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Intelligent Building Management Decision Support System Integrating Digital Twins and Augmented Reality

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SUMMARY: *Currently, digital twin technology and augmented reality technology have been applied across multiple fields. This paper proposes an intelligent building management method based on digital twin and augmented reality technologies. It constructs a smart operation and maintenance system using digital twin technology, fully mines and displays information and data through digital twin application techniques, and establishes a novel building energy consumption control system. The paper discusses its application effectiveness in intelligent building management. Subsequently, the Analytic Hierarchy Process (AHP) is employed to establish an intelligent building health evaluation framework. A specific smart building serves as the case study for assessment analysis. Evaluation results indicate a health rating score of 7.2371, corresponding to a moderate health level. The average score for each of the five evaluation indicators is ≥8 points, demonstrating the effective operational performance of the designed intelligent building management decision support system.*

KEYWORDS: *Digital Twin; Augmented Reality; Smart Building Management; Analytic Hierarchy Process*

1 Introduction

In recent years, with the rapid advancement of technologies such as embedded systems, the Internet of Things, and artificial intelligence, smart technologies have permeated every facet of society, propelling the intelligent transformation of social life into high gear [1]. From early standalone smart devices and smart homes to today's smart buildings, smart technology is undergoing a shift from innovation to integration. As a prime example of highly integrated smart technology, smart buildings have gradually entered the market, completing the transition from concept to application. Building intelligence is not merely the simple combination of architecture and smart devices; it is a product born from the convergence of modern technology and social development, incorporating multiple disciplines including architecture, computer science, communications, and control systems [2, 3]. Only by establishing intelligent buildings as the foundation and integrating scientific management can the integration of smart devices and systems be driven, thereby achieving true building intelligence. China's smart building market exhibits substantial overall scale. Furthermore, the government explicitly outlined the goal of accelerating the development of new smart cities in December 2020. This demonstrates that building intelligence not only meets extensive market demand but also aligns with current

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policy requirements, presenting broad development prospects [4].

The concept of smart buildings was first defined by the American Institute of Architects: "A smart building is one that optimally integrates its internal structure, operational systems, services, and management to provide users with an efficient, economical, and comfortable environment" [5]. Borhani et al. pioneered the classification and comparison of smart buildings and sustainable buildings. They conceptualized smart buildings using ontologies of intelligence and sustainability to define their context and applications [6]. Subsequently, Ghaffarianhoseini et al. further defined the concept of smart buildings based on prior work and analyzed their primary components. They proposed that smart building systems integrate three elements: mechanical and electrical equipment, information technology, and functional applications. Functional applications must prioritize user needs, considering system optimization from a functional perspective to achieve the optimal combination of functionality and efficiency during building operation and maintenance [7].

Today, the application market for smart buildings spans diverse scenarios—from hotels and office towers to hospitals, campuses, and museums—transcending theoretical concepts. Li et al. proposed a simulation-based energy-comfort optimization model employing multi-objective optimization to determine ten critical building parameters. They validated this smart building model using a school building in Wuhan, China, as a case study [8]. Lu et al. studied a multifunctional building on the National University of Singapore campus, proposing a decision-making framework for optimizing energy retrofits. This framework integrates energy simulation, mixed methods for quantifying retrofit benefits, cost contextualization procedures, standardized cost-benefit analysis charts, and metrics to construct a decision matrix [9]. Elhadad et al. evaluated changes in thermal comfort and energy efficiency during model simplification using a typical residential building as a case study [10]. Serrano proposed a distributed artificial intelligence technology embedded within intelligent buildings (iBuildings), capable of adapting to external environments and diverse user demands. This technology aims to monitor building variables in real-time and make accurate predictions through intelligent algorithms [11]. AlMuharraqi et al. examined the characteristics, challenges, and obstacles encountered by the Kingdom of Bahrain's intelligent building project throughout its lifecycle, and conducted the first study on challenges faced during intelligent building project implementation [12].

In our literature review of smart building system optimization research, we found that quantifying occupant comfort primarily relies on data-driven intelligent collection devices within smart buildings to gather comfort metrics [13-15]. For instance, Cheng et al. proposed a method for optimizing sensor placement in multi-zone environments to enhance thermal comfort and indoor air quality [16]. Manic et al. emphasized that constructing cyber-physical ecosystems constitutes a core component of smart buildings. The deployment of smart devices and sensors can accommodate user comfort preferences across diverse scenarios while contributing to energy conservation and emission reduction in building structures [17]. Beyond the three comfort parameters of thermal, visual, and air quality, Malik et al. incorporated relative humidity. They conducted comparative studies on building energy consumption and user comfort management using three optimization methods: Multi-Objective Genetic Algorithm (MOGA), Hybrid Multi-Objective Genetic Algorithm (HMOGA), and Multi-Objective Particle Swarm Optimization (MOPSO) [18]. In summary, while academic research on smart buildings remains in its early stages, significant breakthroughs have been achieved in energy conservation, emissions reduction, and cost management. Nevertheless, most existing studies analyze single smart buildings as case studies, leading to relatively narrow conclusions that fail to integrate user characteristics with building features.

This paper first establishes a decision support system for intelligent building management.

It designs a smart operation and maintenance system based on digital twin technology, projecting physical buildings into a virtual space through four-dimensional mapping. This achieves comprehensive digitalization, virtualization, real-time status monitoring, and visualization of all building elements. Subsequently, it proposes an integrated design methodology for intelligent buildings based on digital twins and constructs the functional architecture of the application system. Detailed design of the energy consumption management system is also presented.

2 Development of an Intelligent Building Management Decision Support System

2.1 Smart Operations and Maintenance System Built on Digital Twins

2.1.1 Main Architecture of Digital Twins

The digital twin engine serves as the core component of a digital twin system, connecting the physical entity that provides data and the virtual entity that provides the model foundation. It primarily consists of five major modules: the interaction-driven module, the data storage and management module, the model management module, the model and data fusion module, and the intelligent computing module.

