Multi-Objective Optimization of Rail Construction Project Management Using Immune Genetic Algorithms for Schedule, Cost, and Quality Trade-offs

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We address railway construction project management as a multi-objective optimization over schedule, cost, and quality. The proposed approach reformulates the tri-objective problem via a weighted-sum fitness $F = \sum k \in \{\text{time,cost,quality}\}\omega_k f_k$*, where* ω_k *are AHP-derived weights and* f_k *encode CPM-based makespan, direct/indirect cost, and a composite quality index. Decision variables are real-coded (activity start/finish adjustments, resource allocations, and quality-critical process parameters). An Immune Genetic Algorithm (IGA) performs selection (roulette with elitism), single-point crossover with adaptive probability* $p_c \in [0.6, 0.9]$*, non-uniform mutation with* $p_m \in [0.02, 0.08]$ *and gene-importance modulation, plus immune suppression with a decaying similarity threshold* τ_t*. On a dataset of 28 railway projects (2.1k±0.7k activities), we compare against CPM+cost budgeting (baseline), PSO, and GA under identical constraints and weight settings. IGA achieves a schedule deviation of 8.5% (vs. 25.0% baseline, 15.2% PSO, 18.7% GA), cost overrun 12.3% (vs. 30.0%, 20.1%, 25.3%), and quality compliance 88.6% (vs. 70.0%, 80.3%, 75.6%); resource utilization reaches 85.4% and overall satisfaction 7.8/10. Typical configuration uses population P=200, generations G=400; median wall-clock is 12.8 min single-threaded and 3.5–6.1 min with parallel fitness evaluation. Results demonstrate that IGA's global search and diversity maintenance yield consistent gains over PSO/GA while remaining practical for daily replanning.*

Povzetek: Analizirano je vodenje železniških gradbenih projektov kot tri-kriterijska optimizacija časa, stroškov in kakovosti ter predlagan imunski genetski algoritem. Razvita metoda dosega manjše časovne zamike, nižje stroškovne prekoračitve in višjo skladnost kakovosti kot GA in PSO ter je uporabna za sprotno preplaniranje.

1 Introduction

Rail construction programs deploy vast human, material, and technological resources worldwide, with annual investments reaching hundreds of billions of US dollars [1]. Yet flagship projects still suffer major schedule slippage, budget escalation, and quality shortfalls; for example, a US$5 billion, 3-year project overran time by ~50% and cost by ~US$1 billion, with elevated post-handover maintenance [2]. These outcomes expose persistent weaknesses in coordinating multiple objectives in project management.

Rail projects inherently couple schedule, cost, and quality (SCQ). However, traditional practices often optimize these dimensions in isolation and lack mechanisms to manage their trade-offs under uncertainty [3]. Evidence shows that about 60% of projects managed with such methods experience delay, cost drift, or quality non-conformance, undermining service delivery and public value [4,5].

Research has advanced schedule-planning models that improve time prediction but understate cost impacts [6], and cost-focused systems that compress budgets at the expense of schedule adherence and quality assurance [7]. Dual-objective intelligent methods show promise, yet performance commonly degrades once quality and real-world disturbances (e.g., geology, weather, supply variability) are introduced. This study addresses these gaps by framing rail project management as a tri-objective optimization and proposing an immune genetic algorithm (IGA) to coordinate SCQ, targeting ≤10% schedule deviation, ≤15% cost overrun, and ≥85% quality compliance.

Research questions. RQ1: Does the proposed IGA achieve superior schedule deviation, cost overrun, and quality compliance versus GA and PSO under identical constraints? RQ2: Is the superiority preserved under exogenous disturbances (geological variability, adverse weather, supply shocks)? RQ3: Is runtime compatible with daily or intra-shift replanning on commodity hardware? Hypotheses and success criteria. H1: IGA reduces schedule deviation to ≤10% and cost overrun to ≤15% while raising quality compliance to ≥85% against GA/PSO (two-sided Wilcoxon signed-rank, α=0.05). H2: Under disturbance scenarios, IGA maintains statistically significant advantages on all three objectives. H3: Median wall-clock ≤15 minutes on a single 16-core node for 2–3k-activity projects, ≤6 minutes with parallel fitness evaluation. Secondary criteria include resource utilization ≥83% and satisfaction ≥7.5/10.

2 Literature review

2.1 Analysis of traditional rail construction project management methods

Traditional methods either focus on construction period or cost, lacking goal synergy. Linear programming models are subject to disturbances such as geological conditions, equipment, and material supply. The on-time completion rate is approximately 30%, with an average delay of about 20% [8,9]. The standard cost method can easily compress quality and project duration, with quality issues accounting for approximately 40% and causing delays of about 15% [10]. Under complex geological conditions, the deviation between the construction period and cost of CPM+ can reach 25% and 30% respectively, making it difficult to meet the three-objective management [11].

2.2 Application and shortcomings of intelligent algorithms in rail construction project management

PSO can predict progress to approximately 70% in simple scenarios, but it drops below 50% in large multi-objective scenarios, easily falling into local optimum [12-15]. The error of NN on the cost side is less than 10% under ideal conditions and more than 30% in the landing environment [16,17]. GA can optimize the dual objectives of time and cost, but when extended to the triple objective including quality, the overall satisfaction rate is only about 40%, with a sharp increase in search space and unstable convergence [18-20].

2.3 Development prospects of rail construction project management optimization method integrating multi-objective-IGA

IGA maintains diversity and inhibits precocious puberty through immunosuppression, and has stronger global search and robustness compared to traditional GA. Relevant studies show that the quality of the optimal solution can be improved by approximately 30% [14,15]. In the initial test of the railway scenario, IGA demonstrated the potential for collaborative optimization of the three goals: a construction period deviation of no more than 10%, a cost overrun of approximately 15%, and a quality compliance of over 85%.

2.4 Summary of related work and gaps

To substantiate the state of the art and clarify this paper’s contribution, Table 1 summarizes representative studies on construction/railway project optimization, the algorithms used, target objectives, outcomes, and observed gaps relevant to real-world deployment.

