



Metaheuristic Optimization of Temporary Facility Layouts in Large-Scale Dam Projects

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Abstract

This study develops a novel Genetic Algorithm (GA)-based framework for multi-objective optimization of workshop layouts in dam construction projects, explicitly addressing curved dam geometry, crane operational constraints, and differentiated safety requirements. The proposed approach employs a hierarchical penalty mechanism to enforce constraint feasibility and a three-phase optimization strategy combining global exploration and adaptive genetic operators to improve convergence and solution quality. The framework is validated through a real-world case study of the Divarsh Rudbar Dam in Iran, optimizing the placement of worker accommodation, cement silos, and material storage facilities. The optimized layout achieves a 21% reduction in transportation distance while satisfying all safety and operational constraints. Sensitivity analysis demonstrates the robustness of the solution under variations in safety parameters. The results highlight the effectiveness of the proposed method as a practical decision-support tool and its capability to address highly constrained, real-world engineering optimization problems.

Keywords: Dam construction; Workshop layout; Genetic algorithm; Multi-objective optimization; Safety management

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1. Introduction

Large-scale dam construction projects are among the most complex forms of civil engineering production because they combine massive material flows, heavy equipment operation, geotechnical uncertainty, strict safety requirements, long project durations, and highly constrained working environments. In such projects, the arrangement of temporary facilities is not a secondary managerial task but a core determinant of project performance, because the location of worker accommodation, cement silos, material storage areas, workshops, access routes, crane zones, and support facilities directly affects transportation distance, equipment productivity, site safety, congestion, and total construction cost. Temporary facility layout planning becomes especially critical in dam projects because the construction site is usually shaped by topographical limitations, reservoir geometry, river diversion structures, access restrictions, slope stability requirements, and the

spatial hazards associated with dam bodies and crane operations. Traditional layout decisions in construction have often depended on expert judgment and field experience; however, the growing scale and complexity of infrastructure projects increasingly require systematic, computational, and optimization-based decision-support methods capable of handling multiple objectives and practical constraints simultaneously [1, 2].

Construction site layout planning is generally concerned with determining the most appropriate spatial arrangement of temporary facilities so that site activities can be performed efficiently, safely, and with minimum unnecessary movement. Poorly arranged facilities can increase internal transportation, create interference among equipment and workers, intensify site congestion, delay material delivery, and increase exposure to hazardous zones. Conversely, a well-optimized layout can reduce travel distance, improve material handling, minimize conflicts between site



functions, and support safer work execution. Abdelalim et al. demonstrated the relevance of genetic algorithm techniques in construction site layout planning by considering both traveling distance cost and safety relationships, showing that construction layout optimization must address efficiency and risk simultaneously rather than treating safety as an afterthought [1]. Duong and Peansupap similarly emphasized that genetic algorithm-based models can provide structured and reproducible solutions for construction site layout problems, particularly where multiple facilities and movement paths must be coordinated within limited site boundaries [2]. These studies indicate that facility layout optimization is increasingly understood as a multi-objective construction management problem rather than a purely spatial design exercise.

The specific context of dam construction intensifies the importance of layout optimization. Dam projects involve extensive concrete or earthwork operations, aggregate and cement handling, heavy lifting, material stockpiling, worker accommodation, and continuous interaction between temporary and permanent structures. The geometry of the dam body, crane accessibility zones, material supply routes, and safety buffers around hazardous structures create a constrained search space in which seemingly efficient locations may be infeasible or unsafe. The International Commission on Large Dams has long emphasized the need for rigorous engineering procedures in dam design and safety assessment, particularly where seismic and structural risks are relevant to construction and operation [3]. Ghiasi et al. further highlighted the role of monitoring results, numerical analysis, and back-calculation in understanding embankment dam behavior, reinforcing the point that dam engineering decisions should be based on systematic analysis rather than simplified assumptions [4]. Therefore, layout planning in dam construction must account not only for transportation cost but also for dam proximity, crane swing range, safety separation, site boundaries, and operational accessibility.

Optimization methods have become increasingly important in water resources and dam-related engineering because such problems typically include nonlinear relationships, multiple objectives, and strict feasibility conditions. Nicklow et al. reviewed the state of the art for genetic algorithms and related methods in water resources planning and management, showing that evolutionary algorithms are particularly valuable when conventional mathematical programming is limited by complex search spaces and nonconvex constraints [5]. In reservoir operation,

Mohammadi et al. applied the Whale Optimization Algorithm and a hybrid genetic algorithm approach to dam reservoir operation, demonstrating the effectiveness of metaheuristic models in minimizing deficits and improving multi-criteria operational performance [6]. Olukanni et al. also used genetic algorithms to evaluate optimization-based reliability in a multipurpose hydropower reservoir, showing that evolutionary computation can support reliability-oriented decisions in dam systems [7]. Latif et al. employed a charged system search algorithm for optimizing dam operation release policy, further confirming the growing relevance of metaheuristic methods in reservoir and dam management problems [8]. Chong et al. reviewed metaheuristic algorithms for optimal dam and reservoir operation in irrigation and hydropower generation, showing that these approaches can address complex trade-offs among water supply, energy production, and operational constraints [9]. Su et al. extended this optimization logic to life-cycle cost optimization for dam design and reinforcement using fuzzy clustering and a backtracking search algorithm, indicating that dam-related optimization can support both design-stage and long-term infrastructure decisions [10].

Beyond water resources, the broader civil engineering literature shows a rapid movement toward artificial intelligence, machine learning, BIM, GIS, and hybrid metaheuristic optimization. Bakhshi et al. presented a hybrid scheme combining machine learning and metaheuristic optimizers for predicting final project cost and time, illustrating how computational intelligence can support construction management under uncertainty [11]. Huang and Hsieh used random forest and simple linear regression to predict BIM labor cost, showing that data-driven methods can improve cost estimation in construction environments where labor productivity and project conditions are difficult to model deterministically [12]. Wang et al. reviewed BIM and GIS integration in sustainable built environments, emphasizing that spatial data integration can enhance planning, visualization, and decision-making in complex built-environment projects [13]. Hu et al. applied geostatistical analysis to intelligent compaction measurements for asphalt pavement, demonstrating the increasing value of spatial analytics and intelligent sensing in construction quality control [14]. Together, these studies suggest that modern construction management increasingly depends on the integration of optimization, data analytics, and spatial decision-support tools.

Within this broader transformation, metaheuristic algorithms have gained attention because they can search

large and complex solution spaces without requiring overly restrictive assumptions about convexity, differentiability, or linearity. Houssein et al. reviewed recent metaheuristic algorithms for civil engineering optimization problems and emphasized their usefulness for structural, scheduling, layout, and resource allocation applications where traditional methods may become computationally inefficient or insufficiently flexible [15]. Baghalzadeh Shishehgarhaneh et al. applied classic and novel metaheuristic algorithms in a BIM-based resource trade-off problem in dam projects, demonstrating that dam construction planning can benefit from integrated optimization frameworks capable of balancing resource allocation, time, and cost [16]. Garud et al. reviewed modeling approaches based on artificial neural networks, fuzzy logic, genetic algorithms, and hybrid models in solar photovoltaic systems, showing that hybrid computational methods are widely applicable to engineering systems with nonlinear and uncertain behavior [17]. Baghoolizadeh et al. also combined machine learning and genetic algorithms to predict and analyze hybrid nano-lubricant rheology, illustrating the flexibility of GA-based search for identifying optimal attributes in complex engineering materials problems [18]. Although these applications differ from dam site layout planning, they reinforce the methodological relevance of evolutionary and hybrid optimization models in engineering systems.