2.1.2 Application Architecture of Digital Twins

Collect spatial scene data, intelligent sensing data, and indoor/outdoor positioning data from the physical world to construct digital twins in the digital realm. Through BIM scene modeling, IoT-driven real-time simulation, and trajectory tracking based on GIS positioning technology, a “digital building” is recreated in the digital world. This enables visual monitoring and control over operational personnel, users, fixed assets, equipment, facilities, and management tasks. Data analytics diagnose infrastructure operations to deliver more effective operational control strategies. The architecture comprises four layers: intelligent sensing devices, intelligent control devices, intelligent data acquisition devices, and the smart platform.

2.1.3 Applications of Digital Twins in the Construction Industry

Digital twin technology in the construction sector can be summarized into four distinct phases:

(1) Conceptual validation phase: Leveraging spatial data models and AI algorithms, this stage evaluates and verifies design proposals through data comparison and simulation analysis, assessing dimensions such as investment costs and construction timelines.

(2) Immersive Collaboration During Design: Submitting 3D building models enables immersive navigation and virtual experiences that accelerate user comprehension of architectural concepts. Multi-disciplinary systems also enhance inter-professional communication efficiency.

(3) Synchronized Management During Construction: Employing AR and AI technologies throughout construction enables comprehensive simulation, monitoring, and documentation of project progress, quality, cost, and safety. Critical milestones are simulated in real-time during construction to achieve collaborative management, eliminating discrepancies between actual construction and the original model.

(4) Digital Lifecycle Operations and Maintenance: Digital delivery integrates complete building information and material data into asset management systems, establishing digital twins and unified management platforms to optimize energy efficiency and enable low-carbon

operations.

(5) Providing Modeling Foundations for Smart Cities: Buildings constitute a vital component of CIM. Through the delivery of building twins and their interaction with digital city models, real-time, visualizable modeling foundations are provided for surrounding road traffic management and refined urban governance.

2.2 Application Modules of Digital Twin Technology in Smart Building Management

2.2.1 Decision Support

On the integrated management platform for smart buildings, data analysis and information security are key concerns, while more efficient utilization of sensor data presents a significant challenge. Leveraging digital twin technology enables comprehensive data analysis and application through historical equipment simulation and real-time mapping. This approach facilitates intelligent management while enabling predictive maintenance, both of which contribute to enhancing the operational efficiency of management personnel.

2.2.2 Heterogeneous Integration

Within intelligent building integrated systems, networking components include industrial control networks, local area networks, wide area networks, fieldbus systems, and more. Operating systems and databases encompass multiple mainstream products available on the market, while development tools utilize various languages such as Java and VB. Consequently, the system exhibits pronounced heterogeneity and high complexity. Regarding specific system integration applications, the most frequently requested user requirements involve visual integrated management and control, along with real-time data integration—needs that can be addressed through digital twin technology.

To address these common challenges, this paper proposes constructing a digital twin-based intelligent building system that enhances automation while ensuring information security.

2.2.3 Smart Building System Integration Based on Digital Twins

This paper proposes an integrated application method combining digital twins with intelligent building systems. By collecting data on building information, low-voltage systems, security systems, and other aspects, this method digitally models the actual physical structure of the space. Based on the requirements of full lifecycle management for building projects, it creates simulation and visualization models. This approach not only meets system integration requirements but also enables intelligent applications for single devices, multiple devices, single buildings, and multiple buildings. The primary advantage of this digital twin-based intelligent building system integration design theory lies in its ability to model individual devices and construct complex building entities through the combination of single models, enabling both horizontal and vertical interoperability [19]. Simultaneously, to better achieve virtual-physical interaction, the comprehensive visualization and management of diverse collected data is crucial. By acquiring subsystem device information, it fulfills fundamental functions such as data reading, monitoring, early warning, and alarm notification. Furthermore, it enables more efficient operation and maintenance based on data—a key engineering application problem addressed by the digital twin integrated management platform.

This paper analyzes the current status and requirements outlined above, proposing an overall architecture for digital twin-based intelligent building system integration, as shown in Figure 1.

