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Research on high-rise building construction cost optimization based on BIM and genetic Algorithm

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SUMMARY: *Aiming at the problems of complex cost composition, strong coupling of resource constraints and response lag of static control methods in the construction process of high-rise buildings, this paper proposes a construction cost optimization method based on BIM and genetic algorithm. BIM is used as the unified information carrier to construct the component-task-resource-expense integrated cost model, and the construction state is mapped to the computable optimization node through the structural design of task-cost unit. On this basis, genetic algorithm is introduced to realize the rolling optimization and scheme reconstruction for dynamic construction conditions. The experiment was carried out on the dataset of 32-floor residential project. The results show that the cost compression rate of the proposed method reaches 12.8%, which is 7.9 percentage points and 5.4 percentage points higher than that of the traditional method and the BIM static optimization method respectively. The time deviation rate is reduced to 3.6%, the resource utilization rate is increased to 86.7%, the average re-optimization response time is only 2.1 s, and the instability rate of the scheme is controlled at 2.9%. Research shows that this method can maintain good cost control ability and execution stability under complex construction disturbances, and provide a landing calculation path for digital cost control of high-rise buildings.*

KEYWORDS: *BIM; Genetic algorithm; High-rise building construction; Cost optimization*

1 Introduction

In the process of high-rise building construction, the project volume is large, the professional intersection is dense, and the process connection is long. The cost formation mechanism is no longer represented by the linear accumulation of a single checklist item, but is more reflected by the dynamic evolution results under the coupling of schedule arrangement, resource input, spatial organization and design change. Traditional cost control methods mostly rely on manual statistics, quota comparison and stage accounting. Although they can complete the cost summary at the static level, they are difficult to respond to the frequent process interchanging, material fluctuation and mechanical scheduling changes in the construction site in a timely manner, and it is also difficult to support the management needs of high-rise building projects for whole-process, fine-grained and traceability cost optimization. With the continuous advancement of the digital transformation of the construction industry, cost management is shifting from "ex post accounting" to a continuous closed loop of "process perception-state

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analysis-scheme optimization", and construction cost control is also gradually moving from experience-driven to data-driven and model-driven.

In recent years, BIM technology provides a new realization path for construction cost fine management. By mapping component geometry information, quantity information, schedule information and resource information into a unified data environment, BIM not only improves the accuracy of quantity extraction and cost correlation, but also makes it possible to integrate multi-source data in real time during construction. Previous studies have shown that the cost estimation and control mode based on 5D BIM can significantly enhance the transparency of project costs and improve the response efficiency of plan adjustment. At the same time, the global search ability of genetic algorithm in complex optimization problems makes it show strong adaptability in construction scheduling, resource allocation and time-cost collaborative solution. Related studies have found that the introduction of genetic algorithm into the BIM-driven construction optimization process can obtain a better cost-time combination under multiple constraints, thereby reducing the risk of bias caused by local experience decision-making.

However, the existing research still focuses on local task optimization, single-stage cost estimation or static scheme selection, and lacks discussion on the key issues such as "how to code the cost unit", "how to map the task relationship", and "how to write the optimization results back to the BIM model and form a collaborative operation mechanism" in the construction process of high-rise buildings. Especially in complex construction scenarios, without a unified information model and dynamic update rules, although the algorithm can output numerical solutions, it is difficult to truly transform into on-site executable cost optimization schemes. Based on this, this paper focuses on the construction cost optimization requirements of high-rise buildings, constructs a BIM-driven cost information model, designs the structural expression of construction tasks and cost units, and uses genetic algorithm to establish the cost optimization strategy for dynamic construction conditions, and then further forms the deployment and collaborative operation mechanism of BIM and genetic algorithm integration. The goal of this paper is not only to improve the calculation or price comparison accuracy at a certain stage, but to establish a set of computable, iterative and landing high-rise building construction cost optimization framework, so as to provide a more engineering suitable technical path for construction cost control under digital conditions.

2 Related Research

High-rise building construction cost control has long been subject to static quota accounting, manual account comparison and stage summary analysis and other traditional ways. This kind of method can still maintain the basic management order in projects with relatively stable engineering conditions and low change frequency, but its limitations quickly appear in the face of vertical transportation conflicts, professional interweaving, overlapping resource periods and frequent design changes that are common in high-rise building construction: The update of cost information is lagging behind, the quantity and schedule are disjoint, the local decision is difficult to transfer to the overall scheme, and the management chain shows obvious segmentation and passivity. In order to change this situation, researchers begin to introduce BIM into construction cost management, which carries multi-dimensional data such as components, schedules, resources and costs through a unified digital model, so that cost analysis changes from two-dimensional inventory logic to object-oriented data association logic. Alzara et al. constructed a 5D project time-cost optimization model combining genetic algorithm and BIM, and proved that the model expression could improve the effectiveness of collaborative solution of time and cost [1]. Wefki et al. further pointed out that BIM can not only support the automatic generation of construction plans, but also serve as the constraint carrier of optimization algorithms, so that the scheduling results are closer to the actual construction conditions [2]. Yu et al. completed the joint optimization experiment of BIM and genetic algorithm in the scene of deep and large foundation pit, indicating that the dynamic adjustment of time-cost under complex constraints has strong computability [3].

From the existing research progress, the contribution of BIM in the field of cost mainly focuses on three types of problems. One is the digital reconstruction of quantity extraction, cost mapping and payment management. Pishdad et al. believe that the value of 5D BIM in cost estimation, cost control and payment management is not only reflected in the improvement of calculation efficiency, but also in the enhanced continuity of cost tracking after the unification of data sources [4]. Alathamneh et al. pointed out from the perspective of quantity extraction that the BIM-driven automatic extraction of engineering quantities has gradually moved away from manual statistical methods, laying a data foundation for subsequent cost prediction and deviation identification [5]. The second is the optimization extension for multi-objective scenarios. Sherif et al. combined automated BIM structural design with cost optimization, so that design parameters and cost targets of reinforced concrete buildings could be adjusted synchronously [6]. Liu et al. introduced NSGA-II into the BIM conflict resolution problem, indicating that BIM models can not only serve for visual management, but also serve as the state space expression basis for complex optimization problems [7]. The third is the optimization of resource organization and spatial configuration at the construction site level. Zavari et al., Tao et al respectively proved in their research on dynamic layout of construction sites that the combination of BIM and GIS or multi-objective optimization algorithms could effectively improve the rationality of resource layout and the efficiency of construction operation [8, 9]. Wang et al. further emphasized that under the constraints of multi-dimensional spatial resources, automatic construction plan generation is no longer a simple schedule scheduling problem, but a comprehensive solution process involving the collaboration of space, equipment and processes [10].

Despite this, there are still obvious breaks in the existing research. Many studies have been able to use BIM to integrate cost data, and can also use genetic algorithm to complete local optimization. However, in the highly dynamic and strongly coupled scene of high-rise buildings, there is often a lack of uniform structural coding method among construction task units, cost units and resource units, which leads to unclear sources of optimization variables and unstable constraint boundaries. However, it is difficult to map directly to management actions that can be executed in the field. At the same time, many studies pay more attention to the improvement of single-stage estimation accuracy or a certain type of objective function, and there are still insufficient discussions on how to write back the optimization results to the BIM model, how to trigger re-optimization after schedule update and resource change, and how to form a continuous operation cost coordination mechanism. Hosamo et al.'s summary of 5D BIM application practice also shows that what really restricts its implementation is not the visualization itself, but the cross-stage data consistency, interface compatibility and the degree of decision-making mechanism embedding [11]. Zhang et al. tried to combine BIM and Elman neural network for construction cost optimization and prediction, and although the prediction ability was improved, their method focused more on result fitting and still had deficiencies in combinatorial search and discrete decision support in the construction process [12].

