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Optimization of Structural Design Parameters in BIM Using Grid Search and Immune Genetic Algorithm

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Abstract: As competition in the construction industry intensifies, construction companies must optimize structural design to enhance their competitiveness. However, traditional methods of structural optimization heavily rely on manual experience, which results in inefficiency and lack of accuracy. Therefore, this study proposes a structural design parameter optimization model based on Building Information Modeling, integrating Grid Search (GS) and Immune Genetic Algorithm (IGA). Accuracy is determined by calculating the average deviation rate, while convergence speed is assessed by the number of iterations required for the algorithm to reach converge. This model fully utilizes the global optimization capabilities of grid search method and the immune genetic algorithm to solve the problems of BIM technology lacking quantitative computing ability and low efficiency in processing large amounts of data. The results indicate that the GS-IGA model achieves a curve area of 0.97 under the Zero-Conductivity Transition test function, an F1 score of 0.98, an accuracy of 95.6%, and fast convergence speed, outperforming the genetic algorithm, particle swarm optimization, and simulated annealing algorithm. In addition, in the structural optimization case study of a factory building, the GS-IGA model reduced the required steel reinforcement weight by 7.8%, concrete weight by 8.7%, and overall cost by 9.5% compared to the original structure. These results indicate that the GS-IGA model demonstrates excellent efficiency and applicability in structural design parameter optimization, effectively solving the problems of inefficiency and inaccuracy in traditional optimization methods. It offers an innovative approach for building structure optimization and contributes to the advancement of intelligence in the construction industry.

Povzetek: Model optimizacije parametrov konstrukcijskega oblikovanja v BIM uporablja kombinacijo metode Grid Search in Imunskega genetskega algoritma za učinkovitejšo obdelavo podatkov in optimizacijo stroškov ter materialov pri gradnji.

1 Introduction

With the continuous progress of society, the development of the construction industry in China is exceptionally rapid [1]. In order to stand out in the highly competitive construction industry and enhance competitive advantages, it is of great significance for construction enterprises to pay attention to project cost issues and improve cost-effectiveness without compromising engineering safety [2]. Therefore, optimizing structural design parameters for construction projects to reduce project costs is crucial. Currently, due to the rapid development of the construction industry, the construction period of various projects is minimized, leaving designers with less time to consider structural optimization and cost-saving measures [3]. Traditional structural optimization methods lack efficiency and feasibility, leading to the urgent need for a method that can improve design efficiency and reduce construction costs. Building Information Modeling (BIM), as a new structural design model in the construction field, can assist designers in structural design during the design phase, improving design efficiency and optimizing the design structure [4]. In the actual process of optimizing building structural design parameters, a large amount of theoretical data calculation usually involved. However, BIM technology lacks the ability for quantitative calculations and has low efficiency in processing complex data, making it difficult to comprehensively and accurately evaluate various optimization schemes [5]. Grid Search (GS) is an exhaustive search technique that can quickly find the optimal solution within a limited area by setting a search range and step size in advance. It can accurately optimize discrete variables such as component cross-sectional dimensions, which helps improve the quantitative calculation ability and efficiency of BIM technology for discrete variables. Immune Genetic Algorithm (IGA) simulates the mechanism of the biological immune system to quantitatively analyze data, and can handle continuous variables such as concrete strength and steel strength, which helps improve the quantitative calculation ability of BIM technology for continuous variables. Therefore, in response to the issue of BIM's lack of quantitative data calculation ability, the study proposes using GS and IGA to perform parameter theoretical calculations on BIM technology in order to improve it, and propose a structural design parameter optimization model based on this technology. The research aims to propose an effective measure to optimize the quantitative data calculation capability of BIM technology, thereby achieving optimization of building structure design parameters, minimizing building material costs, and improving optimization efficiency.

The innovation of this study lies in the following aspects: (1) combining GS with IGA, efficiently processing discrete variables using GS, and globally optimizing continuous variables using IGA, which compensates for the limitations of a single algorithm. (2) By integrating GS and IGA, the problem of BIM technology lacking quantitative computing capabilities and low efficiency in processing large-scale data has been solved.

The main contribution of this study is: (1) providing new ideas for intelligent optimization of building structures and promoting the deep integration of BIM technology and artificial intelligence. (2) Provide multi-objective optimization solutions that significantly reduce material costs and carbon emissions while ensuring structural strength. (3) The full process automation of design, analysis, optimization, and construction simulation has been achieved, reducing manual intervention and design conflicts.

2 Related works

BIM enables collaborative design with designers, showcasing effective design ideas to achieve cost reduction and efficiency improvement. Yu et al. proposed a combination of BIM and time cost optimization models for optimizing large-span steel structures in airports, in order to control the cost and schedule during the structural optimization process. The results indicate that the proposed method effectively reduces the cost of structural optimization and has certain feasibility [6]. Zou et al. proposed using BIM for structural design of prefabricated buildings, and explored the impact of different factors on the cost of structural optimization engineering based on a large number of practical engineering cases [7]. Pan et al. proposed combining BIM and artificial intelligence technology for data processing in order to address the structural optimization and management issues of intelligent buildings. They also gained an understanding of the current status and future trends of utilizing artificial intelligence throughout the entire lifecycle of BIM projects [8]. Datta et al. developed a 3D model simulation of a three-story residential building and conducted conflict detection, structural analysis, and cost estimation for an integrated project delivery technology centered on BIM. The results indicate that BIM can effectively optimize the structural defects of buildings and reduce construction costs [9]. Fan et al. investigated the architectural design process based on a platform, proposed a structural design method based on this platform, and compared it with commonly used structural analysis software, proving the accuracy of BIM platform structural design [10].

