired multi-objective optimization model capable of adaptively balancing conflicting constraints under resource limitations. Zhang et al. [12] further analysed hybrid- and data-driven metaheuristic methods to improve the efficiency and scalability of large-scale construction scheduling. More recent approaches integrate evolutionary computation with decision support mechanisms to improve convergence reliability and solution stability under uncertainty [13]. Collectively, these methodological advances provide a strong foundation for applying advanced algorithms, including the harmony search (HS) algorithm, to optimise complex time–cost–quality trade-offs in construction projects. The TCQTP assumes that project activities can be executed at different combinations of time, cost, and quality levels. The primary objective is to select the execution mode of each activity such that the project meets its deadline with the minimum cost and maximum achievable quality, despite the inherent conflicts among these criteria [14]. In 2024, Son et al. [15] applied artificial intelligence techniques to construction project optimization using a hybrid adaptive slime mould algorithm

and demonstrated improved convergence and Pareto-front performance. Similarly, a novel hybrid algorithm combining particle swarm optimization (PSO) with an enhanced genetic algorithm was shown to outperform the standard PSO in identifying shorter and more cost-efficient schedules [16]. Kebriyaii et al. [17] further developed a multi-objective time–cost–quality optimization model incorporating the time value of money, a critical factor in long-term projects. Other studies have addressed quality- and uncertainty-related challenges in construction projects characterised by complex technologies and stringent constraints [18]. Nguyen et al. [2] employed a multi-objective SOS algorithm to investigate the effects of uncertainty on time, cost, and quality, which demonstrates competitive performance compared with that of other widely used methods. Other studies have investigated hybrid genetic algorithms, resource-based scheduling policies, and resource-constrained project scheduling problems, confirming the effectiveness of advanced metaheuristic approaches for solving the TCQTP [19; 20; 21]. These studies collectively highlight the growing importance of robust optimization frameworks for improving the productivity and profitability of construction projects.
In recent decades, the optimization of construction project management has emerged as a critical research area, attracting considerable attention from both researchers and practitioners. Hussein et al. [22] examined the simulation and optimization methods for off-site construction projects, highlighting the role of metaheuristic techniques in enhancing project efficiency. ElSahly et al. [23] conducted a systematic review of time-cost optimization models to identify key challenges and opportunities for further development. Guo and Zhang [24] emphasised the role of multi-objective optimization in improving construction project management, whereas Son and Khoi [25] proposed a mutation–crossover slime mould algorithm to optimise time, cost, and quality constraints, as well as to maintain workflow continuity. Bakhshi et al. [26] introduced a hybrid framework combining machine learning and metaheuristic optimisers to predict the final project duration and cost, as well as to strengthen decision-support systems. Zhan et al. [27] focused on the Pareto-front development in multi-objective optimization, underscoring its importance for intelligent decision-making in construction management. Banihashemi et al. [28] applied a fuzzy SWARA-TOPSIS approach to analyse time-cost-quality trade-offs, whereas Agarwal et al. [29] developed a time-cost trade-off optimization model using the MOPSO technique. Pham and Nguyen Dang [30] addressed time-cost optimization using an adaptive multi-verse optimiser. Additionally, Wang et al. [31] analysed time-cost-quality trade-offs in project planning. Collectively, these studies demonstrated the growing importance of advanced optimization techniques for construction project success.
Despite these advances, much of the existing research has focused on reducing project duration through building information modelling or by applying isolated optimization techniques that address time or cost constraints independently. Few studies have examined fully integrated frameworks that simultaneously optimise time reduction, cost efficiency, and quality enhancement within a unified algorithmic structure. To address this gap, this study proposes an adaptive and integrated optimization framework that combines quantitative index analysis with an enhanced HS algorithm. By improving exploration-exploitation balance and maintaining convergence stability under uncertainty, the proposed framework bridges the gap between theoretical optimization advances and practical implementation in large-scale construction projects, thereby providing a scalable and reliable decision support tool for optimising time, cost, and quality objectives.

2 Case study area

The Iran Mall project, one of the largest commercial, cultural, and social developmental project in Iran, was selected as a large-scale case study to evaluate the proposed time–cost–quality optimization framework. The extensive scope of the project and the strong interdependencies between the design, procurement, and construction phases create a complex managerial environment suitable for assessing the efficiency of multi-objective metaheuristic optimization under real-world conditions. Projects require continuous coordination among multiple engineering, procurement, and execution teams, making effective scheduling and resource allocation critical. The complex nature of the project renders conventional project-management approaches based on linear assumptions and limited scenario evaluations insufficient. Accordingly, this study applied a hybrid metaheuristic optimization framework to simultaneously minimise project duration and control costs and to maintain a predefined level of quality throughout the project lifecycle. Although the Iran Mall serves as the primary case study, the proposed framework is not project-specific and can be generalised to other large-scale construction and infrastructure projects characterised by complex time, cost, and quality constraints. Potential applications of the framework include urban infrastructure development projects, power plant construction, and manufacturing systems, where efficient resource allocation and trade-off management are essential. Accordingly, this study adopted an integrated quantitative-computational framework supported by simulation techniques and metaheuristic optimization [32]. Project scheduling is employed to complete activities within the minimum time and cost while satisfying resource constraints. Although mathematical optimization methods can guarantee optimal solutions, their computational efficiency decreases markedly as the project scale expands. Metaheuristic algorithms offer greater flexibility for large-scale problems but may compromise guaranteed optimality. To address this trade-off, the present study adopted an integrated quantitative-computational approach that combined validated empirical data with metaheuristic optimization.

Data were collected across the design, procurement, and construction phases of the Iran Mall project. The internal consistency of the collected data was assessed using Cronbach's alpha. Following validation, the HS algorithm was employed as the core optimization engine owing to its capability to preserve population diversity, avoid premature convergence, and efficiently explore nonlinear solution spaces. By integrating HS-based optimization with quantitative index analysis, the proposed framework converts empirical project data into actionable managerial insights, thereby supporting evidence-based decision-making in complex construction environments.