In order to more clearly present the differences of different research paths, this paper summarizes traditional cost management, BIM-driven cost management, and BIM and optimization algorithm coupling modes based on existing literature, as shown in Table 1.

Table 1: Comparison of characteristics of different construction cost optimization paths

Comparison Dimension	Traditional Cost Management Approach	BIM-driven Cost Management Approach	BIM and Genetic Algorithm Coupling Approach	Difference Focus
Data Source	Quotas, ledgers, and manual aggregation	Model components, quantities, and schedule data	Joint input of model data and optimization encoding	Data timeliness and consistency
Cost Representation	Static recording of bill items	Component-level and stage-level associated representation	Linked representation of tasks, resources, and costs	Cost granularity and computability
Optimization Method	Experience-based adjustment and post-event correction	Visual analysis and local comparison	Multi-constraint search and dynamic reconstruction	Solving capability and globality
Update Mechanism	Periodic reporting	Local refresh after model updates	Recalculation triggered by state changes	Dynamic responsiveness
Application Boundary	Suitable for low-complexity projects	Suitable for digitally managed projects	Suitable for highly complex and strongly coupled scenarios	Scope of scenario adaptation

It can be seen from Table 1 that the core problem of the traditional method is not "can not calculate the cost", but that the cost information is difficult to enter the dynamic decision-making kernel. Although the simple BIM method improves the information organization structure, it may not naturally have the ability of global search and combination optimization. Only when the data expression ability of BIM and the discrete optimization ability of genetic algorithm form a stable coupling, the construction cost optimization can move from static analysis to continuous adjustment. Essam et al. also pointed out in their review of BIM multi-objective construction scheduling optimization that the key to future research is not just algorithm replacement, but to build an integrated optimization framework that can undertake multi-source data, constraint relationships and execution feedback [13]. Afzal et al and Peng et al also showed in their research on sustainable architectural optimization that the closed-loop mapping relationship between models, parameters, constraints and execution results must be established if multi-objective optimization really serves engineering practice [14, 15]. Based on this understanding, BIM is regarded as a platform for cost information modeling and state expression, and genetic algorithm is regarded as a dynamic optimization engine. In this paper, a unified cost information model, structured task-cost unit and collaborative operation mechanism are constructed in the high-rise building construction scenario, so as to answer the shortcomings of existing research in dynamics, executability and deployment continuity.

3 The proposed cost optimization scheme

3.1 BIM-driven construction cost information model construction of high-rise building

The construction cost of high-rise building is not a simple superposition of several list prices. In the process of formation, it is continuously affected by the joint effect of component attributes, process timing, resource input, space conflict and design change. If the method of separate management of two-dimensional drawings and breakdown accounts is still used, although the cost data can be counted, it is difficult to enter the dynamic optimization process, especially to support the subsequent genetic algorithm to solve the construction scheme continuously. Based on this, this paper takes BIM as the core carrier of cost information modeling, organizes the component model, schedule node, resource consumption and cost parameters into a unified data object, and constructs the cost information model for the whole process of high-rise building construction. The model does not regard BIM as a visualization platform only, but as an infrastructure for cost state expression, constraint transfer and optimization input generation.

In order to ensure the computability of the model, the integration of architectural, structural and electromechanical professional models is completed in Revit modeling environment, and the IFC standard is used for semantic mapping, and the floors, partitions, components, processes and resource batches are encoded into the same data domain. For any construction object e_i, define its attribute vector as

$$x_i = [g_i, q_i, s_i, r_i, p_i] \tag{1}$$

Here, g_i represents geometric and positioning information, q_i represents engineering quantity characteristics, s_i represents construction timing status, r_i represents resource occupancy information, and p_i represents price parameters and cost rules. In this way, components are no longer just geometric entities, but are translated into cost unit nodes that can participate in the calculation.

On this basis, this paper establishes the component level cost mapping function. The dynamic cost to node e_i at time t, denoted by

$$c_i(t) = q_i \cdot u_i(t) \cdot \eta_i(t) + m_i(t) + a_i(t) \tag{2}$$

where, $u_i(t)$ is the comprehensive unit price per unit quantity, $\eta_i(t)$ is the construction state correction coefficient, which is used to reflect the amplification effect of factors such as aerial work, cross construction and night construction on the cost. $m_i(t)$ and $a_i(t)$ denote the machinery input cost and the management apportionment cost, respectively. Furthermore, the total cost state of the project at time t can be expressed as

$$C(t) = \sum_{i=1}^{N} c_i(t) + \sum_{(i,j)\in\Omega} \phi_{ij}(t) \tag{3}$$

Here, $\phi_{ij}(t)$ represents the additional cost term caused by operation conflict, resource contention or spatial interference, and Ω is the set of task pairs with coupling relationship. Equation (3) enables the BIM model to not only describe "how much each object costs", but also further express "how the objects jointly affect the total cost".

The model as a whole is composed of four layers (as shown in Figure 1): the bottom layer is the BIM entity layer, which is responsible for carrying geometric and semantic information of components, floors and professional systems. In the middle is the task-resource association layer, which maps the model objects to construction tasks, material batches, equipment teams and time Windows. The above layer is the cost calculation layer, which completes the extraction of engineering quantity, the attachment of unit price, the correction of measure cost and the calculation of coupling cost. The top layer is the optimization interface layer, which is used to output the cost nodes, constraint matrix and fitness evaluation parameters required for chromosome coding to the genetic algorithm. Through this structure, the status update in the BIM model can be directly transferred to the cost solution process, avoiding the break of "model to model and accounting to accounting" in the traditional cost management.