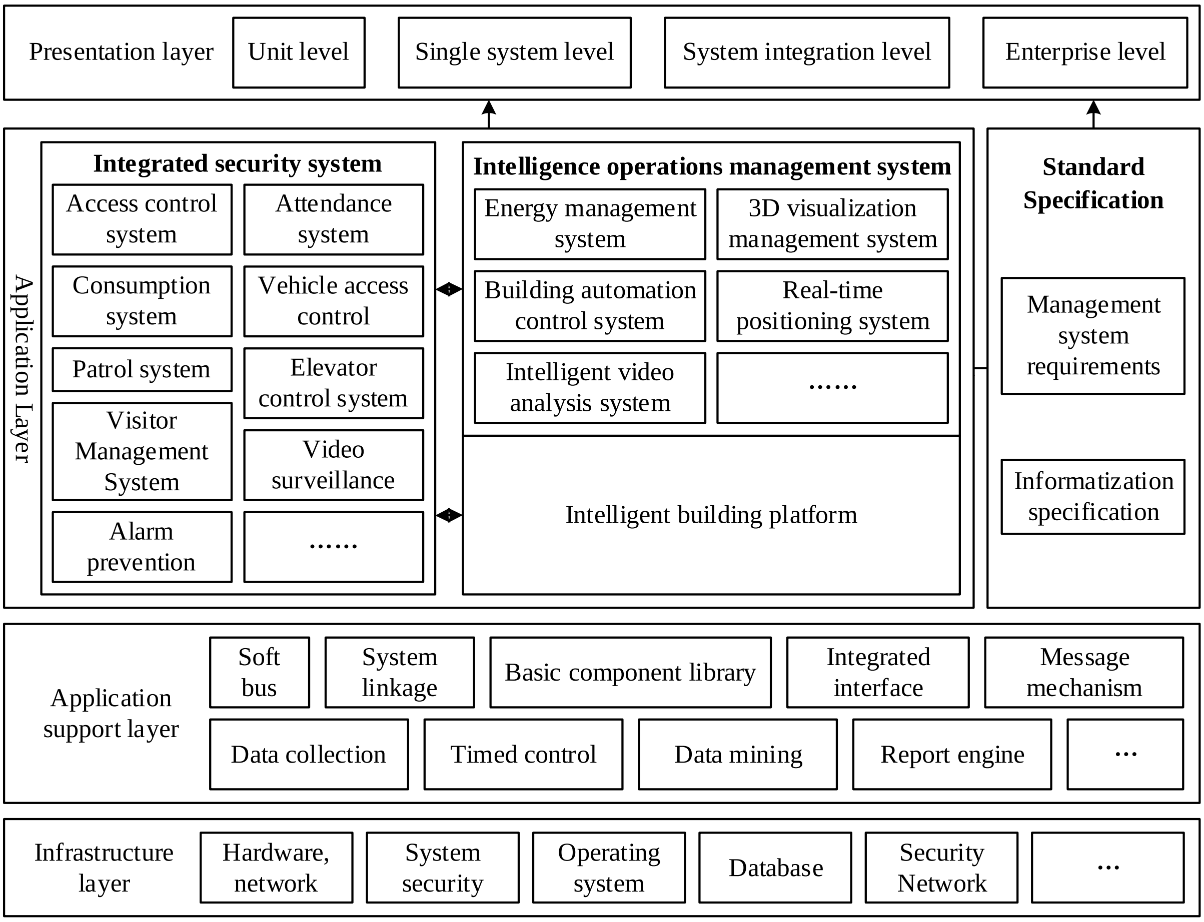


Figure 1: Overall architecture

The overall architecture consists of four layers. The first layer is the infrastructure layer, primarily addressing the smart building network and basic information technology hardware environment. The second layer is the application support layer, handling data collection, data reporting, and integration interfaces required by multiple smart building application systems. The third layer is the application layer, focusing on the integrated security system, which mainly includes access control systems, consumption systems, attendance systems, patrol systems, elevator control systems, and video surveillance systems. Another critical application system is the Intelligent Operations and Maintenance Management System, which integrates energy management systems, building automation control systems, intelligent video analytics systems, and real-time positioning management systems. The final layer is the Presentation Layer, primarily comprising the Digital Twin Integrated Control Platform. This platform operates at four levels: unit-level, single-system-level, system integration-level, and enterprise-level, each implemented using digital twin technology. The unit level primarily targets equipment such as power equipment and construction equipment, performing virtual-physical mapping and coordination of their status and operations. The single-system level focuses on application subsystems within the application layer, such as building security and building automation. It primarily handles data interaction and virtual-physical coordination, integrating business data and multi-factor units from various application subsystems to support data analysis and decision-making. The system integration level integrates multiple application subsystems within two major systems at the application layer, as well as integrates these two application systems themselves. This builds a comprehensive digital twin management platform driven by data, featuring virtual-physical interaction and control. The enterprise level, built upon the system integration level, achieves more holistic, full-lifecycle, and multidimensional management. It primarily enhances digital twin data analysis and simulation capabilities, making buildings more intelligent.

The overall architecture reveals key technical characteristics of digital twin-smart building integration: real-time visual interaction, multi-faceted precision control, big data-driven decision support, and full-domain virtualization of physical models. Additionally, this architecture adheres to two sets of standards: management system requirements and information technology specifications. This ensures standardized constraints and enhances the application's replicability, offering significant market promotion value.

The digital twin integrated management platform described herein also incorporates big data technologies. Employing a multi-server cluster approach based on the Hadoop platform, it achieves the integration of big data analytics with digital twin technology in specific smart building applications. This integration is primarily manifested in simulation and the negative feedback loop of simulation results. The main functional architecture is illustrated in Figure 2.

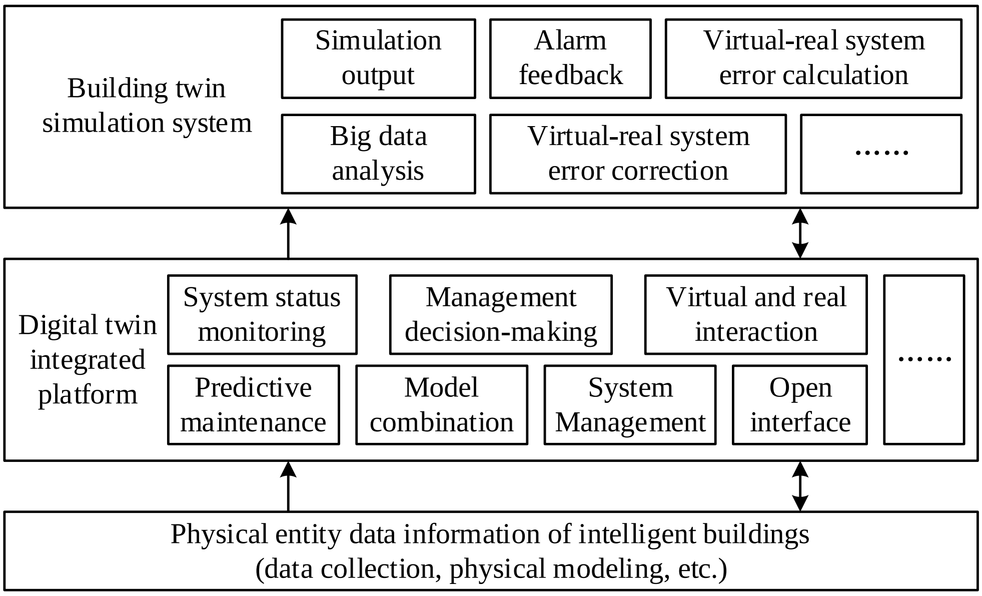


Figure 2: Functional Architecture of the Digital Twin Integrated Platform

2.3 Detailed Design and Implementation of the Energy Consumption Management System

2.3.1 System Architecture

The system architecture is divided into four layers: application layer, platform layer, network layer, and perception layer. The application layer serves as the front-end interface directly accessible to users. All chart data display and user operations are executed at this layer. Developed using technologies like HTML5 and VUE within a B/S (Browser/Server) architecture, it ensures excellent compatibility across diverse user terminals. The platform layer constitutes the software's back-end infrastructure. All data analysis and storage, diagnostic report generation, optimization plan creation, and alarm generation occur at this layer, developed using the Java programming language. The Network Layer serves as the bridge connecting hardware and software, utilizing real-time communication technologies like wireless or wired networks for data transmission to ensure seamless system operation. The Perception Layer constitutes the lowest hardware tier, employing sensors such as smart water meters, air flow meters, and electricity meters to collect energy consumption data from devices and regulate their energy usage.