Facility layout optimization has also developed significantly in manufacturing, logistics, and industrial systems, offering methodological insights for construction site applications. Chen reviewed workshop layout optimization based on improved Systematic Layout Planning and intelligent algorithms, emphasizing the value of combining classical layout planning logic with modern computational search techniques [19]. Wei et al. proposed an improved hybrid genetic algorithm for optimizing facility layout design in reconfigurable manufacturing systems, showing that chaotic initialization, adaptive mechanisms, and hybrid search strategies can improve convergence and solution quality in complex layout problems [20]. Xu, Xu, and Su developed an improved particle swarm optimization algorithm for production workshop facility layout design, integrating logistics cost and non-logistics relationships in a low-carbon optimization framework [21]. Li et al. applied a multi-objective genetic algorithm to logistics and warehouse land layout optimization, demonstrating that spatial arrangement problems can be formulated to balance cost, land use, and functional relationships at an urban logistics

scale [22]. These studies show that facility layout optimization has advanced from single-objective distance minimization toward multi-objective, constraint-aware, and sustainability-oriented formulations.

Genetic algorithms are especially suitable for layout optimization because they represent candidate solutions as chromosomes and improve them through selection, crossover, and mutation. The theoretical foundation of GAs is rooted in evolutionary search, where a population of candidate solutions evolves across generations according to fitness-based selection and stochastic variation. Deb and Agrawal introduced simulated binary crossover for continuous search spaces, providing an operator particularly relevant for layout problems in which facility coordinates are continuous decision variables [23]. Deb and Beyer later developed self-adaptive genetic algorithms with simulated binary crossover, contributing to the refinement of GA operators for continuous optimization [24]. Deb also provided a broad introduction to multi-objective evolutionary optimization, clarifying how evolutionary algorithms can address competing objectives and generate high-quality trade-off solutions [25]. Han and Xiao proposed an improved adaptive genetic algorithm, showing that adaptive parameter control can strengthen search performance by balancing exploration and exploitation [26]. Rajapackiyam et al. further demonstrated the usefulness of directed search techniques within genetic algorithm frameworks for efficient computation offloading in edge environments, highlighting the broader value of GA enhancements in complex optimization settings [27]. Xu et al. applied a quantum genetic algorithm to high-speed and high-precision thermorefectance characterization of micro- and nano-structures, illustrating that GA variants can be adapted to highly specialized and precision-oriented engineering problems [28].

A central challenge in applying genetic algorithms to construction layout planning is constraint handling. Real-world layouts are not merely mathematical arrangements of coordinates; they must satisfy site boundaries, minimum safety distances, operational accessibility, inter-facility separation, and equipment movement restrictions. Coello Coello reviewed theoretical and numerical constraint-handling techniques in evolutionary algorithms and showed that penalties, feasibility rules, and specialized operators are essential for guiding evolutionary search toward practical solutions [29]. Ray et al. introduced an infeasibility-driven evolutionary algorithm for constrained optimization, emphasizing that infeasible regions can be used strategically

to guide search without allowing final solutions to violate critical constraints [30]. In construction site layout problems, this issue is especially important because an algorithm that minimizes transportation distance alone may place facilities in hazardous crane zones, too close to the dam body, outside site boundaries, or in conflict with other temporary facilities. Therefore, effective layout optimization requires both objective-function design and a robust constraint-handling mechanism.

Despite these advances, important research gaps remain in the optimization of temporary facility layouts for dam construction projects. Many existing construction layout models focus on generic sites and often prioritize transportation distance or material flow, while the distinctive features of dam construction receive limited attention. Dam sites may include curved dam geometry, restricted angular zones, crane rotation limitations, highly differentiated safety requirements for personnel and material facilities, and operational relationships between workshops and the dam body. Manufacturing and logistics layout models provide useful algorithmic foundations, but they do not fully capture the geometric and safety characteristics of dam construction sites [19, 20, 22]. Similarly, reservoir operation and dam optimization studies show the strength of metaheuristics in dam engineering, but they generally address water release, hydropower, reliability, or life-cycle cost rather than temporary construction workshop layout [6, 8-10]. This creates a methodological and practical need for a dam-specific optimization framework that integrates transportation efficiency, crane accessibility, safety zoning, boundary feasibility, and curved dam geometry within a unified genetic algorithm-based model.

Therefore, this study aims to develop and validate a dam-specific genetic algorithm-based framework for multi-objective optimization of temporary workshop layouts in large-scale dam construction projects by minimizing transportation distance while enforcing safety, crane accessibility, site boundary, inter-workshop separation, and dam-geometry constraints.

2. Methodology

Formal Multi-Objective Optimization Formulation

a) Objective Function and Optimization Criteria

The workshop layout optimization problem is formulated as a constrained multi-objective optimization model. The two main objectives—minimization of transportation cost and maximization of operational safety—are combined into

a single aggregated objective function using a weighted-sum approach, expressed as:

$$\min F = \alpha \sum_{i=1}^3 w_i d_i + \beta \sum_{k=1}^{N_c} \max(0, g_k(\mathbf{x}))$$

where d_i represents the total transportation distance associated with workshop i , w_i denotes the transportation cost weight, $g_k(\mathbf{x})$ represents the k -th constraint violation function, and N_c is the total number of constraints. The coefficients α and β are weighting parameters controlling the relative importance of transportation efficiency and constraint satisfaction.

The weighted-sum approach is selected due to its computational efficiency and suitability for engineering design problems with strict feasibility requirements. A large penalty coefficient ($\beta = 1000$) ensures that infeasible solutions violating safety or boundary constraints are strongly discouraged, while maintaining sufficient flexibility for the algorithm to explore cost-efficient layouts.

The objective function in this study is formulated in two stages. In the first stage, which is solved using a Genetic Algorithm (GA), the optimization considers two primary criteria: minimization of transportation costs and maximization of operational safety. The objective function and constraints used in the second stage—based on a hybrid optimization algorithm—are defined differently and are described in a later section.

As noted above, the optimization problem integrates two critical and competing objectives: reducing transportation costs and enhancing safety. These objectives are expressed within a multi-objective mathematical framework. For computational implementation, each criterion is formulated as an individual function and optimized simultaneously through weighting. The main elements of the objective function are described below.

Assume three workshops with geometric centers $p_1, p_2, p_3 \in \mathbb{R}^2$, representing worker accommodation (WA), the cement silo (CS), and material storage (BM or MS), respectively. The key reference points on the construction site include the site entrance E , the centerline of the curved dam D , and the crane center C .