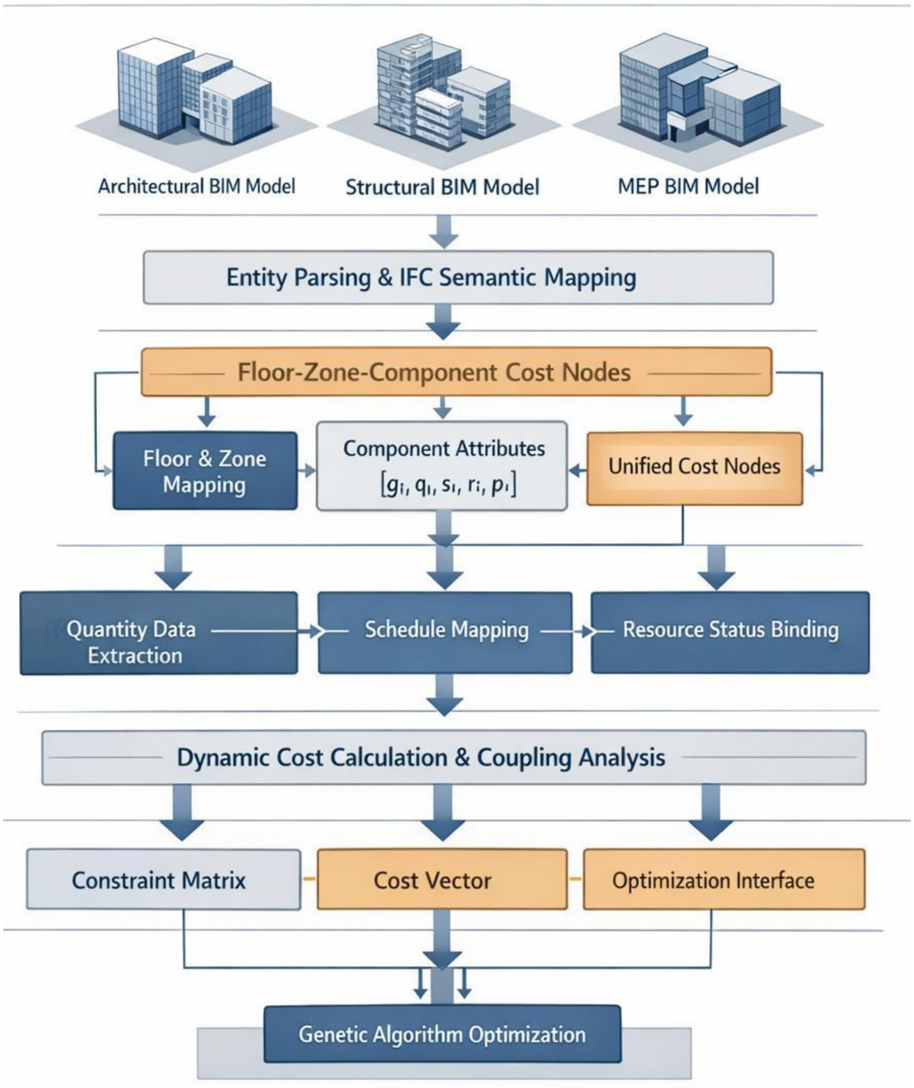

Figure 1: Construction cost information model construction framework for high-rise buildings

3.2 BIM-based structural design of construction task and cost unit

High-rise building construction is not only a problem of process sequence arrangement, but also a problem of cooperative organization of tasks, resources and costs under uniform time and space constraints. If the traditional schedule is still used as the main way of expression, construction activities can be listed, but it is difficult to stably map the relationship between floor division, component type, team investment, equipment occupation and cost collection into a computable structure. Especially in the scenario of high-rise buildings, where vertical transportation is limited, cross operations are intensive, and local changes are transmitted rapidly, the delay or resource deviation of any task node may cause a chain change in the subsequent cost distribution. Based on this, this paper reconstructs the activity units in the construction process into structured nodes with state attributes, dependencies, resource binding and cost mapping capabilities on the basis of BIM model objects, and further forms the task-cost coupling network for optimization solution.

In the proposed method, any construction task node is denoted as T_i, and its structured expression is defined as:

$$T_i = \langle b_i, \tau_i, R_i, D_i, C_i \rangle \tag{4}$$

where b_i represents the component or component set identification obtained by BIM model parsing, τ_i represents the task time window, R_i represents the resource demand vector, D_i represents the dependency set composed of sequential tasks, parallel tasks and mutually exclusive tasks, and C_i represents the set of cost units directly associated with the task. In this way, construction tasks are no longer just "pouring", "tying" or "installing" in the textual sense, but become discrete computing nodes that can be recognized by scheduling engines and encoded by optimization algorithms.

In order to enhance the correspondence accuracy between tasks and costs, this paper further constructs the hierarchical mapping rules of cost unit U_i. For any task T_i, its cost unit value can be expressed as:

$$U_i = w_m M_i + w_l L_i + w_e E_i + w_a A_i \tag{5}$$

where, M_i、L_i、E_i and A_i respectively represent material cost, labor cost, equipment cost and management allocation cost; w_m,w_l,w_e and w_a are the modified weights of different cost components, which are used to describe the cost fluctuations caused by differences in floor height, working surface density and construction conditions in high-rise building construction. If the coupling effect between tasks is considered, the total cost of the project phase can be further written as:

$$C_{stage} = \sum_{i=1}^{n} U_i + \sum_{(i,j)\in\Gamma} \psi_{ij} \tag{6}$$

Here, Γ is the set of task pairs with conflict or synergy relationships, and ψ_{ij} is the additional cost caused by process interference, equipment contention, or waiting time. Equation (6) means that the cost is no longer determined independently by a single task, but is jointly generated by the overall organizational state of the task network.

Figure 2 illustrates the structured design framework of this paper. The system first extracts the semantics of floors, partitions and components from BIM models, and regenerates them into construction task nodes. Then it establishes dependency edges, resource edges and cost edges, and finally forms a coding network that can be directly called by genetic algorithm. In this structure, the node state can change synchronously with the progress update, and the impact of delay, resource shortage or job conflict on a task can be propagated backward along the dependency and cost mapping chain, so as to provide a clear boundary for the subsequent dynamic optimization.

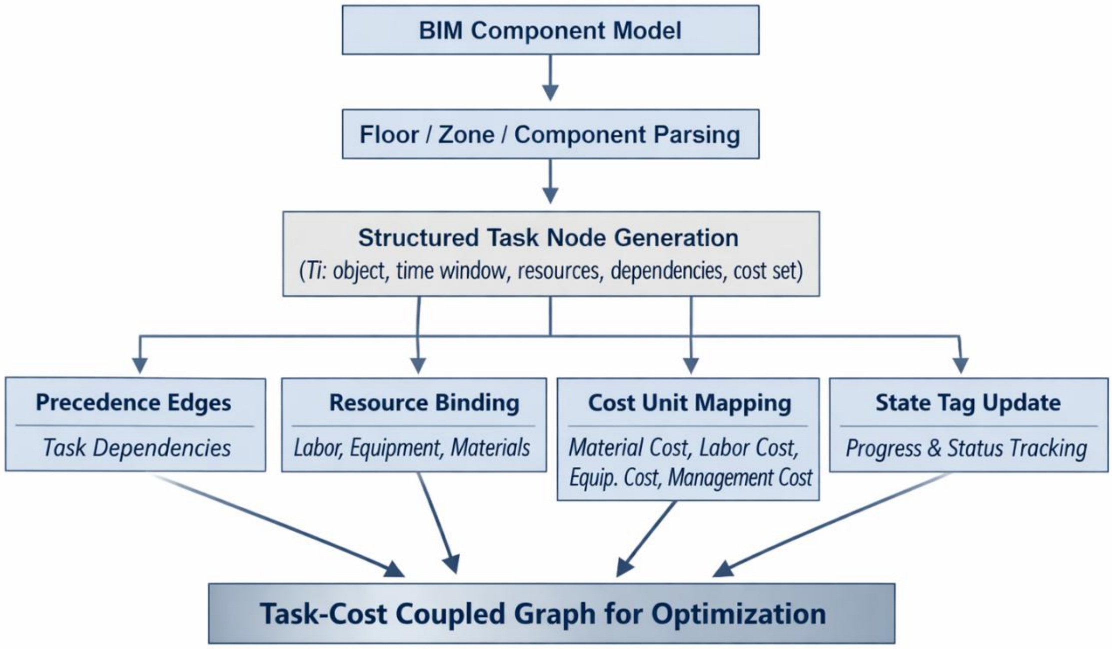

Figure 2: BIM-based structural design framework for construction task and cost unit

3.3 Dynamic optimization strategy of construction cost supported by genetic algorithm

There is not a long-term stable "optimal path" for cost optimization in high-rise building construction. Floor work advancement, tower crane and construction elevator occupancy, material arrival deviation, and cross process insertion will continuously change the cost structure and constraint boundaries. If the static optimization method of one-time modeling and one-time solution is still adopted, the obtained scheme often only corresponds to the ideal construction conditions, and it is difficult to deal with the resource reallocation and cost drift caused by site state disturbance. Based on the above BIM cost information model and task-cost coupling network, this paper introduces genetic algorithm to construct a dynamic optimization strategy, so that the construction plan can be continuously recalcated and maintain a better cost level in the state update process.