The development of architectural structural design optimization methods has become relatively mature, with several theoretical and practical applications already established. Scholars from many countries have been researching optimization and improvement technologies, applying them in real-world construction projects. For instance, Xiao's team, addressing the issue of BIM's lack of application in prefabricated building design, proposed a BIM-based PCP collaborative design concept model to determine the accuracy of BIM models at different design stages. The results showed that the BIM-based collaborative design method was validated effectively through practical examples [11]. Xue and other scholars, addressing the issue of excessive CO_2 emissions in construction that do not align with sustainable development principles, proposed a simulation-based multi-objective optimization method that minimizes both the lifecycle cost and CO_2 emissions of buildings. The research indicated that the proposed optimization method could significantly improve building performance [12]. Lu's team, addressing the limitation of data quantity and quality on the performance of GAN-based intelligent structural design, proposed a structural mechanics model to train and optimize the inherent accuracy of physical estimators. The study demonstrated that the proposed physics-enhanced GAN could generate structural designs from architectural drawings and specified design conditions, outperforming data-driven design methods by 44% [13]. Long, addressing the common focus of building structural design optimization on improving building energy efficiency when detailed design drawings are available, proposed a new integrated model for energy-efficient building envelope design in the early stages. The results showed that the model achieved savings in both cost and energy, with cost savings of 7.52% and energy savings of 8.48% [14]. Prathyusha and Babu, addressing the high cost of traditional manufacturing processes that construct products layer by layer using complex CAD models, proposed a method combining topology optimization with additive manufacturing technology. The research results indicated that this approach reduced the number of parts to be assembled, developing lightweight components and thereby lowering costs and saving materials [15]. The summary table of the relevant studies mentioned above is shown in Table 1.

Table 1: Summary table of related research

References	Key research work	Method	Quantitative results
[6]	Optimization of large-span spatial steel structures in airports	Combining BIM and time cost optimization model	Cost reduction of 12% -15%
[7]	Cost optimization of prefabricated buildings	Based on BIM and finite element simulation	Reduce engineering costs by 8% -10%
[8]	BIM and AI integrated intelligent management	Integrated BIM and AI based intelligent management framework for the entire lifecycle	Improve data analysis efficiency by 30%
[9]	BIM integration project delivery technology verification	3D model based on BIM	Reduce construction costs by 10% -15% and structural defects by 20%
[10]	BIM platform design accuracy verification	Compare the design accuracy of BIM platforms	BIM design error rate<3%
[11]	Prefabricated BIM Collaborative Design Model	BIM based PCP collaborative design model	Collaborative design efficiency increased by 25%, design conflicts reduced by 30%
[12]	Multi objective low-carbon building optimization	Simulation and Multi Objective Optimization	Cost reduction of 12%, CO2 emissions reduction of 18%
[13]	Design of physically enhanced GAN structure	Design of physically enhanced GAN structure	Design efficiency increased by 44%, and the compliance rate of structural strength increased to 95%
[14]	Optimization of energy-saving enclosure structure	Optimizing early building envelope design based on AI models	Cost savings of 7.52% and energy consumption reduction of 8.48%
[15]	Topology Optimization and Additive Manufacturing	Combining topology optimization and additive manufacturing technology	Reduce material costs by 15% -20% and parts weight by 30%

In summary, although scholars at home and abroad have conducted comprehensive research on BIM, most existing studies still have the problem of relying on a single algorithm, which cannot handle both discrete and continuous variables simultaneously, as seen in references [6, 7]. In addition, there are still studies that have not proposed algorithm enhancement solutions for the lack of quantitative computing capabilities in BIM, such as references [8-11]. Therefore, this study proposes a BIM technology that combines GS and IGA, which can achieve joint optimization of discrete and continuous variables through the collaboration of mixed algorithms, and enhance the quantitative computing ability of BIM through GS search, filling the gap in existing literature on joint optimization of discrete and continuous variables and BIM computing efficiency.

3 Construction of BIM and its structural optimization model combined with GS and IGA

3.1 Improved BIM design combined with GS and IGA

To avoid the increase in computational complexity caused by directly putting all variables into IGA for optimization, this study first used GS to optimize the cross-sectional dimensions of the components separately in the early stage of structural optimization design, and then integrated the optimal cross-sectional dimensions obtained by GS into the initial population of the IGA algorithm. BIM is an innovative design concept that effectively improves project quality and accurately transmits various types of information throughout the entire life cycle of the building structure. This approach significantly enhances the quality, efficiency, and integration of building structures design [16].

However, it has the disadvantage of insufficient quantitative data computation capabilities, while IGA, as a global optimization method based on optimization models, can perform quantitative analysis of data [17]. By combining BIM with IGA, the advantages of intelligent algorithms can be leveraged to effectively address data processing and computation challenges, thus providing strong support for the digital transformation of the construction industry. The basic process of IGA is shown in Figure 1.

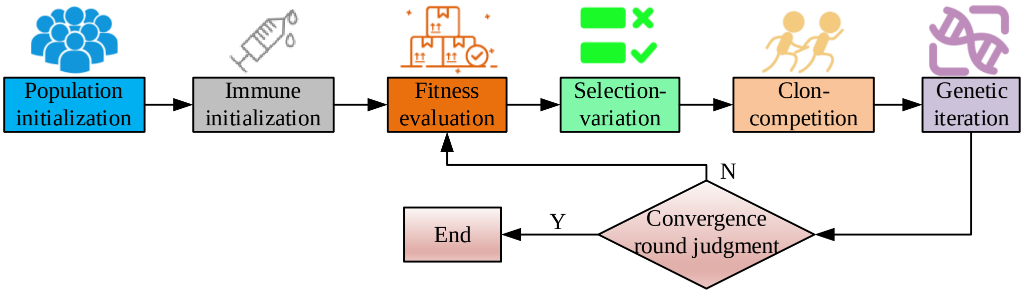


Figure 1: Basic process of IGA

As shown in Figure 1, IGA first requires population initialization, where the population size is determined. During this process, the initial individuals are generated to form the initial population, and the calculation process is shown in Equation (1).

$$\begin{cases} P(0) = p_1, p_2, \ldots, p_N \\ p_i = (a_{i1}, a_{i2}, \ldots, a_{iL}) \end{cases} \tag{1}$$

In Equation (1), $P(0)$ represents the initialized population set, N denotes the number of individuals within it, and p_i indicates that each individual i is composed of L factors. Afterward, the population undergoes immune initialization, during which key immunity conditions are defined, and the process is shown in Equation (2).

$$\begin{cases} F_i = \dfrac{1}{D_i} \\ D_i = \sum_{j=1}^{L} (p_{ij} - A_{ij})^2 \end{cases} \tag{2}$$

In Equation (2), F represents the individual fitness, and D denotes the distance between the individual and the antigen. This process evaluates the population's fitness to quantify how well individuals adapt to the problem environment. Then, selection and mutation are performed, where the selected high-quality antibodies undergo mutation operations, introducing a degree of randomness to encourage new genetic variations in the population. Subsequently, cloning and competition are carried out, where a large number of antibodies with higher fitness values are cloned to accelerate the propagation of high-quality antibodies. After cloning, individuals with relatively higher fitness values are selected for genetic iteration, and crossover and mutation operations are conducted to further increase the genetic diversity and complexity of the population. Finally, convergence rounds are judged to determine whether the population has met the desired convergence conditions. If the conditions are met, the current result is regarded as the optimal solution and output, otherwise, the entire IGA process is repeated in a loop. The BIM structure optimization system combined with IGA is shown in Figure 2.

