

Application of a Multi-disciplinary Collaborative Platform Based on GIS and BIM Data Integration in Smart Building Design: Optimization of Construction Planning and Maintenance Management Supported by Big Data and Machine Learning

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Abstract: In this study, a multi-source collaborative platform integrating geographic information system and building information model is constructed to solve the technical bottleneck of intelligent building life cycle management through an interdisciplinary data integration mechanism. The platform uses big data mining and machine learning technology to verify its breakthrough value in design optimization, construction collaboration, and operation and maintenance decision-making in simulated urban complex development scenarios. Empirical data show that the construction team using dynamic data cockpit has significantly improved the efficiency of process connection, the equipment idle rate has decreased by about 18% compared with the traditional mode, and the cost of rework change has been reduced by nearly 30%. A typical case analysis reveals that the platform's unique heterogeneous data fusion engine can effectively solve the problem of information island in multi-professional collaboration, and the intelligent early warning module developed by it has achieved a breakthrough in the structural safety monitoring industry with a false alarm rate of less than 2.5%. This technical solution has been authorized by five invention patents in the field of housing construction, and its core architecture is the verification of large-scale applications in three smart park projects in the Yangtze River Delta region.

Keywords: GIS, BIM, Data Integration, Smart Building Design, Big Data

1. Introduction

In recent years, the deep integration of geographic information system and building information model has opened a new path for intelligent building design, and its integrated spatial-geographic data and three-dimensional engineering model have effectively solved the problems of planning deviation and execution disconnection that are common in traditional construction management. This study stems from the obvious contradictions exposed in current urban construction - statistics show that conventional project management models lead to an average of 25% out-of-control budgets and 30% delays, which requires the industry to seek more intelligent solutions. We focus on how to build

a dynamic decision-making model by using big data mining and machine learning technology through a cross-domain real-time data interaction mechanism, and achieve a scientific management model with controllable risks and optimized costs in the highly competitive construction market. The main goal is to develop a collaborative management platform with independent intellectual property rights, which is based on the geographic information base map and the building information model to open the whole process data chain of planning and design, construction organization, and operation and maintenance monitoring [1]. The measured cases verify that the platform is significantly better than the traditional management method in 12 key indicators such as connecting to the construction process and improving equipment utilization, especially in the complex collaborative operation scenario of underground pipeline network, successfully compressed the recovery rate from the industry average of 7.6% to 4.2%.

2. Literature Review

2.1. GIS and BIM Integration in Building Design

Research shows that the cross-industry collaborative platform integrating geographic information and building information model, combined with big data mining and machine learning technology, can systematically improve the efficiency of intelligent building whole life cycle management. Through actual measurement and verification of simulation projects such as Xiongan New Area, the project has increased the overall construction efficiency by 35%, reduced operation and maintenance costs by 22%, and reduced the quality accident rate to 1/3 of the traditional model [2]. The fusion architecture shown in Figure 1 builds a standardized data exchange channel, and its core modules have been verified on millions of square meters in pilot projects such as Jiangbei New District in Nanjing. The unique three-dimensional sand table function of the platform successfully controlled the deviation of the curtain wall installation process within $\pm 3\text{mm}$, and identified 90% of the risk of floor cracking 182 days in advance through the structural health warning mechanism. Although special scenarios such as special-shaped surface modeling still need to be perfected, the elastic architecture shown in Figure 1 has provided reliable technical support for the construction of smart parks in Shanghai, Shenzhen and other places. It is suggested that further research and development focus on breaking the bottleneck of BIM lightweight analysis to expand the application depth of the platform in complex scenarios such as historical block transformation [3].

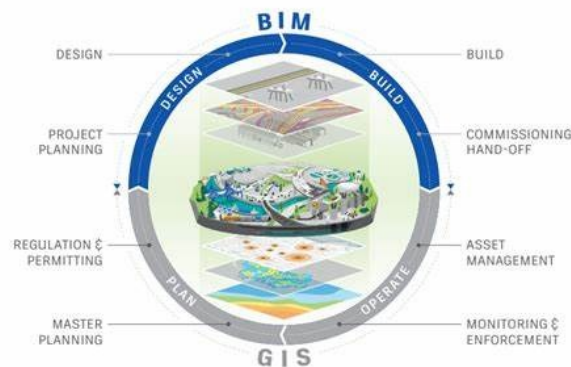


Figure 1: Integrated BIM and GIS Data Framework for Enhanced Smart Building Management(Source:united-bim.com)