At the beginning of optimization, the system reads the task node set, resource occupancy matrix and cost parameter table at the current time from the BIM model and its associated database, and encodes the construction scheme as a chromosome individual. For any chromosome X, its code can be expressed as:

$$X = [x_1, x_2, \ldots, x_n] \tag{7}$$

Here, x_i represents the execution period, resource assignment, or construction sequence status of the ith task node. The encoding not only preserves the task sequence constraint, but also allows the adjustment of resource allocation and job window within the feasible range, so that the genetic search can cover the common multi-plan combination space in high-rise building construction.

In order to avoid the algorithm only pursuing a single low-cost result and ignoring the project duration and conflict risk, this paper constructs a comprehensive fitness function:

$$F(X) = \alpha \cdot \frac{C_{min}}{C(X)} + \beta \cdot \frac{T_{min}}{T(X)} + \gamma \cdot \frac{1}{1 + R(X)} + \mu \cdot \frac{1}{1 + S(X)} \tag{8}$$

where C(X) is the total cost of the scheme, T(X) is the total construction period, R(X) is the resource conflict penalty term, and S(X) is the construction state offset penalty term. α,β,γ,μ are the weight coefficients, which satisfy $\alpha+\beta+\gamma+\mu=1$. In this way, the fitness evaluation is no longer limited to "the lowest cost", but also considers the cost, timeliness, resource coordination and site state consistency, so that the engineering feasibility of the solution is stronger.

Figure 3 shows the operation process of the proposed dynamic optimization strategy. The system does not output the results directly after the initial population is generated, but completes the selection, crossover and mutation first, and then combines with the real-time state of BIM to determine whether the individual still meets the current construction conditions. If there is a waiting, equipment failure or material delay on a certain floor, the corresponding constraints are immediately written back to the population evaluation process, triggering fitness recalcuation and feasible solution update.

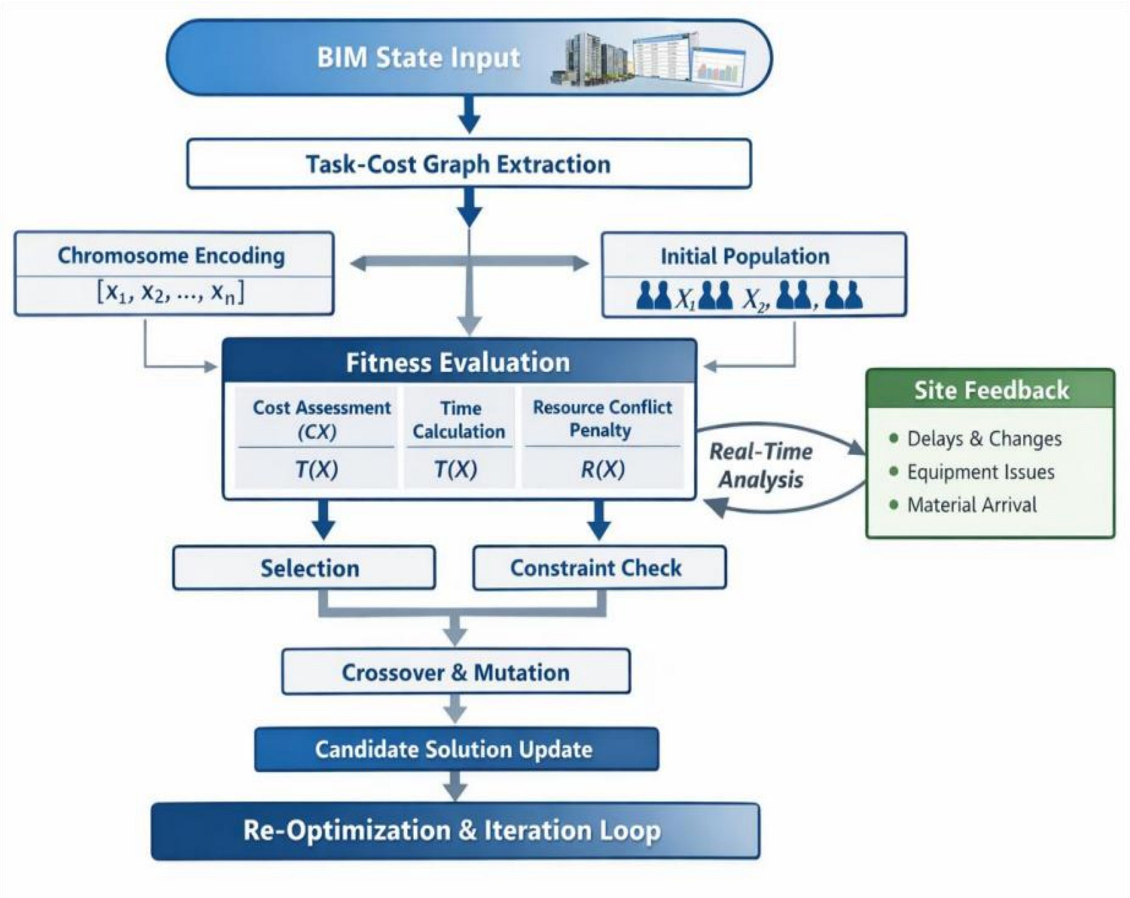

Figure 3: Dynamic optimization process of construction cost supported by genetic algorithm

In the process of population iteration, this paper uses the combination of elite retention and adaptive mutation to control the search direction. Let the population optimal solution at generation k be $X^{(k)}$, and when the field state vector is updated from Z(t) to Z(t+Δt), the scheme correction process can be written as:

$$X^{(k+1)} = \Phi(X^{(k)}, Z(t + \Delta t), \Omega) \tag{9}$$

Here, $\Phi(\cdot)$ represents the recode and re-evolution operation based on state feedback, and Ω is the constraint set composed of operation dependence, resource limit and space accessibility. The significance of Equation (9) is that the genetic algorithm is no longer an off-line solver, but is embedded in the BIM-driven dynamic cost control chain, which can continuously revise the search direction with the change of construction status.

Through this strategy, the cost optimization process is transformed from static scheme selection to a rolling solution mechanism for field disturbances. It not only uses the advantages of genetic algorithm to deal with discrete combinatorial optimization problems, but also provides real-time and structured state input with the help of BIM, so that the high-rise building construction cost control has stronger response ability, constraint consistency and dynamic adaptation ability, and also lays the algorithm foundation for the system integration and cooperative operation mechanism in the next section.

3.4 Cost optimization deployment and cooperative operation mechanism of BIM and genetic algorithm integration

Only with the support of stable system deployment and cross-module collaboration mechanism, the cost optimization results obtained by genetic algorithm can be truly transformed into executable solutions in high-rise building construction. For such projects, cost control is not a calculation link running independently, but a process that is continuously coupled with BIM model update, schedule feedback, resource status synchronization, and field execution correction. If the interface between model layer, algorithm layer and business layer is loose, it is easy to lead to problems such as the delay of optimization results, the distortion of state mapping and the breakage of execution feedback. Based on this, this paper constructs the collaborative operation framework of the integration of BIM and genetic algorithm, so that the cost optimization can form a closed loop in the chain of "model analysis - strategy generation - on-site execution - feedback correction".