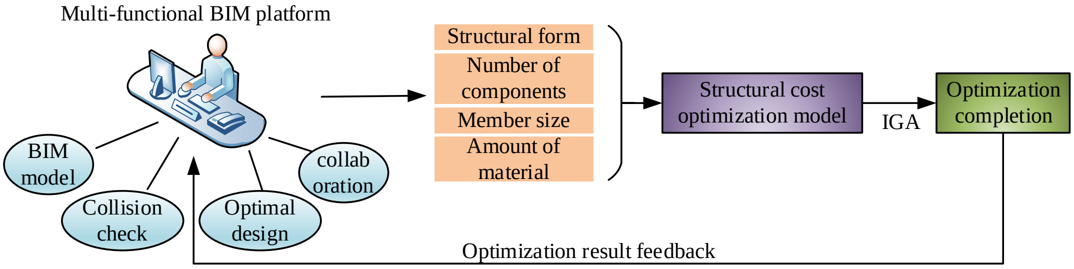


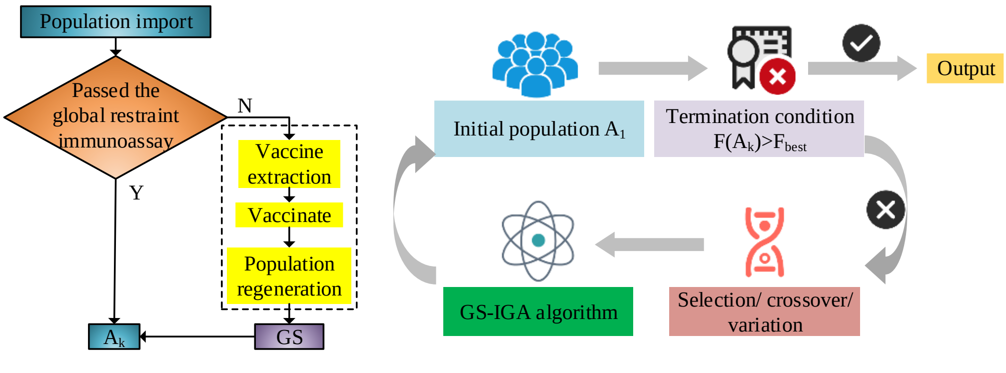
Figure 2: BIM structure optimization system combined with IGA

As shown in Figure 2, first, based on the design plan, BIM modeling software is used to accurately construct the building structure model, which is then imported into structural analysis software to complete the calculation of structural parameters. Next, the IGA program is run to optimize the engineering data related to structural design parameters and costs, outputting the optimization results. When using IGA for solving, if all component cross-sectional dimensions are included in the population evolution, the population size will increase several times, thereby extending the convergence time and reducing computational efficiency. To address this, the study uses

GS to separately optimize the component cross-sectional dimensions. As an exhaustive search method, GS can significantly reduce the time required to process large-scale population data. Only after completing the GS search can the individual fitness be calculated [18]. Although GS is typically computationally expensive due to its exhaustive nature, in this study, the search space is reasonably constrained and the step size is predefined, which effectively reduces the number of iterations and accelerates the processing of large-scale population data. In addition, GS can be parallelized, further improving computational efficiency. Its fitness function is shown in Equation (3).

$$Fit(f)=\begin{cases} c_{\max}-f & f<c_{\max} \\ 0 \end{cases} \tag{3}$$

In Equation (3), $c_{\max}$ represents the preset maximum acceptable cost threshold, which is a constant value set based on engineering budget or cost constraints to constrain the upper limit of costs during the optimization process. And f represents the objective function, representing the engineering cost, which is calculated by integrating multiple cost factors such as material cost, transportation cost, design cost, and construction cost. According to formula (3), when the objective function value is less than the threshold, the fitness value is inversely proportional to the cost, which prompts the optimization algorithm to prioritize the design scheme with lower cost in the search process. In addition, the fitness function indirectly protects the structural integrity by setting $c_{\max}$ as the cost upper limit. Finally, the optimization results are imported into structural analysis software for further analysis and calculation, forming the final structural optimization design method, which is then output. The final structural optimization method can be applied to construction optimization and coordination through BIM. Therefore, the BIM model flow chart combining GS and IGA is shown in Figure 3.



(a) Flow chart of GS-IGA algorithm (b) The overall process of BIM technology

Figure 3: BIM model flow chart combining GS and IGA

Figure 3(a) shows the flow chart of GS-IGA algorithm. Figure 3 (b) shows the overall process of BIM technology. The BIM technology workflow consists of five main steps: initial modeling, model parameterization settings, integration with optimization algorithms, model updates, and collision checks. Initial modeling refers to creating a 3D building structure model using BIM software. Model parameterization refers to the integration of architectural, structural, and electromechanical design information into BIM models. Integration with optimization algorithms refers to the interaction between data in BIM models and optimization algorithms. Model update refers to the feedback of parameter updates obtained from optimization algorithms to the BIM model, in order to achieve automatic model updates. Collision checking refers to using collision checking tools in BIM software to perform collision checks on updated models. To prevent increased computational complexity from directly using all variables in IGA for optimization, this study first employed GS to separately optimize the cross-sectional dimensions of components early in the structural optimization design process, then integrated the optimal dimensions form GS into the initial IGA population. During the initialization process of the population, its fitness evaluation function is shown in Equation (4).

$$P_{select}=p\,|\,RWT(p)\le F_i/\sum F_k \tag{4}$$

In Equation (4), P_{select} represents the selected individual group, and $RWT(p)$ represents the roulette wheel probability. Under the IGA framework, the crossover operation selects one or more gene encoding loci of the parent individuals and performs position exchanges on these loci to generate new offspring, which form the new generation of the population. The mutation operation, based on a predefined mutation rate, generates individuals with new genetic traits, introducing new genetic diversity into the population. The process is shown in Equation (5).

