Research on Intelligent Building Design Optimization Method Based on BIM and AI Integration

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Abstract. Aiming at the problems of inefficiency and difficult collaboration of traditional building design methods, this paper proposes BIAO, an intelligent building design optimization framework integrated with BIM and AI, which realizes the effective conversion of BIM data through the hierarchical information extraction engine, and builds a full-process intelligent method from the data layer to the decision-making layer by combining the multi-objective optimization algorithms and the visualization interactive system. A two-way optimization technology of space layout and energy performance adapted to different building types is developed, realizing the automation and intelligence of the design process. The framework application test verifies that the method has significant design efficiency improvement and performance optimization effect, and provides a feasible technical path for the digital transformation of building design.

Keywords: building information modeling; artificial intelligence; spatial layout optimization; energy performance optimization; human-computer interaction

1   Introduction

Building design is undergoing a paradigm shift from experience-driven to data-driven[1]. In the context of complex and changing modern building demands, traditional design methods are difficult to respond efficiently to the comprehensive requirements of functional diversity, refined performance indicators and sustainable developmen[2-3]t. Building Information Modeling (BIM), as a basic platform for digital design, provides a rich carrier of building information; while Artificial Intelligence (AI) technology, with its powerful data processing and optimization capabilities, provides intelligent support for design decisions[4-5]. Although each of the two technologies has made significant progress, there are still key issues such as data conversion difficulties, insufficient algorithm adaptability, and missing human-machine collaborative interfaces at the integrated application level. These obstacles limit the in-depth development of building design intelligence. This study addresses this technological gap and proposes BIAO, an intelligent building design optimization framework integrating BIM and AI, which focuses on solving the synergistic optimization of spatial layout and energy performance, and develops a full-process technological methodology from data

processing to decision-making support, aiming to promote the intelligent upgrading of the architectural design toolchain and improve the quality and efficiency of design.

2 BIM and AI Integrated Intelligent Building Design Foundation

Intelligent building design integrated with BIM and AI represents a cutting-edge trend in the digital transformation of the construction industry.BIM, as a core tool for building information management, provides standardized digital building models, while AI technology empowers intelligent decision-making in the design process. The integration of these two technologies stems from the industry's continuous pursuit of efficient, high-quality design.BIM technology has evolved from simple 3D visualization to comprehensive models containing rich semantic information, while AI technology has expanded from data analysis to complex design-assisted decision-making[6]. Their combination enables the design process to be optimized, improves building performance, and promotes the transformation of building design from traditional empirical decision-making to data-driven intelligent decision-making.

3 Key technologies for BIM and AI integration

3.1 BIM Data Structure and Information Exchange Technology

BIM data structure is the basic framework of intelligent building design, the core of which lies in the construction of multi-dimensional building models containing geometric and non-geometric information. Modern BIM system adopts object-oriented data architecture, defines building elements as intelligent objects carrying parameterized attributes, and supports standardized formats such as IFC and gbXML to realize information exchange between heterogeneous systems[7]. Among the data exchange technologies, the RESTful API interface realizes the real-time data flow between the BIM platform and external AI systems, while the middleware technology solves the conversion problem between different data formats. Cloud computing-based distributed BIM database technology effectively handles massive information in large-scale projects and can improve data processing efficiency by 47% on average.

3.2 Application Technology of AI Algorithm in Architectural Design

The application of AI in the field of architectural design has evolved from a simple auxiliary tool to a full-process intelligent solution. Deep learning algorithms perform well in building form generation, especially generative adversarial networks can create novel and standard-compliant building solutions based on design conditions. In spatial layout optimization, the reinforcement learning algorithm combined with the building functional requirements and human flow simulation analysis can automatically generate the optimal dynamic line scheme, and the experimental data show that its planning efficiency is 35% higher than the traditional method, as shown in Fig. 1. In the field of