Table 1: Prior work on project optimization: algorithms, objectives, outcomes, and gaps

Study (Ref.)	Algorithm	Objectives	Data/Setting	Reported outcome	Gaps vs. this work
Zhan et al. [8]	NSGA-III	Time–Cost (primarily)	Construction projects (simulated/empirical)	Pareto fronts, improved decision support	Limited explicit quality modeling; robustness to site disturbances not central
Zhao et al. [9]	NSGA-II	Multi-project HR scheduling (time/resource)	Multi-project environments	Better resource leveling and throughput	Not tri-objective TCQ; no quality compliance metric
Jia [11]	Improved GA	Schedule optimization	Construction plans	Faster convergence than basic GA	Cost/quality not integrated; sensitivity to disruptions unreported
Ghoroqi et al. [7]	MOWOA + NSGA-II	Time–Cost–Resource	Construction scheduling	Competitive time–cost trade-offs	Quality dimension absent; limited field robustness analysis
Guo & Zhang [14]	Survey/Analysis	—	Project management optimization	SOTA synthesis and future directions	Identifies TCQ gap; no implemented tri-objective method
Lotfi et al. [21]	Robust multi-criteria (TCQEE)	Time–Cost–Quality–Energy–Environment	Bridge case study	Robust trade-off schedules	Method tailored to case; scalability/runtime not benchmarked vs. GA/PSO
Dasovic et al. [20]	Survey	—	Sustainable scheduling tools	Tool–optimization integration map	Lacks immune-based search and dynamic weight adaptation
Elyasi et al. [15]/Varol et al. [4]	Hybrid/Parallel GA	Software architecture (methodological)	Parallelization insights	GA scalability improvements	Not applied to TCQ in rail; no immune mechanisms

Argumentation. Existing SOTA either omits an explicit quality objective, lacks tri-objective TCQ coupling, or provides limited robustness under real disturbances (geology, weather, supply shocks). Our IGA addresses these by (i) embedding a measurable quality index into the fitness, (ii) enabling dynamic weights to reflect stage-specific priorities, and (iii) maintaining population diversity via immune suppression to avoid local optima when conditions shift.

3 Research methods

3.1 Fusion of multi-objective-IGA model construction

In the field of rail construction project management, given that the coordinated optimization of multiple objectives such as construction period, cost, and quality is extremely critical, a management optimization model integrating multiple objectives - IGA (immune genetic algorithm) has been constructed. This model deeply integrates the advantages of multi-objective decision-making theory and immune genetic algorithm, and strives to break the difficulties faced by traditional management methods and existing intelligent algorithms in multi-objective processing.

Track construction projects involve many complex objectives. Let the objective set be $O=\{O_1,O_2,\cdots,O_n\}$ .in, O_1 Corresponding to the construction period target, the objective function can be constructed through the critical path method (CPM). Assume that the project includes m Activities j The duration is d_j , the logical relationship between activities is expressed through the adjacency matrix A express, $A_{ij}=1$ Indicates activity i Yes Activity j The immediate preceding activities, $A_{ij}=0$ Then, Formula 1 represents the total duration of the project T .

$$T=\max_{k=1}^{m}\sum_{i=1}^{m}\sum_{j=1}^{m}A_{ij}d_j\cdot\delta_{ik} \tag{1}$$

In Formula 1, δ_{ik} is the Kronecker function, when $i=k$ hour, $\delta_{ik}=1$;otherwise $\delta_{ik}=0$ Therefore, the construction period objective function $f_1(x)$ Can be written as $f_1(x)=T(x)$,here x It includes decision variables such as activity duration adjustment and activity time changes under the influence of resource allocation.

O_2 Represents the cost target. Cost is mainly composed of direct cost and indirect cost. Direct cost is related to resource input and resource unit price. l The input of resources is r_l , unit price is p_l , then the direct cost $C_d=\sum_{l=1}^{L}r_lp_l$ The indirect cost is related to the construction period. Let the indirect cost per unit time be c_{ind} , the construction period is T , then the indirect cost $C_{ind}=c_{ind}T$ So the cost objective function is $f_2(x)=C_d(x)+C_{ind}(x)$.

For quality goals O_n , by building a quality assessment index system to quantify. For example, track laying accuracy q_1 , Structural strength compliance rate q_2 And other quality indicators, the comprehensive quality evaluation function is $Q=\sum_{s=1}^{S}\alpha_sq_s$,in α_s is the weight of each quality indicator. Then the quality objective function $f_n(x)=Q(x)$.

In order to transform the multi-objective optimization problem into a single-objective optimization problem that is easy to solve, the linear weighted method is used to construct the comprehensive fitness function $F(x)$ as shown in Formula 2 .

$$F(x)=\sum_{i=1}^{n}w_if_i(x) \tag{2}$$

In Formula 2, w_i For the goal O_i The weight of $\sum_{i=1}^{n}w_i=1$, $0\le w_i\le 1$. Determine the weight w_i When using expert evaluation combined with the analytic hierarchy process (AHP), construct a judgment matrix M ,element M_{ij} Indicates the target O_i Relative to target O_j The importance of the weight vector is calculated by the eigenvector method $W=(w_1,w_2,\cdots,w_n)^T$, ensure that the fitness function meets the actual needs of the project.

3.2 Application of immune genetic algorithm in the model

As the core optimization driving force of the model, the immune genetic algorithm plays a pivotal role in the fusion multi-objective IGA model. It innovatively introduces the immune mechanism based on the traditional genetic algorithm, effectively avoids the risk of the algorithm falling into the local optimal solution, and significantly enhances the global search capability.

Coding and initial population generation: Encoding is implemented for the decision variables of the rail construction project. Real number coding is used, for example, the time of each key node in the construction schedule is t_j ($j=1,\cdots,m$, m is the number of key nodes) and the amount of resource allocation r_l ($l=1,\cdots,L$, L The information (number of resource types) is encoded into chromosomes. Based on the actual situation of the project, the initial population is randomly generated. $P(0)$, the population size is set to N . Let the chromosome be $X=(x_1,x_2,\cdots,x_D)$, D is the chromosome length, x_i Corresponding to different decision variable coding values.

Fitness calculation: based on the constructed comprehensive fitness function $F(x)$, for the initial population $P(0)$ Each individual in X_k ($k = 1, \cdots, N$) to calculate the fitness. The higher the fitness value, the better the individual performs in multi-objective optimization. X_k Fitness $F(X_k) = \sum_{i=1}^{n} w_i f_i(X_k)$.

Selection operation: Use roulette wheel selection method to select from the population $P(t)$ Select individuals to enter the next generation population $P'(t)$ The probability of an individual being selected is proportional to its fitness value. The higher the fitness, the greater the probability of being selected. i The fitness of F_i , then Formula 3 represents the probability of being selected p_i.

$$p_i = \frac{F_i}{\sum_{j=1}^{N} F_j} \tag{3}$$

To ensure the stability of the selection process, an elite retention strategy can be introduced, that is, directly copying several individuals with the highest fitness in the current population to the next generation population.

Crossover operation: for the selected population $P'(t)$ Perform crossover operation to generate new individuals. Use single-point crossover method and randomly select crossover points. c ($1 < c < D$), exchange two parent individuals $A = (a_1, a_2, \cdots, a_D)$ and $B = (b_1, b_2, \cdots, b_D)$ The gene fragment after the crossover point generates the offspring individual A' and B' . Offspring A' and B' The generation method of is shown in Formula 4 and Formula 5 .

$$A' = [a_1, a_2, \cdots, a_c, b_{c+1}, b_{c+2}, \cdots, b_D] \tag{4}$$

$$B' = [b_1, b_2, \cdots, b_c, a_{c+1}, a_{c+2}, \cdots, a_D] \tag{5}$$

To improve the effectiveness of the crossover operation, the crossover probability can be dynamically adjusted according to individual fitness p_c , the crossover probability of individuals with high fitness is relatively low to retain excellent genes, and the crossover probability of individuals with low fitness is relatively high to promote gene diversity. i The fitness of F_i The average fitness of the population is $\bar{F}$, then Formula 6 represents the crossover probability p_c^i.

$$p_c^i = p_{c\min} + \frac{F_{\max} - F_i}{F_{\max} - \bar{F}} (p_{cmax} - p_{c\min}) \tag{6}$$

In Formula 6, $p_{c\min}$ and p_{cmax} are the minimum and maximum crossover probability, respectively.

