Optimized BIM Rendering and Cloud-Based Evaluation for Green Construction in High-Rise Residential Buildings

Qi Zhao[1], Xinle Wang[2,*]
[1]Department of Infrastructure, Yan'an University. Yan'an 716000, China
[2]Northwest Engineering Corporation Limited, Xi'an 710000, China
E-mail: wainitiant@163.com, jxly222@163.com
[*]Corresponding author

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To address the serious waste of resources in high-rise buildings during the urbanization process, weak green awareness among construction personnel (only 42.3% theoretical accuracy), and rendering delays (102.7ms) and management virtualization in BIM technology applications, this study proposes a three in one solution of "technology management evaluation": the technical layer adopts an improved Hermite interpolation algorithm to achieve dynamic rendering of internal and external components separation, and the frame rate is increased to 58.7 FPS (compared to the optimal baseline+16.7%). The management team has built a digital platform that integrates VR training, sensor networks, and ontology reasoning. After testing and verifying with 200 workers, the training effectiveness has been improved by 112% (with a post training accuracy rate of 89.7%), and the material waste rate has been reduced by 69% (to 7.3%). The improved cloud model introduced by DPSIR framework in the evaluation layer reduced the evaluation bias rate to 4.7% (61.8% lower than fuzzy logic). The experiment shows that the framework significantly improves rendering efficiency (with only 1.2GB of memory usage), management collaboration (with a decision accuracy of 92.4%), and evaluation objectivity (expert consistency Kappa=0.82), forming a reusable green construction full chain optimization paradigm for high-rise residential buildings and overcoming the three major bottlenecks of delay, virtualization, and subjectivity.

Povzetek: Opisan je celovit okvir za zeleno gradnjo visokih stanovanjskih stavb z uporabo BIM (informacijsko modeliranje gradenj). Tehnični del izboljša dinamično izrisovanje, vodenje podpira digitalna platforma z VR usposabljanjem in ontološkim sklepanjem, vrednotenje pa izboljšan oblačni model (DPSIR).

1 Introduction

With the advancement of urbanization, there are more and more high-rise buildings, and the requirements design for high-rise building construction projects are getting higher and higher. How to make projects more scientific and efficient on the basis of meeting the daily needs of high-rise buildings, and at the same time enhance the experience of related users, is what relevant construction units need to study and think about. BIM (Building Information Modeling) technology has good visualization, simulation and high efficiency, and has many advantages such as intelligent control of the whole process and collaborative work. Therefore, the full application of BIM technology in high-rise building design can greatly improve the accuracy, experience and scientificity of design, and promote the promotion of green construction technology in high-rise buildings.

High rise buildings are different from general residential buildings due to their unique structural form, construction height, construction equipment, and construction technology. But in terms of the composition of construction personnel and management methods, it is no different from other projects, such as using construction personnel and labor teams from general residential or commercial projects, and there is no distinction in the hierarchical structure of management personnel. Since then, on-site management has always felt inadequate and the utilization rate of resources is relatively low. Temporary water use and vertical transportation inside high-rise buildings are key items during the construction process, but in practice, the construction unit cannot consider them in the long run. For example, first of all, municipal water sources are still connected in terms of water facilities and usage, and rainwater collection or water reuse are not used; Secondly, Linshui is only used for construction water and does not directly convert temporary water pipelines into formal water. Instead, the existing pipelines are abandoned and replaced. In this way, not only does it cause great waste of water sources, but it also leads to secondary consumption of pipes, which is not conducive to green construction [1].

In construction, workers are the main body responsible for all construction activities. Therefore, the subjective cognition of these relevant personnel has an important impact on the implementation of construction activities. Therefore, whether green construction can be smoothly promoted and implemented is greatly influenced by whether these subjects have a strong awareness of green construction. Through research interviews, it was found that in practical engineering, the most basic construction personnel lack awareness of green construction, have a relatively shallow understanding of it, and do not understand what true green construction is, why and how to achieve green construction. The understanding of green construction by management personnel is only limited to verbal and superficial understanding, without integrating green construction into their construction management system, and without setting a model for construction personnel; The entire construction project lacks awareness of green construction and lacks promotion and education on green construction; These situations have seriously affected the effective implementation of green construction measures. Therefore, in the process of green construction management, the first and most important thing is to strengthen the publicity and education of workers on the project, impart relevant knowledge, improve the green construction awareness of construction and management personnel, constrain their construction behavior, and ensure the effective implementation of green construction [2].

Project implementation is an important step for the implementation or effective implementation of green construction objectives. If the green construction scheme is well designed but not effectively implemented, then green construction will be useless. In order to ensure the effective implementation of green construction scheme, it is necessary to strengthen the process management and control of green construction. This paper combines the improved algorithm model to evaluate the application effect of BIM green construction technology on modern high-rise buildings, so as to provide relevant reference for the construction and management of follow-up high-rise residential buildings.

To improve the current BIM green construction technology in high-rise residential buildings, which has shortcomings such as weak real-time dynamic response of technical models, undefined management systems, and strong fuzziness of evaluation indicators, this study proposes a "technology management evaluation" three in one solution: the research objective is to improve the green construction efficiency and precise control level of high-rise buildings through innovative methods. The research method integrates the improved Hermite interpolation viewpoint prediction algorithm to achieve dynamic rendering optimization of internal and external components of BIM models, and constructs a digital management platform that integrates VR training, sensor networks, and ontology reasoning to support full lifecycle collaboration. The improved cloud model algorithm based on DPSIR framework is introduced to generate multi-dimensional evaluation cloud maps for effect quantification. The innovation lies in the integration of dynamic rendering technology, ontology-driven decision-making, and cloud model evaluation into a unified framework for the first time, which overcomes the three bottlenecks of rendering delay, management virtualization, and subjective evaluation. Moreover, it helps to form a reusable full-chain optimization paradigm for green construction of high-rise residential buildings, which can significantly improve rendering efficiency, management collaboration and evaluation objectivity through experimental verification.