2.3.2 Design of the Energy Consumption Data Acquisition Module

The database field design for the energy consumption data acquisition module is shown in Table 1.

Table 1: Intelligent terminal information collection field design table

Attribute	Name	Type	Length	Must
itemId	Energy dissipation device id	Character	35	YES
code	Energy dissipation equipment number	Character	30	NO
area	The area of the energy dissipation device	Character	30	NO
sensorName	Monitor device name	Character	35	YES
sensorCode	Monitoring device number	Character	20	YES
floor	The floor of the monitor	Character	10	NO
recoTime	Identification time	Character	20	NO
sensorType	Monitor device type	Character	15	NO
sensorStatus	Monitor equipment free state	Character		NO
status	Energy dissipation equipment state	Character	55	YES

2.3.3 Visualization of Energy Consumption Data

This module utilizes SQL Server to aggregate data collected from the previous module, generating real-time power consumption, real-time water flow, time-of-use electricity consumption, time-of-use water consumption, total water consumption, and total electricity consumption. These metrics are presented to front-end users through graphical representations. Additionally, it generates statistical reports in the background, constructing two-dimensional charts based on detailed temporal and spatial dimensions. These are supplemented with granular item displays to enhance data analysis.

3 Smart Building Energy Consumption Analysis

3.1 Energy-Saving Operation Effect of Intelligent Temperature Setting

The intelligent building management decision support system monitored the summer cooling setpoint temperatures for indoor units. The temperature attainment rates for different setpoints are shown in Table 2. Additionally, this may cause discomfort due to excessive cooling indoors. Similarly, the project faced issues with excessively high setpoint temperatures during winter heating operations.

Table 2: Different temperature setting temperature

	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Degree of delta/%	4	1	6	15	18	26	35	54	63	75	88	94	97	95

To validate the energy-saving effectiveness of the intelligent temperature setting, a two-week energy consumption test was conducted. The same system alternated between activating and deactivating the energy-saving algorithm on a daily basis. During the comparison period, the number of indoor air conditioning units in operation, their locations, and operating times remained identical. Additionally, to eliminate the impact of varying outdoor temperatures on the results, only data with an average outdoor temperature difference within ±1°C was compared. The energy consumption comparison is shown in Figure 3. A total of 100 valid data points were recorded, with outdoor temperatures ranging from 26.0 to 36.0°C. Without the intelligent building management decision support system activated, the hourly average energy consumption was 4.12 kWh. With the system activated, the hourly average energy consumption dropped to 1.95 kWh, achieving an energy savings rate of 51.26%. The system configuration reduced instances of excessively low temperature settings, lowered the operating power of multi-unit compressors, shortened runtime, and automatically entered standby mode upon reaching target temperatures. This demonstrates that optimizing setpoint temperatures can significantly reduce system operational energy consumption.

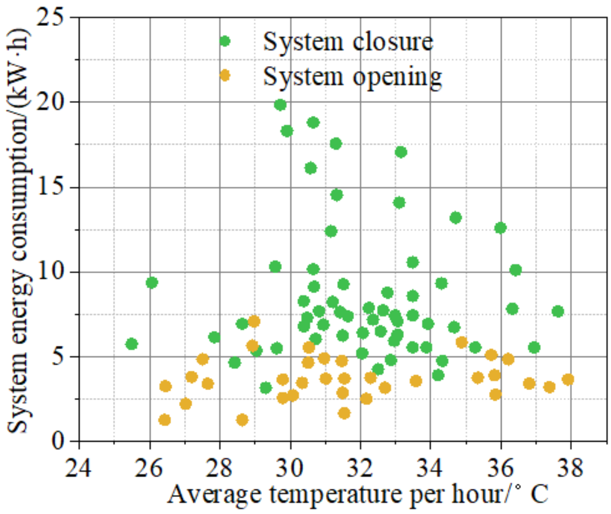


Figure 3: Energy consumption comparison

3.2 Intelligent Start-Stop Energy Saving

Common issues in office building air conditioning operations include forgetting to turn off indoor units, leading to energy waste. Indoor occupancy patterns are illustrated in Figure 4. Analysis by the intelligent building management decision support system reveals that occupancy outside the 8:00 AM to 8:00 PM period accounts for only 6% of the total daily occupancy.