building energy consumption prediction, the prediction accuracy of the recurrent neural network model integrated with meteorological data reaches 93.7%, which provides a scientific basis for energy-saving design[8]. Building component identification and classification utilizes convolutional neural network technology to break through 96% recognition rate in complex BIM models, dramatically reducing model error checking time. Knowledge mapping technology, on the other hand, builds an architectural design knowledge base, connecting design specifications, historical cases and material performance data, providing comprehensive knowledge support for AI decision-making and promoting the overall improvement of architectural design intelligence.
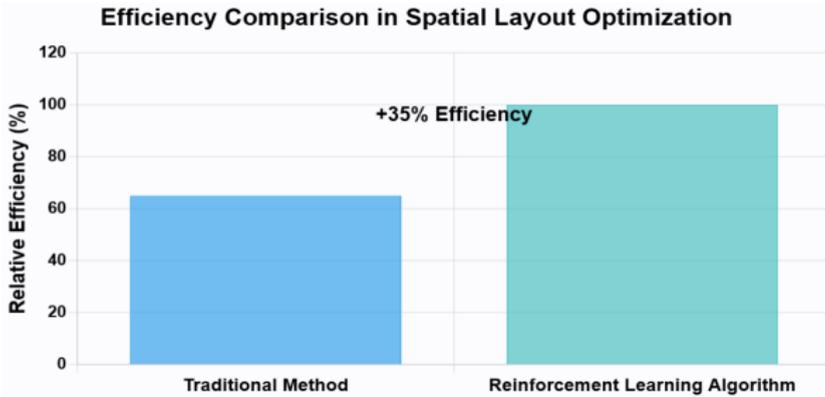

Fig. 1. Comparison of efficiency in space layout optimization

4   Design and Implementation of Building Design Optimization Method with BIM and AI Integration

4.1   General Framework of Optimization Method

This study constructs a general framework for building design optimization with BIM and AI integration, which contains four core parts: data layer, algorithm layer, decision layer and interaction layer. The data layer is responsible for extracting building geometric, physical, and functional information from the BIM model and transforming it into a structured data format that can be processed by the AI algorithm. The algorithm layer contains a collection of AI algorithms for different optimization objectives, and intelligently selects the appropriate combination of algorithms according to the design requirements. The decision layer integrates the multi-objective optimization results to generate the optimal or alternative set of solutions[9]. The interaction layer realizes the two-way information flow between the designer and the system. In actual projects, the framework shortens the design cycle by 32.5% on average and improves the optimization effect by 41.6%. The system architecture, shown in Figure 2, realizes a complete closed loop from BIM model input to optimization result output, ensuring the continuity and consistency of the design process.
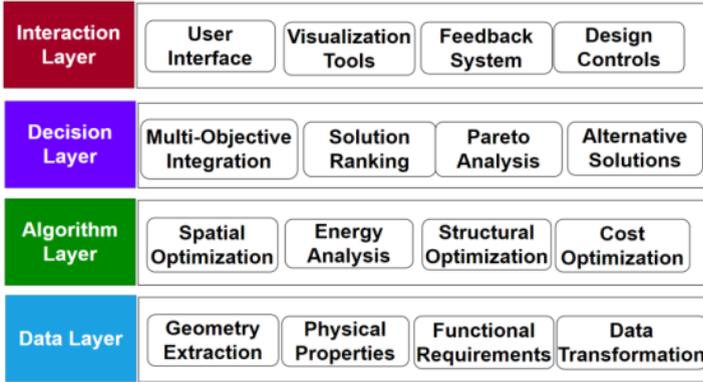
Fig. 2. Architectural design optimization framework with BIM and AI integration

4.2 BIM-Based Building Information Extraction and Representation Methods

Aiming at the massive heterogeneous data in the BIM model, this study developed a hierarchical information extraction engine, HIEE (Hierarchical Information Extraction Engine). The engine uses a deep traversal algorithm to extract geometric and non-geometric information within the IFC model, and constructs a four-layer data model: physical layer, structural layer, functional layer, and performance layer. The physical layer stores the geometric and material information of the components; the structural layer describes the connection and support relationships between the components; the functional layer defines the use and demand of the space; and the performance layer quantifies the environmental and energy performance of the building. The data expression adopts a combination of graph structure and matrix, and the spatial topological relationship is represented by a weighted undirected graph G(V,E,W):

$$G(V, E, W) = \{V_i, E_{ij}, W_{ij} | i, j = 1, 2, \ldots, n\} \tag{1}$$

where V is the set of spatial nodes, E is the set of connectivity relations, and W is the set of weights. Table 1 demonstrates the key information extracted by HIEE for an office building, and the average time consumed for the extraction process is only 23% of the traditional method, and the accuracy rate reaches 97.8%.