2 Related work

Due to its unique green construction characteristics, high-rise buildings are different from ordinary buildings in terms of green construction, thus requiring new policies, standards, and management systems. With the promotion of green construction in China, green construction management has made certain progress, and research on green construction management theory and methods has also achieved certain results. However, these are not fully applicable to high-rise green construction. When many high-rise buildings carry out green construction, their construction plans and management systems are based on the content of green construction, without unified norms and standards, and the basis for green construction in high-rise buildings is weak [3]. There is a formalistic phenomenon in the management of high-level green construction. The construction unit or construction unit regards green construction as a form, which is a way to obtain some benefits. It emphasizes departmental inspection over practical implementation, and cannot penetrate green construction into all stages of construction. Therefore, a reasonable and standardized high-level green construction management system needs to be constructed [4]

BIM is based on various relevant information data of construction projects as the model, establishing building models and simulating the real information of buildings through digital information simulation. Through the application of BIM technology, the construction process of building engineering has effectively improved work efficiency, shortened the construction period to the greatest extent, and can reduce construction costs while ensuring construction quality. BIM technology is the full integration of construction information from various aspects of engineering projects, involving a large number of participants, including construction units, design units, operation units, etc [5]. Therefore, the use of BIM technology can establish a multi-party communication foundation platform, which is more conducive to communication and exchange among engineering project participants. A dual objective optimization model was developed using social network analysis and collaboration theory, fully considering the synergistic impact between assembly construction services and service quality. The results indicate that the system balances efficiency and safety [6].

The study proposes a new model of refined construction management based on BIM, and discusses the application measures and benefits of BIM technology in refined management from four aspects: quality management, schedule control, cost management, and safety management. Practice has proven that BIM technology has brought good economic and social benefits to refined management [7].

Due to issues such as the structure and construction methods of high-rise buildings, the buried engineering pipelines during the construction process are complex and dense. If only based on construction experience, it is easy to cause material waste. BIM technology can simulate the construction process before construction, use the coordination function of BIM to optimize the burial of engineering pipelines, minimize pipeline usage while ensuring normal construction, and develop material supply plans through simulation to reduce the difficulty of construction material management and achieve the material saving goal of green construction [8].

The construction volume of high-rise buildings is large, and the construction site is limited, facing a very tight land demand. In order to ensure timely and efficient construction, it is necessary to optimize the construction site, make reasonable arrangements, and ensure that the site utilization follows the construction progress. BIM technology has strong three-dimensional visualization effects and dynamic simulation and adjustment capabilities. Therefore, BIM technology can be applied to optimize construction sites, visually observe the physical effects of different schemes, select the optimal scheme, and improve land and space utilization [9].

In terms of lighting energy conservation, BIM technology can simulate the spatial range of lighting, plan the installation location of lighting equipment reasonably, reduce the occurrence of lighting blind spots and reduce the number of repeated lighting positions. The use of electrical equipment and energy can maximize efficiency. The visualization technology of BIM can also be applied to supervise and inspect the lighting situation, which can quickly detect abnormal problems and solve them in a timely manner.[10]

In terms of water conservation, BIM technology can be applied to quickly and effectively arrange the temporary water pipe network on the construction site, saving time; BIM technology can be applied to arrange sewage recovery and rainwater collection pipeline systems, establish a water resource recycling system, arrange sewage reuse routes, and use reclaimed water for car washing, road flushing, etc. in the shortest possible route, promoting the efficient utilization of water resources [11].

For high-rise residential buildings, the construction process can cause serious damage to environmental resources, so corresponding measures need to be taken to enhance the environmental protection work of the building project. Through the full application of BIM technology, a three-dimensional dynamic model can be established on the construction site, and the garbage treatment stations on the construction site can be reasonably arranged, thereby achieving the unified storage and centralized treatment of construction waste and domestic waste [12]. By using BIM technology to optimize steel structures, the installation efficiency of steel structures on the ground can be improved, installation time can be saved, and interference with the surrounding environment can be minimized to the greatest extent, ensuring that residents around high-rise residential buildings can work and live normally.

The system concept based on Hall multi-dimensional structure and the theory and practice of lean management of prefabricated building cost are studied, and a lean management and control system of prefabricated building cost based on Hall multi-dimensional structure model is proposed and constructed. At the same time, the application of Hall multidimensional structure model in lean management is discussed from the perspectives of time, logic and knowledge [13]. From the perspective of green construction, the collection of information on materials related to green construction is the focus of the selection of green demonstration projects, because only through these materials can the construction process and effect of green construction of the project be more vividly presented. These materials can include green construction organization and plan documents, green construction technology application records, green construction process pictures and detailed records, etc. [14].

Green construction target control mainly includes target decomposition, comparison between actual and expected results, deviation analysis, and deviation correction. In the goal decomposition stage, it is necessary to comprehensively consider the actual situation of the project and decompose the green construction goals according to the organizational management system. The goals should be decomposed into different parts of different construction stages, and each goal must have a clear responsible person. At the same time, the goal decomposition process should pay attention to hierarchy and integrity [15]. After the goal decomposition enters the construction phase, it is necessary to track and monitor the green construction plan, timely collect construction site data, regularly compare the actual effect of the project with the planned goals, and discover errors. After discovering deviations, carefully and comprehensively analyze the causes of deviations from multiple perspectives, providing a basis for corrective measures [16]. In the deviation correction stage, effective measures are taken from multiple dimensions such as organization, management, and construction to correct deviations, eliminate or weaken errors, summarize experience, and provide reference for similar green construction in the future. To reduce target deviation, it is necessary to strengthen the process control of each construction link, minimize errors, and accelerate the construction progress [17].

The research models, results, and deficiencies of relevant literature are presented in Table 1:

Table 1: Research models, results, and deficiencies of related literature.