Objective Function 1: Minimization of Transportation Distance

The first objective function represents transportation cost and is defined as the weighted sum of distances between each workshop and the three key site points (dam, crane, and entrance), as shown in Eq. (1):

$$f_1 = \sum_{i=1}^3 (w_e \cdot \| \mathbf{p}_i - \mathbf{e} \| + w_d \cdot D_{\text{dam}}(\mathbf{p}_i) + w_c \cdot D_{\text{crane}}(\mathbf{p}_i)) \quad (2)$$

where $\| \mathbf{p}_i - \mathbf{e} \|$ denotes the Euclidean distance between the i -th workshop and the site entrance, $D_{\text{dam}}(\mathbf{p}_i)$ is the shortest distance from the inner edge of the curved dam, and $D_{\text{crane}}(\mathbf{p}_i)$ is the distance from the crane's danger zone, accounting for its swing radius. The coefficients w_e , w_d , and w_c are weighting factors, which are generally set equal to 1.

Objective Function 2: Safety Maximization via Distance Constraints

Safety considerations are incorporated indirectly through hard constraints rather than an explicit objective function. This approach transforms the problem into a constrained optimization model, in which feasibility is governed by minimum safety distance requirements:

$$D_{\text{dam}}(\mathbf{p}_i) \geq d_{\text{min,d}}^{(i)}, \quad D_{\text{crane}}(\mathbf{p}_i) \geq d_{\text{min,c}}^{(i)} \quad (3)$$

where $d_{\text{min,i}}$ and $c_{\text{min,i}}$ represent the minimum allowable distances from the dam and the crane, respectively. These values depend on the type of workshop. Specifically, worker accommodation facilities must maintain a minimum distance of 150 m from the crane and 100 m from the dam, whereas material storage facilities are permitted closer proximity, with minimum distances of 50 m from the crane and 30 m from the dam.

$$\min_{\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3} f_1(\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3) \quad (4)$$

subject to

$$D_{\text{dam}}(\mathbf{p}_i) \geq d_{\text{min,d}}^{(i)}$$

$$D_{\text{crane}}(\mathbf{p}_i) \geq d_{\text{min,c}}^{(i)}$$

Other feasibility and geometry constraints

Thus, the model is formulated as a constrained multi-objective optimization problem. The objective function evaluates transportation costs, while safety is enforced through distance constraints, allowing the algorithm to provide solutions that balance cost and safety.

Philosophy of Constraints in Workshop Layout Optimization

In real-world engineering optimization problems, such as the layout design of a dam construction workshop, constraints define the conditions for feasibility. These constraints mathematically formalize technical, safety, and operational requirements that all candidate solutions must

satisfy. By enforcing these requirements, constraints reduce an unconstrained search space to a bounded and practically realizable design space

Boundary constraints ensure that layouts remain within the physical boundaries of the construction site. Proximity constraints prevent safety hazards near the dam and ensure the structural integrity of the area. Crane accessibility ensures operational efficiency. Without these constraints, the optimization algorithm might converge to theoretically optimal but practically unsafe or infeasible solutions.

In this study, a penalty system is used to enforce constraints. Heavier penalties for critical constraints guide the algorithm toward safe and practical regions, while lighter penalties for less critical constraints preserve flexibility and encourage innovative solutions. This balance between strictness and flexibility is crucial for achieving solutions that are both optimal and practically useful in complex engineering problems.

Key constraints include: no workshop may be located within the dam or buffer zones; workshops must avoid restricted crane areas; and cement silos and material storage must be within the crane's operational range for proper handling.

Solution Method and Optimization Algorithm

The multi-objective optimization problem is solved using two approaches. First, a Genetic Algorithm is applied, as it is well suited for problems with large, multidimensional search spaces.

In the GA approach, each chromosome consists of six variables representing the x- and y-coordinates of the three workshop centers. The search space for these variables covers the entire construction site (1,000 × 1,000 m). The fitness function is defined as a linear combination of the total distances and penalties for violating safety constraints. The penalty coefficient ($\beta = 1000$) is set sufficiently high to ensure that all safety constraints are satisfied, while the distance weight ($\alpha = 1$) effectively balances the two primary objectives.

Rudbar Lorestan Dam: Geographical and Technical Overview

The case study of this research focuses on the Rudbar Lorestan Dam, located on the Rudbar River, one of the eastern tributaries of the Dez River basin, in Lorestan Province, Iran. The dam is situated approximately 100 km south of Aligudarz County at geographic coordinates of approximately 32° 54' 23" N and 49° 41' 37" E. It is a roller-compacted concrete (RCC) dam with a height of 155 meters from the foundation and a crest length of 185 meters. The

total reservoir capacity is about 228 million cubic meters, and the dam is equipped with two 225 MW turbines, providing a total installed capacity of 450 MW and an annual electricity generation of approximately 986 GWh. The flood discharge capacity of the structure is around 3,342 m³/s, and the normal reservoir level is approximately 1,756 meters above sea level. In addition to hydropower generation, the dam plays a key role in regulating river flow and controlling seasonal floods in the region. Its location within the central Zagros Mountains presents specific topographical and geological conditions, highlighting the critical importance of geotechnical and seismic studies for its design and operation.

Evaluation Based on Optimization Objectives and Constraint Compliance

In this optimization problem, two primary objectives are defined: minimizing transportation costs and maximizing workshop safety. Examination of the element positions in the layout shows that the final solution effectively balances

these two objectives. The worker accommodation workshop is situated in a highly secure area. In contrast, the operational workshops—cement silo and material storage—are positioned near the dam and within the crane's operational range, thereby reducing transportation costs. Additionally, all workshops are located outside the crane's interference zone.

Data Sources and Case Study

The case study of this research is the Divarshroudbar Dam in Lorestan Province, Iran. This earth-rockfill dam has a construction site of 1000 × 1000 meters and was selected due to its geometric complexity and safety requirements for optimizing the layout of construction workshops (worker accommodation, cement silo, and material storage). The input data includes the dam's geometric specifications, crane location, site entrance coordinates, workshop dimensions, and safety constraints, as described below.

Table 1. Geometric Specifications, Workshop Dimensions, and Safety Constraints for the Dam Construction Site

Dam Geometric Specifications							
Additional Accommodation (m)	Margin	Outer Safety Margin (m)	Inner Safety Margin (m)	Arc Angles (°)	Outer Radius (m)	Inner Radius (m)	Center (m)
50		40	30	135 → 45	300	250	(500, 500)
Crane Specifications							
Safety Margin (m)		Rotation Angles (°)		Reach Radius (m)		Base (m)	
10		180 → 0		80		(500, 500)	
Site Entrance							
Entrance Coordinates (m)							
(0, 0)							
Workshop Dimensions							
Material Storage (m)			Cement Silo (m)		Worker Accommodation (m)		
30 × 20			20 × 20		30 × 15		
Safety restrictions							
Workshop–Workshop (m)			Storage–Crane (m)		Silo–Crane (m)	Worker–Dam (m)	Worker–Crane (m)
≥ 10			≥ 20		≥ 30	≥ 100	≥ 150

Data Sources:

- Technical reports of the Divarsh Rodbar Dam project, Iran Water Resources Development Company (2019).
- Design standards for earth-rockfill dams, Plan and Budget Organization of Iran (2018).