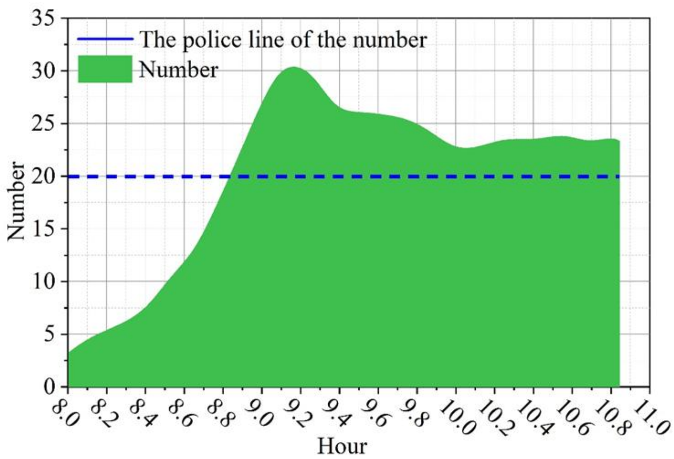


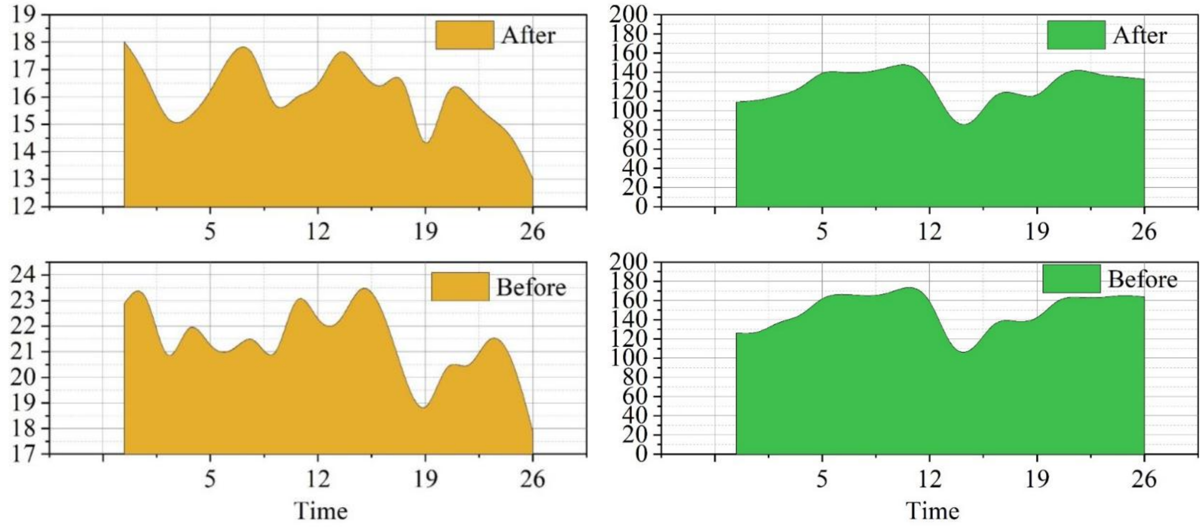
Figure 4: Indoor abortion

System uptime and average number of people present in the room are shown in Table 3. The period from 00:00 to 06:00 accounts for 14% of the total, indicating that a significant number of users forget to shut down the system during operation.

Table 3: The number of people in the room is in the room

	Running time proportion	Average number of people in the room
0	1.03	0
1	1.23	0
2	1.39	0
3	1.89	0
4	1.98	0
5	2.45	0
6	3.01	0
7	5.06	2
8	5.04	29
9	6.01	27
10	6.43	24
11	6.5	24
12	4.03	28
13	5.73	31
14	6.41	26
15	6.44	20
16	6.03	19
17	5.95	22
18	5.95	19
19	5.1	17
20	4.34	9
21	4.36	2
22	1.43	0
23	0.98	0

The comparison of operating hours and energy consumption during weekdays is shown in Figure 5 (Figure a displays operating hours, Figure b shows energy consumption). Figure a illustrates the comparison of air conditioning operating hours on weekdays before and after algorithm implementation. The average operating duration on weekdays in July was 22.63 hours, which decreased to 16.3 hours per day after algorithm application. The total operating hours for working days in July and August were 432.65 hours and 432.65 hours, respectively. Operating hours in August decreased by 26.21%. Figure b shows that air conditioning energy consumption decreased by 18.02%, indicating that the intelligent building management decision support system has a positive effect on reducing operational energy consumption.



(a) Running time (b) Energy consumption

Figure 5: Comparison of operating hours and energy consumption on working days

4 Building Health Assessment

4.1 Building Health Evaluation System Development

4.1.1 Evaluation Model

(1) Fundamental Principles of the Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process is based on the principle of ranking. When studying an object, we first examine the hierarchical relationships among its constituent factors to determine whether the object can be divided into hierarchical levels. The hierarchical structure in AHP typically includes the goal level, criterion level, indicator level, and factor level. Each level comprises numerous elements, and the specific hierarchical division of a research object generally depends on the object's inherent properties [20]. First, AHP simplifies complex problems by introducing hierarchical structure. Elements are constrained by both superior and subordinate levels, forming progressive hierarchical relationships. This structure ultimately clarifies the most fundamental factors, transforming comprehensive evaluation into weighting and ranking of underlying indicators. Second, AHP leverages human learning and engineering experience by integrating qualitative and quantitative approaches. It employs quantitative methods to measure non-quantifiable phenomena, offering high flexibility and practicality. Furthermore, AHP is highly user-friendly during application, allowing users to input information based on their own choices and judgments, making the method more adaptable.

(2) Basic Steps of the Analytic Hierarchy Process

When applying AHP to solve problems, the following four steps are followed:

(a) Problem Analysis

Establish a hierarchical structural model. When employing AHP, the first step is to thoroughly analyze the problem and establish a hierarchical analytical model based on its nature and characteristics. Complex problems are decomposed layer by layer to establish structured relationships, minimizing coupling between elements. This ensures each element is constrained only by its immediate upper and lower layers, while relationships between elements at the same layer become weak. When decomposing the super high-rise building system, we divide it into the objective layer, criterion layer, indicator layer, and factor layer. The objective layer is the topmost layer, containing only one element: the overall health status of the super high-rise building. The criterion layer, also known as the intermediate layer, represents the intermediate steps for achieving the system objective and includes multiple elements. For instance, the determinants of the overall health status of a super high-rise building include the structural subsystem, envelope subsystem, fire protection subsystem, and foundation system. The indicator layer comprises factors and measures influencing the intermediate layer. For example, factors affecting the structural subsystem include giant columns and core tubes. The factor layer, the lowest tier, represents the most direct elements for achieving the system objective. The hierarchical analysis structure is illustrated in Figure 6.