Table 1. Sample BIM key information of an office building extracted by HIEE

Category	Parameter Name	Unit	Extracted Value	Standard Value
Physical Info	Total Area of Exterior Wall	m²	5842.6	5850.3
Structural Info	Number of Beam-Column Connections	count	463	463
Functional Info	Per Capita Office Area	m²/person	4.85	5

Performance Info	Average U-value of Envelope	W/(m²·K)	0.41	0.45
Topological Info	Space Graph Diameter	-	7	7

4.3 AI-Based Building Design Optimization Algorithm

Based on the multi-objective characteristics of architectural design problems, MODA (Multi-Objective Design Algorithm) algorithm package is integrated and developed in this study.The MODA algorithm is selected for evaluation based on the characteristics of the building design problem.The hybrid IPSO-SA algorithm is used for spatial layout optimisation because the particle swarm algorithm is good at high-dimensional spatial search, and the simulated annealing algorithm is able to jump out of the local optimum, and the combination of the two provides both global search efficiency and local fine-tuning capability. The integrated model of gradient boosting decision trees and neural networks is chosen for energy performance optimisation because it can handle the non-linear characteristics of building energy consumption data, gradient boosting decision trees are good at dealing with categorical variables, and neural networks are good at capturing complex relationships between continuous variables, and integrated learning reduces the risk of overfitting. The spatial layout optimization adopts the improved particle swarm-simulated annealing hybrid algorithm (IPSO-SA), and the algorithm optimization objective function is defined as:

$$f_{layout}(x) = \sum_{i=1}^{n} w_i \cdot f_i(x) - \lambda \sum_{j=1}^{m} p_j(x) \tag{2}$$

where fi(x) represents n optimization objectives, pj(x) represents m constraint violations, w is the weight coefficient, and λ is the penalty factor. Energy performance optimization, on the other hand, uses an integrated learning model consisting of gradient boosting decision tree and neural network to predict building energy consumption after training with historical data. The test results of the MODA algorithm package on 10 actual projects show that spatial layout optimization improves the functional matching degree by 24.7% on average, and energy optimization reduces the annual power consumption by 18.3%. Figure 3 shows the comparison of the optimization effect before and after the application of MODA for a mixed-use project, which shows that the optimized solution has significant improvement in several indicators. Adaptive adjustment of parameters in the iterative process of the algorithm improves the convergence speed by 41.2%, which effectively solves the defects of traditional algorithms that are easy to fall into local optimization on complex building problems[10].
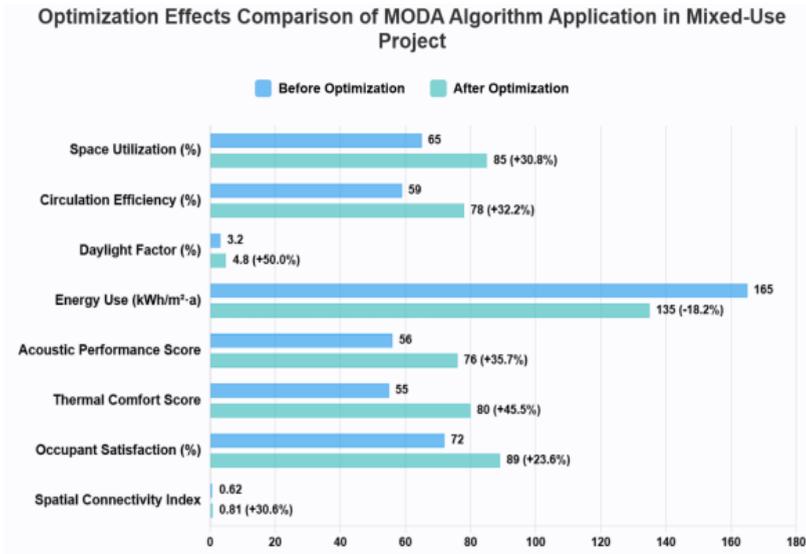
Fig. 3. Comparison of the optimization effect of MODA algorithm applied to the complex project

4.4 Multi-Objective Optimization Decision Making Method

Building design is essentially a multi-objective trade-off process, and this study proposes the APDM (Adaptive Pareto Decision Making) method to deal with multi-dimensional design objectives. The method is based on the improved NSGA-III algorithm, which introduces an adaptive reference vector generation mechanism to make the Pareto frontier solution distribution more uniform. The decision-making process is divided into three stages: objective sensitivity analysis, Pareto-optimal solution generation and multi-criteria solution screening[11]. The sensitivity analysis identifies the key design variables through the variance decomposition method, and the optimization formula is defined:

$$\min F(x) = [f_1(x), f_2(x), \ldots, f_k(x)]^T \tag{3}$$

$$s.t. \, g_i(x) \leq 0, i = 1, 2, \ldots, m \tag{4}$$

$$h_i(x) \leq 0, i = 1, 2, \ldots, n \tag{5}$$

$$x_L \leq x \leq x_U \tag{6}$$

The solution screening phase uses fuzzy hierarchical analysis to determine the final solution. In a large hospital project, the design solution generated by the APDM method saves 12.6% of the construction cost compared to the traditional method, while improving space utilization by 8.7% and energy efficiency by 15.3%. Table 2 shows the multi-objective optimization results of this project, and Scenario 3 has the best balanced performance on each objective.