The system as a whole adopts a hierarchical decoupled structure, which is composed of data access layer, BIM modeling layer, optimization decision layer and execution feedback layer. The data access layer is responsible for gathering on-site information such as component changes, progress filling, material arrival and equipment occupancy. The BIM modeling layer completed component semantic parsing, cost node updating and task relationship reconstruction. The optimization decision layer calls the genetic algorithm module in the Python environment to output the resource allocation and cost optimization scheme of the current cycle. The execution feedback layer maps the scheme into construction instructions, resource adjustment suggestions and deviation warning information, and writes the results back to the model database. Figure 4 shows the cooperative operation process. In the figure, each layer is not isolated in series, but continuously exchanges state quantities and constraint parameters through a unified data interface.

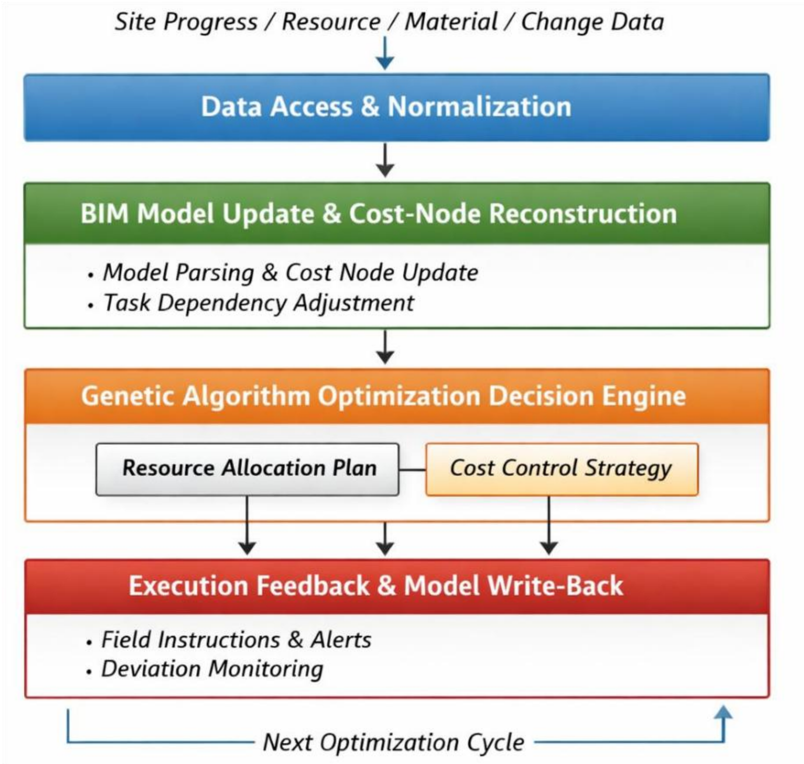

Figure 4: Cost optimization cooperative operation mechanism of BIM and GA integration

To ensure the consistency between the model states and the optimization results in each cycle, the system scheduling process is written as in this paper:

$$S_{t+1} = f(S_t, R_t, M_t) \tag{10}$$

S_t represents the state vector of cost optimization at time t, which contains information such as task schedule, resource occupancy and cost deviation. R_t is the field real-time resource state. M_t is the mapping result of component and task after updating BIM model. $f(\cdot)$ denotes the policy generation function driven by the genetic algorithm. Equation (10) illustrates that the optimization is not a one-time output, but is continuously updated with state changes in each scheduling cycle.

In order to avoid the failure of cost control caused by feedback hysteresis, this paper sets the task deviation monitoring index:

$$\Delta_t = \frac{N_{delay}}{N_{all}} \tag{11}$$

Here, N_{delay} represents the number of tasks that are delayed or over budget offset in the current cycle, and N_{all} represents the total number of tasks. When Δ_t exceeds the threshold θ, the system automatically triggers the recoding and re-optimization process to readjust task priorities and resource allocation paths.

Through this deployment method, BIM is no longer just a carrier container for cost data, and genetic algorithm is no longer an off-line solver off the field. The two form a continuous collaboration under a unified interface and a periodic feedback mechanism. The operation mechanism constructed in this way can maintain the continuity and enforceability of cost control in the context of frequent changes in high-rise building construction conditions, and also provides a complete system basis for subsequent experimental verification.

4 Results

4.1 The dataset

In order to verify the applicability of the integrated cost optimization model of BIM and genetic algorithm constructed in this paper in the construction scenario of high-rise buildings, this paper establishes an experimental data set based on a 32-story frame-shear wall structure residential project in a certain place. The data construction process revolves around "model analysis-task mapping-cost collection-optimization verification", covering four types of core data: BIM component information, construction task information, resource status information and cost record information. The original data of the project comes from Revit model, construction progress ledger, material entry records, mechanical equipment use records and on-site visa files, which are imported into MySQL database after unified coding and structured through Python interface.

The dataset contains a total of 18642 component nodes, 1248 construction tasks, 96800 resource status records, and 21460 cost detail records. In order to ensure the repeatability of subsequent optimization experiments, this paper establishes a task-cost correlation index according to floor, zone and professional type, and additionally labels 18 groups of disturbance samples such as material delay, equipment waiting and cross-operation conflict, which are used to test the dynamic response ability of the model under complex construction conditions. Table 2 shows the data structure of each class. This data set has been field consistent with the BIM cost information model, and can be directly used for subsequent data preprocessing, index calculation and ablation experiments.

Table 2: Data set structure and experimental purposes

Data Type	Number of Samples	Main Fields	Update Method	Experimental Use
BIM Component Data	18,642	Component ID, floor, zone, quantity, and discipline type	Updated through model parsing	Constructs cost nodes and task mapping
Construction Task Data	1,248	Task ID, start time, end time, predecessor–successor relationships, and responsible crew	Updated according to the construction schedule	Generates the task network and optimization encoding
Resource Status Data	96,800	Tower crane occupancy, construction elevator status, labor input, and material arrival status	Updated through daily sampling	Reflects changes in resource constraints
Cost Record Data	21,460	Labor cost, material cost, machinery cost, management cost, and deviation value	Updated at settlement nodes	Supports fitness calculation and result validation

4.2 Data preprocessing

The data used in this paper includes BIM component attributes, construction task logs, resource occupancy records and cost details at the same time. The sources are heterogeneous, the granularity is different, and the collection cycle is not completely synchronized. If the genetic algorithm is directly used to solve the cost optimization problem, it is easy to cause mismatching of task states, drift of cost attribution and distortion of constraint boundaries, which will affect the discrimination effect of genetic algorithm for feasible solutions and optimal solutions. In order to ensure the consistency and stability of the model input, this paper adopts the preprocessing process of "time alignment - abnormal cleaning - structure mapping - standardized coding" to automatically sort out multi-source data.

In the time alignment stage, the daily construction cycle is used as a unified window, and the BIM model update records, task start and end times, material arrival times, and equipment occupancy status are resampled and matched, so that the cross-module data are causally consistent in the same time scale. The missing fields were logically completed by combining the construction log and the sequence relationship. For continuous variables such as task duration and equipment waiting time, a sliding window is used to detect outliers, and records that deviate more than 3σ from the mean are eliminated. In order to weaken the interference of different dimensions on the solution process, this paper performs Z-score normalization on the input features, which is expressed as:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{12}$$

where x_{ij} is the original value of the ith sample on the JTH feature, μ_j and σ_j represent the mean and standard deviation of the feature, respectively. In the structural mapping stage, the construction tasks and their dependencies are transformed into the task graph structure, and the resource status, cost parameters and schedule deviation information are uniformly organized into 3D input tensors:

$$X \in \mathbb{R}^{T \times N \times F} \tag{13}$$

where T represents the length of the time window, N represents the number of task-cost units, and F represents the feature dimension, covering core fields such as engineering quantity, resource occupancy, material arrival status, labor input, and cost deviation. Accordingly, the output label vector is constructed:

$$Y \in \mathbb{R}^{T \times N} \tag{14}$$

It is used to mark the cost status category and execution result of each task unit in a given time window. After the above processing, the original construction data is converted into a standard input form suitable for BIM-genetic algorithm collaborative solution, which provides a reliable data basis for subsequent evaluation index calculation and ablation experiments.