3 Comprehensive quantitative index analysis

A comprehensive quantitative index analysis provides an objective foundation for evaluating project performance through the examination of historical data, identification of trends, forecasting, and inferential assessment. Statistical indices such as mean, mode, range, and root mean square support informed decision-making by improving scheduling efficiency and cost control. The analysis of time-related data enables optimised planning, whereas cost-related indices enhance financial management and project profitability. The application of quantitative indices facilitates the identification of critical bottlenecks that lead to delays or cost overruns, improves resource allocation, and enhances productivity and quality.

This study adopted a holonic methodological structure in which the design, procurement, and construction phases function as interconnected subsystems within an integrated project environment. The design phase defines strategic constraints; the procurement phase translates them into resource and contractual structures; and the construction phase operationalises managerial decisions. A continuous information exchange process ensures system coherence. Within this framework, the HS algorithm serves as a coordinating mechanism, synchronising interphase interactions by optimising the time, cost, and quality relationships in alignment with the real project dynamics.

Table 1 lists the descriptive quantitative indices derived from questionnaires across the design, engineering, procurement, and construction phases. These measures represent the initial analytical layer and confirm the statistical coherence of the dataset.

The design and engineering phase exhibits the highest probability values, whereas the procurement phase shows a narrower response dispersion, indicating a stronger consensus. The greater variability in the construction phase reflects the dynamic and multifactorial nature of on-site operations. These descriptive results establish a reliable quantitative basis for the subsequent inferential analysis and metaheuristic optimization.

Table 1. Descriptive quantitative index of collected questionnaires based on phase type

Quantitative Index					
Phase	Number	Minimum	Maximum	Mean	Std. dev.
Design and Engineering Phase	32	3,78	4,33	4,0617	0,13839
Procurement Phase	32	3,94	4,22	4,0730	0,07831
Construction and Implementation Phase	32	3,61	4,17	3,9306	0,12621

4 Metaheuristic algorithms

Metaheuristic algorithms are high-level search strategies designed to efficiently identify near-optimal solutions for complex optimization problems in which exhaustive enumeration is infeasible. These algorithms can effectively balance exploration and exploitation by sampling subsets of the solution space and employing stochastic search mechanisms. Although metaheuristic algorithms do not guarantee global optimality, their flexibility and limited dependence on problem-specific assumptions render them suitable for diverse and large-scale optimization problems. In this study, descriptive statistical analysis was integrated with a metaheuristic optimization framework that simultaneously addressed time, cost, and quality objectives. The enhanced HS algorithm functioned as an analytical core, enabling adaptive refinement and convergence towards balanced trade-off solutions.

4.1 Optimization methods for the HS algorithm

The HS algorithm is a music-inspired metaheuristic optimization method that models the solution search process as an improvisation procedure analogous to the achievement of musical harmony. The harmony memory (HM) stores the candidate solution vectors, which are iteratively updated through memory consideration, pitch adjustment, and random selection. Each harmony represents a potential solution defined by decision variables (nVar), whereas the harmony memory size controls the population diversity [33; 34].

$$HM = \begin{bmatrix} Position_{1,1} & \cdots & Position_{1,nVar} \\ \vdots & \ddots & \vdots \\ Position_{HMS,1} & \cdots & Position_{HMS,nVar} \end{bmatrix} \tag{1}$$

As previously mentioned, each row of the harmony memory (HM) is a harmony with nVar variables. Each variable in a harmony is identified by its position or location within the solution vector. In this study, the original HS algorithm was enhanced by integrating it with genetic algorithm mechanisms, thereby enhancing convergence speed, exploration capability, and solution stability. This hybrid structure mitigates premature convergence and demonstrates excellent adaptability to multi-objective problems involving time, cost, and quality constraints. Compared to conventional methods, such as PSO and standalone GA, the adopted HS-based framework yields consistent well-distributed near-optimal solutions with lower computational demands, enhancing both computational efficiency and managerial applicability.

4.2 Governing equations

Construction project optimization involves three interdependent objectives cost, time, and quality, which are typically represented by the project management triangle (Fig. 1). Variations in any objective directly influence others, with cost remaining a dominant parameter throughout the project life cycle.

To ensure analytical reliability, the internal consistency of the questionnaire-based dataset was evaluated using Cronbach's alpha. This study used Cronbach's alpha as a validation mechanism, confirming that the measured indicators formed a coherent construct suitable for higher-order optimization modelling. Alpha values above 0,9, 0,8, and 0,7 indicate excellent, good and acceptable reliability, respectively. Following data screening, the covariance matrix was computed using Eq. (2) and the alpha coefficient was calculated using Eq. (3). This validation step establishes a robust empirical foundation and ensures consistency between statistical reliability and computational optimization.

Figure 1. Project management triangle

$$Cov(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X}) \times (Y_i - \bar{Y})}{n-1} \tag{2}$$

Where X_i and Y_i denote variables X and Y for observation i; $\bar{X}$ and $\bar{Y}$ denote mean values of X and Y; and n is the number of variables.
The Cronbach's alpha coefficient was calculated using the following formula:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right) \tag{3}$$

Where α denotes the Cronbach's alpha coefficient; k is the number of questions in the questionnaire; σ_i^2 observed for each question; and σ_T^2 total variance for the questionnaire.

5 Discussion and results

5.1 Methodology

This study adopted a holonic multi-phase structure reflecting the organisational complexity of large-scale construction projects, such as the Iran Mall project. Each project phase design and engineering, procurement, and construction and implementation was modelled as a holon, maintaining analytical autonomy while remaining systemically interconnected. This structure ensures that the effect of localised decisions within each phase on the overall project performance is traceable. Using structured questionnaires, data were collected covering 48 delay factors (Y_1-Y_{48}) distributed across three phases (10, 15, and 23). Industry professionals evaluated each factor using a five-point Likert scale, providing a comprehensive dataset that captured the interrelated effects of time, cost, and quality objectives within a dynamic project environment.