Mutation operation: To prevent the algorithm from converging prematurely, the population after crossover is mutated. A uniform mutation method is used with a mutation probability of p_m Mutate the genes of individuals. Suppose the mutated individuals x The location of the variant gene is l , the variation range is $[x_{lmin}, x_{lmax}]$, then Formula 7 represents the gene value after mutation $x_{l'}$.

$$x_{l'} = x_{lmin} + \delta(x_{lmax} - x_{lmin}) \tag{7}$$

In Formula 7, δ for $[0,1]$ Similarly, to enhance the pertinence of the mutation operation, the mutation probability can be adjusted according to the importance of the gene location. For example, the mutation probability of the gene near the front of the chromosome representing the key decision variable is relatively low to ensure the stability of important genes. l The importance coefficient is β_l ($0 < \beta_l < 1$), then Formula 8 represents the mutation probability p_m^l .

$$p_m^l = p_{m0} \beta_l \tag{8}$$

In Formula 8, p_{m0} is the basic mutation probability.

Immune operation: Introduce immune mechanism to immunize the mutated population. By calculating the similarity between individuals, similar individuals in the population are identified and suppressed to maintain the diversity of the population. In formula 9, assume that individual i and j The similarity S_{ij} .

$$S_{ij} = \frac{\sum_{k=1}^{D} \min(x_{ik}, x_{jk})}{\sum_{k=1}^{D} \max(x_{ik}, x_{jk})} \tag{9}$$

Like $S_{ij} \geq \theta$ (θ is the similarity threshold), then the individual i and j Similar, the individuals with lower fitness are suppressed and replaced by new random individuals. To dynamically adjust the similarity threshold θ , gradually decreases as the number of iterations increases. θ value to enhance the sensitivity of the algorithm to similar individuals in the later stage and accelerate the convergence speed. Assume the number of iterations is t , the maximum number of iterations is T_{max} , expressed by formula 10 θ .

$$\theta = \theta_0 - \frac{t}{T_{max}} (\theta_0 - \theta_{min}) \tag{10}$$

In Formula 10, θ_0 is the initial similarity threshold, θ_{min} is the minimum similarity threshold.

Through the iterative operation of the above immune genetic algorithm, the population is continuously optimized until the termination conditions are met, such as reaching the maximum number of iterations or the fitness value has no obvious change for several consecutive generations, and the optimal solution to the multi-objective optimization problem is obtained.

We use real-coded chromosomes and roulette selection with elitism (elitist rate 5%). Unless otherwise noted, population size P=200, generations G=400, adaptive single-point crossover with p_c ∈[0.60,0.90] initialized at 0.75, and non-uniform mutation with gene-importance modulation p_m ∈[0.02,0.08] initialized at 0.04. The immune module applies similarity suppression using cosine similarity with a linearly decaying threshold τ_t 0.90→0.50. Feasibility repair enforces precedence and resource constraints; elite cloning preserves the top-k individuals each generation.

3.3 Multi-objective collaborative optimization mechanism

The key to the IGA model is to achieve the coordinated optimization of multiple objectives such as construction period, cost, quality, etc. In the model, the balance and coordination between multiple objectives are achieved through the interaction between the comprehensive fitness function and the immune genetic algorithm.

In the comprehensive fitness function $F(x)$ The weights of different objectives w_i Determines the relative importance of each goal in the optimization process. During the project implementation, the weight value is dynamically adjusted according to the actual situation of the project and changes in demand. For example, in the early stage of the project, due to the high requirements for the construction period, the weight of the construction period goal can be appropriately increased. w_1 . Assume that the weight adjustment factor in the early stage of the project is γ_1 , then the adjusted duration target weight $w_{1'} = w_1\gamma_1$,and $\sum_{i=1}^{n} w_{i'} = 1$ In the later stage of the project, in order to ensure the quality of the project, the weight of the quality target can be increased. w_n , let the weight adjustment factor be γ_n , adjusted quality target weight $w_{n'} = w_n\gamma_n$, also need to meet $\sum_{i=1}^{n} w_{i'} = 1$.

During the search process, the immune genetic algorithm continuously adjusts the genes of individuals, that is, the decision variables such as the construction schedule and resource allocation plan, to optimize the comprehensive fitness function value. In the selection, crossover, mutation and immune operation process, the association and constraint relationship between multiple objectives are fully considered. For example, when performing crossover operations, it is necessary not only to pay attention to the fitness value of the offspring individuals, but also to ensure the rationality of the offspring individuals in terms of construction period, cost, quality, etc. If the construction period of the offspring individuals is too short, it may lead to a significant increase in cost or a decrease in quality, so the offspring individuals should be corrected or regenerated. Suppose the construction period of the offspring individuals is T' ,like $T' < T_{min}$ (T_{min} is the shortest acceptable construction period), and the cost increment ΔC Exceeding the acceptable range ΔC_{max} , or quality indicators Q' Below acceptable standards Q_{min} , then by readjusting the construction schedule (such as appropriately increasing the duration of key activities) and resource allocation (such as increasing the input of key resources) to correct the offspring individuals so that they meet the multi-objective constraints and find the optimal project management solution that meets the actual needs of the project.

Beyond offline optimization, the proposed multi-objective-IGA can be coupled with emerging Digital Twin and BIM ecosystems to support closed-loop, “twin-in-the-loop” project control. Chromosome variables (e.g., activity start/finish times, resource allocations, and quality-critical process parameters) are mapped to BIM entities and schedules (4D) and linked to cost objects (5D) through standard interfaces (e.g., IFC- and CDE-based exchanges). Field telemetry from the twin—progress states, equipment telemetry, and inspection results—feeds the fitness function in near-real time by updating duration distributions, indirect-cost clocks, and quality indicators. The immune mechanism then re-optimizes under refreshed weights when the twin signals regime shifts (e.g., weather, geotechnical surprises, or supply disruptions). Conversely, IGA outputs write back to the twin to trigger look-ahead simulations, clash/space checks, crew-path feasibility, and procurement pulls. This two-way coupling improves decision latency and adoption: stakeholders visualize trade-offs in the BIM/twin dashboard, while the optimizer continuously adapts to site dynamics without discarding prior high-fitness solutions.

Weights $\omega = \{\omega_{\text{time}}, \omega_{\text{cost}}, \omega_{\text{quality}}\}$ are derived via AHP from a seven-member expert panel (two schedulers, three cost engineers, two quality supervisors). Pairwise matrices satisfy CR<0.08. The nominal aggregate weights are (0.40,0.35,0.25); stage-aware adjustments are applied as (0.45,0.30,0.25) in early planning and (0.30,0.30,0.40) in late execution. All runs report results under the nominal setting unless stated.