4.3 Evaluation Metrics

In order to test the comprehensive performance of the proposed model in high-rise building construction cost optimization, the experiment sets up evaluation indicators from five aspects: cost compression ability, project time coordination level, resource utilization efficiency, re-optimization response speed and scheme stability, and compares it with the traditional checklist control method and BIM static optimization method. The testing process was repeated 100 times based on the same project data platform to eliminate accidental bias due to a single perturbation. Cost compression ratio is used to measure the decrease of the total cost after optimization compared with the baseline scheme. The time deviation rate reflects the deviation degree between the planning schedule and the actual execution. Resource utilization rate is used to describe the effective investment level of tower cranes, construction elevators, labor and key machinery. The reoptimization response time represents the average time required for the system to complete a new scheme generation after a state change occurs. The instability rate of the scheme is used to describe the proportion of scheme failure caused by task conflict, resource breakage or local over-budget.

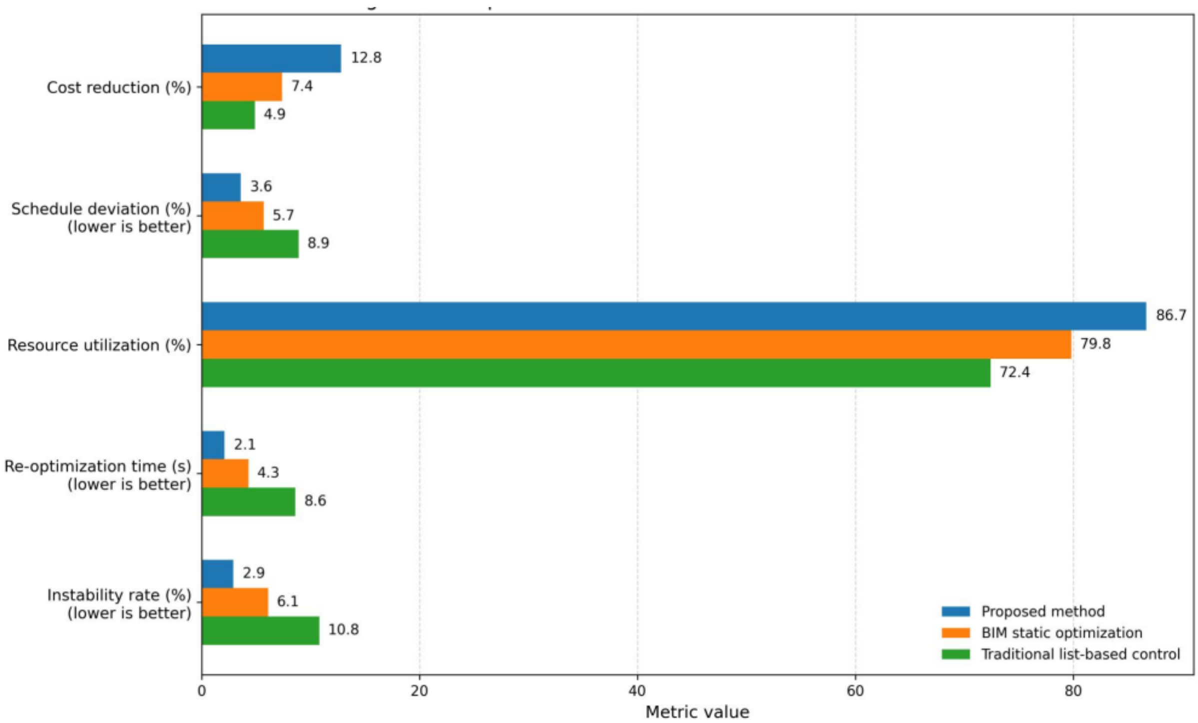

Figure 5: Comparison results of different methods on five evaluation indicators

As shown in Figure 5, the proposed method outperforms the comparison methods in all five indicators. Specifically, the average cost compression rate of the proposed model reaches 12.8%, which is significantly higher than that of the traditional inventory control method (4.9%) and the BIM static optimization method (7.4%), indicating that the genetic search and BIM state linkage can identify the implicit redundant cost more effectively. The deviation rate of construction duration was reduced to 3.6%, while the traditional method and the static optimization method were 8.9% and 5.7%, respectively, indicating that the proposed model did not sacrifice the construction rhythm while controlling the cost, but enhanced the stability of task cohesion. The resource utilization rate reaches 86.7%, which is significantly higher than 72.4% and 79.8%, which indicates that the structured task-cost unit design strengthens the matching accuracy of resource allocation.

In terms of dynamic response, the average re-optimization response time of the proposed model is only 2.1 s, compared to 8.6 s for the traditional method and 4.3 s for the BIM static optimization method. The short response time means that the system is able to complete the scheme reconstruction more quickly after material delays, equipment waits, and cross operation disturbances appear. The instability rate of the scheme is only 2.9%, which is lower than 10.8% and 6.1% of the comparison methods, indicating that the proposed method has better continuous operation ability under complex construction conditions.

4.4 Ablation Study

In order to further identify the specific contribution of each core module to the optimization effect of high-rise building construction cost, this paper carries out ablation experiments under the same project data set, the same parameter Settings and the same disturbance conditions. A total of four groups of models were set up in the experiment. One group removed the BIM dynamic update mechanism and only retained the static model input. A group of cancelled task-cost unit structural design, still using the ordinary task list description; One group did not enable the adaptive genetic re-optimization mechanism, and only executed the initial optimization scheme. The other set is the complete model. Each model was run independently for 100 rounds, and the four indicators of cost compression rate, duration deviation rate, resource utilization rate and program instability rate were counted, and the results are shown in Table 3.

Table 3: Comparison of ablation experiment results

Model Configuration	Cost Reduction Rate / %	Schedule Deviation Rate / %	Resource Utilization Rate / %	Plan Instability Rate / %
Without BIM Dynamic Updating	7.1	6.8	75.9	8.7
Without Structured Task–Cost Units	8.6	5.9	79.4	6.5
Without Adaptive Genetic Re-optimization	9.8	4.7	82.1	5.1
Full Model	12.8	3.6	86.7	2.9

The experimental results show that after removing the BIM dynamic update mechanism, the model cannot absorb component changes, schedule amendments and resource occupancy changes in time, resulting in the cost compression rate decreasing to 7.1% and the scheme instability rate increasing to 8.7%. This shows that although the optimization process can still run without continuous refresh of the model state, its solution basis will gradually deviate from the real construction conditions, thus weakening the effectiveness of cost control. When the task-cost unit structure design is removed, the expression of the sequence constraint, the resource binding relationship and the cost transmission relationship in the model is significantly weakened. The resource utilization rate of this group of experiments is only 79.4%, and the time deviation rate increases to 5.9%, indicating that although the common task list can support the basic sorting, it is difficult to support the fine collaborative optimization in complex high-rise building scenarios. In contrast, when the adaptive genetic re-optimization is not enabled, the model still retains a relatively complete data structure and state mapping, so its basic performance is better than the first two groups, but the cost compression ratio and stability are still significantly lower than the full model because the search direction cannot be corrected in time after the disturbance occurs.