The research model used	The results obtained	The deficiencies of this study
Construction water management model	It reveals that the unreasonable arrangement of high-rise buildings near water is not conducive to green construction.	Lack of long-term planning and failure to integrate sustainable water resource utilization
Green construction awareness education model	It is pointed out that the awareness of green construction among construction personnel and management personnel is weak	The model focuses on qualitative analysis and lacks quantitative evaluation tools
High-level green construction management system model	The lack of unified standards for high-level green construction has led to an imperfect management system.	The model is not customized for high-rise specificities, such as structural height and construction technology
Basic application model of BIM technology	BIM technology enhances work efficiency and improves communication among participants.	The model has strong universality but does not focus on high-rise residential complexes
BIM-Green Construction Integration Model	The integration of BIM and green construction technology enables lean and dynamic management	The model lacks specific operational guidelines and fails to quantify energy-saving benefits
BIM site planning and optimization model	Optimize the layout of the construction site and the machinery access route, ensuring precise and reliable design results; utilize 3D visualization to enhance land utilization and spatial allocation efficiency.	The model relies on manual data input and has weak real-time dynamic adjustment capabilities
BIM pipeline optimization model	Optimize the laying of engineering pipelines through pre-construction simulation to reduce material waste and lower management difficulty; formulate an efficient material supply plan.	The model does not cover the entire lifecycle of pipelines; the optimization effect relies on empirical data
BIM construction site dynamic optimization model	3D visualization and dynamic simulation capabilities optimize site arrangements, enhance land utilization, and ensure efficient construction progress.	The model responds slowly to real-time data; its application scenarios are limited.
BIM lighting energy-saving simulation model	Simulate lighting schedules and location planning to improve the efficiency of electrical equipment; visualize supervision to quickly identify issues.	The model does not take into account changes in natural lighting at high levels; the energy-saving effect has not been empirically verified
BIM water-saving management model	Rapidly set up temporary water pipe networks to promote efficient water use.	The model does not quantify the amount of water saved; pipe network optimization relies on static data
BIM environmental protection optimization model	Optimize the layout of waste disposal stations and the installation of steel structures through 3D modeling to reduce environmental damage	The model does not cover ecological indicators; there is a lack of horizontal comparison data for environmental protection measures.
Information management integration model	Collect multi-source information during construction, and analyze data to enhance the scientific nature and efficiency of management	The model focuses on data collection and lacks intelligent analysis tools
Green construction information collection model	Primarily used for the selection of green demonstration projects	The model is primarily qualitative, lacking quantitative standards; the authenticity of information relies on manual review
Target control management model	Including goal decomposition, comparison between actual and expected results, deviation analysis, and correction	The implementation of the model is complex, and the process control mechanism is not perfect

There are significant shortcomings in the current research on the application of BIM green construction technology in high-rise residential buildings. At the technical level, existing BIM models (such as pipeline optimization and site planning models) rely on manual data input and have weak real-time dynamic response capabilities. Energy saving models such as water-saving and lighting lack quantitative validation, and large-scale component loading delays lead to low rendering efficiency. At the management level, the green construction management system has not been customized for the special characteristics of high-rise buildings, and there is a tendency towards formalization. The information collection model focuses on qualitative description and lacks intelligent analysis tools; At the evaluation level, traditional methods are difficult to handle the ambiguity of indicators (such as construction personnel awareness and ecological impact) and have not established a dynamic feedback mechanism. Aiming at these problems, this paper innovatively puts forward a trinity solution. Technically, this paper breaks through the first solution of "separation and dynamic rendering of internal and external components of BIM model", and combines the optimized Hermitian interpolation viewpoint prediction algorithm and external contour detection mechanism to greatly improve rendering efficiency. Secondly, this paper builds a digital platform integrating VR training, sensor network, and ontology reasoning in management collaboration, and establishes a green construction ontology through a seven-step method to realize a closed-loop data and intelligent decision-making in the whole life cycle. In addition, this paper introduces the improved cloud model algorithm (DPSIR framework) into the evaluation system, combines multi-dimensional monitoring data to generate a dynamic evaluation cloud image, objectively quantifies the construction effect, solves the problem of index fuzziness, and finally forms the whole chain innovation framework of technical management evaluation.

3 Green construction rendering of BIM in high-rise buildings

3.1 Rendering algorithm model

In BIM model rendering, 3D scene management is a research focus and difficulty. The purpose of 3D scene management is how to organize the data in the scene reasonably and effectively, so as to provide convenience for subsequent applications. There are many BIM models in the 3D scene, and each BIM model contains a large number of triangular patches, materials, textures and other data. The more complex the BIM model is, the more complex the 3D scene is. If we don't take effective data organization methods for complex 3D scenes, we will not be able to meet the real-time rendering requirements of 3D scenes. On the contrary, if we can take an effective way to organize 3D scene data, we can speed up the efficiency of visibility culling algorithm, so that users can accurately and quickly locate each component in the scene.

In actual projects, it is usually necessary to adopt different scene data structures to organize the data in the scene according to the characteristics of each scene. Usually, the scene is divided into static scene and dynamic scene. Among them, static scene means that the model in the scene is fixed after being established; Dynamic scene means that some components in the scene may change after the model is established, such as rotation, translation and so on. In most cases, spatial partition structure is used to organize static scene data. Because the spatial partition data structure is divided according to the spatial relationship of data when organizing data, it is beneficial to visibility clipping, collision detection algorithm and so on. In most cases, dynamic scenes use scene graph to organize data. Because the structure of scene graph is more flexible and changeable, the operation of interacting with dynamic objects in the scene can shorten the update time and improve the rendering speed.

When browsing the BIM model, the viewpoint browses the whole or part of the BIM model according to a certain motion trajectory. In this scenario, the viewpoint prediction algorithm can accurately predict the next position of the viewpoint according to the motion track of the viewpoint, and load the components that can be observed at this position from the disk to the memory in advance, which can effectively improve the fluency during roaming.

Because BIM models are generally large in scale and complex in structure, the number of components contained in them is huge. Even if the visual cone elimination algorithm is applied, the number of components contained in the visual cone may still be large at some moments when the viewpoint moves. It takes a lot of time to read a large number of geometric data of components from the disk, which slows down the real-time rendering speed of BIM models. Therefore, this paper puts forward the optimization of view cone elimination algorithm based on view prediction. View prediction predicts the possible position of view at the next moment through the position and motion direction of view at the previous moments, calculates the components existing in the view cone at the next moment in advance, and loads the geometric data of these components into memory in advance from the disk to avoid the situation of large-scale component data loading from the disk, thus reducing the frame rate fluctuation when browsing BIM model and making it smoother and improving the visual experience of users [18].