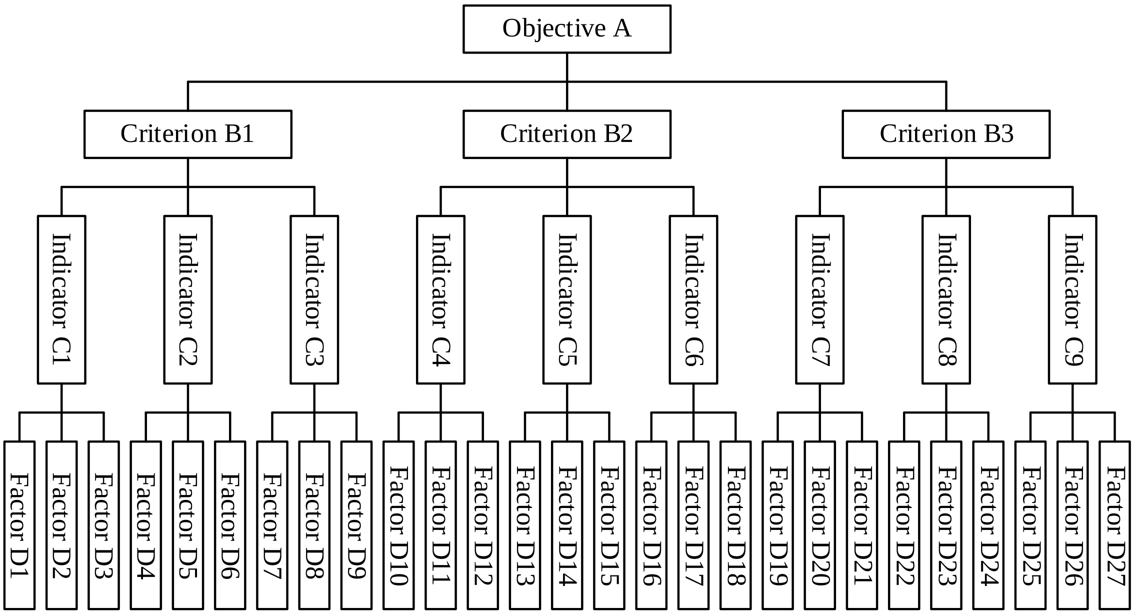


Figure 6: Structure Diagram of the Analytic Hierarchy Process

(b) Constructing the Judgment Matrix

The hierarchical structure model establishes membership relationships between levels. Based on these relationships, a judgment matrix can be constructed. The judgment matrix is typically constructed using pairwise comparisons. Let the lower layer of an upper-level element Y contain n elements, denoted as $x_1, x_2, \cdots, x_n$. This allows for the construction of the judgment matrix A for Y.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

Here, a_v denotes the importance of x_i relative to x_i, referred to as the judgment scale. Currently, there are two methods for determining judgment scales: one is the 1–9 scale proposed by Sasty, also known as the reciprocal scale. The other is the fuzzy scale (0.1–0.9) method, also known as the complementary scale.

Different judgment matrices result from using different scaling methods. The reciprocal judgment matrix is obtained when the reciprocal scale is used, while the complementary judgment matrix is obtained when the complementary scale is used. This paper employs the reciprocal scale method.

When constructing a judgment matrix, it must satisfy the following three conditions:

1) The diagonal elements of the matrix are 1.

2) Elements in mutually exclusive rows and columns of the judgment matrix are reciprocals of each other, i.e., $a_{ij} = 1/a_{ji}$.

3) Based on the transitivity between elements, the relationship in equation (2) holds.

$$a_{ij} = \frac{a_{ik}}{a_{jk}} \quad i, j = 1, 2, \cdots, n \tag{2}$$

(c) Solving for the Weight Matrix

After constructing the decision matrix A, the weight matrix for $x_1, x_2, \cdots, x_n$ can be obtained through a series of calculations as follows:

1) Solve for the matrix's eigenvectors and eigenvalues to obtain the maximum eigenvalue $\lambda_{\max}$ and its corresponding eigenvector $W = [\omega_1, \omega_2, \cdots, \omega_n]$.

2) Normalize w according to equation (3) to obtain $W' = [\omega_1', \omega_2', \cdots, \omega_n']$ This represents the weight matrix corresponding to $x_1, x_2, \cdots, x_n$.

$$\omega_i' = \frac{\omega_i}{\sum_{j=1}^{n} \omega_j} \tag{3}$$

(d) Consistency of Judgment Matrix and Its Verification

Due to the limitations of engineers' understanding, it is difficult to guarantee the transitivity of elements in the judgment matrix during practical implementation. At this point, conducting a consistency verification on the judgment matrix determines whether it is usable. The consistency verification method is as follows:

1) Calculate the consistency index CI based on Equation (4):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4}$$

Among these, n denotes the dimension of the judgment matrix.

2) Select the random consistency index RI based on the judgment matrix dimension n

3) Calculate the consistency ratio cR according to Equation (5):

$$CR = \frac{CI}{RI} \tag{5}$$

4) Assessing Judgment Matrix Validity

If $CR < 0.1$, the judgment matrix consistency is acceptable. Otherwise, the judgment matrix requires appropriate adjustment.