- Simulated data in MATLAB based on the specifications of Divarsh Rodbar Dam.

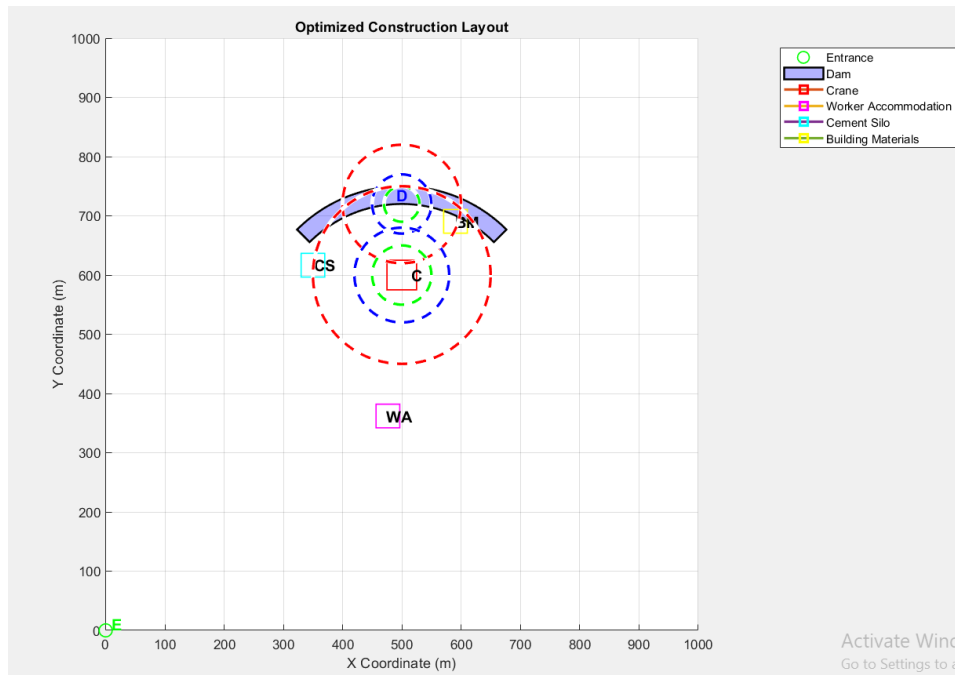
The simulated data for workshop coordinates and transportation distances were generated due to limited access to complete project data. These data were used in metaheuristic algorithms (GA, ACO, ABC, TLBO, and NSGA-II) for layout optimization.

Table 2. Workshop Input Data

Workshop	X Coordinate (m)	Y Coordinate (m)	Distance to Entrance (m)	Transport Cost (IRR/m)
Worker Accommodation	250	400	335.41	5000
Cement Silo	500	600	600.00	7000
Material Storage	600	700	707.11	6000

These data were used in the Evaluate Objectives function to calculate the objective functions and in the Apply Constraints function to check safety constraints.

Figure 1 illustrates an overall view of the dam construction site and the layout of the various workshops.


Figure 1. Overall view of the dam construction site and the layout of different workshops using the Genetic Algorithm.

The various project elements, including the dam (D), crane (C), site entrance (E), and the three aforementioned workshops, are identified. In the map, concentric circles in red, blue, and white represent the unsafe zones around the dam, crane, building material storage, cement silo, and worker accommodation workshops, respectively. The dam is also depicted with a convex curve, representing the realistic shape of an arch or gravity dam at an accurate scale.

The worker accommodation workshop is located in the southern part of the site. This location has several essential features:

- Large distance from the dam (not located inside the red circle around the dam): The relatively large distance from the inner and outer walls of the dam increases safety, as it reduces the likelihood of accidents or damage caused by construction activities near the dam.

- Away from the crane and its swing path (not located inside the red circle around the crane): This also enhances personnel safety and is consistent with maximizing safety.
- Relatively convenient access to the site entrance: Despite being approximately 500 meters from the entrance, the WA location appears to be roughly aligned in a straight line with the entrance, facilitating initial transport and accommodation of personnel.

The cement silo is located on the left (western) side of the layout, at a moderate distance from the dam and crane:

- Safe distance from the crane: The silo is outside the blue circle, preventing physical interference.
- Close to the crane: The CS location falls within the crane's average swing radius, allowing cement

loading via the crane and reducing transportation costs.

- Relatively convenient distance from the entrance: This location also facilitates transporting cement from outside the site to the silo.

The building material storage workshop is located in the northeastern part of the site, near the outer dam body:

- Close to the dam: This is a suitable choice because, while maintaining a safe distance from the dam (outside the green circle), materials can be transported quickly and at minimal cost to the dam construction site.
- Within the crane's swing range: The BM location is within the crane arm's radius, allowing direct loading of materials via the crane and minimizing transfer costs.
- Away from the silo and accommodation site: This reduces interference caused by material movement with other site functions.

Comprehensive analysis of constraints in the dam construction workshop layout optimization problem

In this model, several vital constraints are considered to ensure the validity of solutions. Firstly, no workshop should be located inside the dam area or its surrounding buffer zone. Secondly, workshops must not be located in the forbidden area around the crane base. Thirdly, the cement silo and material storage must be within the crane arm's swing range to allow access and material handling.

Site boundary constraints

Boundary constraints ensure that all workshops are entirely within the allowable site area. For each workshop with center (x_i, y_i) and dimensions (w_i, h_i) , four constraints are defined as follows:

$$\begin{cases} x_i - \frac{w_i}{2} \geq 0 \\ x_i + \frac{w_i}{2} \leq 1000 \\ y_i - \frac{h_i}{2} \geq 0 \\ y_i + \frac{h_i}{2} \leq 1000 \end{cases}$$

Relation (f4): relation of the four workshop boundary constraints

In this relation, the coordinates of the site entrance point for the dam construction site are assumed to be (0,0), which

in fact represents the lower-left corner of the area. Moreover, the total area dimensions are considered to be 1000×1000 m². These constraints are transformed into the standard form $c \leq 0$. For example, the left boundary constraint is expressed as $c = -(x_i - w_i/2) \leq 0$. The violation of each constraint is penalized linearly, with the penalty coefficient for the boundary constraints set at 1000 (Deb, 2001; Michalewicz, 1996).