5.2 Analytical framework and algorithmic architecture

This study identified a total of ten delay factors related to the design and engineering phase, which showed a Cronbach's alpha value of more than 80 %, indicating appropriate internal consistency.
The reliability analysis indicated strong internal consistency for the design and engineering phase (α = 0,804) and satisfactory reliability for the procurement phase (α = 0,769). The construction and Implementation phase showed a lower alpha value (α = 0,593) than the other phases, suggesting increased operational complexity and contextual variability in later project stages. Such reliability levels are typically observed in exploratory studies addressing

multidimensional managerial and behavioural constructs. Overall, the observed reliability pattern confirmed that the method adequately captured phase-specific heterogeneity while maintaining sufficient consistency for subsequent quantitative and optimization analyses. The probability of occurrence for each of the 48 delay factors across the three project phases is presented in Tables 3, 4, and 5 and illustrated in Figures 2, 3, and 4.

Table 2. Reliability test of data for different phases

Phase	Cronbach's Alpha	Number of Factors
Design and Engineering Phase	0,804	10
Procurement Phase	0,769	15
Construction and Implementation phase	0,593	23

Table 3. Symbol Y classification for identifying delay factors in design and implementation

Factors related to the design and implementation phase	
Y_1	inability to recruit personnel with adequate experience and expertise
Y_2	insufficient technical competence of the employer's representative in aligning the consulting team with the contractor and resolving project-related issues efficiently
Y_3	inadequate coordination mechanisms between the employer and the design consultant or contractor
Y_4	use of unsuitable or ineffective procedures
Y_5	slow reaction of the contractor's (or consultant's) technical team to essential drawing modifications owing to weak coordination and collaboration with the design engineering department
Y_6	allocation of the project to a consortium-based firm comprising multiple contractors
Y_7	inability to accurately assess required goods or quantities resulting from incomplete lists provided by the procurement engineering team
Y_8	design inaccuracies, including errors in the specification of dimensions, materials, or technical items
Y_9	delays in launching engineering activities owing to prolonged hiring and team formation processes
Y_{10}	engineering department's delayed feedback on required plan/document changes during the project

Table 4. Symbol Y classification for identifying delay factors in procurement

Factors related to the procurement phase	
Y_{11}	unclear outcomes from nuclear talks and persistent sanctions affecting project cost estimations, influenced by currency volatility
Y_{12}	lack of participation by international contractors in EPC projects due to economic instability within the region
Y_{13}	complex and slow administrative processes within the employer's organization
Y_{14}	failure to hire skilled and qualified professionals in the procurement and commercial departments
Y_{15}	international sanctions imposed on Iran by certain countries
Y_{16}	government regulations disrupting supply chains (e.g., restrictions on importing essential project materials)
Y_{17}	price instability caused by inflation and deviation from initial cost estimates made at the tendering stage
Y_{18}	unrealistically low bidding prices by contractors, aimed at winning the project without realistic budgeting
Y_{19}	employer-related delays in processing and settling contractor claims
Y_{20}	contractor's inadequate financial strength

Y_{21}	fluctuations in the foreign exchange rate
Y_{22}	delivery of substandard or non-compliant materials
Y_{23}	failure to supply materials in line with the engineer's specified list, including insufficient quantities or inconsistency with the bill of materials
Y_{24}	neglect by project managers in tracking and resolving procurement-related challenges
Y_{25}	shipment delays from suppliers and material damage or degradation during transit

Table 5. Symbol Y classification for identifying delay factors in construction and implementation

Factors related to the construction and implementation phase	
Y_{26}	restriction of supplier options (vendor list) by the national oil company, requiring procurement solely through approved vendors
Y_{27}	contractor's selection of underqualified or inexperienced manufacturers and suppliers
Y_{28}	prolonged procedures in opening bank accounts and issuing/activating letters of credit (LC)
Y_{29}	delays and complications in customs clearance processes
Y_{30}	contractor's failure to recruit skilled and knowledgeable personnel
Y_{31}	inadequate performance by the technical inspection unit
Y_{32}	delay in payment of contractor's receivables by the employer
Y_{33}	engagement of less skilled or second-hand contractors and labor owing to lower costs
Y_{34}	poor project planning and lack of effective control and monitoring methods
Y_{35}	involvement of project owner's management and expert team in multiple projects, reducing attention to the current project
Y_{36}	contractor's diversion of project funds to unrelated activities due to poor financial planning
Y_{37}	project delays resulting from unavailability or malfunction of contractor's equipment and tools
Y_{38}	disruptions due to extreme or unsuitable weather conditions (e.g., rain, wind, dust)
Y_{39}	employer's project managers failing to adequately pursue and resolve internal and external project issues
Y_{40}	contractor's lack of sufficient manpower and inefficient allocation of labor across different work areas
Y_{41}	weak coordination and collaboration between employer and contractor
Y_{42}	ambiguity or incompleteness in job descriptions provided by the employer
Y_{43}	delays in making the hazardous project site safe and secure for work execution
Y_{44}	performing out-of-scope tasks and misallocating workforce, funds, or resources to such activities
Y_{45}	lack of cooperation from factory or field personnel involved in project execution
Y_{46}	delays caused by unforeseen incidents such as on-site fires or emergencies
Y_{47}	challenges in securing fuel for operational equipment (e.g., vehicles, diesel engines, compressors)
Y_{48}	employer's delays in making land-related decisions or resolving land-use conflicts at the project site