$$\begin{cases} p_c'=p_c+N(0,\sigma_c) \\ P_c'=P_{select}\cup p_c' \end{cases} \tag{5}$$

In Equation (5), p_c' represents the cloned individual, and P_c' represents the collection of cloned individuals. After the population initialization, an overall constraint immune check is performed. Individuals that do not pass the check are vaccinated, while antibodies with higher fitness values are cloned extensively and released into the population, effectively increasing their proportion in the population. Through this process, antibodies carrying advantageous genes spread more widely, significantly increasing the probability of these advantageous genes being passed on in the population. The process is shown in Equation (6).

$$p'' = p' + N(0, \sigma_m) \tag{6}$$

In Equation (6), p'' represents the mutated individual, and σ_m represents the number of mutated individuals. Finally, genetic iteration is performed to update the population and increase its complexity. The process is shown in Equation (7).

$$p'' = P_c' - p'' \mid RWT(p'') \le \frac{C_k}{\sum_k C_k} \tag{7}$$

In Equation (7), p'' represents the new generation of individuals with high fitness values, and C_k represents the concentration of k antibodies. After the population update is complete, GS is used for exhaustive search to obtain the optimal individual. If the individual's antibody reaches the best state, the result is output, otherwise, the next iteration is performed. In the BIM modeling process, parametric methods define the key dimensions and positions of components as adjustable parameters. Integration BIM models with GS and IGA requires data interface and format conversion. BIM software needs to support exporting building structural models and related information into data formats compatible with optimization algorithms, such as Industry Foundation Classes (IFC). Additionally, a real-time data synchronization mechanism is needed to update the BIM model with optimized parameters form GS and IGA algorithms, achievable through the BIM software's Application Programming Interface (API).

3.2 Construction of GS-IGA based BIM structural optimization model

Based on the constructed BIM, the study further integrates it into the optimization of building structure design parameters. Reinforced concrete structures account for the majority of the building structure and have the greatest impact on construction costs. Therefore, the study focuses on reinforced concrete building structures. During the construction process, the design phase needs to determine the material type, concrete strength grade, and the size of the components [19]. Although design costs account for only 1%-5% of the total cost, they have a significant impact, accounting for up to 75% of the total construction cost. This highlights the crucial importance of optimizing building structure design parameters [20]. The problems in the traditional building structure optimization process and its problems are shown in Figure 4.

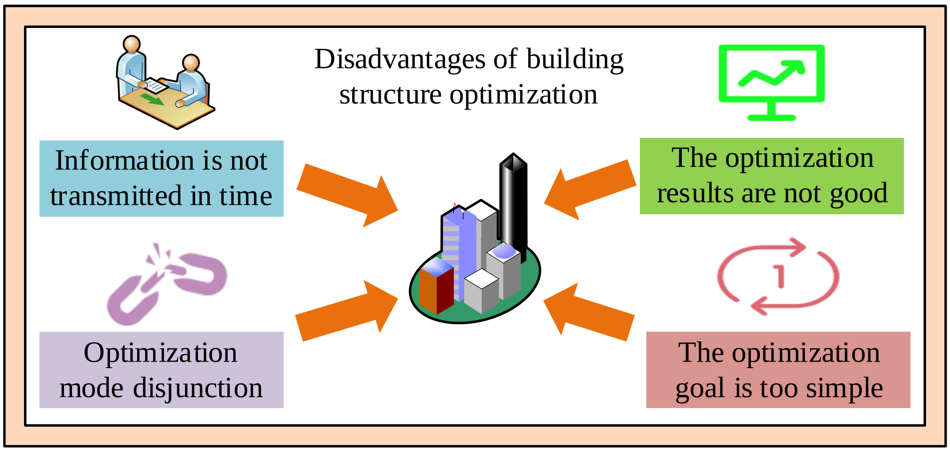


Figure 4: Traditional building structure optimization process and its problems

As shown in Figure 4, the traditional building structure optimization process faces four problems. Firstly, delayed information transfer can cause conflicts in design space and other factors, impacting optimization efficiency. The disconnect in the optimization process can lead to errors in information transmission, which may only be discovered during the construction phase, requiring last-minute changes to the design and delaying project progress. A single optimization objective can result in the failure to ensure the accuracy and practicality of the optimization plan, with unclear cost optimization effects. The overall project cost function is shown in Equation (8).

$$F_c(x) = \alpha C_e(x) + \beta C_d(x) + \gamma C_m(x) + \delta C_t(x) \tag{8}$$

In Equation (8), C_e represents the project cost, C_d indicates the transportation cost, C_m is the total cost of materials, and C_t stands for design costs. α, β, χ, and δ represent the respective weights of different costs. A single optimization objective has limits the effectiveness of overall cost optimization. Lastly, the presentation of optimization results is poor. The traditional optimization results are presented in two dimensions, requiring workers to rely on spatial imagination and manual experience to implement the design, which affects efficiency and accuracy. Therefore, based on the integration of GS and IGA into BIM, this study applies it to structural design parameter optimization, establishing a new structural optimization model. The elemental composition of the structural optimization model is shown in Figure 5.