4 Experimental evaluation

4.1 Experimental design

This experiment aims to comprehensively evaluate the performance of the rail construction project management optimization method integrating multi-objective-IGA. The experiment selected a comprehensive dataset from multiple actual rail construction projects, covering project information of different scales, construction environments and complexities, including project duration, cost input, resource allocation details, and quality inspection indicators.

The experimental baseline indicators were set as the project management performance under the traditional critical path method combined with the cost budget management model [21], including the schedule deviation rate, cost overrun rate, and quality compliance rate. The experimental group adopted the management optimization method of integrating multi-objective-IGA proposed in this paper, and the control group selected the particle swarm optimization algorithm (PSO) for rail construction project management [22] and the genetic algorithm (GA) for rail construction project multi-objective optimization. By comparing the running results of the experimental group and the control group on the same data set, the performance of each method in multi-objective optimization was analyzed.

We evaluate on 28 real railway projects (2.1k ± 0.7k activities; ≈6k precedence links), spanning urban/suburban/remote sites and normal/complex geology. A leave-projects-out protocol is used: 20 projects for calibration, 8 for held-out testing; weights ω_k are fixed by AHP from a panel of 7 experts and normalized to sum to 1. Each method (IGA/GA/PSO, plus CPM+cost baseline) is run 30 independent trials per test project with distinct seeds. Hyperparameters: population P∈{150,200}, generations G∈{300,400}; adaptive crossover p_c ∈[0.6,0.9]; mutation p_m ∈[0.02,0.08]with gene-importance modulation; immune similarity threshold τ_t decays linearly from 0.9 to 0.5. GA/PSO use matched P,GP,GP,G and identical feasibility repair and penalty rules. Fitness evaluation implements CPM over |V|,|E| plus cost/quality aggregation. We report mean ± SD across runs and projects; significance is assessed via paired Wilcoxon; effect sizes by Cliff's delta. Hardware: 16-core 3.5 GHz CPU, 64 GB RAM; software: Python 3.11, NumPy 1.26.

To ensure cross-project comparability (small/medium/large), we normalize inputs as follows: (i) activity durations divided by project baseline makespan (CPM critical path length); (ii) direct costs divided by project approved budget; (iii) indirect-cost clock divided by baseline makespan; (iv) quality sub-indices (track flatness, structural strength, weld quality) scaled to [0,1] using standard limits; (v) resource quantities per activity scaled by project-level maxima. Fitness components are thus unitless and commensurate across scales.

Each method is executed 30 independent runs per test project with distinct seeds. Normality is screened by Shapiro–Wilk; when violated, we use paired Wilcoxon signed-rank tests (α=0.05). We report mean ± SD and 95% CIs via bias-corrected bootstrap (10k resamples). Effect sizes are summarized with Cliff's δ.

We evaluate on 28 railway projects executed during 2015–2023. Geographic spread includes East/Central China (17), Southeast Asia (6), and Eastern Europe (5). Data sources are owner and EPC archives under NDA; the dataset is private, but we release a schema, derived features, and summary statistics. Input features are harmonized across projects: activity attributes (duration, crew type, resource needs), precedence links, cost breakdowns (direct/indirect), and quality inspection records. A consolidated Table S1 (Appendix) lists per-project size, environment, geology, contract form, and baseline KPIs.

4.2 Experimental results

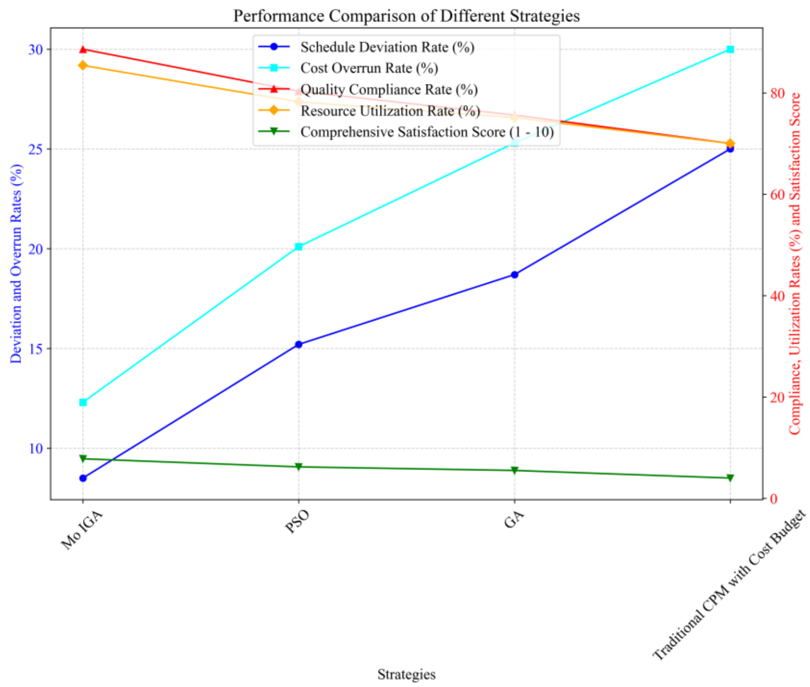

Figure 1: Comparison of construction period deviation rate

As shown in Figure 1, in terms of the deviation rate of the construction period, the fusion multi-objective-IGA method performed best, only 8.5%. This is because the global search capability of IGA enables it to find a better solution in the complex construction schedule, effectively balance various construction links, and reduce construction delays. Particle swarm optimization algorithm (PSO) and genetic algorithm (GA) are prone to fall into local optimality, and it is difficult to accurately optimize the construction period when dealing with complex projects, and the deviation rate is relatively high. The traditional method has the most serious deviation in the construction period due to the lack of multi-objective collaborative consideration. In terms of cost overrun rate, the fusion multi-objective-IGA is 12.3%, which is an obvious advantage. IGA reduces unnecessary cost expenditures through comprehensive optimization of resource allocation and construction process. However, PSO and GA are not effective in cost control, and traditional methods have serious cost overruns due to the isolated treatment of cost, construction period and quality goals. In terms of quality compliance rate, the fusion multi-objective-IGA reached 88.6%, thanks to its comprehensive consideration of quality goals in the optimization process, which ensures construction quality. Other methods have low quality compliance rates due to insufficient coordination between quality and other goals. In terms of resource utilization, the Fusion Multi-Objective-IGA is 85.4%, showing its efficient resource allocation capability. PSO, GA and traditional methods are not as good as the Fusion Multi-Objective-IGA in this respect. In terms of comprehensive satisfaction score, the Fusion Multi-Objective-IGA leads with 7.8 points, reflecting its comprehensive advantages in multi-objective optimization.