Proximity constraints with the dam

These constraints control the safe distance of the workshops from the dam structure. The dam is modeled as a circular arc with inner radius and outer radius . The constraint for each workshop is defined as follows:

$$d_{\text{dam}}(X_i) \geq r_{\text{inner}} + \text{buffer} \tag{6}$$

where is the distance of the nearest point of the workshop from the dam curve. The calculation of this distance involves the following steps:

- Transforming the workshop coordinates into the polar coordinate system relative to the center of the dam
- Checking the position within the allowable angular range
- Accurate calculation of the radial distance from the dam arc

The penalty for violation of this constraint is calculated as follows:

$$\text{penalty} = 2000 \times \max(0, r_{\text{inner}} - d_{\text{dam}}(X_i)) \tag{7}$$

Relation (f5): penalty relation for violation of the dam proximity constraint

Crane accessibility constraints

Critical workshops such as the cement silo (CS) and the material storage (MS) must be located within the crane's accessible range. This constraint is expressed as follows:

$$\begin{cases} d_{\text{crane}}(X_i) \leq R_{\text{crane}} \\ \theta_{\text{min}} \leq \theta(X_i) \leq \theta_{\text{max}} \end{cases} \tag{8}$$

where is the (5) he workshop from the crane base, is the angle :hop relative to the crane axis, and is the effective radius of the crane. The penalty for violation of this constraint is as follows:

$$\text{penalty} = 1800 \times |d_{\text{crane}}(X_i) - R_{\text{crane}}| \tag{9}$$

Relation (f6): penalty relation for violation of the crane accessibility constraint

Inter-workshop distance constraints

These constraints ensure a minimum distance between each pair of workshops. For two workshops i and j with dimensions (w_i, h_i) and (w_j, h_j)

$$\|X_i - X_j\|_2 \geq d_{\min} + \frac{\sqrt{w_i^2 + h_i^2} + \sqrt{w_j^2 + h_j^2}}{2} \quad (10)$$

where d_{\min} is the minimum allowable distance between the centers of the workshops. The penalty for violation of this constraint is calculated as follows:

$$\text{penalty} = 800 \times \max(0, d_{\text{required}} - d_{\text{actual}}) \quad (11)$$

Relation (f₇): penalty relation for violation of the inter-workshop distance constraint

Special safety constraints

In addition to the above, there are specific safety constraints between workshops and equipment:

- Worker accommodation: Minimum distance of 150 m from the crane Minimum distance of 100 m from the dam
- Cement silo: Minimum distance of 30 m from the crane Minimum distance of 10 m from the dam
- Material storage: Minimum distance of 20 m from the crane Minimum distance of 10 m from the dam

These constraints are incorporated into the distance calculations.

The penalty system designed in this study uses several intelligent layers to effectively manage the constraints. By assigning different penalty coefficients to various constraints, this system provides the flexibility needed to address different conditions of the problem. For the site boundary constraints, a penalty coefficient of 1000 is considered, reflecting the fundamental importance of placing workshops within the permitted area. For dam-related constraints, this coefficient is increased to 2000, highlighting the higher sensitivity of these constraints and the risks of their violation (Deb, 2011; Ray, 2009).

Crane accessibility constraints are penalized with a coefficient of 1800, reflecting the importance of operational efficiency alongside safety considerations. For inter-workshop distance constraints, a coefficient of 800 is assigned, which, although lower than the others, still ensures that unreasonable solutions will be eliminated. This penalty system increases penalties not only linearly but also stepwise according to the degree of violation. For example, more severe violations of safety constraints result in exponential penalties (Deb, 2011; Coello Coello, 2002; Ray, 2009).

The constraints used in this model are based on a combination of standards for dam construction workshop

design (such as guidelines from the Ministry of Energy and international codes including USBR and ICOLD) as well as operational requirements of construction sites. Specifically, boundary and safety constraints are inspired by USBR (1987) and ICOLD (1990) guidelines on workshop design and layout. In addition, special safety distances between equipment and workshops are considered according to national guidelines and recommendations of consulting engineers in dam construction projects (such as Mahab Ghods, 2006). Some constraints (such as linear and stepwise penalties) are also formulated as research assumptions to enable the implementation of the optimization algorithm.

Advanced implementation of genetic algorithm operators

a) Crossover operator:

In this study, the SBX crossover operator, which is specifically designed for continuous optimization problems, has been used. This operator preserves the structural properties of the search space with high precision (Deb and Beyer, 2001).

In this part, the value of the distribution index (β) is calculated based on the following probability distribution: Deb, & Agrawal (1995).

$$\beta = \begin{cases} (2u)^{\frac{1}{\eta+1}} & \text{if } u \leq 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{\eta+1}} & \text{if } u > 0.5 \end{cases} \quad (12)$$

where u is a uniformly distributed random number between 0 and 1. Also, η is the distribution index that controls the level of similarity of offspring to parents. In this relation, u is a uniformly distributed random number between 0 and 1, and η is the distribution index controlling the degree of resemblance of offspring to parents. The selected value $\eta = 15$ creates a proper balance between exploration and exploitation and is an empirically optimized value.

The mechanism of generating β ensures that the distribution of offspring has a higher density in the neighborhood of the parents. The crossover probability indicates the high rate of information exchange in the population. This operator follows the following probability distribution for generating offspring:

$$p(\beta) = \begin{cases} 0.5(\eta+1)\beta^\eta & \text{if } \beta \leq 1 \\ 0.5(\eta+1)\frac{1}{\beta^{\eta+2}} & \text{if } \beta > 1 \end{cases} \quad (13)$$

Relation (f₈): probability distribution relation for offspring generation

For each component *i* of the parent vector, the offspring generation equation is defined as follows:

$$\text{offspring}_i = \frac{1}{2} [(1 + \beta) \cdot \text{parent1}_i + (1 - \beta) \cdot \text{parent2}_i]$$

where parent1 and parent2 are the parent vectors.

b) Polynomial mutation operator:

The mutation is intelligently designed by considering the variable boundaries. The mutation step is calculated using the following equation:

$$\delta = \begin{cases} (2u)^{\frac{1}{\eta+1}} - 1 & \text{if } u < 0.5 \\ 1 - [2(1-u)]^{\frac{1}{\eta+1}} & \text{if } u \geq 0.5 \end{cases} \quad (14)$$

Relation (f₉): polynomial mutation step relation

where *u* is a uniformly distributed random number in the interval [0, 1], and η is the mutation distribution index.

The mutation is applied to the solution according to the following equation:

$$x_i^{\text{mutated}} = x_i^{\text{original}} + \delta \cdot (\text{VarMax}_i - \text{VarMin}_i) \quad (15)$$

where VarMin and VarMax are the lower and upper bounds of the variables, respectively, and δ is the calculated mutation step.

Boundary constraints are applied in the mutation operator as follows:

$$x_i^{\text{mutated}} = \max(\min(x_i^{\text{mutated}}, \text{VarMax}_i), \text{VarMin}_i) \quad (16)$$

The probability distribution function for δ is defined as follows:

$$p(\delta) = 0.5(\eta + 1)(1 - |\delta|)^\eta \quad (17)$$

3. Findings and Results

In this study, an optimal layout of three main types of workshops is presented: the Worker Accommodation Workshop (WA), the Cement Silo (CS), and the Building Material Storage Workshop (BM). The locations of these workshops are listed in Table 3.