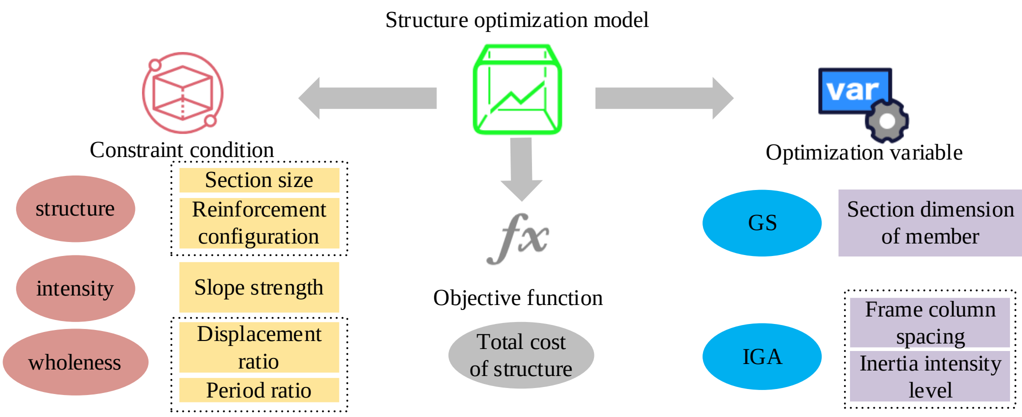


Figure 5: Element composition of structural optimization model

As shown in Figure 5, the model consists of three components: optimization variables, objective function, and constraints. The optimization variables mainly include parameters such as concrete strength, the cross-sectional size and spacing of components, and steel reinforcement strength, which significantly affect the project cost. The objective function is the total cost of all components in the building structure. In the structural optimization model, BIM, GS, and IGA work together in stages to achieve optimization goals. Firstly, BIM provides a complete parametric model of the building structure and exports the range of discrete variables. Secondly, GS conducts exhaustive search on discrete variables such as component cross-sectional dimensions and outputs preliminary optimization results. The GS optimization results are then used as the initial population of IGA. Iterative calculations are performed using constraints updated in real-time by BIM. Finally, the optimization results are fed back to the BIM model for structural analysis and collision checking. If conflicts are found, the constraints are adjusted and re-optimized. In the specific cost calculation, the cost of the i-th component is shown in Equation (9).

$$C_i = C_c b_i h_i + C_s W_0 (nl \cdot l_i + nst \cdot l_{sv}) \quad (9)$$

In Equation (9), C represents the unit price, c represents the volume of concrete, s represents the weight of steel reinforcement, W_0 represents the theoretical weight of steel reinforcement, nl represents the number of longitudinal reinforcements, nst represents the number of stirrups, and l_{sv} represents the length of the stirrups. Therefore, the total cost of the structure is shown in Equation (10).

$$C = \sum_{i=1}^{n} C_i \quad (10)$$

In Equation (10), n represents the total number of components in the structure. The constraints are the conditions that must be adhered to in the optimization process in order to obtain the optimal values. These include global constraints on the structure, such as displacement ratio, inter-story drift angle, and period ratio, as well as strength constraints, such as axial and shear section strength, steel reinforcement strength, and concrete strength. There are also geometric constraints, such as component cross-sectional dimensions and reinforcement configuration. These constraints lay a solid foundation for the safe construction of the building project, ensuring that the structural design has adequate strength. Based on the above factors, the process of the BIM structure optimization model combined with GS-IGA is shown in Figure 6.

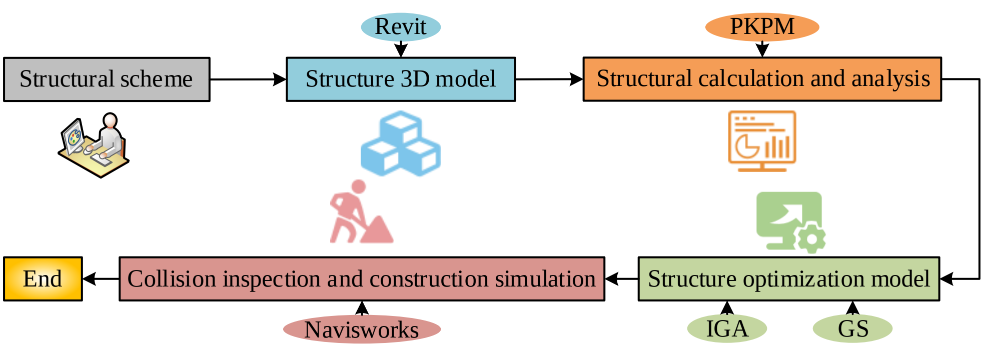


Figure 6: The process of the BIM structure optimization model combined with GS-IGA

In Figure 6, the GS-IGA model begins with the model creation stage, where all BIM functions rely on the BIM model. Therefore, modeling is not only the first step in the process but also the most critical phase. During the structural calculation and analysis stage, data interfaces are used to transform the BIM model into a structural analysis model, and this phase is carried out using structural analysis software. Then, the process enters the structural optimization stage. In this stage, GS and IGA are applied to optimize the structure while ensuring that the structural performance is not compromised and that structural strength and safety are maintained. The process of solving the optimization model is shown in Equation (11).

$$X = (X_1, X_2, \ldots, X_n)^T \tag{11}$$

In Equation (11), X represents the design variables. The appropriate design variables are then selected, and the constraints at both the overall and component levels are comprehensively considered, as shown in Equation (12).

$$\begin{cases} g_i(X) \leq 0 & i = 1,2,\ldots,p \\ h_j(X) = 0 & j = 1,2,\ldots,q \end{cases} \tag{12}$$

In Equation (12), i and j represent the number of variables, respectively. Next, an optimal structural design is sought, one that not only meets spatial usage and safety standards but also maximizes economic efficiency. The search process is represented by $f(X) \to \min/\max$, where $f(X)$ represents the objective function, i.e., the total construction cost of the project. Finally, in the construction simulation phase, visualization simulation software is used to test the structural 3D model based on the optimization results and conduct a simulated construction to check for any collision issues. Regarding the algorithm's convergence characteristics, IGA offers strong global convergence and the ability to avoid local optima by simulating the biological immune system mechanism. However, the convergence speed and effectiveness of IGA may be affected by parameter settings. The convergence of GS mainly depends on the setting of search step size and search range. A smaller search step size can improve accuracy, but it will increase computational complexity and convergence time. A larger search step size may reduce accuracy, but it can accelerate convergence speed. In terms of iterative complexity, IGA's iterative complexity is similar to GA. Assuming the population size is M, the number of iterations is N, and the gene length of each individual is L, the iteration complexity of IGA is usually O (MNL). Assuming there are K parameters in the search space, with each parameter's value range divided into S step sizes, the iteration complexity of GS is O (K·S). The GS-IGA algorithm combines the advantages of GS and IGA, resulting in slightly higher iteration complexity compared to benchmark methods like traditional GA and particle swarm optimization.

4 Validation of GS-IGA Based BIM structural optimization model

4.1 Performance validation of GS-IGA

To verify the search and optimization capabilities of the improved GS-IGA in BIM, as well as whether its performance could meet the vast data computation requirements of BIM, the study compared it with commonly used optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). The experimental environment and equipment were set up as shown in Table 2.