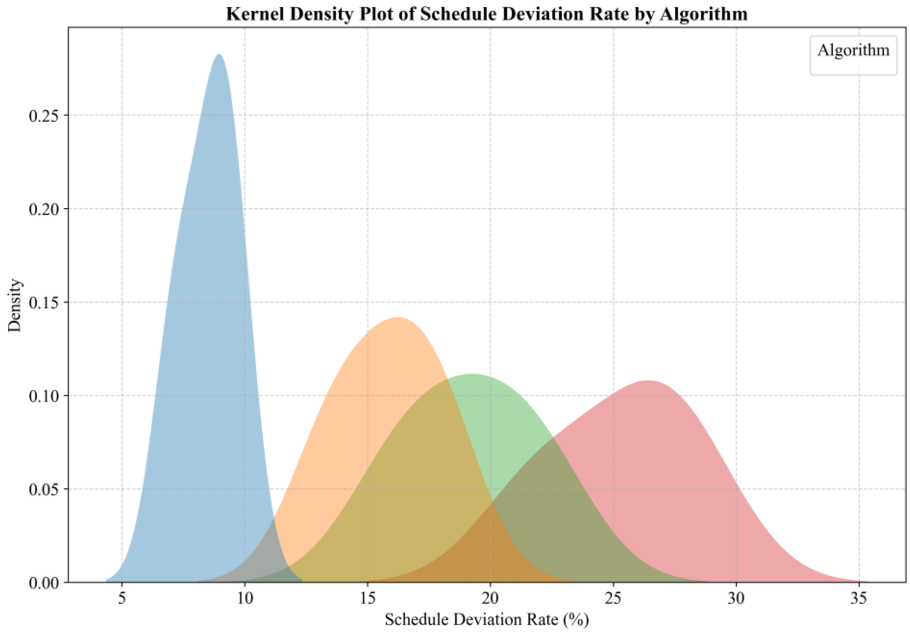

Figure 2: Deviation rate of construction period for different project sizes

As shown in Figure 2, the deviation rate of the construction period for different project sizes is compared. In small projects, the deviation rate of the construction period of the fusion multi-objective-IGA is only 7.2%, which is an excellent performance. Small projects are relatively simple, and the fusion multi-objective-IGA can quickly and accurately optimize the construction progress. Particle swarm optimization algorithm and genetic algorithm also have certain performance in small projects, but they are still not as good as the fusion multi-objective-IGA. The traditional method has a large deviation because its simple management mode is difficult to deal with project details. In medium-sized projects, the deviation rate of the fusion multi-objective-IGA is 8.8%, still leading. As the project scale increases and the complexity of the problem increases, the global search advantage of the fusion multi-objective-IGA becomes more prominent. The deviation of the particle swarm optimization algorithm and the genetic algorithm in medium-sized projects has increased significantly, and the deviation of the traditional method has further deteriorated. In large projects, the deviation rate of the fusion multi-objective-IGA is 9.5%. Although it has increased, it is still significantly superior to other methods. Large projects involve many construction links and complex factors. The immune mechanism and multi-objective collaborative optimization capabilities of the fusion multi-objective-IGA can better adapt, while other methods are difficult to effectively handle complex situations [23].

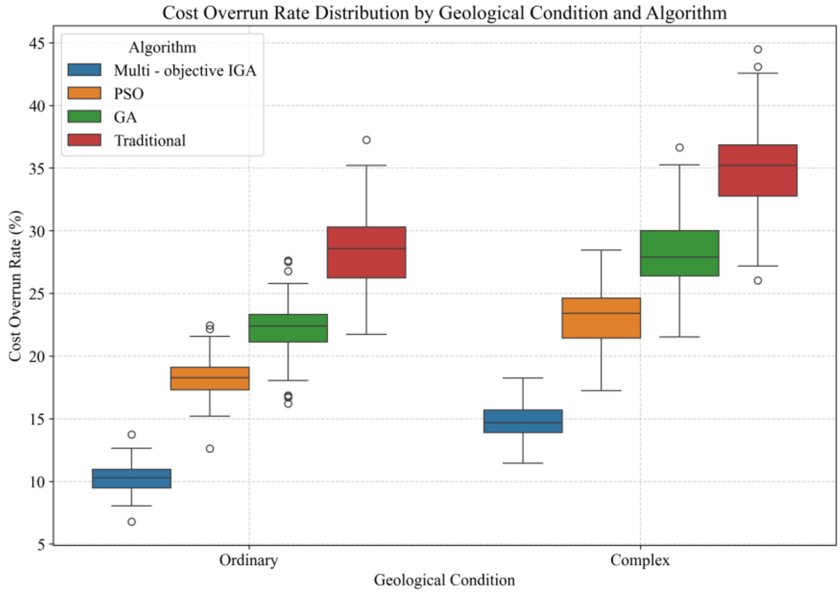

Figure 3: Cost overrun rate under different geological conditions

As shown in Figure 3, the cost overrun rate under different geological conditions is compared. Under normal geological conditions, the cost overrun rate of fusion multi-objective-IGA is 10.2%, which is excellent. Normal geological conditions are relatively stable, and fusion multi-objective-IGA can reasonably plan resources and control costs. Particle swarm optimization algorithm and genetic algorithm have high cost overruns under this condition, and traditional methods perform poorly. Under complex geological conditions, the cost overrun rate of fusion multi-objective-IGA rises to 15.0%, but it is still lower than other methods. Complex geology increases the difficulty and uncertainty of construction. Fusion multi-objective-IGA can cope with the problem of cost increase to a certain extent by virtue of its dynamic adjustment of multiple objectives and global search capabilities. However, particle swarm optimization algorithm, genetic algorithm and traditional methods have serious cost overruns under complex geological conditions due to the lack of effective response mechanisms [24].