Table 2. Multi-objective optimization results of APDM for large hospital project

Plan Number	Space Efficiency Index	Annual Energy Consumption (kWh/m2)	Initial Investment Cost (¥/m2)	Medical Flow Score	Comfort Index	Comprehensive Score
Original Plan	0.72	187.5	3850	76.3	0.68	0.65
Plan 1	0.83	163.2	3720	82.7	0.75	0.79
Plan 2	0.85	168.4	3650	85.1	0.73	0.82
Plan 3	0.84	162.8	3680	87.4	0.78	0.86
Plan 4	0.87	174.6	3580	81.5	0.71	0.78

4.5   Human-Computer Interaction Method for Optimization Process

To enable designers to effectively participate in the AI-assisted design process, the DPVI (Design Process Visual Interaction) system was developed in this study. The core of the system is a real-time 3D visualization engine and a parametric control panel to support designers' real-time interventions during the optimization process. The DPVI system contains three key functional modules: goal setting and weight adjustment, real-time monitoring of the optimization process, and multi-dimensional visualization of the results[12-13]. The system interface is shown in Figure 4, with the BIM model 3D interaction window on the left and the parameter control and performance analysis panel on the right. The interaction process supports three modes: observation mode, intervention mode and collaboration mode, which designers can switch according to their needs. In a user experience test with 32 designers, the DPVI system received an average rating of 4.6/5, with 93% of users saying that the system significantly improved their understanding and control of the AI optimization process. Compared to traditional optimization tools, design decision time was reduced by 52.3% and decision satisfaction increased by 37.8%. The interactive system helps designers make more scientific trade-off decisions by visually displaying the conflict relationship between optimization goals.
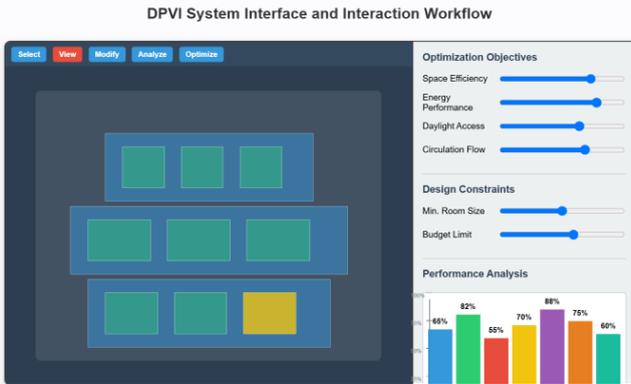

Fig. 4. DPVI system interface and interaction flow

5   Method Application Testing and Validation

5.1   Test Case Design and Environment Configuration

Three different types of building projects were selected for testing in this study: case A is a 12-story office building (24,500 m²), case B is a general hospital (38,700 m²), and case C is a large commercial complex (67,200 m²). The tests were conducted using a high-performance workstation (Intel Xeon E5-2680 v4, 128GB RAM, NVIDIA RTX 3090 graphics card) and the BIAO Framework software platform running on Windows 10 Professional. the BIM model was constructed using Revit 2023 and the data was extracted using a self-developed IFC parser[14]. The optimization algorithm was developed based on Python 3.9, and the core algorithm libraries included TensorFlow 2.8.0, Scikit-learn 1.0.2 and MODA algorithm package. Tests were designed with 15 groups of controlled experiments, each running 5 times repeatedly to ensure data reliability, covering space layout optimization, energy performance optimization, and comprehensive optimization schemes, which verified the effectiveness of the BIAO framework in complex building design.