As shown in Figure 2, in the design and engineering phase, the highest delay is attributed to the delayed responses of the consultant to the required changes in project drawings. Among the evaluated factors, the delayed response of the contractor's (consultant's) engineering team to drawing modifications (Y_5) exhibits the highest probability of occurrence, reaching 92 % and accounting for a substantial portion of scheduling delays in large-scale construction projects. This high probability is primarily attributed to limitations in the supervision and notification system, which restrict accountability within the administrative structure of the project. Factors (Y_{10}) and (Y_4), related to delayed employer response to drawings and the use of inappropriate work methods, respectively, also demonstrate high probabilities of occurrence: 87,89 and 86,87 %, respectively. The elevated probability of factor (Y_{10}) is linked to inadequate supervisory mechanisms, suggesting that strengthening project oversight can markedly mitigate its occurrence. In large-scale projects, factor (Y_4) inadequate execution methods is often associated with insufficient practical experience and limited capability to manage existing technical bottlenecks. Other design and engineering factors exhibit comparatively lower probabilities, reflecting more effective control of technical deficiencies and execution processes across projects. The lowest probability of occurrence is observed for factor (Y_2), which relates to the coordination between the consultant and contractor in resolving technical issues.

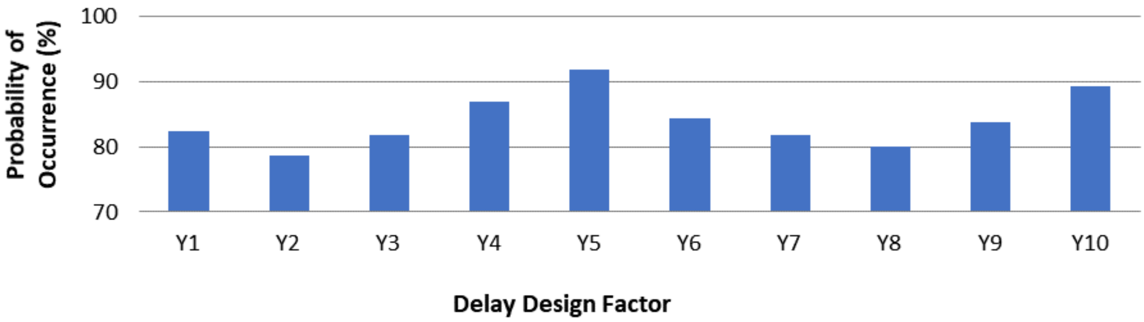

Figure 2. Probability of occurrence of delay factors in the design and engineering phase

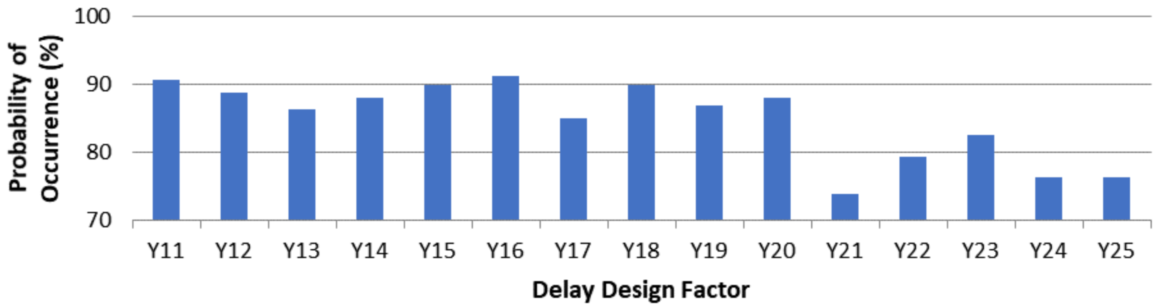

Figure 3. Probability of occurrence of delay factors in the procurement phase

Figure 3 presents the probability of variance for each event in the procurement phase. These results indicate that procurement-related factors substantially influence delays in EPC projects. Among these factors, the impact of government policies and regulations on supply chain activities (Y_{16}) exhibits the highest probability of occurrence at 91,25 %. This factor reflects major limitations in program implementation and ineffective follow-ups by the responsible authorities. Contributing factors include import restrictions, delays in budget allocation, and prolonged credit approval processes, all of which hinder supply chain performance. Factor (Y_{11}), associated with uncertainty arising from nuclear negotiations, persistent sanctions, and currency volatility affecting cost estimations, also demonstrates a high probability of occurrence of 90,62 %. Similarly, factor (Y_{18}), which is related to unrealistically low bidding prices submitted by contractors to secure project awards without realistic budgeting, shows a probability of 90,00 %. The high probability of factor (Y_{11}) is primarily linked to political and economic instability, weak policy enforcement, and limited compliance with governmental strategies. Strengthening economic conditions, administrative reforms, and improving policy implementation can substantially reduce the occurrence of this problem. Factor (Y_{18})—low bidding behaviour is often motivated by the strategic intent of contractors to enhance future project acquisition opportunities. Other procurement-related factors exhibit comparatively lower probabilities but warrant careful consideration because of their potential complexity and disruptive impact upon their occurrence. The lowest probability of occurrence is associated with factor (Y_{21}), which is related to exchange rate fluctuations; however, such variations can still lead to delays, implementation failures, and disruptions in project continuity.

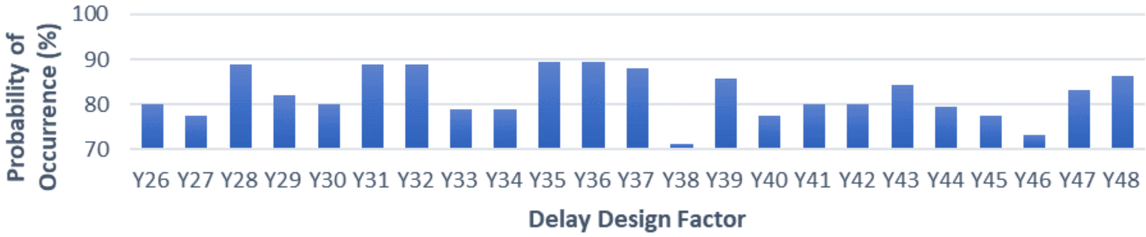

Figure 4. Probability of the occurrence of delay factors in the construction and implementation phase