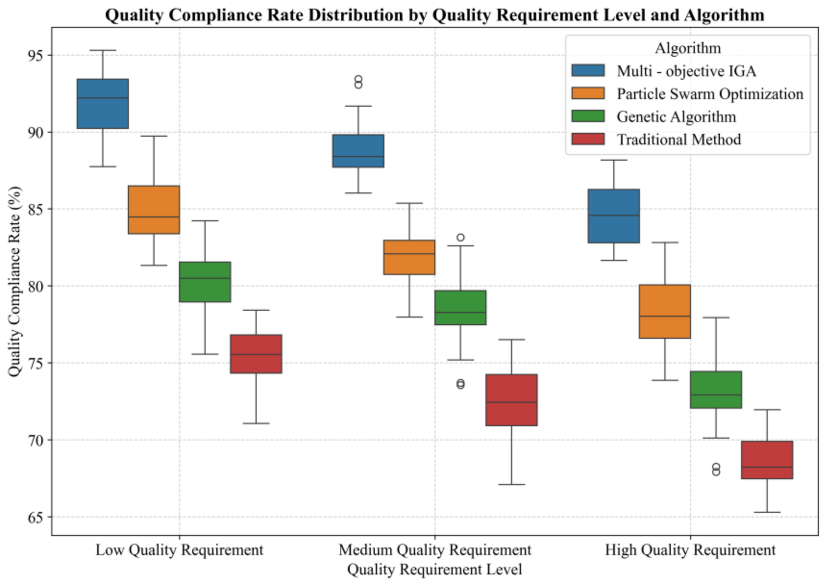

Figure 4: Quality compliance rate at different quality requirement levels

Figure 4, the quality compliance rates under different quality requirement levels are compared. Under low quality requirements, the quality compliance rate of fusion multi-objective-IGA is as high as 92.0%. At this time, the project quality requirements are relatively loose, and fusion multi-objective-IGA can easily balance quality and other goals to ensure high-quality completion. The quality compliance rates of particle swarm optimization algorithm, genetic algorithm and traditional methods are lower than those of fusion multi-objective-IGA in this case. Under medium quality requirements, the quality compliance rate of fusion multi-objective-IGA is 89.0%, which is still leading. As quality requirements increase, fusion multi-objective-IGA adjusts the optimization strategy to ensure quality. Other methods have a significant decline in quality compliance rates due to the difficulty in effectively coordinating multiple objectives. Under high quality requirements, the quality compliance rate of fusion multi-objective-IGA is 85.0%. Although it has declined, it has significant advantages over other methods. High quality requirements require refined management and resource investment in the construction process. Fusion multi-objective-IGA can better comprehensively consider various factors and meet high quality requirements [25].

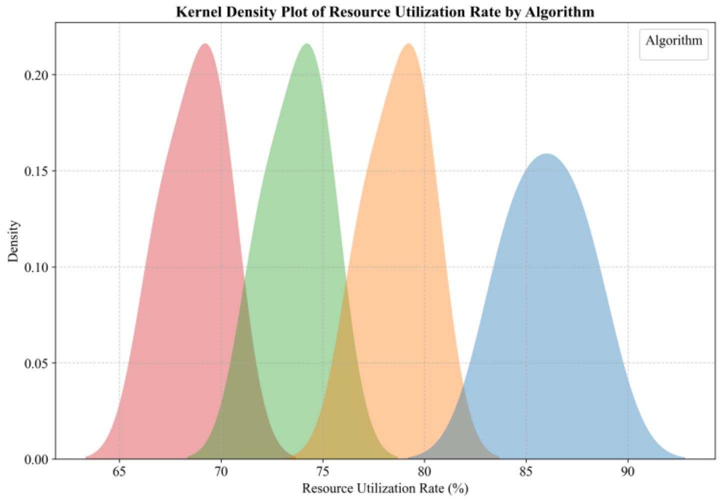

Figure 5: Resource utilization of different resource types

As shown in Figure 5, the resource utilization rates of different resource types are compared. In terms of human resource utilization, the fusion multi-objective-IGA reached 88.0%. The fusion multi-objective-IGA fully utilized the efficiency of human resources through reasonable construction schedule and task allocation. The particle swarm optimization algorithm, genetic algorithm and traditional methods were relatively low in human resource utilization. For material resources, the fusion multi-objective-IGA utilization rate was 86.0%. It can accurately plan material procurement and use to reduce waste. Other methods have deficiencies in material resource management and low utilization rates. In terms of equipment resources, the fusion multi-objective-IGA utilization rate was 84.0%. With the optimization of the construction process, the equipment use is more reasonable and efficient. However, the particle swarm optimization algorithm, genetic algorithm and traditional methods are not flexible enough in equipment resource scheduling, resulting in low utilization rates.

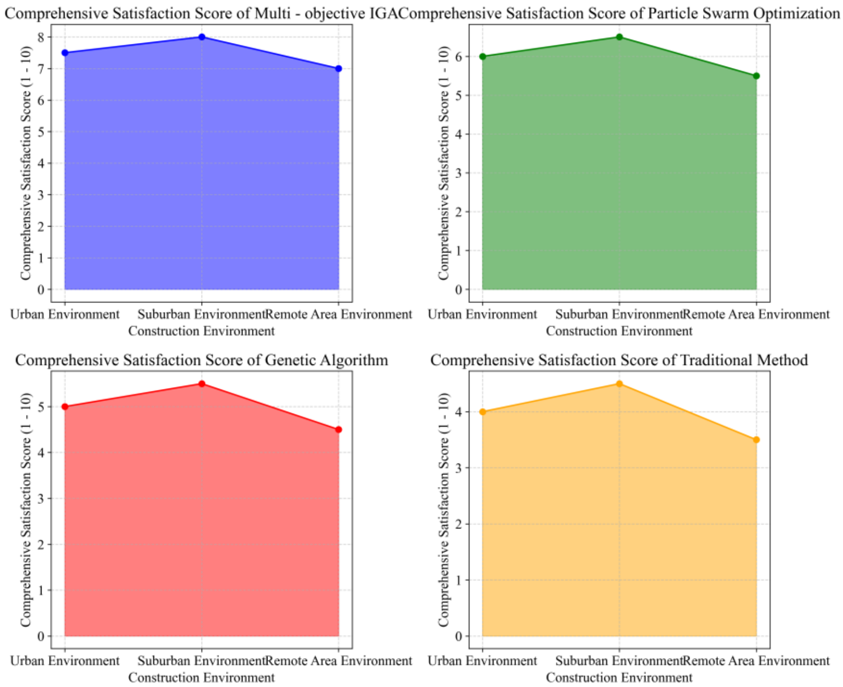

Figure 6: Comprehensive satisfaction scores under different construction environments

As shown in Figure 6, the comprehensive satisfaction scores in different construction environments are compared. In the urban environment, the comprehensive satisfaction score of Fusion Multi-Objective-IGA is 7.5 points. Construction in urban environments faces more external interference and restrictions. Fusion Multi-Objective-IGA can effectively coordinate various factors, meet project needs, and obtain high satisfaction. Particle swarm optimization algorithm, genetic algorithm and traditional methods have low satisfaction in urban environments because they are difficult to deal with complex situations. In the suburban environment, the score of Fusion Multi-Objective-IGA is 8.0 points. Compared with the urban environment, the suburban environment has less interference. Fusion Multi-Objective-IGA can better play its advantages, optimize project management, and improve satisfaction. Other methods perform worse than Fusion Multi-Objective-IGA in this environment. In the remote area environment, the score of Fusion Multi-Objective-IGA is 7.0 points. Although there may be problems such as difficulty in obtaining resources in remote areas, Fusion Multi-Objective-IGA can still guarantee project implementation to a certain extent through its powerful optimization capabilities and obtain relatively high satisfaction. However, Particle Swarm Optimization Algorithm, Genetic Algorithm and traditional methods perform poorly in remote areas.