5 Discussion

5.1 Performance advantage analysis of existing construction cost optimization methods

Compared with the existing construction cost optimization methods, the advantages of the proposed model are not only reflected in the decrease of cost value, but also reflected in the synchronous improvement of information expression, dynamic solution and execution adaptation. The traditional inventory control method mainly relies on manual accounting and stage correction, which is prone to the lag of cost identification and the disconnection of resource adjustment in the high-rise building scene with frequent disturbances. Although the BIM static optimization method improves the ability of model visualization and engineering quantity correlation, its optimization process is mostly based on one-time input, and its continuous response to site state changes is still limited. The model in this paper combines BIM status update, task-cost unit structured representation and genetic search, which makes cost control change from "result checking" to "state-driven rolling optimization". From the results in Chapter 4, the proposed method is superior to the comparison methods in the three indicators of cost compression rate, time deviation rate and resource utilization rate. This advantage does not come from a single solution speed improvement, but from the linkage mechanism between BIM state mapping, task-cost unit structured expression and genetic search. More notably, the average re-optimization response time of the system is only 2.1 s, while the traditional method and the BIM static optimization method are 8.6 s and 4.3 s, respectively, indicating that the proposed method can complete the new scheme generation faster when the material delay, equipment waiting or cross operation are increased. The instability rate of the scheme is only 2.9%, which is also significantly lower than 10.8% and 6.1%, which indicates that the scheme is not only effective under ideal conditions, but also maintains good execution continuity under complex construction disturbances.

5.2 Verification of model adaptability and stability under complex construction conditions

The construction site of high-rise buildings is significantly affected by design changes, resource occupancy fluctuations and cross-operation interference. If the optimization model is only applicable to ideal conditions, its engineering value is very limited. In order to verify the adaptability and stability of the model under complex construction conditions, this paper sets up four kinds of typical disturbance scenarios, including temporary task insertion, key equipment switching, high concurrent cross construction and vertical transportation limited reconstruction, and conducts 100 rounds of tests on the unified data platform. The success rate, the average re-optimization time and the system stability score of the scheme were counted. Among them, the success rate of scheme maintenance is defined as the proportion of executable schemes that can still output within the constraint range after the disturbance occurs, and the system stability score is calculated on a 10-point scale based on three criteria: cost fluctuation, task delay and resource conflict.

Experimental results show that the proposed model maintains high usability in four types of complex situations. The success rate of maintaining the scheme in the temporary task insertion scenario reaches 93.1%, the average re-optimization time is 2.4 s, and the stability score is 9.2, which indicates that after the linkage of BIM status update and genetic search, the impact of new construction tasks on the cost network can be quickly absorbed. In the scenario of key equipment switching, the occupancy change of tower crane or construction elevator will directly affect the process connection. The model still achieves 90.4% success rate, the average re-optimization time is 2.9 s, and the stability score is 8.9. Figure 6 shows the comparison results in different scenarios, and it can be seen that although each index fluctuates slightly with the enhancement of disturbance, it remains in the optimal interval as a whole.

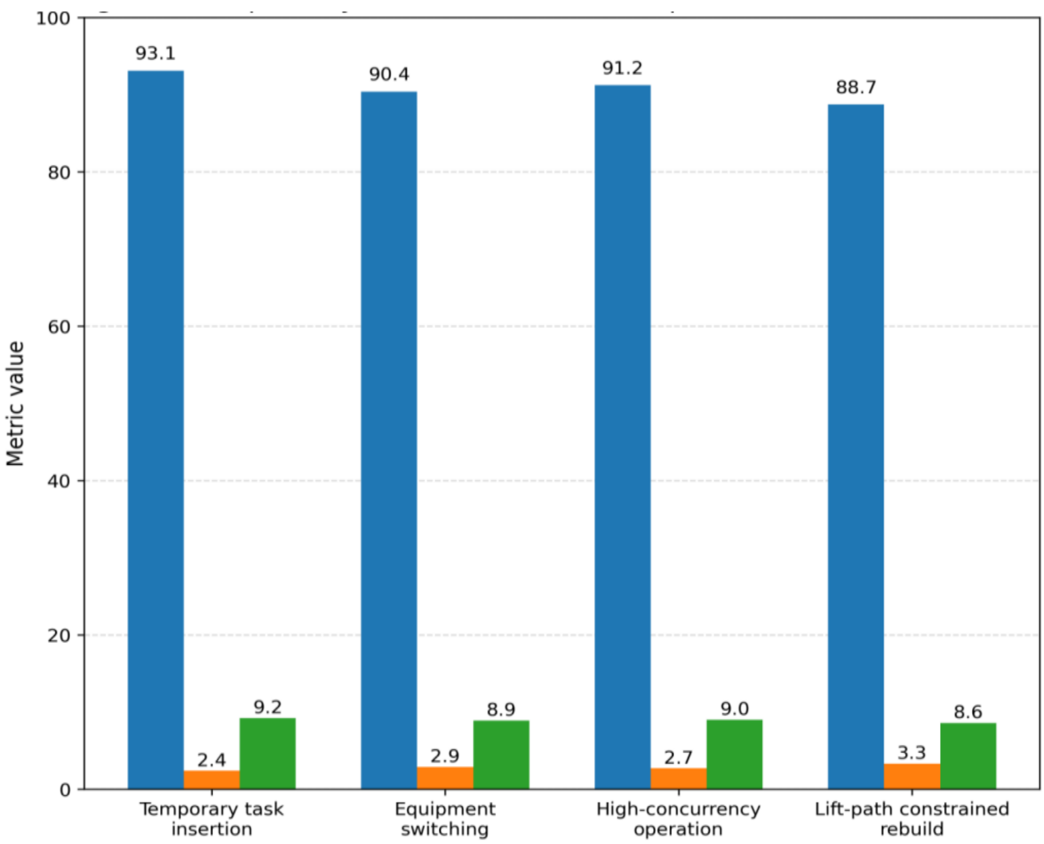

Figure 6: Results of model adaptability verification under complex construction conditions

In the high concurrent cross-construction situation, the success rate of the model is 91.2%, which indicates that it has a good coordination ability for multi-shift parallel jobs and resource competition. In the reconstruction scenario with vertical transportation constraints, the success rate slightly decreased to 88.7%, and the average re-optimization time increased to 3.3 s. However, the system did not suffer from large-scale instability, and the stability score remained at 8.6. In general, the proposed model can still maintain more than 88% of the scheme retention success rate and the response level within 3.3 seconds under complex construction conditions, indicating that it is not only effective on static data, but has the continuous adaptation ability for real construction disturbances.

5.3 System resource overhead and feasibility evaluation of high-rise building construction scenario deployment

Whether the high-rise building construction cost optimization model can enter the real project depends on the computational load, communication overhead and site deployment threshold in addition to the solution effect. If the system relies too much on high-performance hardware, or the interface link is too long, even if the optimization result is ideal, it is difficult to run continuously in the construction scene. Based on this, this paper evaluates the system resource cost from three levels: data access, BIM processing and optimization decision, and visual interaction, and analyzes the deployment feasibility combined with the actual project scale.