Figure 4 presents the probability of occurrence of variance for events in the construction and implementation phase. The highest probabilities are associated with the involvement of project managers and experts in multiple projects, resulting in a reduced focus on the current project (Y_{35}), and the diversion of project funds by contractors to unrelated activities owing to inadequate financial planning (Y_{36}). Both factors exhibit a probability of occurrence of 89,37 %, reflecting time pressure, resource constraints, weak prioritisation, and deficiencies in the project management system. These conditions contribute to project delays, quality reduction, increased operational risk, and decreased satisfaction among executing organisations. Factors (Y_{28}), prolonged opening of accounts and activation of letters of credit; (Y_{31}), inadequate performance of the technical inspection unit; and (Y_{32}), delays in the payment of contractors' receivables by the employer, also demonstrate high probabilities of occurrence, each at 88,75 %. The elevated likelihood of these factors is primarily attributed to insufficient supervision and control, shortages of human and financial resources, and ineffective process regulation. Strengthening the organisational infrastructure, improving resource availability, enhancing automation, and reinforcing supervisory and control mechanisms can substantially reduce the occurrence of these factors. Other construction and implementation factors exhibit comparatively lower probabilities and reflect improved technical conditions and execution performance. Among these, the lowest probability of occurrence is associated with factor (Y_{38}), which is related to disruptions caused by extreme or unsuitable weather conditions (e.g., rain, wind, and dust). Although less frequent, these environmental factors can affect project continuity and should be considered in comprehensive risk management strategies.