4.1.2 Evaluation Indicator Construction

(1) Evaluation Indicator Collection and Setting

Smart buildings should integrate hard attributes such as safety and durability with soft attributes like convenience and comfort. Therefore, building health encompasses not only maintaining structural integrity, component safety, and high durability, but also emphasizes comfort, favorable indoor and outdoor environments, convenience, operational management, and economic efficiency. With the continuous advancement of building performance evaluation theories and methodologies, its characterizing indicators now encompass numerous aspects including safety and durability, health and comfort, resource conservation, indoor and outdoor environments, construction and operation, and sustainability. Based on a comparative analysis of the aforementioned evaluation methods, this study's indicator system structures the building health evaluation framework as shown in Figure 7. The target layer represents the building health evaluation system, while the criterion layer is divided into five categories: comfort performance, safety performance, environmental performance, operational management, and economic performance. The indicator layer comprises 19 metrics. Comfort performance metrics include spatial dimensions, spatial privacy, surrounding service facilities, and elevators. Safety performance metrics encompass structural safety, building age, water quality, and fire protection systems. Environmental performance metrics cover green plant coverage, indoor natural daylighting, drainage, indoor natural ventilation, and indoor thermal environment. Operations management metrics include waste disposal, equipment management, sanitation, and management organizational structure. Economic performance metrics encompass energy consumption per unit area and direct utilization of natural resources.

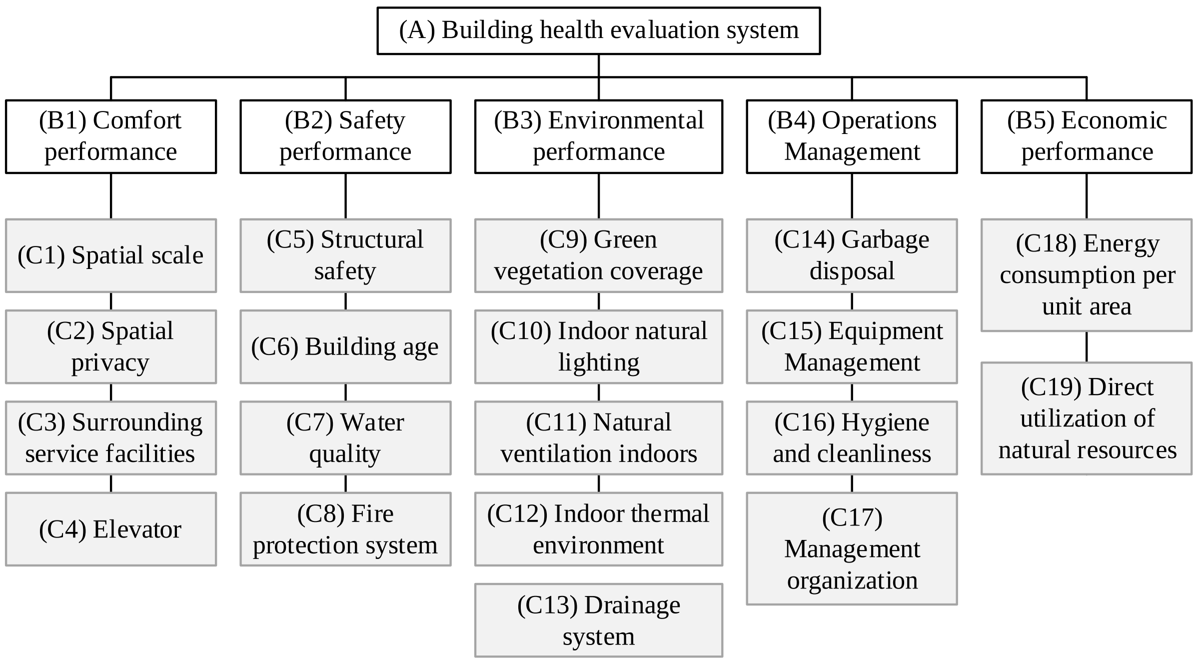


Figure 7: Structure Diagram of the building health Evaluation System

(2) Decision Outcomes from Multiple Decision-Makers

Given the significant subjectivity inherent in the Analytic Hierarchy Process (AHP), the judgment of a single expert may exhibit certain biases. To ensure the rationality and accuracy of judgment outcomes, it is necessary to synthesize the opinions of multiple experts. The arithmetic mean weighting method is the most widely applied AHP group decision analysis technique, whose core principle is “divide and integrate.” The specific steps are as follows: First, decision-makers make judgments and calculate both the weight results and the consistency level of the judgment matrix. Any judgment matrix failing the consistency test is invalid and requires revision. Subsequently, the arithmetic mean of all weight results is calculated to obtain the final weight results. Given m decision-makers, where the nth decision-maker assigns weight $W_i(n)$ to the i th evaluation object, the average valid weight judgment for this object across all m decision-makers is:

$$\bar{w}_i = \frac{\sum_{n=1}^{m} wi^{(n)}}{m} \tag{6}$$

The expert panel for this study comprised five members. All five experts assessed the constructed matrix and passed the consistency test. The weighted evaluation results from the five assessors are presented in Table 4.

Table 4: Weight evaluation result

Indicator	Expert A	Expert B	Expert C	Expert D	Expert E	Final weight
Spatial scale (A1)	0.0001	0.001	0.0051	0.0125	0.012	0.0022
Privacy of space (A2)	0.009	0.009	0.009	0.0121	0.0103	0.0093
Surrounding service facilities (A3)	0.014	0.01	0.0312	0.0123	0.0158	0.0137
Elevator (A4)	0.0126	0.0276	0.0313	0.0101	0.0171	0.0218
Structural safety (B1)	0.3244	0.3293	0.4082	0.4204	0.0874	0.3131
Building age (B2)	0.0323	0.0008	0.0866	0.0283	0.0278	0.0353
Water quality (B3)	0.037	0.0159	0.0269	0.1027	0.3765	0.112
Fire protection system (B4)	0.0069	0.0176	0.0969	0.0391	0.1141	0.0551
Green vegetation coverage (C1)	0.0185	0.0181	0.0042	0.0132	0.0126	0.0131
Indoor natural lighting (C2)	0.3041	0.2478	0.0291	0.0126	0.0085	0.1196
Drainage (C3)	0.0585	0.0661	0.0605	0.0634	0.0442	0.0577
Indoor natural ventilation (C4)	0.052	0.0137	0.0498	0.0241	0.0157	0.0317
Indoor thermal environment (C5)	0.0237	0.042	0.0088	0.035	0.0298	0.0278
Garbage disposal (D1)	0.0093	0.0244	0.0096	0.0765	0.0427	0.0339
Equipment Management (D2)	0.0066	0.0469	0.0045	0.0262	0.0167	0.02
Sanitation and cleaning (D3)	0.0263	0.0145	0.0159	0.0104	0.0085	0.016
Management organization structure (D4)	0.058	0.0631	0.0705	0.0147	0.0792	0.0554
Energy consumption per unit area (E1)	0.0208	0.0421	0.0363	0.0944	0.0513	0.0486
Direct utilization of natural resources (E2)	0.0013	0.0123	0.0221	0.0025	0.045	0.0166

The weights assigned by the five experts were averaged using a weighted average method to derive the final weights for the building health evaluation system. The final weighting results for the indicators are shown in Figure 8.