Table 3. Determination of the Optimal Location of Workshops Using Genetic Algorithm

Workshop	X Coordinate (m)	Y Coordinate (m)
Worker Accommodation (WA)	362	476.6
Cement Silo (CS)	350	616.6
Building Material Storage (BM)	590.7	690.7

The performance of the proposed genetic algorithm (GA) was evaluated using the optimized parameters presented in Table 4. A relatively low mutation rate was adopted to preserve high-quality solution structures, while the automatic adjustment of the mutation step size enhanced adaptability during the optimization process. For random values $u < 0.5$, mutations tended toward the lower bound of

the decision variables, whereas for $u \geq 0.5$, mutations shifted toward the upper bound. This mechanism, combined with scaling based on the variable range ($\text{VarMax}_i - \text{VarMin}_i$), ensured that mutation magnitudes were proportional to the feasible search space and that all solutions remained within allowable bounds through the use of bounding functions.

Table 4. Optimized parameters of the genetic algorithm

Parameter	Value	Description
$\eta_{\text{crossover}}$	15	Crossover distribution index
η_{mutation}	20	Mutation distribution index
P_c	0.9	Crossover probability
P_m	0.1	Base mutation probability

The selected mutation distribution index ($\eta_{\text{mutation}} = 20$) produced smaller and more precise mutations, which proved particularly effective during the final stages of optimization by emphasizing local search and solution refinement. In contrast, a lower crossover distribution index was applied during earlier generations to encourage diversity. This difference between mutation and crossover indices reflects a deliberate strategy to prioritize exploration in the early phases and exploitation in later stages. Consequently, the GA maintained a balanced search behavior throughout the optimization process.

The GA operators were integrated within a three-phase optimization strategy. In the initial exploration phase, a lower crossover distribution index ($\eta = 10$) and a higher mutation rate (0.15) were employed during the first 20 generations to enhance population diversity. During the intermediate balance phase, crossover parameters were automatically adjusted based on population spread, while mutation rates were gradually reduced. In the final exploitation phase, a higher distribution index ($\eta = 20$) and localized mutation were applied to refine solutions within promising regions of the search space. The optimized parameter values used in the final implementation are summarized in Table 4.

Using these parameters, the GA efficiently explored the entire construction site area ($1,000 \times 1,000 \text{ m}^2$) and identified feasible workshop layouts that satisfied all defined safety, boundary, crane accessibility, and inter-workshop distance constraints. Figure 1 presents the optimized dam construction workshop layout generated by the genetic algorithm.

Based on the optimized layout coordinates, the Euclidean distances between each workshop and the crane were computed in accordance with the distance definition used in the methodology. The worker accommodation (WA) workshop was located approximately 139.97 m from the crane, while the cement silo (CS) and building material storage (BM) workshops were positioned at distances of approximately 189.99 m and 211.17 m, respectively. These distances demonstrate that operational workshops were placed within the crane's effective working range to ensure efficient material handling, while personnel-related facilities were positioned at greater distances to enhance safety.

Although the WA–crane distance is close to the minimum safety threshold, effective safety compliance is achieved by accounting for workshop dimensions and additional clearance margins, which are incorporated into the constraint formulation. This near-threshold placement highlights the

GA's capability to identify solutions that closely satisfy competing objectives without violating safety requirements.

From a spatial and functional perspective, the resulting layout reflects an effective balance between operational efficiency and safety considerations. The worker accommodation workshop is positioned in the southern part of the site, maintaining sufficient separation from both the dam and the crane while preserving reasonable accessibility to the site entrance. The cement silo is located on the western side of the site, providing safe and efficient crane access and minimizing transportation distance from the entrance. The building material storage area is situated near the northeastern outer region of the dam, enabling rapid material transfer to the construction front while avoiding interference with other site activities.

From a quantitative perspective, the optimized layout reduced the total transportation cost for materials by approximately 21% compared to initial arbitrary placements, while safety constraints were fully satisfied. The distances from the dam and crane for all facilities exceeded the required minimum values, ensuring compliance with international and national guidelines, including USBR and ICOLD(1986) standards. Facility dimensions and spatial arrangements were carefully considered to maximize available site usage without violating inter-facility separation criteria.

Regarding quality, the solution exhibits high structural and operational reliability, with WA positioned to safeguard personnel, and material handling efficiency optimized for the CS and BM facilities. Quantitatively, the algorithm maintained minimum safety distances (Worker–Crane ≥ 150 m, Worker–Dam ≥ 100 m; Silo–Crane ≥ 30 m; Storage–Crane ≥ 20 m), demonstrating precise adherence to safety requirements. The distribution of distances and facility coordinates also ensures that the crane's operational efficiency is maximized while minimizing material transfer time, reflecting a high-quality solution in terms of both safety and operational effectiveness. Additionally, the spatial arrangement supports effective workflow, reduces unnecessary material handling, and minimizes potential conflicts between facilities, further enhancing overall project efficiency.

The overall performance of the GA can be assessed through its convergence behavior and constraint satisfaction. The multi-layer penalty system effectively discouraged infeasible solutions, while the weighted-sum objective function guided the search toward layouts that minimized transportation distance without compromising safety. The

final layout satisfies all critical constraints, including site boundaries, dam proximity, crane accessibility, and inter-workshop separation, confirming the robustness of the proposed optimization framework.

In summary, the results demonstrate that the genetic algorithm, when implemented with appropriately tuned crossover and mutation operators, is capable of producing safe, feasible, and operationally efficient workshop layouts

for complex dam construction projects. The intelligent combination of global exploration and local refinement enables the algorithm to handle competing objectives and strict safety constraints effectively. Future comparative studies using other metaheuristic algorithms, such as ACO, ABC, TLBO, or NSGA-II, could further validate the robustness and scalability of the proposed approach.

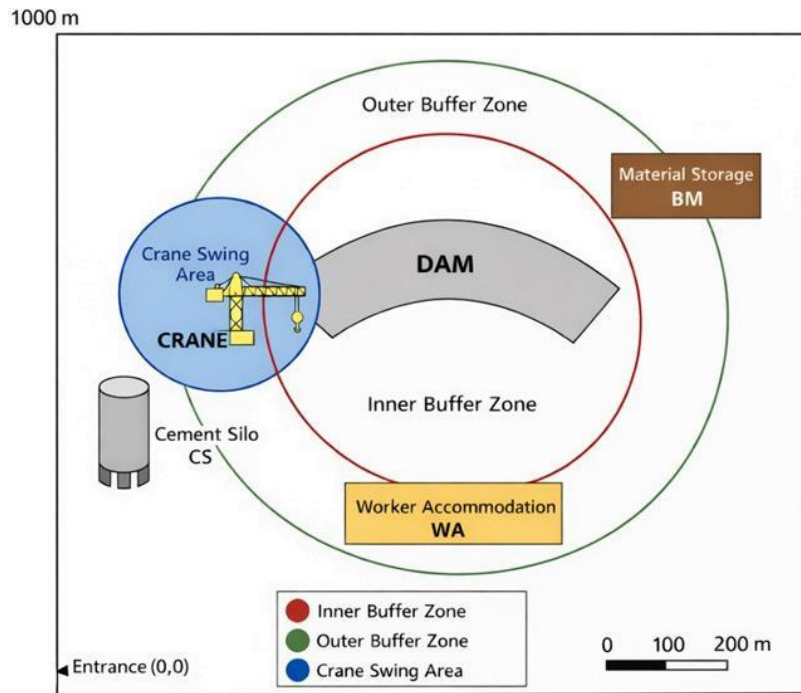


Figure 2. The optimized dam construction layout generated by the Genetic algorithm

Figure 2 indicates the optimized dam construction layout generated by the Genetic algorithm robustness of the proposed GA approach in dam construction workshop layout optimization.