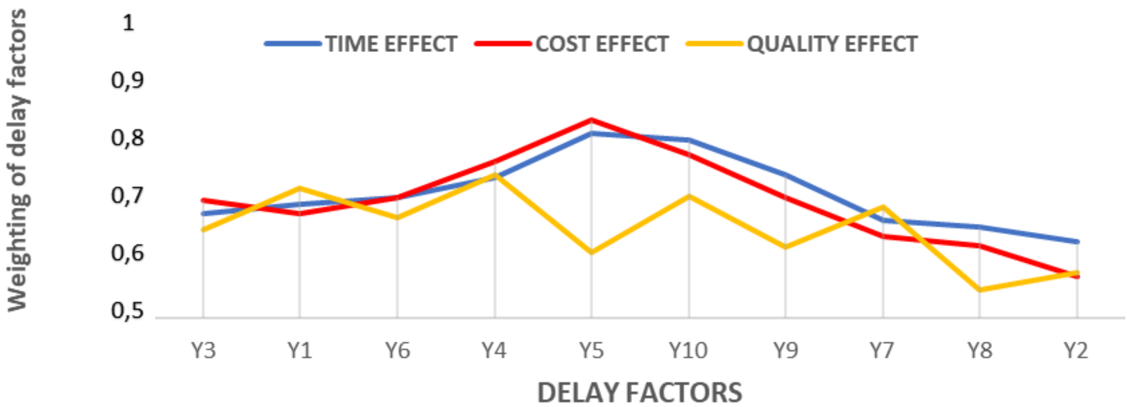

Figure 5. Impact of delay factors in the design and engineering phase

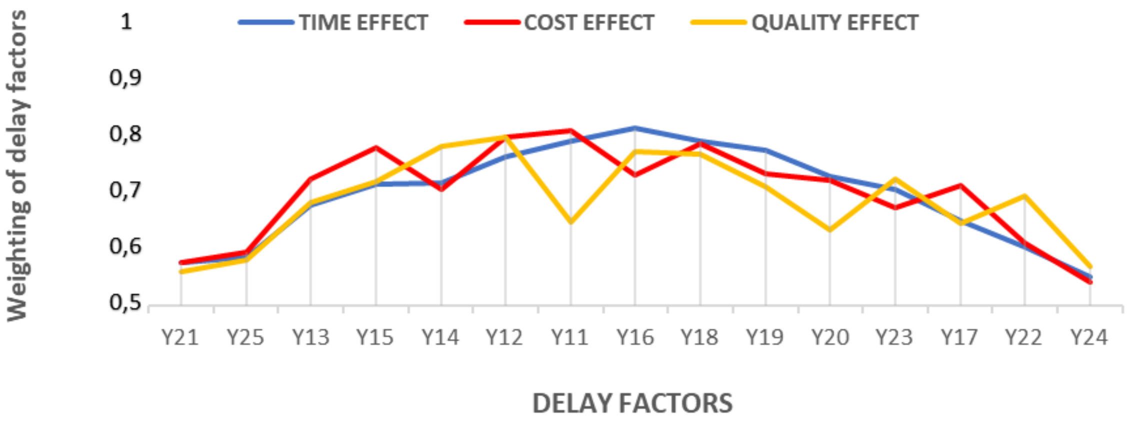

Figure 6. Impact of delay factors in the procurement phase

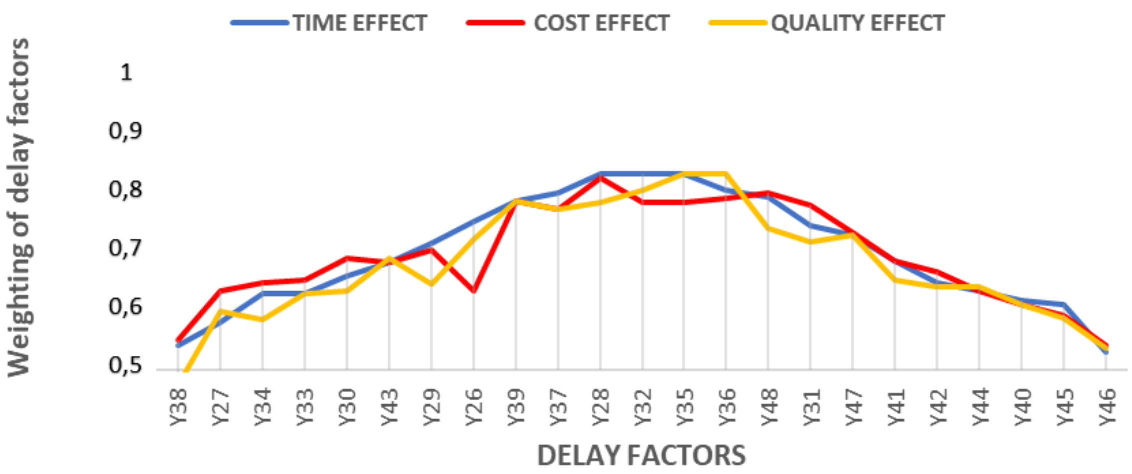

Figure 7. Impact of delay factors in the construction and implementation phase

The impact values of delay-related factors across the three project phases are presented in Figures 5, 6, and 7. Based on Figure 5 and the assumed linearity of variables, factor (Y_5) exhibits the highest discrete impact on delays in the design phase within the time and cost domains, whereas factor (Y_4) shows the greatest impact on the execution quality. The results further indicate that factor (Y_{10}) has the highest influence on delays in both the time and cost domains, with a numerical difference of approximately 2,8 %, suggesting an almost equal impact on the two domains. Factor (Y_4), which is related to inappropriate execution procedures, demonstrates the strongest effect on project quality. As shown in Figure 6, factor (Y_{16}), which reflects the influence of government programs and regulations on the procurement process, has the highest impact on project timeline. Factor (Y_{11}), associated with uncertainty in nuclear negotiations, persistent sanctions, and exchange rate volatility, has the greatest impact on project cost. By contrast, factor (Y_{12}), representing the lack of professional foreign contractor investment in EPC projects due to economic instability, has the highest impact on procurement quality. The difference between the three impact values is less than 10 %. According to Figure 7, factors (Y_{28}), (Y_{32}), and (Y_{35}) demonstrate the greatest influence in the time domain, parameter (Y_{28}) in the cost domain, and factors (Y_{35}) and (Y_{36}) in the quality domain. Conceptually, factors (Y_{28}) and (Y_{35}) exhibit a higher degree of interaction with other factors, and their prioritisation provides a coherent interpretation of the patterns observed across Figures 5, 6, and 7.

5.3 Prioritizing factors based on importance levels

In the present study, because of the high probability level (over 70 %) of most of the influential parameters in the delay process, the factors with a probability of more than 75 % were classified as having "high" importance. The factors with a probability of impact (PI) of more than 70 % were classified as having moderate importance, and the factors with a PI of less than 70 % were classified as having low importance.
Some of the factors (Y_1-Y_{48}) have a greater weight of influence than other parameters. As per the general principles of multicriteria weighting, the elements within each level are compared pairwise with respect to the elements in the immediately higher level, and their relative weights are subsequently calculated. To construct the hierarchical levels, the relationships among the components in each level with those in different levels must be identified, linking each level to its corresponding higher and lower levels. Based on these relationships, pairwise comparison matrices are constructed, where the comparison matrix of the alternatives is of size $m \times m$ and that of the criteria is of size $n \times n$.
The elements of the pairwise matrix are denoted as $[a_{ij}]$. Therefore, if a factor exhibits the highest weight in at least two of the three domains of time, cost, and quality, that factor is considered to have a considerable influence on the progress and timely completion of the project. Based on the above criterion, the factors (Y_{35}), (Y_{28}), (Y_{18}), (Y_{16}), (Y_{12}), (Y_{11}), (Y_{10}), and (Y_5) were found to have the highest impact on project delays.

5.4 Results of the metaheuristic algorithm

Based on the optimization of time, cost, and quality objectives across the design, engineering, procurement, construction, and implementation phases, this study evaluated the impact of the 48 identified factors using a metaheuristic algorithm to validate the quantitative index results. The results showed that, with increasing iterations, the influence of the objective parameters became more pronounced. In the time-oriented optimization, factor (Y_{16}) exhibited an impact of 91 %, whereas factor (Y_{26}) exhibited the highest impact value of 88,1% in the quantitative index evaluation, as illustrated in Figure 8 and Table 6. Except for a small number of high-impact factors whose rankings were rearranged, the remaining factors followed trends consistent with the results of the quantitative index analysis. This result indicates systematic but limited differences between the results of metaheuristic optimization and the quantitative index evaluation for the time objective.

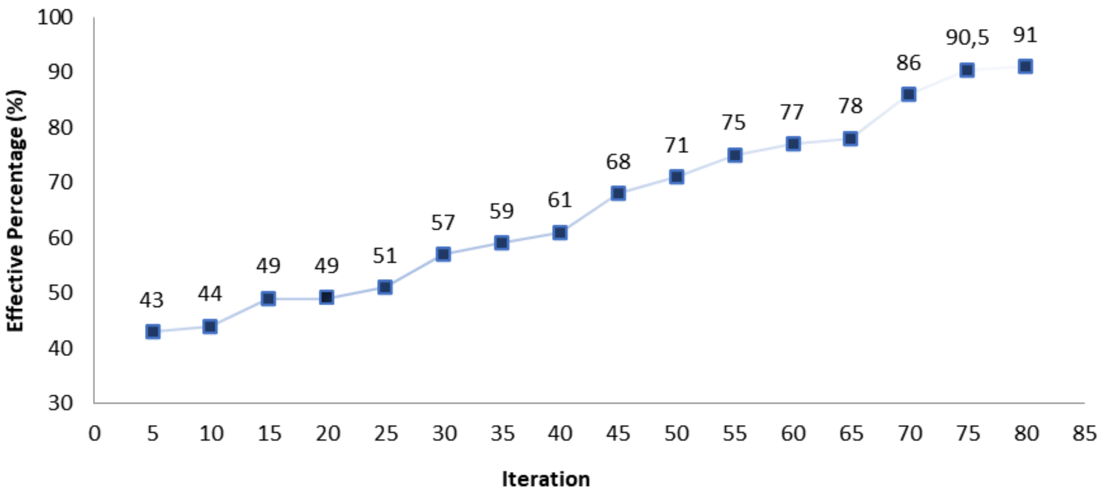

Figure 8. Results of the metaheuristic algorithm considering the time function for all factors