Table 2: Experimental environment and equipment

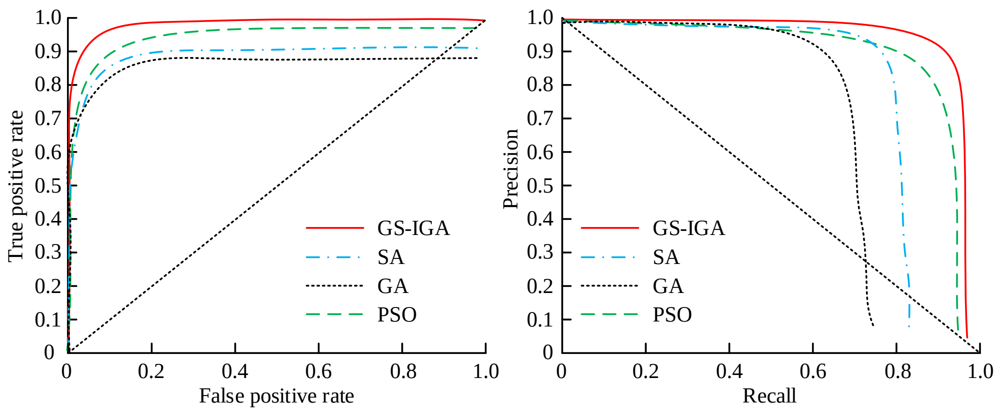
Item	Disposition
Operating system	Microsoft Windows 10
CPU	AMD Ryzen 7 3750H
GPU	NVIDIA RTX 3070 s
Internal memory	32 G
Video memory	16 G
Hard disk	Colorful SL500 1 TB
Modeling software	Revit
Structural analysis software	PKPM
Simulation software	Navisworks

Sensitivity analysis was conducted on key hyperparameters of the GS algorithm, with step sizes set to 50 mm, 100 mm, and 150 mm, and search ranges set to 10%, 20%, and 30%. By comparing the optimization performance under different parameter combinations, the optimal parameter combination was found. The sensitivity analysis results are shown in Table 3.

Table 3: Sensitivity analysis results

Hyper-parameters		Convergence time/s	Area Under the Curve (AUC)	F1
Step length	50 mm	320	0.92	0.94
	100 mm	210	0.97	0.98
	150 mm	1180	0.89	0.91
Search scope	10%	190	0.90	0.92
	20%	210	0.97	0.98
	30%	260	0.93	0.95

From Table 3, it can be seen that when the step size is 100 mm and the search range is 20%, the AUC value and F1 score of the GS algorithm are the highest. Therefore, this parameter combination was used for subsequent experiments in the study. The iteration count was set to 250, the population size to 50, the crossover probability to 0.5, the mutation probability to 0.2, the vaccination probability to 0.2, and the learning rate to 0.001. Based on the experimental environment described above, the study measured the performance of the four algorithms using metrics such as the AUC of the ROC curve, F1 score, accuracy, and convergence speed. The ROC curve is plotted with true positive rate as the y-axis and false positive rate as the x-axis. The AUC value refers to the area under the ROC curve, which ranges from 0.5 to 1. The larger the value, the better the classification performance of the model. The Precision Recall (PR) curve dynamically adjusts the classification threshold to demonstrate the trade-off between precision and recall of the model at different thresholds. The F1 score is the harmonic mean of precision and recall, ranging from 0 to 1, with higher values indicating better performance of the model. Accuracy refers to the proportion of correctly predicted samples by a model to the total number of samples. The convergence speed refers to the speed at which a model reaches a stable state during the training process, usually measured by the number of iterations or training time. The performance of the four algorithms was first tested on the Zero-Ductility Transition (ZDT) function, ZDT is a testing function used to test the performance of multi-objective optimization algorithms. It is mainly used to evaluate the performance of multi-objective optimization algorithms when dealing with problems with multiple objective functions and constraints. The comparison of the PR curve and ROC curve of four algorithms is shown in Figure 7.



(a) Area under the ROC curve (b) Area under PR curve

Figure 7: Comparison of PR curve and ROC curve of four algorithms

As shown in Figure 7(a), the GS-IGA curve is closest to the upper-left corner, with an AUC value closest to 1, achieving the best result among the four methods. The AUC values of the four algorithms, ranked from high to low, were 0.97, 0.93, 0.88, and 0.85. After statistical significance testing, the differences in AUC values between GS-IGA and other algorithms were significant ($p<0.05$), and their 95% confidence intervals were [0.96, 0.98], indicating stable and reliable performance advantages. As shown in Figure 7(b), in the PR curve of the four algorithms, GS-IGA achieved the highest precision and maintained a relatively high recall rate under high precision. Its area under the curve showed a significant advantage over the other algorithms, with values ranked from high to low as 0.98, 0.96, 0.86, and 0.78. The 95% confidence interval for the PR curve area of GS-IGA is [0.97, 0.99], further confirming its excellent performance in accuracy and recall. Overall, GS-IGA outperformed the comparison algorithms in both precision and recall, exhibiting better robustness and stronger quantitative computation capabilities when handling large amounts of data. To further verify the solution performance of GS-IGA, the accuracy of the four algorithms was compared under different sample sizes as a function of iteration number. The comparison of detection accuracy of four algorithms is shown in Figure 8.