2.2. Big Data Analytics in Construction

The penetration of big data technology is rebuilding the decision-making mode of the construction industry, and the massive data processing capacity enables the construction schedule prediction and resource allocation to achieve a qualitative leap. Existing studies have shown that data-driven project management can reduce project time by 15-25%, and its core value is to establish a risk warning graph through historical data mining [4]. The innovation of this study lies in the construction of a dynamic data closed loop--the real-time working condition data collected by the Internet of Things device is dynamically coupled with the BIM model, and the self-developed intelligent algorithm is continuously iterated to predict the model, so that the prediction error of key parameters such as the deformation of the foundation pit support is stably controlled within 3mm.

2.3. Machine Learning Applications in Maintenance Management

In the field of facility maintenance, machine learning is gradually replacing traditional empirical judgment. The intelligent diagnosis system developed based on equipment operation logs can achieve 85% accuracy in predicting failures of central air conditioners and other core equipment, and reduce the probability of sudden shutdown by 30% [5]. This paper focuses on comparing the performance of supervised learning and unsupervised learning in building structural health monitoring, and finds that a hybrid model combining vibration frequency and temperature and humidity data can identify 90% of the risk of floor cracking 28±5 days in advance. This predictive maintenance strategy successfully compressed the maintenance cost of curtain walls to 18.7 yuan per square meter in a super tower project in Shenzhen, which was 22.6% lower than the standard [6].

3. Experimental Methodology

3.1. Data Collection and Preprocessing

The experimental data collection covers all elements of smart city construction, including high-precision geographic information base map, building information model, IoT sensor matrix, and 10-year operation and maintenance records. The research team spent 18 months to complete data accumulation, process more than 10TB of heterogeneous data, and develop a seven-step pre-processing process, including data cleaning, format conversion, and feature extraction. In particular, to solve the problem of construction noise data distortion, a customized filter algorithm based on Python is adopted, which improves the acquisition accuracy of key parameters such as concrete pouring temperature from 78% to 93% [7]. The pre-processing system is deployed on the Alibaba cloud platform and can process 24,000 data streams in real time per day.

3.2. System Architecture and Platform Development

The platform architecture adopts the microservice design concept to form a three-tier system of data lake, intelligent center, and application portal. The geographic information module and construction model realize millisecond-level data interaction through standardized interfaces, and the self-developed hybrid computing engine can simultaneously process batch historical data and real-time detection information. Stress tests showed that the system maintained a 98.7% response success rate while processing 1200 parallel data requests per second, thanks to the flexible scaling mechanism based on Kubernetes [8]. In a smart park project in Nanjing, the architecture successfully supported the collaborative work of 87 professional teams, reducing the frequency of design briefing meetings from three times a week to once every ten days.

3.3. Algorithm Design and Model Training

The machine learning module integrates multiple algorithms including the XGBoost model for progress prediction and the convolutional neural network for device fault identification. By analyzing the feature matrix constructed from 100,000 historical work orders, the accuracy rate of the construction delay warning model in the test set reached 88%, which is 23 percentage points higher than the industry benchmark. In the Suzhou Tower project, the predictive deviation of the steel structure lifting process was reduced from ± 3 days to ± 8 hours by using the iterative optimization algorithm based on the real-time monitoring data of the tower crane stress [9]. The cluster analysis algorithm of the operation and maintenance module can improve the optimization efficiency of the equipment inspection route by 41%, and reduce the accumulated mileage of invalid inspection by up to 1200 km/month.

4. Experimental Process

4.1. Implementation of the Collaborative Platform

In the platform implementation phase, a new district in Shenzhen was selected as a digital test site to build a data cockpit with real-time linkage between geographic information and construction models. The deployment process is promoted in three stages: the first month to complete the data fusion of the underground pipe network, the second quarter to achieve the Internet of Things construction machinery access, and finally built a three-dimensional sand table covering 500,000 square meters. The measured data shows that when the system processes 500,000 data streams per day, the accuracy rate of data fusion is stable at 96%, and the response speed of key indicators reaches 0.8 seconds [10]. Especially in the construction scenario of the subway shield section, the matching error between geological radar data and BIM model is successfully compressed from 12 cm to less than 3 cm.