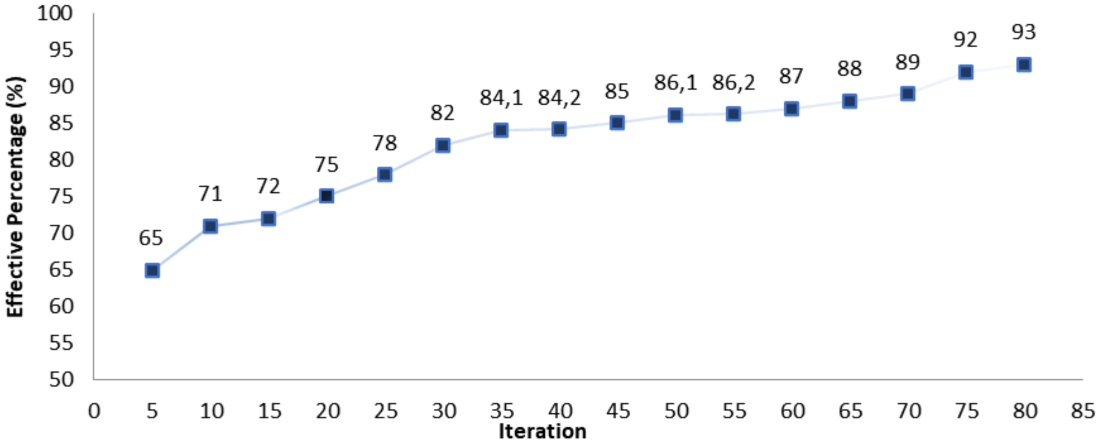

Figure 9. Results of the metaheuristic algorithm considering the cost function for all factors

As per the results of the optimization algorithm, factor (Y_{11}) showed the greatest impact of 93% on the total cost of the project, and factor (Y_{13}) had the least impact (65 %) on the project cost (Figure 9). Additionally, with respect to the acceptable response range related to cost, several factors that showed the greatest impact in the algorithmic results differed from those that showed the highest impact in the quantitative index, indicating the favourable performance of the meta-heuristic algorithm.

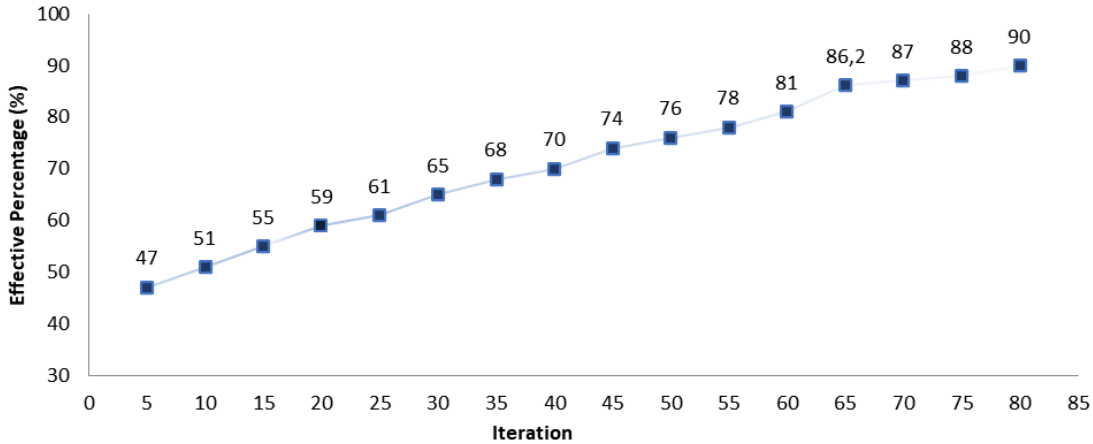

Figure 10. Results of the metaheuristic algorithm considering the quality function for all factors

As shown in Figure 10, factor (Y_{14}) influences approximately 90 % of the quality performance, marking the highest impact. By contrast, factor (Y_{47}) exhibits the lowest impact of approximately 47 %. Tables 6, 7, and 8 present the general comparative trend between the performance of different factors in the time, cost, and quality domains, respectively.

The identified delay factors (Y_1-Y_{48}) were interpreted analytically within established domains of project management, particularly within the PMBOK framework, to demonstrate their managerial relevance. Each factor was mapped to key process areas, such as schedule management, procurement management, and risk monitoring, establishing a clear relation between the empirical findings and practical project control mechanisms. This alignment transforms quantitative outputs into decision-oriented managerial indicators that support planning and monitoring across the project phases. The high-impact factors identified in the procurement and construction phases correspond closely to proactive scheduling and early risk-response processes, highlighting the importance of integrating data-driven insights into established management frameworks.