In this paper, Hermite interpolation algorithm is selected to realize viewpoint prediction. The derivation of Hermite interpolation equation first requires $2n+1$ interpolation basis functions $\alpha_j\left(x_k\right)$ and $\beta_j\left(x\right)\left(j=0,1,2,...,n\right)$, and each interpolation basis function needs to be guaranteed to be a $2n+1$ polynomial of terms and satisfy the conditions:

$$\begin{cases} \alpha_j\left(x_k\right)=\delta_{jk}=\begin{cases}0, j\neq k,\\ 1, j=k,\end{cases}\alpha_j^{'}\left(x_k\right)=0 \\ \beta_j\left(x_k\right)=0,\beta_j^{'}\left(x_k\right)=\delta_{jk}\left(j,k=0,1,2,...,n\right)\end{cases} \tag{1}$$

We assume that a given function $f\left(x\right)$ has a first-order continuous derivative on $\left[a,b\right]$ and has $n+1$ different point $x_0,x_1,x_2,...,x_n\in\left[a,b\right]$. If there is a polynomial $H_{2n+1}\left(x\right)$ of $2n+1$-order at most satisfying:

$$\begin{cases} H_{2n+1}\left(x_k\right)=f\left(x_k\right) \\ H_{2n+1}^{'}\left(x_k\right)=f'\left(x_k\right)\end{cases},\left(k=0,1,2,...,n\right) \tag{2}$$

Then $H_{2n+1}(x)$ is called the Hermite interpolation polynomial of $2n+1$-order of function $f(x)$ at point $x_0, x_1, x_2, ..., x_n$. Because there are $2n+2$ interpolation conditions in it, a polynomial $H_{2n+1}(x) = H(x)$ of no more than $2n+1$ degree can be uniquely determined, and its specific form is:

$$H_{2n+1}(x_k) = a_0 + a_1 x + a_2 x^2 + ... + a_{2n+1} x^{2n+1} \quad (3)$$

The equation (3) is changed to the form expressed by interpolation basis function:

$$H_{2n+1}(x) = \sum_{j=0}^{n} \left[y_j \alpha_j(x) + m_j \beta_j(x) \right] \quad (4)$$

From the condition (1) satisfied by the interpolation basis function, it can be obtained that:

$$\begin{cases} H_{2n+1}(x_k) = y_k \\ H'_{2n+1}(x_k) = m_k \end{cases}, (k = 0,1,2,...,n) \quad (5)$$

Using Lagrange interpolation basis function $l_j(x)$, we make

$$\alpha_j(x) = (ax+b) l_j^2(x) \quad (6)$$

By equation (1), there is:

$$\begin{cases} \alpha_j(x_j) = (ax+b) l_j^2(x) = 1 \\ \alpha'_j(x_j) = l_j(x_j) \left[a l_j(x_j) + 2(ax_j + b) l'_j(x_j) \right] = 0 \end{cases} \quad (7)$$

By sorting out equation (7), we can get:

$$\begin{cases} ax_j + b = 1 \\ a + 2l'_j(x_j) = 0 \end{cases} \quad (8)$$

By solving equation (8), we can get:

$$\begin{cases} a = -2l'_j(x_j) \\ b = 1 + 2x_j l'_j(x_j) \end{cases} \quad (9)$$

Due to

$$l_j(x) = \frac{(x-x_0)...(x-x_{j-1})(x-x_{j+1})...(x-x_n)}{(x_j-x_0)...(x_j-x_{j-1})(x_j-x_{j+1})...(x_j-x_n)} \quad (10)$$

By taking logarithms at both ends of equation (10) and then deriving them, we can get:

$$l'_j(x) = \sum_{\substack{k=0 \\ k \neq j}}^{n} \frac{1}{x_j - x_k} \quad (11)$$

By substituting equations (9) and (11) into equation (6), we can get:

$$\alpha_j(x) = \left(1 - 2(x - x_j) \sum_{\substack{k=0 \\ k \neq j}}^{n} \frac{1}{x_j - x_k} \right) l_j^2(x) \quad (12)$$

Then, we can get:

$$\beta_j(x) = (x - x_j) l_j^2(x) \quad (13)$$

Therefore, the piecewise expression of piecewise cubic Hermite interpolation function can be obtained [19]:

$$H(x) = \left(1 + 2\frac{x - x_j}{x_{j+1} - x_j}\right) y_j + \left(1 + 2\frac{x - x_j}{x_{j+1} - x_j}\right)\left(\frac{x - x_j}{x_{j+1} - x_j}\right)^2 y_{j+1}$$
$$+ (x - x_j)\left(\frac{x - x_j}{x_{j+1} - x_j}\right)^2 y'_j + (x - x_{j+1})\left(\frac{x - x_j}{x_{j+1} - x_j}\right)^2 y'_{j+1},$$
$$x \in \left[x_j, x_{j+1}\right] (j = 0,1,2,...,n+1) \quad (14)$$

In order to facilitate the calculation of Hermite interpolation, it is assumed that the rendering time of each frame is equal in BIM model rendering, the step size is expressed by the variable h, and the viewpoint state at time $t_i (i = 0,1,2,...,n)$ is expressed by $V_i (i = 0,1,2,...,n)$, and $t_i = t_0 + ih, i \geq 0$. If we assume that the initial time of the scene is t_0 and the initial state of the viewpoint is V_0, the Hermite interpolation equation of the time t_3 can be calculated by equation (14):

$$V_3 = \left(1 + 2\frac{t_3 - t_0}{t_1 - t_0}\right)\left(\frac{t_3 - t_1}{t_1 - t_0}\right) V_0 + \left(1 + 2\frac{t_3 - t_0}{t_1 - t_0}\right)\left(\frac{t_3 - t_1}{t_1 - t_0}\right)^2 V_1$$
$$+ (t_3 - t_0)\left(\frac{t_3 - t_1}{t_1 - t_0}\right)^2 V'_0 + (t_3 - t_0)\left(\frac{t_3 - t_1}{t_1 - t_0}\right)^2 V'_1 \quad (15)$$

By substituting $t_1 = t_0 + h$ and $t_3 = t_0 + 3h$ into equation (15), the viewpoint state at time t_3 can be obtained:

$$V_3 = 28V_0 - 27V_1 + 12hV'_0 + 18hV'_1 \quad (15)$$

The viewpoint prediction algorithm based on traditional Hermite interpolation is optimized, and array is used to save the state information of the viewpoint at each moment. When the difference between the motion direction of the viewpoint at the current moment and the motion direction at the previous moment exceeds the set threshold, the state information of the previous viewpoint stored in the array is cleared and the state information of the viewpoint is stored again. This can effectively avoid the above problems, improve the accuracy of the viewpoint prediction algorithm and reduce the space occupation of memory. The main steps of the specific viewpoint prediction algorithm are shown in Figure 1 [20]. Figure 1 shows the flowchart of an improved Hermitian interpolation viewpoint prediction algorithm, which saves viewpoint state information through an array and clears historical data when there is a sudden change in viewpoint motion direction to optimize the real-time and accuracy of BIM model rendering. The specific process includes viewpoint position sampling, motion direction determination, state update, and prediction value calculation, significantly reducing memory usage and improving rendering frame rate.