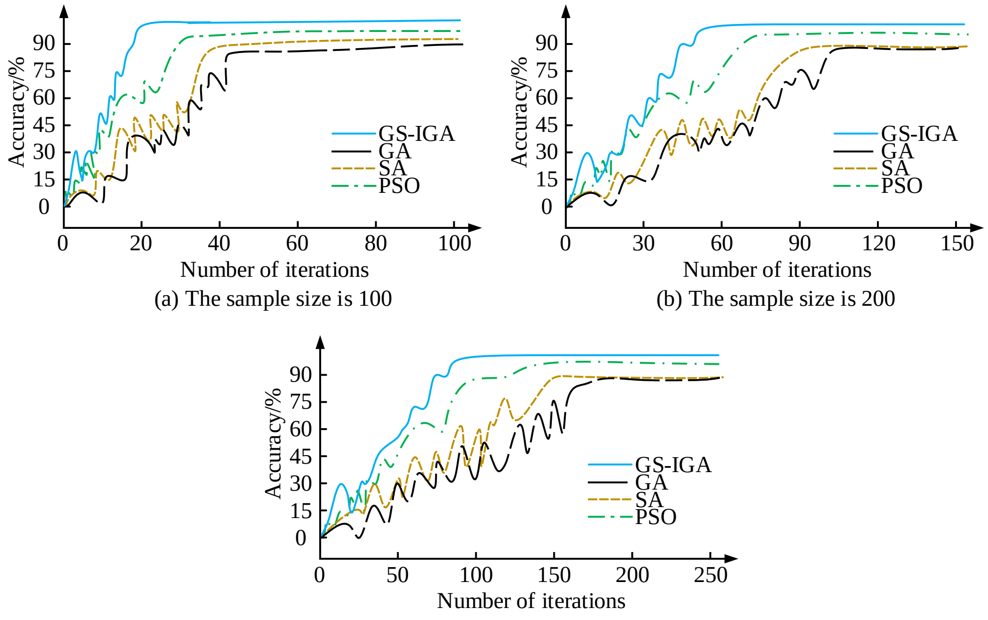
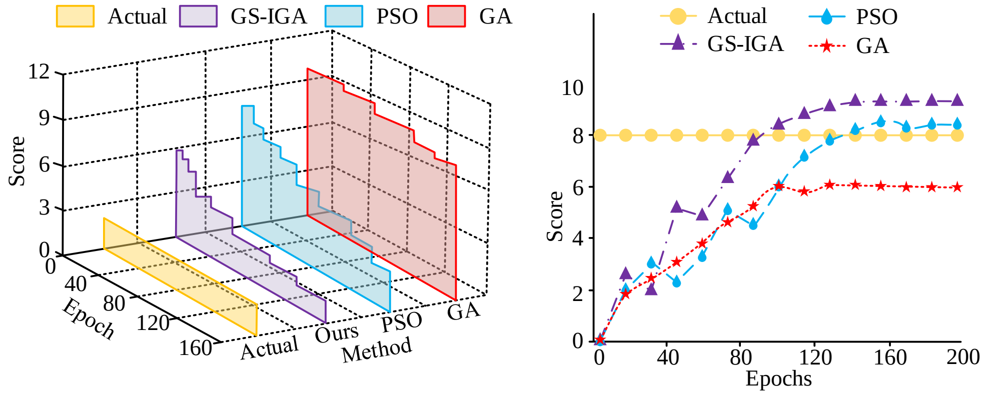


Figure 8: Comparison of detection accuracy of four algorithms

As shown in Figure 8(a), when training the four algorithms, the accuracy of the algorithms gradually improved and stabilized after a certain number of iterations. Among them, GS-IGA had the fastest convergence speed, reaching a stable state after 20 iterations, with the final accuracy stabilizing at 95.6%. The other three algorithms required up to 30 iterations to reach stability, with final accuracy values stabilizing at 88.7%, 80.6%, and 78.3%, respectively. The accuracy of GS-IGA with a 95% confidence interval of [95.0%, 96.2%] is significantly higher than other algorithms, indicating its higher stability and reliability. As shown in Figure 8(b) and Figure 8(c), after increasing the sample size, the convergence speed of all four algorithms decreased to some extent. However, GS-IGA still showed the fastest convergence speed, reaching stability after 50 and 80 iterations, respectively, and maintaining the highest final accuracy. According to statistical analysis, the convergence speed of GS-IGA is significantly better than other algorithms under different sample sizes ($p<0.05$), and its quantitative computing ability is stronger when facing large amounts of data. Overall, GS-IGA had the fastest convergence speed, significantly improved the model accuracy after training, and maintained good stability throughout the model training process.

4.2 Performance validation of GS-IGA based BIM structural optimization model

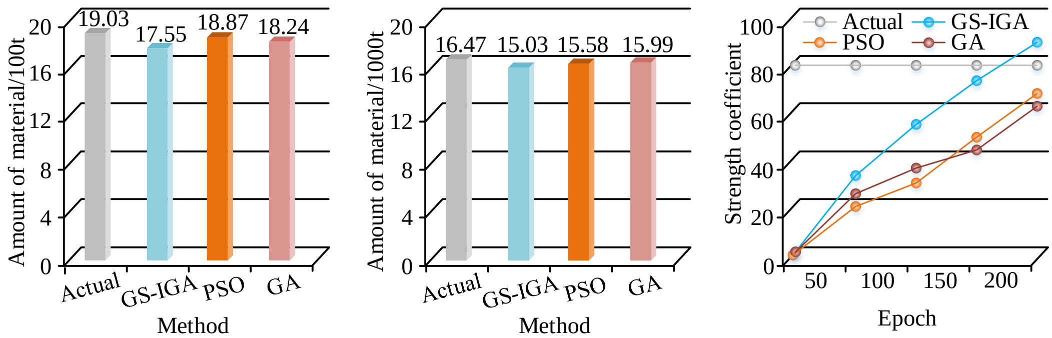
After validating the performance of GS-IGA, in order to further verify whether the BIM-based structural optimization model combined with GS-IGA could meet the structural optimization requirements, the study established a structural optimization model using a factory building as the experimental object. All comparison algorithms are optimized based on the structural parameters of the same factory building. The case data comes from the BIM model of actual engineering projects, which includes complete building structure information. This factory case covers the common reinforced concrete frame structure in industrial buildings, and its parameters comply with the requirements of the "Code for Load of Building Structures" (GB 50009-2012), which is typical in the industry. The factory building consists of 120 components, with a concrete cost of 500 yuan/m^3, a steel reinforcement cost of 4000 yuan/ton, and a design cost of 100000 yuan. Considering that GS is an exhaustive search technique, it cannot be well extended to high-dimensional search spaces. Therefore, the study adopted multi-threaded parallel computing to accelerate the execution of the algorithm, and GPU acceleration was used in the establishment and rendering process of BIM models. The cost parameters include material cost, design cost, transportation cost, and construction cost, which directly reflect the impact of structural optimization design on project cost. The quality parameters take into account factors such as the lightness of the building structure, construction reliability, and design specifications, and are used to evaluate the impact of structural optimization design on the performance of the building structure. The GS-IGA model was compared with optimization models based on GA and PSO in terms of structural optimization performance. The results of the cost and quality parameters were shown in Figure 9.