Table 6. Time variation of key factors: quantitative index vs. algorithm

Row	Agents	Quantitative index [%]	HS [%]	Trend of changes [%]
1	Y_{16}	87,5	91,0	4,00 ↑
2	Y_{10}	87,5	90,5	3,40 ↑
3	Y_{19}	87,5	86,0	1,74 ↓
4	Y_{26}	88,1	78,0	11,46 ↓

Table 7. Cost variation of key influencing factors: quantitative index vs. algorithm

Row	Agents	Quantitative index [%]	HS [%]	Trend of changes [%]
1	Y_{11}	87,500	93	6,1 ↑
2	Y_{12}	88,125	92	4,2 ↑
3	Y_{5}	88,750	89	0,3 ↑
4	Y_{48}	86,250	88	2,0 ↑

Table 8. Quality variation of key influencing factors: quantitative index vs. algorithm

Row	Agents	Quantitative index [%]	HS [%]	Trend of changes [%]
1	Y_{14}	86,875	90,0	3,47 ↑
2	Y_{35}	86,250	88,0	2,00 ↑
3	Y_{36}	86,250	87,0	0,80 ↑
4	Y_{12}	88,125	86,2	2,10 ↓

The proposed optimization framework shows strong potential for integration with widely used project management platforms, including the Primavera P6 and MS projects. Metaheuristic outputs such as optimised schedules, activity prioritisation, and balanced trade-offs among time, cost, and quality objectives can be embedded within conventional planning workflows to enhance managerial decision-making. Through this integration, the model functions as an analytical extension of traditional scheduling systems, enabling scenario evaluation, performance impact assessment, and adaptive resource allocation based on optimization-driven insights. Consequently, the framework effectively bridges computational analysis and managerial practice, supporting a more adaptive and data-informed control of complex construction projects. These findings are consistent with recent advances in multi-objective optimization and project scheduling, where metaheuristic algorithms have demonstrated excellent performance in balancing interdependent time, cost, and quality objectives under resource constraints.

Loung et al. [35] and Tran et al. [36] have confirmed that population-based evolutionary algorithms outperform deterministic approaches in complex construction environments. By contrast, Sharma and Trivedi [37] have demonstrated that advanced frameworks such as NSGA-III effectively address multimode trade-offs in large-scale projects. Building on this body of research, this study advances the literature by integrating empirically derived managerial factors into the optimization process and emphasising interpretability and managerial adaptability rather than computational efficiency alone. In this context, the proposed framework enhances the practical relevance of metaheuristic optimization as a decision support mechanism in construction management.

The numerical results obtained across the analytical components demonstrate the coherent integration of the empirical assessment and computational modelling. Tabular indicators reflect the structural characteristics of the collected data, whereas graphical outputs represent the optimised dynamics derived from the metaheuristic process. Together, these results illustrate continuous analytical progress from descriptive evaluation to algorithmic synthesis, thereby reinforcing the methodological coherence and interpretive depth of the proposed framework.

6 Conclusion

The main findings are as follows:

- The ten factors identified for the design and engineering phase exhibited a Cronbach's alpha of 0,8. The 15 factors studied for the procurement phase and the 23 factors studied for the construction and implementation phase exhibited a Cronbach's alpha of 0,76 and 0,59, respectively, indicating the reliability of the quantitative index data.
- The Cronbach's alpha consistently decreased from the design and engineering phase to the construction and implementation phase, showing a decrease of approximately 26 %.
- Factors (Y_{35}), the involvement of the project owner's management and expert teams in multiple projects, reducing attention to the current project, and (Y_{36}), project delays resulting from the unavailability or malfunction of the contractor's equipment and tools, have the highest probability of occurrence in the construction and implementation phase.
- In the design and engineering phase, (Y_{10}) exhibited the highest impact of approximately 87,50 % on project time, and factor (Y_5) exhibited the highest impact at approximately 88,75 % on project cost. Factor (Y_1) demonstrated the greatest impact (approximately 85,62 %) on the quality of implementation in the design and engineering phases.
- In the procurement phase, factors (Y_{19}) and (Y_{16}) had the highest impact of approximately 87,50 % on project time, cost, and quality. Factor (Y_{12}) had the greatest effect of approximately 88,12 % on both the cost and quality domains, indicating the substantial impact of quantitative indexes.
- The results of the quantitative indices were compared with those of the metaheuristic algorithm across all 48 effective factors. Compared to the quantitative indices, the metaheuristic algorithm showed a 4 % increase in the effect of factor (Y16) on project time. Additionally, (Y_{10}) and (Y_{19}) showed increases of 3,40 and 1,74 %, respectively, indicating the accurate application of the metaheuristic algorithm in collective intelligence problems.
- Comparing the results of the quantitative indices with those of the metaheuristic algorithm, factor (Y_{11}) exhibited the highest increase of 1,6 % in terms of cost impact, and factor (Y_{14}) had the greatest impact of 47,3 % in terms of quality.

Overall, the findings of this study extend beyond computational efficiency by highlighting a systemic understanding of project dynamics across the design, procurement, and construction phases. The integration of empirical delay factors within a holonic optimization framework establishes a multilayered connection between quantitative modelling and managerial interpretation. This approach enables decision-makers to translate algorithmic outcomes into strategic project controls and improve predictability and responsiveness under complex resource-constrained conditions. The developed model provides a foundation for adaptive project governance, in which data-driven insights can be continuously embedded into planning and monitoring systems to enhance resilience, minimise uncertainty, and sustain performance excellence in large-scale construction projects.

The results of this study demonstrate the considerable impact of using hybrid algorithms to optimise the time-cost-quality trade-offs in large construction projects. As projects inherently involve limited resources and complex temporal dependencies, the findings of this research can be highly beneficial for project managers in forming informed decisions and reducing the risks associated with delays and cost overruns. For instance, in the Iran Mall project, the

implementation of this model enabled project managers to markedly reduce the completion time of the project, while accounting for additional costs due to delays. This model can also be applied to other industries such as manufacturing and software development, where multi-objective optimization in complex environments is critical.
The findings of this study indicate that the proposed holonic metaheuristic framework establishes an adaptive bridge between analytical precision and managerial responsiveness across the interconnected design, procurement, and construction phases. By prioritising distributed coordination and systemic learning over isolated optimization, the framework enables the data-driven synchronisation of time, cost, and quality objectives under uncertainty. Within this integrated environment, the embedded HS engine functions not only as a computational optimiser but also as a dynamic mechanism that continually refines trade-offs as project information evolves. In this context, optimization is reframed as an organizational learning process in which empirical reliability and intelligent adaptation reinforce each other, advancing project governance towards anticipatory, evidence-based, and resilient decision-making in large-scale construction contexts.

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