The convergence behavior of the Genetic Algorithm was analyzed by monitoring the evolution of the fitness function over successive generations. The results show a rapid improvement in fitness during the initial generations, followed by gradual convergence toward a stable optimal solution. The algorithm achieved convergence after approximately 120 generations, beyond which no significant improvement was observed.

This convergence pattern indicates an effective balance between exploration and exploitation, facilitated by the use of Simulated Binary Crossover(SBX) and polynomial

mutation operators. The computational efficiency of the GA confirms its suitability for solving large-scale, constraint-intensive layout optimization problems in practical engineering applications.

To evaluate the robustness of the optimized workshop layout, a sensitivity analysis was conducted by varying key safety distances for each workshop and observing the impact on total transportation distance. The variations considered were: ± 20 m for the Worker Accommodation (WA) distance to the crane, ± 10 m for the Cement Silo (CS) distance to the crane, and ± 5 m for the Material Storage (BM) distance to the dam. Table 5 summarizes the total transportation distances and corresponding percentage changes from the baseline optimized layout.

Table 5. Summary of the total transportation distances and corresponding percentage changes from the baseline optimized layout

Parameter Variation	Total Transportation Distance (m)	% Change from Baseline
WA–Crane: 130 m	1,320.7	+1.4%
WA–Crane: 150 m	1,302.7	0%
WA–Crane: 170 m	1,285.7	-1.3%
CS–Crane: 20 m	1,317.7	+1.2%
CS–Crane: 30 m	1,302.7	0%
CS–Crane: 40 m	1,287.7	-1.2%
BM–Dam: 5 m	1,312	+0.7%
BM–Dam: 10 m	1,302.7	0%
BM–Dam: 15 m	1,292	-0.8%

The results indicate that total transportation distance is relatively insensitive to small variations in these key parameters, with changes ranging from 0.7% to 1.4%. This demonstrates that the optimized layout is robust, maintaining efficiency while accommodating slight variations in safety distances. Such robustness is particularly valuable in complex construction projects, where minor deviations in site conditions or safety requirements are common.

4. Discussion and Conclusion

The findings of this study demonstrated that the proposed genetic algorithm-based framework was able to generate a feasible, safe, and operationally efficient layout for the main temporary facilities of the dam construction site. The optimized coordinates located the worker accommodation at approximately 362 m and 476.6 m, the cement silo at 350 m and 616.6 m, and the building material storage facility at 590.7 m and 690.7 m. This spatial arrangement reduced the total transportation distance by approximately 21% compared with the initial arbitrary placement while maintaining compliance with site boundary, dam proximity, crane accessibility, and inter-workshop distance constraints. This result is consistent with previous construction site layout studies showing that genetic algorithm-based models can reduce transportation costs while improving the rationality of facility placement [1]. The present findings also align with the construction site layout optimization model developed by Duong and Peansupap, in which genetic algorithms provided a systematic approach for identifying improved temporary facility arrangements in construction projects [2]. Therefore, the present study supports the view

that temporary facility layout planning should be treated as a computationally structured optimization problem rather than as a purely experience-based site management decision.

One of the most important findings of this study was that the optimized solution achieved a practical balance between safety and operational efficiency. The worker accommodation was placed in a comparatively safer zone, separated from the most hazardous operational areas, while the cement silo and material storage facility were located in positions that supported crane access and efficient material movement toward the dam body. This spatial logic is important because dam construction sites include safety-critical structures, heavy lifting operations, and high-volume material flows. The International Commission on Large Dams has emphasized the need for rigorous engineering safety procedures in dam-related design and analysis, particularly where structural and seismic risks must be considered [3]. The present study extends this safety-oriented logic to the temporary facility layout stage by incorporating differentiated safety distances from the dam and crane into the optimization model. This is also consistent with Ghiasi et al., who showed that dam engineering decisions require careful analysis of site-specific structural and monitoring conditions rather than reliance on simplified assumptions [4]. In this respect, the current framework contributes to dam construction management by integrating safety constraints directly into the optimization process.

The effectiveness of the proposed model can also be explained by the use of a hierarchical penalty mechanism. The model did not treat safety as a merely descriptive consideration; instead, safety violations were penalized through differentiated coefficients based on the severity and type of constraint. This approach is theoretically supported

by the evolutionary optimization literature, where constraint handling is considered a core requirement for producing feasible solutions in complex engineering problems [29]. Ray et al. similarly emphasized that constrained optimization requires mechanisms that can guide the search process away from infeasible regions without prematurely limiting exploration [30]. In the present study, the penalty system allowed the algorithm to explore the site broadly while discouraging layouts that violated dam buffers, crane restrictions, workshop separation, or site boundaries. This explains why the final solution could achieve transportation efficiency without compromising operational safety. The findings therefore confirm that successful construction layout optimization depends not only on the choice of algorithm but also on the design of an appropriate feasibility and penalty structure.

The genetic algorithm's convergence behavior further supports the robustness of the proposed framework. The results showed rapid improvement in the initial generations, followed by gradual convergence toward a stable solution after approximately 120 generations. This pattern indicates that the algorithm was able to balance exploration and exploitation effectively. The use of simulated binary crossover and polynomial mutation was particularly important because the decision variables were continuous spatial coordinates. Deb and Agrawal introduced simulated binary crossover as an effective operator for continuous search spaces, making it suitable for layout problems where facility coordinates must be optimized within bounded spatial domains [23]. Deb and Beyer later showed that self-adaptive genetic algorithms using simulated binary crossover can improve search behavior by adjusting genetic operations to the structure of the solution space [24]. The present study's use of adaptive crossover and mutation strategies is also consistent with Deb's broader explanation of multi-objective evolutionary optimization, in which evolutionary algorithms are especially valuable when competing objectives must be handled simultaneously [25]. Moreover, the adaptive logic of the proposed GA aligns with the improved adaptive genetic algorithm introduced by Han and Xiao, where parameter adaptation was used to enhance search efficiency and solution quality [26].