(a) Cost parameter (b) Quality parameter

Figure 9: The cost parameters and quality parameters

As shown in Figure 9(a), the curves gradually became more convergent as iterations progressed, indicating that the optimization algorithm continuously adjusted the parameters and search space, gradually approaching the optimal solution. The trend of the cost parameter curve in the Figure showed that, after several iterations, the optimization algorithms steadily reduced the cost function value, with the cost parameter of the GS-IGA model ultimately reaching the optimal value of 1.8. As shown in Figure 9(b), as iterations continued, the building's quality parameters steadily increased, with the GS-IGA model achieving the highest quality parameter value of 9.8. The results indicated that by applying the GS-IGA model to the structural design parameter optimization process, significant improvements in economic efficiency could be achieved through precise adjustments and refinements of the design variables, effectively reducing the overall project cost. Subsequently, in order to verify the practical effect of structural optimization of the GS-IGA model, a comparison of the steel reinforcement usage, concrete consumption, and structural strength of the optimization plan was conducted. The comparison of the amount of reinforcement and the amount of concret is shown in Figure 10.



(a) Reinforcement amount (b) Concrete dosage (c) Structural strength

Figure 10: Comparison of the amount of reinforcement and the amount of concrete

As shown in Figure 10(a), the actual steel reinforcement usage for the factory was 1903 tons. After optimization using the GS-IGA model, the usage was reduced to 1755 tons, a decrease of 7.8%, without compromising the structural strength of the building. The usage in the other models was also reduced, but the reduction was smaller than that of the GS-IGA model. As shown in Figure 10(b), the actual concrete usage for the factory was 16,474 tons. After optimization, it was reduced to 15,034 tons, a decrease of 8.7%, which was higher than the reductions achieved by the comparison models. As shown in Figure 10(c), the structural strength coefficient of the optimized plan proposed by the GS-IGA model ultimately reached 91, which was clearly higher than the comparison models. In conclusion, the GS-IGA model was able to optimize the structural design variables while ensuring the structural strength of the building. To further verify the practical optimization effect of GS-IGA model, the three models were applied to the factory cost optimization. The comparison of optimal cost values were shown in Figure 11.

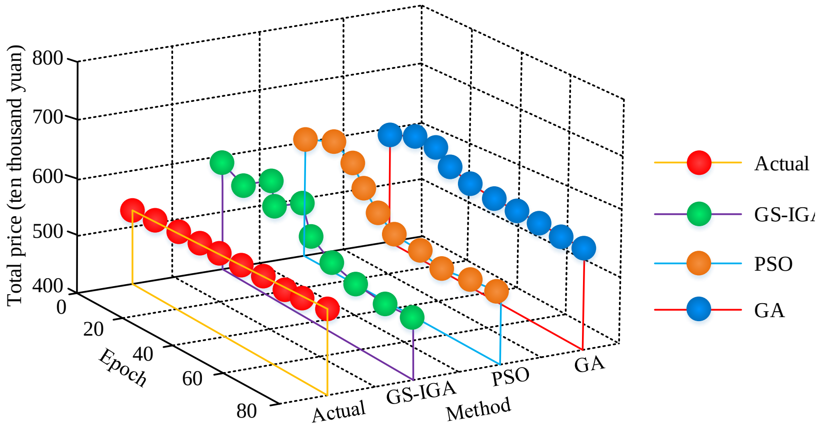


Figure 11: Comparison of optimal cost values

As shown in Figure 11, at the initial generation, the average and optimal values of the four model algorithms were relatively close. Between generations 30 and 50, the GS-IGA model's cost significantly decreased, indicating that the antibodies in the algorithm were effectively optimizing the population. In contrast, the other models' optimization results remained around 5.4056 million yuan after 40 iterations. This was due to the inherent blind search nature of the comparison algorithms, which performed inefficient searches in areas far from the optimal solution. Although this had some effect on optimization, the speed remained slow. In comparison, the GS-IGA model's optimization results improved every 10 generations, showing that the immune operators enhanced the efficiency of reaching the optimal value. After several iterations, the optimization result of the GS-IGA model stabilized, with the final optimized cost of the structure being 4.8043 million yuan. This represented a 9.5% reduction compared to the original structure cost of 5.3068 million yuan.

5 Discussion

A study has proposed a BIM technology-based structural optimization model using GS-IGA. Compared to the single algorithm used in references [6, 7, 12], the GS-IGA model in this study achieves joint optimization of discrete and continuous variables through the collaboration of mixed algorithms. Additionally, compared to references [8-11], the BIM-based structural optimization model using GS-IGA enhances the quantitative calculation ability of BIM through GS search, improving both its calculation efficiency and effectiveness. The experimental results demonstrated that the GS-IGA model performed well across several core metrics, achieving an AUC value of 0.97, an F1 score of 0.98, the fastest convergence speed, and an accuracy rate of 95.6%, significantly higher than the comparison models. Moreover, in the case study of a factory building, the optimization effects were impressive, with the required steel reinforcement weight reduced by 7.8%, concrete weight reduced by 8.7%, and total cost reduced to 4.8043 million yuan, representing a 9.5% decrease. In summary, the GS-IGA model outperforms traditional GS, PSO, and SA across various metrics. This is because GA relies on random crossover and mutation, which can easily get stuck in local optima, PSO is affected by initial distribution, its search range is limited, SA requires fine-tuning, and its convergence speed is slow. The GS-IGA model surpasses traditional algorithms in search ability, convergence speed, robustness, and computational efficiency through a hybrid strategy and immune enhancement mechanism, offering more efficient and reliable solutions for complex engineering optimization problems.

The deployment methods of the GS-IGA model proposed by the study institute are flexible and diverse in real-world applications. Depending on the project scale and actual needs, plug-in integration or independent execution can be selected. For real-world projects of different scales, their computing requirements also vary, requiring reasonable allocation of hardware resources and adapting to the computing needs of large and complex projects through optimizing algorithm parameters, adopting parallel computing, and other means.

6 Conclusion

To address the issues of traditional structural design parameter optimization methods, which heavily rely on manual experience and fail to guarantee the accuracy of optimization solutions, this study proposed a BIM-based structural optimization model combining GS-IGA. The GS-IGA model fully leverages the global optimization capabilities of GS and IGA to enhance the BIM data processing efficiency. Overall, the BIM-based structural optimization model combining GS and IGA demonstrated strong optimization capabilities and accuracy, meeting the high-efficiency optimization requirements for construction engineering. However, this study focused solely on reinforced concrete structures, and there is considerable room for improvement in terms of the model's practical applicability and universality. Future research will need to apply the model to a wider variety of building structures.

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