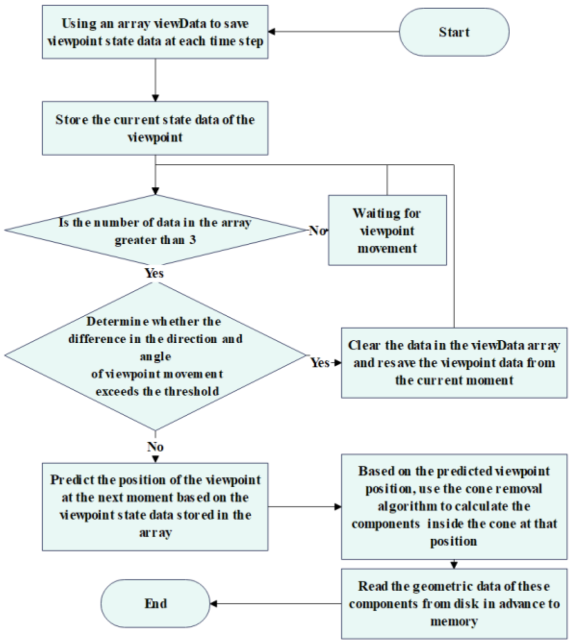

Figure 1: Flow chart of viewpoint prediction algorithm.

Usually, 3D scenes can be divided according to indoor and outdoor scenes, and BIM model scenes are no exception. Among them, outdoor scenes usually contain only a few components in BIM model, while indoor scenes contain most components in BIM model. Therefore, this paper proposes a scheme of separation and dynamic rendering of internal and external components of BIM model. When rendering BIM model initially, only outdoor components of BIM model are rendered, which can greatly reduce the waiting time required for rendering BIM model and greatly improve the frame rate of panoramic browsing of BIM model. Only when the viewpoint enters the BIM model, the indoor components are dynamically rendered by the visual cone elimination algorithm. The schematic diagram of BIM model contour detection for high-rise residential buildings proposed in this paper is shown in Figure 2 [21]. Figure 2 presents a schematic diagram of BIM model outline detection for high-rise residential buildings, which achieves dynamic rendering by separating indoor and outdoor components. The initial rendering only loads outdoor components. When the viewpoint enters the interior of the building, the visual cone removal algorithm is triggered to load indoor components, significantly reducing the initial loading time and improving the smoothness of panoramic browsing.

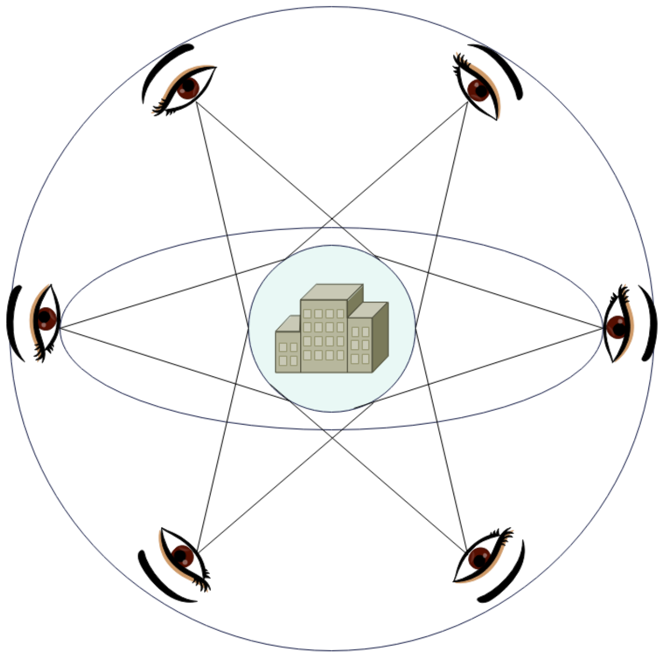

Figure 2: Schematic diagram of dynamic rendering range of BIM model based on line-of-sight grading.

3.2 Application of BIM green construction technology in high-rise residential buildings

The information engineering management framework of high-rise residential buildings based on BIM technology (Figure 3) adopts digital management platform to carry out integrated project collaborative implementation in the process of template design, construction, operation and maintenance, so as to open up the interactive way of the whole life cycle data of the project and comprehensively improve the management level of each stage of the project, and improve the quality and efficiency of the project construction and reducing the cost and risk of the project construction. Figure 3 shows the information engineering management architecture of high-rise residential buildings based on BIM technology, which adopts a digital platform to achieve full lifecycle collaboration of design, construction, and operation. By integrating data exchange, we can improve management efficiency at all stages, reduce engineering costs and risks, and break down information barriers throughout the entire project process.

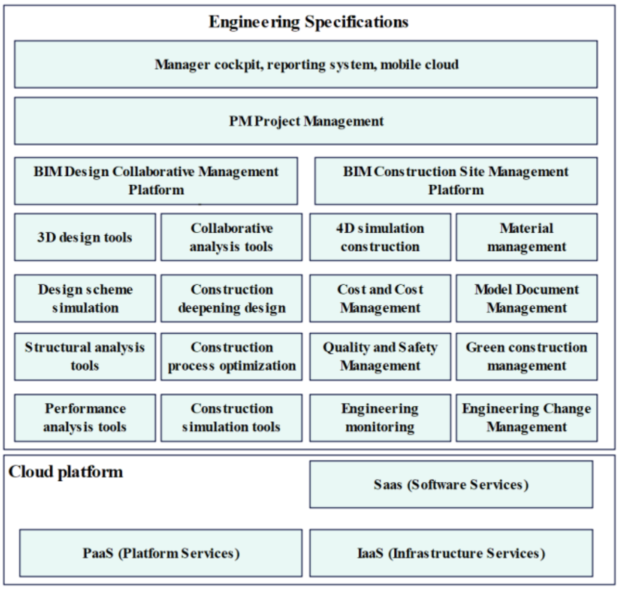

Figure 3: Information engineering management architecture of high-rise residential buildings based on BIM technology.