In the experimental environment, the system runs on Intel Core i7-12700, 32 GB RAM and Ubuntu 22.04 platform, the BIM model analysis is completed by local services, the genetic algorithm and state synchronization module are implemented using Python 3.11, and the database is implemented using MySQL. Taking 1248 construction tasks, 96800 resource status records and 21460 cost records as input, the average CPU occupancy of the data access module is 18.7% and the memory occupancy is 0.9GB in the single-day rolling optimization mode. The CPU occupancy of BIM parsing and cost node reconstruction module was 31.4%, and the memory occupancy was 2.6GB. The average CPU occupancy of the genetic optimization decision module is 43.8%, the peak memory is 4.1 GB, and the average time of a single re-optimization is 2.1 s. It can be seen that the main load of the system is concentrated in the optimization solution stage, but the whole is still within the acceptable range of the conventional engineering terminal.

Figure 7 presents the core deployment metrics. It can be seen that the average network bandwidth occupation of the model under the condition of 1080p visual output is 3.6 Mbps, and the state return delay is 184 ms, which can meet the requirements of real-time interaction in the local area network or ordinary line environment of the project department. According to the calculation of one central workstation, three management terminals and on-site data access service for a 32-story residential project, the initial deployment cost of software and hardware is about 138,000 yuan, of which 89,000 yuan is for hardware and 49,000 yuan is for software and interface integration, which is significantly lower than most heavy-duty digital worksite solutions that require dedicated servers and customized middle platforms.

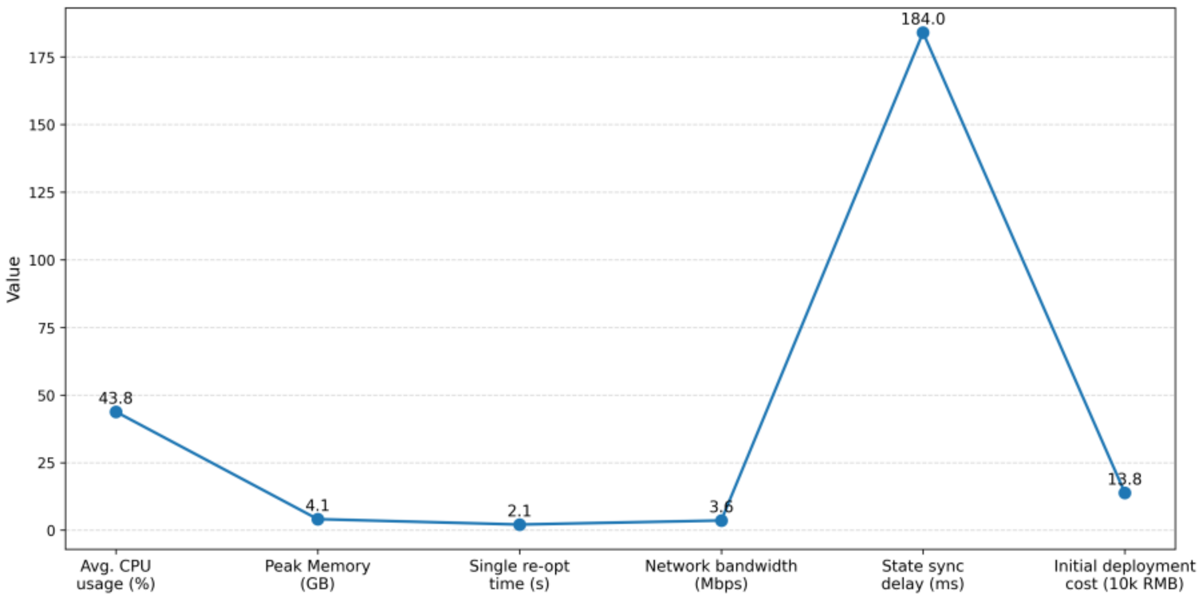

Figure 7: Core resource metrics for system deployment

From the perspective of scene adaptability, the system can be connected with BIM models, progress accounts and cost databases through standardized data interfaces, and there is no need to rebuild the entire project management platform. Its modular structure is also easy to scale according to the project scale: single machine deployment can be used in small and medium-sized projects, and switch to central node plus distributed terminal mode in parallel construction scenarios of multiple buildings. On the whole, the proposed model maintains a good balance between resource overhead, communication burden and deployment cost, and has the practical feasibility to enter the digital cost control scenario of high-rise building construction.

5.4 Application value of the model in digital cost control of high-rise building construction

For the digital transformation requirements of high-rise building construction, the value of the integrated model of BIM and genetic algorithm constructed in this paper is not limited to local cost compression, but lies in bringing the originally scattered component information, task status, resource occupancy and cost changes into the same calculation chain, so that cost control turns from static accounting to process-driven continuous adjustment. The experimental results show that the average cost compression rate reaches 12.8%, the resource utilization rate is stable at 86.7%, and the re-optimization response time is controlled at 2.1 s, which shows that the proposed method can not only reduce redundant expenditure, but also maintain rapid strategy correction ability when construction conditions change. This dynamic adjustment mechanism has a more direct engineering significance for the material delay, equipment waiting, and cross operation interference that are common in high-rise building projects.

From the management level, the BIM platform provides a visual mapping between components, floors, partitions and cost nodes, so that project managers can identify the source of cost deviation and the location of resource bottlenecks in time, and the management mode changes from experience judgment to fine decision-making based on data association. In the extended verification, the system shows good management assistant ability, and the budget deviation warning advance, task conflict alarm decline range and cost correction implementation success rate are better than the original management method.

At the same time, the model maintains good interface compatibility with Revit model base, cost database and schedule management platform, and can be embedded into the existing project digital system without reconstructing all business processes. Its application value is shown in Table 4. Overall, the model in this paper shows strong adaptability in terms of cost control accuracy, dynamic response efficiency, management transparency and platform openness, which can provide a practical and operational technical path for digital cost control of high-rise building construction.

Table 4: Application value of the model in digital cost control of high-rise building construction

Application Dimension	Specific Performance	Validation Result
Cost Optimization	Reduces redundant input and idle waiting costs	Cost reduction rate: 12.8%
Dynamic Response	Rapidly completes re-optimization after disturbances occur	Re-optimization response time: 2.1 s
Resource Coordination	Improves the matching efficiency of tower cranes, elevators, and labor	Resource utilization rate: 86.7%
Risk Warning	Identifies budget deviations and task conflicts in advance	Warning lead time: 1.8 d
Management Execution	Improves the implementation effectiveness of corrective actions	Corrective action execution success rate: 91.5%

6 Conclusions

Focusing on the problems of information dispersion, response lag and optimization results difficult to land in high-rise building construction cost control, this paper constructs a cost optimization model based on BIM and genetic algorithm. In this paper, BIM is used as the unified data base to complete the structural mapping of components, tasks, resources and costs, and genetic algorithm is used to realize the scheme search and rolling correction for dynamic construction conditions, which makes the cost control change from static accounting to continuous updating calculation process. The experimental results show that the proposed model performs better than similar comparison methods, the cost compression rate reaches 12.8%, the construction time deviation rate is controlled at 3.6%, the resource utilization rate is increased to 86.7%, the average re-optimization response time is 2.1 s, and the scheme instability rate is only 2.9%. This shows that the constructed method can not only reduce the redundancy cost, but also maintain good execution continuity and adaptation ability under complex disturbance conditions. From the perspective of engineering significance, the model has strong data compatibility and deployment feasibility, which can provide a feasible technical path for digital cost control of high-rise building construction, and also provide a method reference for the further integration of BIM and intelligent optimization algorithm in construction management.

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