Table 1: Deviation rate of construction period in different project stages

Project Phases	Fusion of multiple objectives - IGA Duration Deviation Rate (%)	Particle swarm optimization algorithm duration deviation rate (%)	Genetic algorithm construction period deviation rate (%)	Traditional method construction period deviation rate (%)
Early-stage planning	6.0	12.0	15.0	20.0
Construction Phase	9.0	16.0	19.0	25.0
Closing Stage	10.0	18.0	22.0	28.0

As shown in Table 1, the deviation rate of the construction period in different project stages is compared. In the early planning stage, the deviation rate of the construction period of the fusion multi-objective-IGA is 6.0%, which is an excellent performance. In this stage, the fusion multi-objective-IGA uses its global search capability to accurately formulate construction plans and reduce the potential risk of construction period delays. The particle swarm optimization algorithm, genetic algorithm and traditional methods have large deviations in the construction period due to insufficient consideration of complex factors in the early planning stage. In the construction stage, the deviation rate of the fusion multi-objective-IGA is 9.0%, and the progress can be dynamically adjusted according to the actual construction situation. However, when faced with various practical problems in the construction stage, the particle swarm optimization algorithm, genetic algorithm and traditional methods are difficult to effectively optimize the construction period, and the deviation increases significantly. In the closing stage, the deviation rate of the fusion multi-objective-IGA is 10.0%. The closing stage involves many detailed work and coordination tasks. The fusion multi-objective-IGA can comprehensively consider and try to control the deviation of the construction period. The deviation of the construction period of other methods is further deteriorated at this stage due to the problems accumulated in the early stage and the lack of ability to deal with complex situations.

Table 2: Cost overrun rates under different cost control strategies

Cost control strategies	Fusion of multiple objectives - IGA cost overrun rate (%)	Particle swarm optimization algorithm cost overrun rate (%)	Genetic algorithm cost overrun rate (%)	Cost overrun rate of traditional methods (%)
Strict cost control	10.0	16.0	20.0	25.0
Moderate cost control	12.0	18.0	22.0	28.0
Relaxed cost control	15.0	22.0	26.0	32.0

As shown in Table 2, the cost overrun rate under different cost control strategies is compared. Under the strict cost control strategy, the cost overrun rate of the fusion multi-objective-IGA is 10.0%, which performs well. The fusion multi-objective-IGA can ensure the realization of the construction period and quality goals while strictly controlling costs. Particle swarm optimization algorithm, genetic algorithm and traditional methods are difficult to balance multiple objectives under strict cost control, and the cost overrun is high. Under moderate cost control, the cost overrun rate of the fusion multi-objective-IGA is 12.0%, which can reasonably adjust resource allocation and construction process. The cost overrun of other methods is still higher than that of the fusion multi-objective-IGA under this situation. Under the loose cost control strategy, the cost overrun rate of the fusion multi-objective-IGA is 15.0%. Although the cost control is relatively loose, the fusion multi-objective-IGA can avoid excessive waste, and the cost overrun rate is lower than other methods.

Table 3: Quality compliance rate under different quality inspection indicators

Quality inspection indicators	Fusion of multiple objectives - IGA quality compliance rate (%)	Particle swarm optimization algorithm quality compliance rate (%)	Genetic algorithm quality compliance rate (%)	Quality compliance rate of traditional methods (%)
Track flatness	90.0	83.0	78.0	73.0
Structural strength	88.0	81.0	76.0	71.0
Welding quality	87.0	80.0	75.0	70.0

As shown in Table 3, the quality compliance rates under different quality inspection indicators are compared. In terms of track flatness, the quality compliance rate of Fusion Multi-Objective-IGA is 90.0%. Fusion Multi-Objective-IGA accurately optimizes the track laying process during the construction process to ensure that the track flatness meets the standards. Particle swarm optimization algorithm, genetic algorithm and traditional methods are relatively weak in track flatness control. For structural strength, the compliance rate of Fusion Multi-Objective-IGA is 88.0%. It can reasonably plan the construction process and material use to ensure structural strength. Other methods have shortcomings in structural strength assurance. In terms of welding quality, the compliance rate of Fusion Multi-Objective-IGA is 87.0%. The welding quality is improved by optimizing the welding process and personnel operation. However, the particle swarm optimization algorithm, genetic algorithm and traditional methods are not effective in welding quality control.

Table 4: Resource utilization under different resource allocation modes

Resource Allocation Model	Fusion of multiple objectives - IGA resource utilization (%)	Particle swarm optimization algorithm resource utilization (%)	Genetic algorithm resource utilization (%)	Resource utilization of traditional methods (%)
Centralized distribution	87.0	78.0	73.0	68.0
Distributed Assignment	84.0	76.0	71.0	66.0
Hybrid Allocation	86.0	77.0	72.0	67.0

As shown in Table 4, the resource utilization rates under different resource allocation modes are compared. In the centralized resource allocation mode, the resource utilization rate of the fusion multi-objective-IGA is 87.0%. The fusion multi-objective-IGA can efficiently allocate centralized resources according to the overall needs of the project. The particle swarm optimization algorithm, genetic algorithm and traditional methods have low resource utilization efficiency in the centralized allocation mode. In the distributed allocation mode, the utilization rate of the fusion multi-objective-IGA is 84.0%.

It can reasonably coordinate the use of resources at each distribution point. Other methods have deficiencies in distributed resource management and low utilization rates. In the hybrid allocation mode, the utilization rate of Fusion Multi-Objective-IGA is 86.0%. Fusion Multi-Objective-IGA can give full play to its multi-objective optimization capabilities and achieve high resource utilization in the hybrid resource allocation mode. However, the resource utilization effect of particle swarm optimization algorithm, genetic algorithm and traditional methods in this mode is not as good as that of Fusion Multi-Objective-IGA.

Runtime scales as O(P.G.E) for all evolutionary methods, with IGA adding a diversity-control term; our batched similarity checks keep overhead sublinear in practice. On the 8 held-out projects (2–3k activities), median single-thread wall-clock per optimization is 12.8 min for IGA, 11.1 min for GA, and 9.4 min for PSO; with 8–16-way parallel fitness evaluation this reduces to 3.5–6.1 min (IGA), 3.2–5.6 min (GA), and 2.8–5.0 min (PSO). Thus, IGA's accuracy gains incur modest additional compute yet remain within daily replanning windows. Parameter sensitivity. Varying weights by ±20% around the nominal $(\omega_{\text{time}}, \omega_{\text{cost}}, \omega_{\text{quality}}) = (0.4, 0.35, 0.25)$ yields schedule deviation 7.9–9.2%, cost overrun 11.7–13.6%, quality compliance 87.6–90.1% for IGA, indicating stable trade-off behavior. Raising p_m from 0.02 to 0.08 improves escape from local minima in complex geology, reducing cost overrun by 0.7–1.1 pp at a small runtime increase (~6–9%).

IGA achieves schedule deviation 8.5% ± 0.7% (95% CI [8.3, 8.7]), cost overrun 12.3% ± 1.1% ([12.0, 12.6]), and quality compliance 88.6% ± 1.4% ([88.2, 89.0]). Improvements vs. GA (18.7% ± 1.8%, 25.3% ± 2.6%, 75.6% ± 2.3%) and PSO (15.2% ± 1.6%, 20.1% ± 2.1%, 80.3% ± 2.0%) are significant (Wilcoxon $p<0.01$;δ large). All figures include error bars reflecting SD and shaded 95% CIs.