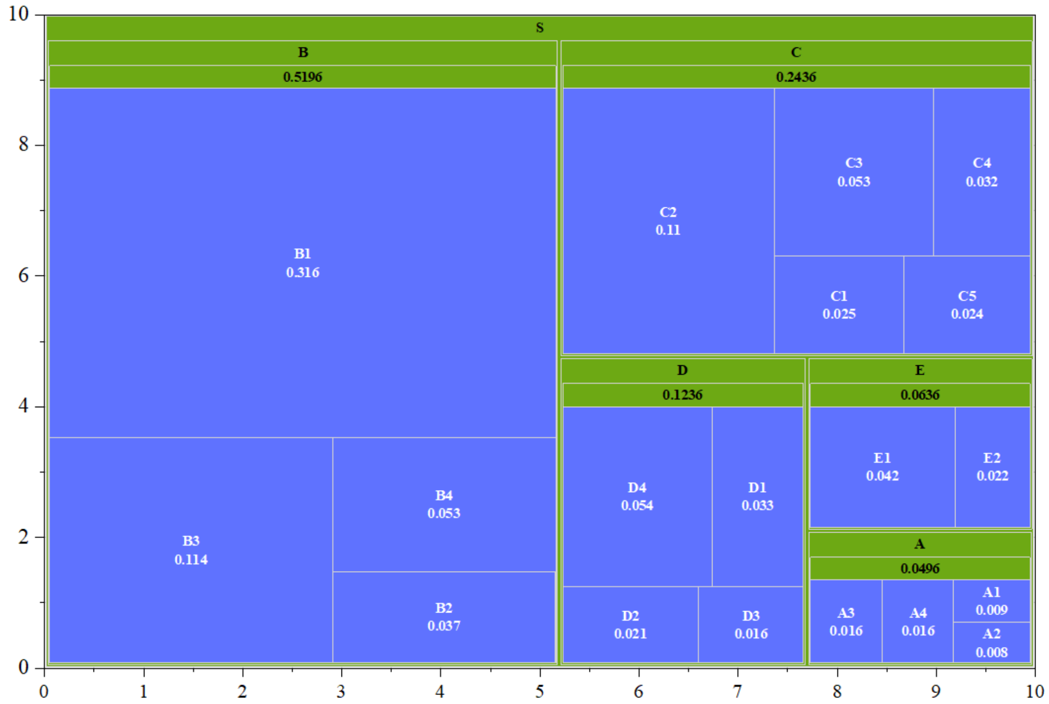


Figure 8: The final weight result of the indicator

(3) Classification of Building Health Evaluation Standards

Referencing relevant evaluation standards, this study categorizes building health evaluation standards into five levels: Excellent, Good, Moderate, Passing, and Failing. The value G of the building health performance index is determined by two parameters: the score V of the evaluation indicators and the weight B corresponding to each indicator. The calculation formula is as follows:

$$G = \sum_{i=1}^{n} W jVj \tag{7}$$

where:

G — Comprehensive score of the building health performance index.

W — Weighting coefficient for the jth building health performance evaluation indicator.

V — Individual score for the jth building health performance evaluation indicator.

The building health performance index calculated for each actual project differs.

4.2 Evaluation Results

This section conducts an empirical analysis using a specific smart building as the research subject. The assessment scores are shown in Table 5. As indicated in the table, the smart building's health assessment score is 7.2371 (out of 10), with its health level classified as moderate. The evaluation results reveal that comfort performance, environmental performance, and operational performance received the highest scores, averaging 8.75 points. The average score for each of the five evaluation indicators is ≥8 points, indicating that the smart building maintains a favorable state in aspects such as spatial privacy, natural lighting, elevators, fire protection systems, drainage systems, and waste management.

Table 5: Evaluation score

Indicator	Sub-indicator	Score	Full score	Weighted score
A	A1	8	10	0.4416
A	A2	8	10	
A	A3	9	10	
A	A4	10	10	
B	B1	9.5	10	3.4659
B	B2	8	10	
B	B3	8	10	
B	B4	8.5	10	
C	C1	8	10	2.3162
C	C2	9	10	
C	C3	9	10	
C	C4	9	10	
C	C5	8	10	
D	D1	9	10	0.9152
D	D2	9.5	10	
D	D3	8	10	
D	D4	8.5	10	
E	E1	8	10	0.0982
E	E2	8	10	
Total score: 7.2371				

5 Conclusion

With the advancement of new-generation information technologies, the informatization applications of intelligent building systems have also undergone gradual upgrades. This paper establishes an intelligent building management decision support system and employs the Analytic Hierarchy Process (AHP) to propose an intelligent building health evaluation framework, thereby conducting a scientific validation of the designed methodology. The conclusions drawn are as follows:

By establishing a digital twin management platform for an office building, this study explores intelligent energy-saving operation technologies. Results indicate that after system implementation, the hourly average energy consumption reached 1.95 kW·h, achieving a 51.26% energy savings rate. The designed intelligent building management decision-making system demonstrates effective results in reducing building operational energy consumption and costs.

Analysis indicates the smart building's health assessment score is 7.2371 (out of 10), classified as moderate health. This demonstrates the effective operational performance of the smart building management decision support system designed in this paper.

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