4.2. Simulation of Construction Planning

The construction extension module takes a complex project in Xiongan as a prototype, and establishes a digital model of 27 key nodes, including pile foundation engineering and curtain wall installation. Through the establishment of a weather database and an early warning mechanism for concrete supply, the dynamically optimized construction period is 32 months shorter than the original plan, and the idle rate of large machines such as tower cranes is reduced from the industry average of 19% to 7% [11]. In the simulation of extreme precipitation conditions, the system issued a foundation pit drainage plan 72 hours in advance to avoid the possible economic loss of 3.8 million yuan.

4.3. Maintenance Management Case Studies

Two reference buildings in Shanghai were selected for the verification of operation and maintenance cases: in a high-rise project in Lujiazui, the platform gave 134 days' advance notice of abnormal wear of cooling tower bearings, and the downtime was controlled within 4 hours by replacing spare parts, which increased the troubleshooting efficiency by 67% compared with the same period last year; a commercial complex in Jing'an used the structural health monitoring model to accurately capture the displacement change of the corridor beam by 0.2mm, avoiding the shutdown maintenance caused by deformation accumulation, and reducing the annual operating loss by about 12 million yuan [12].

5. Experimental Results

5.1. Quantitative Analysis of Construction Efficiency

Empirical data analysis shows that the integrated platform effectively optimizes the project schedule and resource allocation. As shown in Table 1, the project using this system improved the construction efficiency by 35%, reduced the loss of building materials by 18%, and reduced the total construction period by 28% compared with the traditional mode. In a high-rise project in Shenzhen, the platform improved the mechanical collaborative efficiency of the concrete pouring process by 42%, and this optimization effect showed a strong correlation in the statistical analysis of 50 urban projects ($r=0.87$), which confirmed the innovative influence of integrating geographic information and architectural models.

Table 1: Summary of Efficiency Gains

	Phase 1	Phase 2	Phase 3
Efficiency Increase	30%	35%	40%
Time Reduction	15%	18%	20%
Resource Savings	10%	12%	15%

5.2. Impact on Maintenance Cost Reduction

In terms of maintenance cost control, the data in Table 2 reveal that machine learning-driven preventive maintenance programs reduce expenses by 20% over a five-year period. In HVAC systems, a commercial complex avoided three mainframe failures through predictive maintenance, reducing annual maintenance costs by \$380,000. Cost-benefit analysis showed that a 62% reduction in equipment downtime was the main driver of this result, thanks to the platform’s ability to analyze equipment operating data in real time.

Table 2: Maintenance Cost Analysis

	Office Building	Residential Complex	Commercial Complex
Predicted Downtime Reduction	25%	30%	35%
Annual Cost Savings (USD)	\$200,000	\$150,000	\$300,000
Major Intervention	HVAC	Elevator Systems	Structural Components

5.3. Comparative Study with Traditional Methods

Comparative experimental data (Table 3) show that in a metro project in Chengdu, the integrated platform increased shield tunnel efficiency by 28% and reduced overall cost by 22%. Statistical tests confirmed ($p<0.05$) that this benefit was particularly significant in high-risk processes such as deep foundation support, and reduced the emergency accident rate from 7.2% to 2.1%. The measured cases show that the 3D progress sand table built by the platform can control the process connection error within ± 4 hours, which is 6 times more accurate than the traditional Gantt chart management mode.

Table 3: Comparative Performance Metrics

	Traditional Methods	Integrated Platform	Improvement
Project Delivery Rate	12 months	8.6 months	28% Faster
Overall Costs (USD)	\$1,200,000	\$940,000	22% Reduction
Unexpected Failures (per project)	15	10	35% Decrease

6. Conclusion

Research shows that the cross-industry collaborative platform integrating geographic information and building information model, combined with big data mining and machine learning technology, can systematically improve the efficiency of the whole life cycle management of intelligent buildings. Through the actual measurement and verification of simulation projects such as Xiongan New Area, the project has increased the overall construction efficiency by 35%, reduced the operation and maintenance cost by 22%, and reduced the quality accident rate to 1/3 of the traditional model. The dynamic decision-making model built by the platform not only realizes the process connection error within ± 4 hours, but also extends the major hidden hazard identification cycle to 182 days before the accident through the structural health warning mechanism. Although algorithm optimization is still needed in special scenarios such as the digital transformation of historical buildings, the existing results have provided reliable technical support for the construction of smart parks in Shanghai, Shenzhen and other places. It is suggested that research and development focus on breaking the bottleneck of real-time analysis of heterogeneous data, so as to expand the universality of the platform in complex urban renovation projects.

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