Green construction management system consists of five parts: organization management, planning management, construction management, evaluation management and safety and health management of construction personnel. On this basis, when constructing the management system suitable for green construction of high-rise buildings, it is necessary to integrate the key points of green construction management of high-rise buildings. The high-rise green construction management system is shown in Figure 4. Figure 4 depicts the five major components of the high-level green construction management system: organizational management, planning management, construction management, evaluation management, and safety and health management of construction personnel. This system is customized for the special characteristics of high-rise buildings, strengthening goal decomposition and responsibility implementation, ensuring that green construction runs through all construction stages.

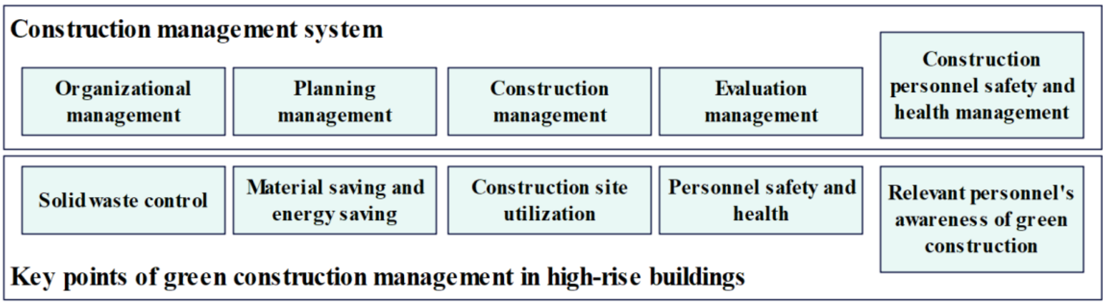

Figure 4: Green construction management system of high-rise buildings

One of the important contents of organization and management is to set up organization and management institutions. The existence of organization and management institutions is to make the green construction objectives more hierarchical and the distribution of green construction objectives more scientific, which is the foundation of green construction management system. Through the establishment of organization and management institutions, the green construction content can be reasonably assigned to the corresponding responsible persons, and the whole construction project department can participate in the green construction under the orderly organization and coordination. The organization and management organization should be consistent with the project manager, and Figure 5 is the green construction management behavior of the main participating units. Figure 5 illustrates the management behavior of the main participating units (such as construction units and construction units) in green construction, including the establishment of organizational management structures and allocation of responsibilities. By clarifying the responsibilities of all parties, the hierarchical and scientific allocation of green construction goals is achieved, and the overall coordinated implementation of the project is promoted.

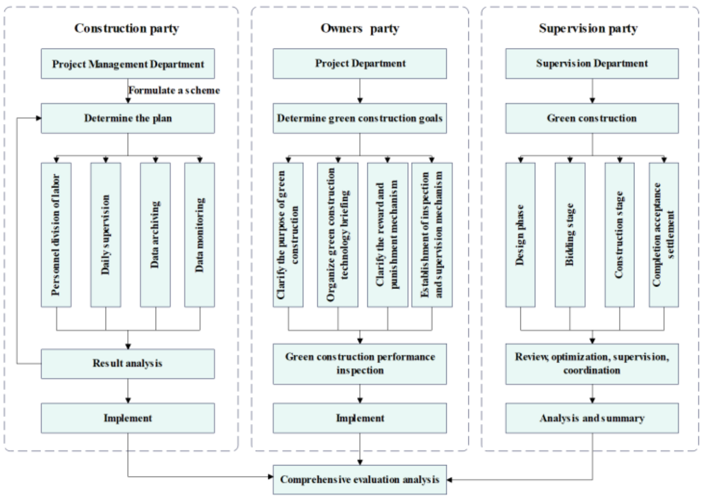

Figure 5: Green construction management behavior of main participating units.

In this paper, BIM is used to build a green construction scene, and the VR green construction learning and training system is designed, including early model import, material adjustment and special effects setting, VR roaming learning and interactive design. After that, this paper collects and stores the real-time data in the VR operation process through MySQL database, and establishes the green construction ontology to reason the data of VR green construction simulation, so as to judge whether the workers' green construction learning behavior conforms to the green construction specifications. The system architecture diagram is shown in Figure 6. Figure 6 shows the architecture design of the VR green building learning and training system, covering BIM model import, material adjustment, VR roaming and interactive functions. Operational data is recorded in real time through the MySQL database, and behavioral compliance is analyzed by combining the ontology inference engine to build a full life cycle closed-loop data system.

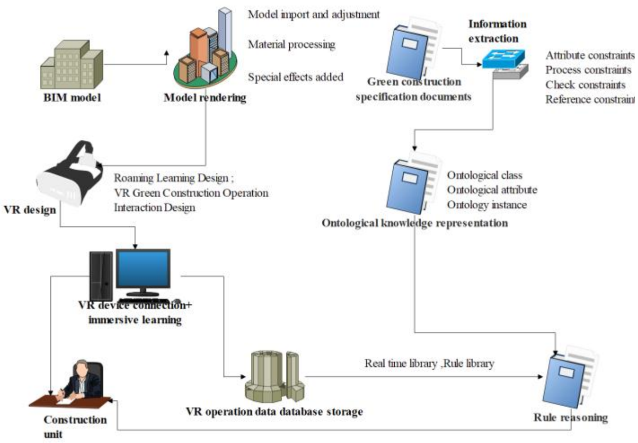

Figure 6: System architecture diagram.