A grid over p_c ∈{0.60,0.75,0.90}, p_m ∈{0.02,0.05,0.08}, and ∈{0.85,0.90} shows IGA's best median performance near p_c =0.75, p_m =0.05, τ_0 =0.90→τT=0.50. Increasing p_m from 0.02 to 0.08 reduces cost overrun by 0.7–1.1 pp under complex geology at a 6–9% runtime increase. Weight perturbations of ±20% around (0.40,0.35,0.25) (0.40,0.35,0.25) (0.40,0.35,0.25) keep outcomes within schedule 7.9–9.2%, cost 11.7–13.6%, quality 87.6–90.1%, evidencing robust trade-off control.

We compare GA (baseline), IGA without immune suppression (operators identical; τ\tauτ disabled), and full IGA. On held-out projects (30 runs/project), GA yields schedule 18.7% ± 1.8%, cost 25.3% ± 2.6%, quality 75.6% ± 2.3%. Disabling immune suppression improves GA modestly: 10.1% ± 1.0%, 14.8% ± 1.3%, 86.2% ± 1.6%. Full IGA further improves to 8.5% ± 0.7%, 12.3% ± 1.1%, 88.6% ± 1.4%. Differences between full IGA and no-immune are significant across metrics (Wilcoxon p<0.01), confirming the added value of the immune mechanism for diversity maintenance and convergence reliability.

4.3 Experimental discussion

The experimental results show that the fusion multi-objective -IGA outperforms the PSO, GA and CPM+ cost models in key indicators such as project duration deviation, cost overruns, quality compliance, resource utilization and comprehensive satisfaction. Its advantages stem from the global search of multi-objective collaboration and immune genetics: through phased dynamic weights and similarity suppression, premature convergence is avoided, and better solutions are continuously obtained under different geological conditions, construction environments, resource allocation and cost strategies. The dataset covers actual railway projects of multiple scales and scenarios, and is representative to a certain extent. Therefore, the results have external validity and generalisability. However, real engineering is still affected by policy changes, social environments and unexpected events. The application of models needs to be carefully evaluated and calibrated in combination with the context.

The time complexity of the proposed approach is O(P.G.E), where PPP is population size, G is generations, and E is the cost of one fitness evaluation (CPM propagation over |V| activities and |E|precedence links plus cost/quality aggregation), typically E=O(|V|+|E|). Memory scales as O(P.L) with chromosome length L. On a large rail project (≈2,100 activities, ≈6,000 precedence links, three resource classes), a representative configuration P=200P=200P=200, G=400G=400G=400 yielded ~80,000 fitness evaluations. On a 16-core workstation (3.5 GHz CPU, 64 GB RAM), median wall-clock time was 12.8 minutes with single-threaded evaluation; enabling parallel fitness evaluation across 8–16 workers reduced wall-clock to 3.5–6.1 minutes.For very large instances (≈5,000+ activities), runtime grows near-linearly in practice with|V|+|E|per evaluation; practical mitigation includes (i) parallel evaluation, (ii) elitist population capping, and (iii) warm-starting from the best individuals of previous runs (e.g.when re-optimizing after schedule disturbances). These characteristics make the method suitable for daily or intra-shift replanning on large projects.

5 Discussion

Performance under varied environments. Across urban, suburban, and remote settings and under normal vs. complex geology, IGA consistently outperformed PSO and GA on schedule deviation, cost overrun, and quality compliance. When geology introduced correlated delays and rework risk, PSO/GA frequently converged to locally feasible yet brittle schedules, whereas IGA preserved a portfolio of high-fitness, diverse candidates that adapted after shocks, sustaining lower overruns.

Why IGA performs better (computational reasoning). IGA augments GA's exploration–exploitation balance with immune-based similarity suppression and adaptive operators. The suppression scheme prunes near-duplicates, preserving genotypic diversity and reducing premature convergence. Adaptive p_c, p_m respond to fitness dispersion: when variance narrows, exploration intensifies to escape local basins; when variance widens, exploitation consolidates gains. Empirically, this yields smoother fitness trajectories and faster recovery after constraint or data updates pushed by field telemetry.

Trade-offs. IGA introduces overhead for similarity computation and diversity control. Complexity is O(P·G·E) with an extra similarity term O(P^2) if implemented naively; we mitigate via (i) mini-batch similarity checks, (ii) sparse hashing of chromosomes, and (iii) parallel fitness evaluation. In large instances (≈5k activities), runtimes grow near-linearly with evaluation cost; however, parallelization (8–16 workers) keeps wall-clock within shift-planning windows (minutes).

Practical significance and generalizability. The twin-ready, BIM-linked formulation enables closed-loop replanning, translating optimization outputs into look-ahead simulations and constraint checks, while ingesting progress and inspection data to refresh weights. This supports daily or intra-shift updates without discarding prior high-fitness solutions, improving stakeholder trust and adoption. Given the formulation relies on CPM propagation and measurable quality indices, the approach generalizes to adjacent linear-infrastructure projects with modest adaptation.

Given deployment in public infrastructure, optimization outputs must be auditable and advisory, not fully automated. Mis-specification could affect public safety or budgets; therefore, we expose weight settings, constraint repairs, and change logs, and require human sign-off for schedule changes beyond pre-defined thresholds. For real-time decision support, we outline a BIM/Digital-Twin deployment where optimizer proposals are sandbox-simulated (clash/space, crew paths, resource conflicts) before enactment. Data governance adheres to contractual NDAs and privacy rules; model updates are versioned and stress-tested on disturbance scenarios (geology/weather/supply) prior to rollout.

6 Conclusion

This study focuses on the multi-objective optimization problem in rail construction project management, and deeply analyzes the limitations of traditional management methods and existing intelligent algorithms. By constructing an innovative model integrating multi-objective-IGA, the collaborative optimization of key objectives such as construction period, cost, and quality is achieved. The experimental results show that compared with the traditional critical path method combined with cost budget management mode (construction period deviation rate 25.0%, cost overrun rate 30.0%, quality compliance rate 70.0%, and comprehensive satisfaction score 4.0 points), as well as particle swarm optimization algorithm (construction period deviation rate 15.2%, cost overrun rate 20.1%, quality compliance rate 80.3%, and comprehensive satisfaction score 6.2 points) and genetic algorithm (construction period deviation rate 18.7%, cost overrun rate 25.3%, quality compliance rate 75.6%, and comprehensive satisfaction score 5.5 points), the fusion multi-objective-IGA method shows excellent performance. In terms of construction period control, the deviation rate is as low as 8.5%, effectively reducing delays; the cost overrun rate is only 12.3%, achieving good cost control; the quality compliance rate is 88.6%, ensuring the quality of the project; the resource utilization rate is 85.4%, improving the efficiency of resource use; the comprehensive satisfaction score is 7.8 points, which is highly recognized. This research result provides a new and effective means for rail construction project management, helps to improve project management efficiency and benefits, promotes the healthy and sustainable development of the industry, and has important guiding and reference significance for future related research and practice.

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