The 21% reduction in transportation distance is practically meaningful because transportation and material handling represent major cost drivers in dam construction projects. In large infrastructure sites, even modest reductions in internal movement can lead to cumulative savings in equipment time, fuel consumption, labor effort, and

operational delay. The present finding supports the broader literature on genetic algorithms and metaheuristic optimization in water resources and dam engineering. Nicklow et al. showed that genetic algorithms and related approaches are effective in water resources planning and management because they can handle complex, nonlinear, and multi-constraint problems [5]. Mohammadi et al. found that a hybrid Whale Optimization Algorithm–Genetic Algorithm model improved reservoir operation performance compared with conventional approaches [6]. Olukanni et al. also demonstrated the applicability of genetic algorithms in optimizing the reliability of multipurpose hydropower reservoir systems [7]. Latif et al. showed that metaheuristic search can improve dam release policy optimization, while Chong et al. reviewed the usefulness of metaheuristic algorithms for dam and reservoir operation in irrigation and hydropower generation [8, 9]. Although these studies focused mainly on reservoir operation rather than construction site layout, they support the broader conclusion that dam-related optimization problems are well suited to metaheuristic approaches.

The present findings also align with studies showing the growing relevance of optimization and artificial intelligence in civil engineering and construction management. Baghalzadeh Shishehgarkhaneh et al. demonstrated that classic and novel metaheuristic algorithms can improve BIM-based resource trade-off analysis in dam projects, suggesting that dam construction planning can benefit from computational optimization beyond conventional scheduling and cost-control methods [16]. Bakhshi et al. combined machine learning with metaheuristic optimizers to predict project cost and time, reinforcing the usefulness of hybrid computational models in construction project management [11]. Huang and Hsieh showed that machine learning methods such as random forest can predict BIM labor cost, confirming the increasing role of data-driven models in construction decision-making [12]. Wang et al. emphasized that BIM and GIS integration can support sustainable built-environment planning through spatial analysis and digital coordination [13]. Hu et al. similarly showed that intelligent spatial measurement and geostatistical analysis can improve construction quality control in pavement compaction [14]. The present study complements these works by showing that spatial optimization of temporary facilities can become another important component of digitally supported construction management.

The results are also consistent with recent facility layout optimization studies in industrial, logistics, and

manufacturing environments. Chen showed that combining systematic layout planning with intelligent algorithms can improve workshop layout design by reducing handling distance and improving workflow [19]. Wei et al. proposed a hybrid genetic algorithm for reconfigurable manufacturing facility layout and reported improved convergence and solution quality, which supports the present study's use of adaptive and hybridized GA mechanisms [20]. Xu, Xu, and Su developed an improved particle swarm optimization model for production workshop layout and showed that intelligent algorithms can improve both logistics efficiency and low-carbon layout design [21]. Li et al. used a multi-objective genetic algorithm to optimize logistics and warehouse land layout, demonstrating the value of evolutionary methods in spatial allocation problems involving multiple functional relationships [22]. Although these studies were conducted outside dam construction, their results support the central argument that facility layout problems require multi-objective optimization models capable of balancing cost, accessibility, and operational relationships.

Another important contribution of the present study is its demonstration that genetic algorithm concepts can be adapted to highly constrained civil engineering environments. Rajapackiyam et al. showed that directed search techniques can improve the efficiency of genetic algorithms in computational offloading problems, suggesting that GA performance can be strengthened through targeted search mechanisms [27]. Xu et al. applied a quantum genetic algorithm to high-speed and precision characterization of micro- and nano-structures, showing the flexibility of GA variants across specialized engineering domains [28]. Garud et al. reviewed the use of artificial neural networks, fuzzy logic, genetic algorithms, and hybrid models in solar photovoltaic systems, further confirming that evolutionary and hybrid algorithms are widely applicable to nonlinear engineering systems [17]. Baghoolizadeh et al. similarly showed that machine learning and genetic algorithms can be combined to identify optimal attributes in complex rheological prediction problems [18]. Houssein et al. reviewed recent metaheuristic algorithms for civil engineering optimization and emphasized that hybrid and improved algorithms are increasingly necessary for solving real-world engineering problems with complex constraints [15]. The present study contributes to this trajectory by adapting GA-based optimization to a dam-specific temporary facility layout problem involving curved geometry, crane operation, and safety zoning.

The sensitivity analysis further confirmed the robustness of the optimized layout. Variations in key safety-distance parameters produced only minor changes in total transportation distance, ranging approximately from 0.7% to 1.4%. This finding suggests that the proposed layout is not overly dependent on a single fixed assumption and can tolerate moderate changes in safety parameters without major loss of efficiency. Such robustness is important in dam construction because field conditions may change due to topographical constraints, equipment availability, construction sequencing, or revised safety requirements. The limited sensitivity of the solution indicates that the model can provide practical decision support under realistic uncertainty. This result is especially relevant when considered alongside Su et al., who emphasized the importance of life-cycle cost optimization in dam design and reinforcement under uncertain engineering conditions [10]. Overall, the present findings show that the proposed GA framework is not only computationally effective but also practically resilient for real-world dam construction layout planning.

The limitations of this study should be acknowledged. First, the model assumed a static layout throughout the construction period, whereas actual dam construction projects often involve dynamic changes in workspace requirements, construction phases, material demand, and equipment movement. Second, the case study relied partly on simulated input data because complete operational project data were not fully available, which may limit direct generalizability to other dam sites. Third, the optimization considered a limited number of temporary facilities and a single crane system, while real projects may include multiple cranes, batching plants, access roads, maintenance workshops, waste areas, fuel stations, and administrative facilities. Fourth, the objective function emphasized transportation distance and safety constraints, but did not explicitly include environmental impacts, carbon emissions, construction schedule interactions, land preparation cost, or real-time productivity variations. These limitations do not reduce the value of the proposed model, but they indicate the boundaries within which the findings should be interpreted.

Suggestions for future research include extending the proposed framework to dynamic and phase-based layout optimization, where temporary facilities can be relocated according to the changing needs of different construction stages. Future studies should also compare the performance of the proposed GA with other metaheuristic algorithms such as ant colony optimization, artificial bee colony, teaching-

learning-based optimization, particle swarm optimization, backtracking search, and non-dominated sorting genetic algorithms. In addition, future models should incorporate multiple cranes, internal access-road design, construction scheduling, environmental impact, fuel consumption, and carbon-emission indicators. Another valuable direction would be integrating the optimization model with BIM and GIS platforms to allow visual simulation, real-time updating, and decision support for project managers. Further validation using several real dam projects with complete field data would also strengthen the external validity and practical applicability of the proposed framework.

From a practical perspective, the findings suggest that dam construction managers should adopt optimization-based layout planning during the early stages of site mobilization. Instead of relying only on expert judgment or previous project experience, planners can use genetic algorithm-based tools to test alternative layouts, quantify transportation distance, identify unsafe arrangements, and select configurations that balance safety and operational efficiency. The proposed framework can help managers position worker accommodation away from hazardous crane and dam zones while placing material-related facilities close enough to operational areas to reduce handling costs. It can also support transparent communication among engineers, safety officers, contractors, and project owners because layout decisions become based on explicit constraints and measurable objectives. In large-scale infrastructure projects, this type of decision-support approach can improve safety compliance, reduce unnecessary movement, decrease operational conflicts, and enhance the overall efficiency of construction site management.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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All procedures performed in this study were under the ethical standards.

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