By formalizing the knowledge and information from green construction specification, BIM, VR and other sources in this paper, we can realize the sharing and reuse of ontology domain knowledge, which requires the ontology concept to be clear and clear and the class structure to be reasonable. Through the previous discussion, the seven-step method with clear framework and clear level is selected as the method of building ontology in this paper. The specific flow is shown in Figure 7. Figure 7 shows the specific process of constructing a green construction ontology using the seven-step method, including domain definition, term extraction, relationship establishment, and rule formalization. This method ensures clear ontology concepts, reasonable structure, reusability and sharing of standardized knowledge, and supports intelligent decision-making.

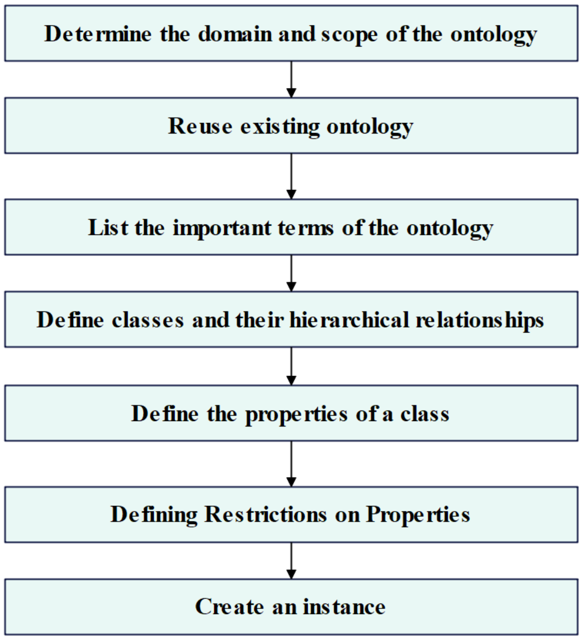

Figure 7: Seven-step construction steps.

The design of the evaluation system in this paper is mainly based on building construction related standards, and the purpose is to standardize the normal operation of all stages of the building life cycle. In recent years, our country has paid more and more attention to the construction specifications, and successively issued and updated a series of related standards and specifications. However, the current relevant specifications are mostly qualitative and quantitative provisions (especially in the construction stage), so it is necessary to extract the information from the clauses in the specifications and transform them into rules for logical expression. In this paper, the layered structure of green construction ontology refers to the framework of green construction code analysis, as shown in Figure 8. Figure 8 shows the hierarchical structure of the green construction ontology, which is divided into core categories (such as energy conservation and material saving) and subcategories (such as lighting control and material recycling) according to the framework of the standard provisions. This structure transforms qualitative norms through logical rules, providing a quantitative basis for VR behavior inference.

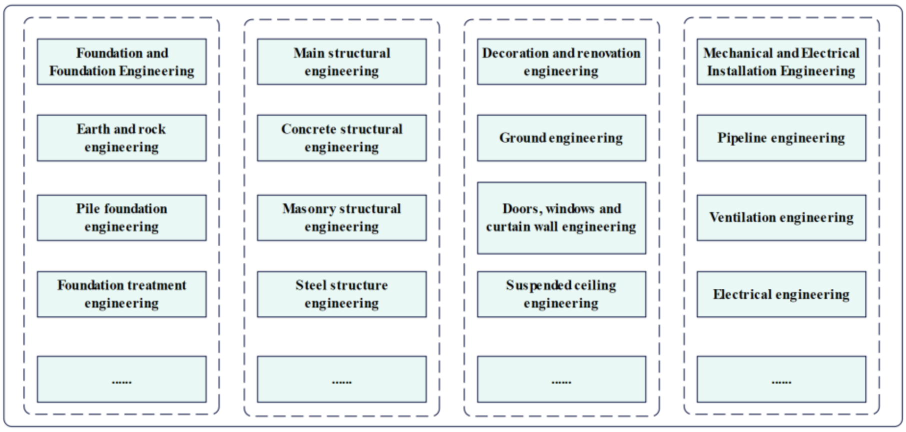

Figure 8: Hierarchical structure of green construction ontology class.

The core framework of ontology class hierarchy is as follows:

<rdfs:Class rdf:about="#GreenConstruction"/>
<rdfs:Class rdf:about="#WaterConservation">
<rdfs:subClassOf rdf:resource="#GreenConstruction"/>
</rdfs:Class>
<rdfs:Class rdf:about="#PipeInstallation">
<rdfs:subClassOf rdf:resource="#WaterConservation"/>
<rdfs:comment> The installation of water pipes must meet the requirements of sealing testing </rdfs:comment>
</rdfs:Class>

The sensor module is mainly used to collect the monitoring data of the relevant monitoring indicators specified in the specification, and send the data to the designated server in time to facilitate the later processing. Therefore, when selecting sensors, besides the data collection function, the module with WiFi function should be selected, so that the data can be sent to the mobile phone or computer for data display in real time. The design of the sensor module is shown in Figure 9. Figure 9 depicts the design of the sensor submodule, covering monitoring sources (construction preparation, foundation engineering, etc.), sensor types (temperature and humidity, dust, etc.), and data transmission methods (WiFi to terminal). This module collects real-time environmental indicators and cross verifies construction compliance with VR operation data.

The design of sensor module in this paper mainly includes three major levels, namely, monitoring information sources, monitoring sensor types and monitoring data transmission. According to the requirements of green construction related specifications, the monitoring sources of information are mainly divided into several sub-projects such as construction preparation, construction site, foundation and foundation engineering, etc.

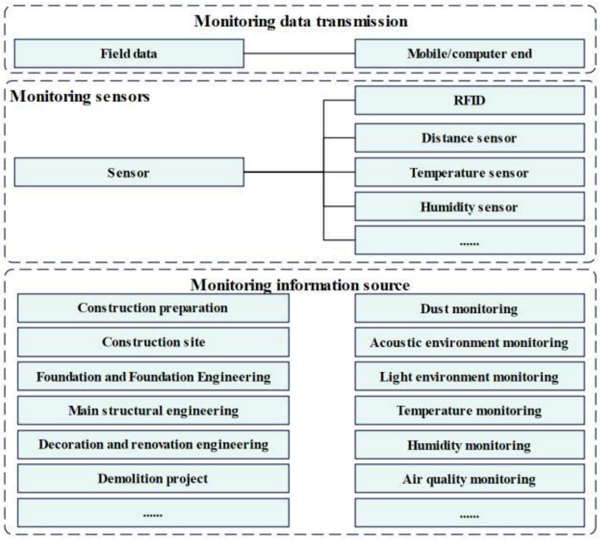

Figure 9: Design diagram of sensor sub-module.