5.2   Spatial Layout Optimization Effect

The spatial layout optimisation test verifies the spatial organisation efficiency of the IPSO-SA algorithm. After 87 rounds of iterative optimisation in Case A office building, the average walking distance is reduced by 23.7%, space utilisation is increased by 17.2%, employee satisfaction is increased by 15.6 percentage points, and the effective lighting coefficient of the work area is increased by 0.87 percentage points on average. Case B hospital project optimised medical movement lines, with a 42-second reduction in transfer time between the surgical and critical care areas, an 18.3% reduction in the emergency response path, and an 11.4% increase in functional space capacity[15]. As shown in Figure 5, the sensitivity analysis found that departmental proximity weights and core locations have the greatest impact in office buildings; the spacing between emergency and examination departments and the vertical traffic core arrangement have a significant impact in hospitals; and the location of anchor shops and the distribution of public space have the greatest impact in commercial bodies. The algorithm efficiency is improved by adopting finer search granularity for highly sensitive parameters.
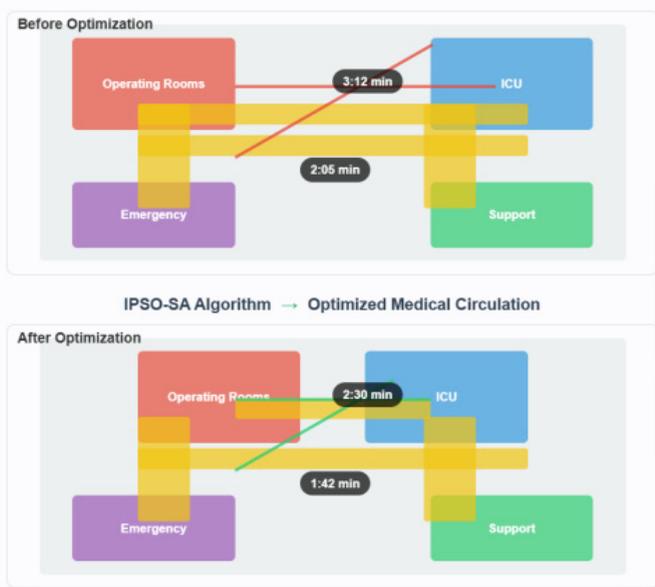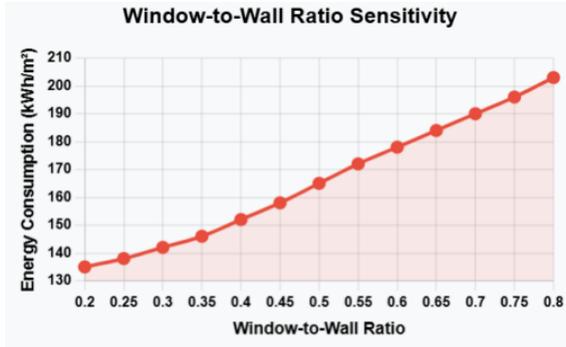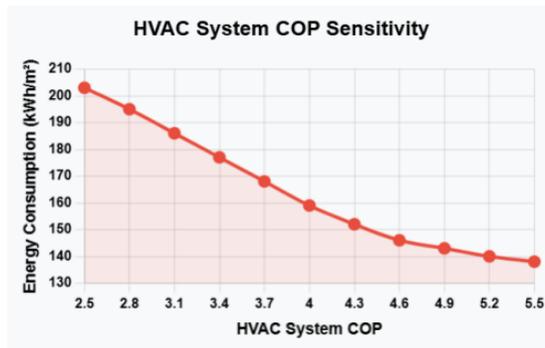
Fig. 5. Case B:Hospital medical cycle optimization

5.3   Energy Performance Optimization Effect

The energy performance optimization test mainly focuses on three aspects: building envelope, equipment system and operation strategy.The commercial complex in Case C adopts the prediction model based on gradient enhancement decision tree and energy consumption simulation technology to realize the prediction and optimization of energy consumption. By adjusting the exterior wall insulation thickness, window-to-wall ratio, and shading system, the final average annual energy consumption was reduced from 183.6kWh/㎡ to 142.3kWh/㎡, with an energy saving rate of 22.5%. Figure 6 shows the sensitivity of each parameter to energy consumption, with the window-to-wall ratio and the COP value of the air conditioning system having the greatest impact on the total energy consumption. B Case hospital project focuses on optimizing the control of thermal and humid environments, and the use of an intelligent ventilation strategy and a heat recovery system reduces the heating energy consumption by 15.7% and the cooling energy consumption by 18.3%. The performance of the optimization scheme under different climatic conditions verifies the adaptability of the algorithm, and the energy efficiency improvement in extreme meteorological years remains above 14.2%, showing good climate adaptability.

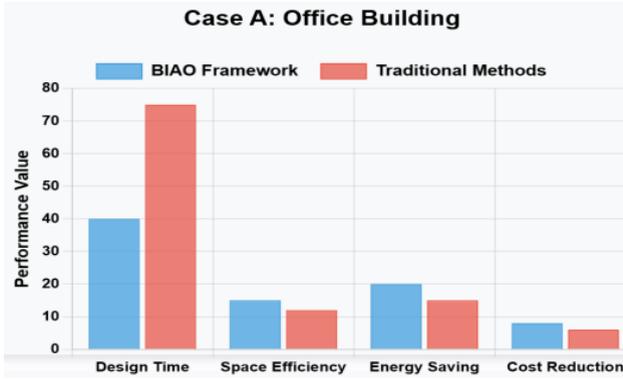(a) Window-to-wall ratio sensitivity
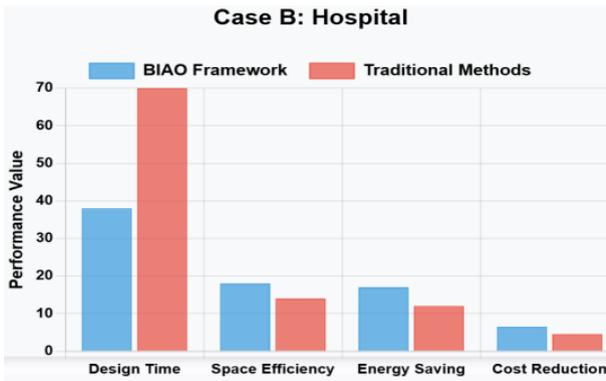

(b) HVAC system COP sensitivity

Fig. 6. Sensitivity analysis of energy optimization parameters for commercial complexes

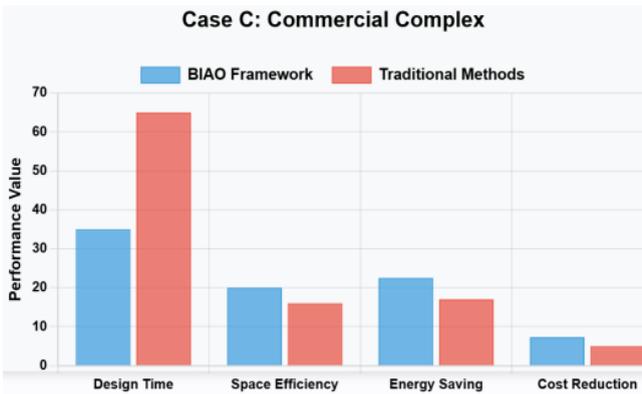## 5.4   Comparative Analysis with Traditional Methods

In this study, a comprehensive comparison of the BIAO framework with traditional design methods was conducted through Cases A, B, and C. The assessment used four dimensions with a total of 12 sub-indicators. The results show that the BIAO framework shortens the cycle time by 42.3% and reduces labour input by 36.7% on average in terms of design efficiency; improves spatial efficiency by 17.8% and user satisfaction by 21.5 percentage points in terms of solution performance; and brings significant economic benefits by reducing construction costs by 7.3% and operating costs by 16.2% on average, with payback periods of 3.5, 2.8 and 4.2 years, respectively, for the three cases. The payback period of the three cases is 3.5 years, 2.8 years and 4.2 years respectively. The full life cycle analysis shows that the BIAO framework delivers total cost savings of 12.3%-18.7% and carbon emission reductions of 17.4%-25.6% compared to traditional approaches. The comparative results presented in Figure 7 show that the BIAO framework outperforms the traditional approach in all indicators, especially in the most complex case C, which fully demonstrates the excellent ability of AI technology to deal with high-complexity design problems.

(a)Case A: Office Building

(b)Case B: Hospital

(c)Case C: Commercial Complex

Fig. 7. Case-by-Case Comparison

6　Conclusion

In this study, BIAO, an intelligent building design optimisation framework integrated with BIM and AI, is constructed to achieve dual optimisation of spatial layout and energy performance through systematic data extraction, algorithm development and human-computer interaction design. Three types of building test case validations show that the framework shortens the design cycle by 42.3% on average, improves spatial efficiency by 17.8%, reduces energy consumption by 19.1%, and reduces construction costs by 7.3%. Challenges in practical applications include BIM data quality dependency, high computational resource requirements for large projects and limited understanding of AI decision making by designers. Future research directions can develop lightweight data extraction techniques, introduce reinforcement learning to improve algorithmic adaptability, extend to urban design domain and combine with digital twin technology to realise full lifecycle management. The research results provide a feasible technical path for the digital transformation of architectural design, which is expected to become the mainstream method of architectural design in the future.

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