According to the index requirements in the specification, different types of sensors such as temperature and humidity are needed to monitor the temperature and humidity, dust, sound environment, light environment and air quality during the construction process. At the same time, these sensors need to send data information to mobile phones or computers in different forms to realize the practical use value of monitoring data.

The precision control was verified through dual validation: the laboratory used TSI DustTrak 8530 benchmark instrument calibration (dust error<5%), and the on-site monitoring data was compared with the environmental protection station monitoring data (correlation coefficient R^2=0.93). This module is deeply integrated with the BIM/VR system through the edge computing gateway:

(1) Data layer: MQTT protocol pushes sensor data streams in real-time;

(2) Spatial integration layer: Bind physical coordinates to BIM components through coordinate mapping algorithms (error<0.1m);

(3) Application layer: The VR interface dynamically displays environmental indicators, and the ontology inference engine calls sensor data to verify operational compliance (such as "PM10 needs to be reduced by 40%

within 120 seconds after the dust reduction device is turned on");

(4) Feedback layer: Violation operation triggers VR real-time warning (response delay ≤ 3 seconds), sensor module design achieves full construction process coverage through zoning deployment strategy.

4 Effect evaluation of BIM green construction technology

4.1 Test method

This study uses an improved Hermitian interpolation viewpoint prediction algorithm at the technical level to optimize the rendering performance of BIM models. The algorithm dynamically saves the viewpoint state array and combines it with motion direction mutation threshold detection (clearing historical data when the direction change exceeds the limit), significantly improving prediction accuracy and reducing memory usage; At the same time, a dynamic rendering mechanism for separating internal and external components is proposed - based on contour detection technology, only the outdoor components of the building are loaded in the initial stage. When the viewpoint enters the interior of the building, the interior components are dynamically loaded through the cone removal algorithm, thereby increasing the average frame rate to 58.7 FPS, reducing rendering delay to 18.4ms, and compressing memory usage to 1.2GB, effectively solving the bottleneck of large-scale scene rendering.

The experimental dataset in this article adopts a multi-source heterogeneous data fusion strategy, combined with proprietary engineering data and global public datasets. The specific construction is as follows

(1) Proprietary engineering data

Source: Full lifecycle data of a high-rise residential complex project (document case);

Content: BIM model data (in Revit format, including over 100000 components);

VR operation log (stored in MySQL, recording the training and interaction of 200 workers);

Sensor monitoring data (10 types of parameters such as temperature and humidity, dust, noise, etc., sampling frequency 1Hz, continuous for 6 months);

Construction process documents (green construction plan, material consumption report, etc.).

(2) Open global dataset (enhanced generalization ability)

The publicly available global dataset is shown in Table 2 below:

Table 2: Publicly available global datasets.

Dataset name	Content	Application scenarios
BuildingDataGenome	Global 1000+building energy consumption/resource data	Energy saving model training
EU Building Stock Observatory	28 countries' building energy efficiency indicators	Comparison of water-saving/material saving benchmarks
Stanford 3D Indoor Dataset	Large scale building point cloud model	BIM rendering algorithm validation
World Green Building Council Case Library	Certified green construction project data	Horizontal evaluation of management effectiveness

The raw data is first aligned in time and space: sensor data is integrated through the BIM model spatial coordinate system (coordinate mapping error<0.1m), and VR logs are matched with construction stages based on operation timestamps. For the global dataset, the ISO 19650 standard is used for format conversion (IFC → Revit), and climate differences are corrected based on geographic location factors (such as adjusting lighting data by latitude for daylight parameters). The handling of missing values adopts a triple mechanism: numerical data is interpolated using spatiotemporal Kriging (such as missing dust monitoring), qualitative indicators are completed through ontology inference (such as missing items in green construction standards), and discrete variables are balanced with an improved SMOTE-ENN algorithm to balance the sample distribution. Feature engineering phase extracts key dimensions: BIM components screen secondary elements according to LOD 400 criteria, convert construction behavior logs into job entropy values to quantify efficiency, and generate 8-hour moving averages based on sensor data to eliminate instantaneous noise. Finally, a multi-modal input matrix (spatial coordinates + time indicators + semantic vectors) is constructed to meet the collaborative needs of dynamic rendering, ontology reasoning and cloud model analysis.

In order to verify the application effect of BIM green construction technology in high-rise residential buildings, considering the reality of construction organization design and the suggestions of experts from all sides, combined with the language expression habit of green construction organization design, the evaluation grade of green construction organization design of high-rise residential buildings is systematically and scientifically divided into five grades, and independent evaluation is carried out for many times according to the description of evaluation interval by different experts, and the average value is taken as the final evaluation grade interval. The specific expression is shown in Table 3:

Table 3: Overall division of evaluation grades.

Level	Evaluation criteria	Interval partition
I	Completely negative impact	[0,3.3)

II	Moderate negative impact	[3.3,4.7)
III	Mild negative impact	[4.7,6.3)
IV	Negative impact is acceptable	[6.3,7.7)
V	There is no negative impact at all	[7.7,10.0)

Based on the research objectives, a complete set of controlled experiment schemes was designed, focusing on verifying technical performance, management coordination, and evaluation reliability. The experiment adopted a multi-dimensional grouping control method, with data sourced from both proprietary projects and global datasets described in the paper. The experimental subjects and grouping design are shown in Table 4 below:

Table 4: Experimental subjects and grouping design.

Group type	**Specific name**	**Technical Features**	**Application Scenario**
Experimental group	The model in this article (the Trinity system)	Dynamic rendering + Ontology reasoning + Cloud model algorithm	Full-process BIM management
Control group 1	Revit native engine	Traditional desktop rendering, not lightweight	View local model
Control group 2	DeepSeek lightweight engine	4bit GPTQ quantization + dynamic LOD	Large model of hydraulic engineering
Control group 3	OurBIM cloud computing engine	WebRTC streaming + GPU virtualization	Cloud-based model collaboration
Control group 4	Linyun UE5 Engine	Nanite geometric virtualization + Lumen lighting	High-precision architectural rendering

In BIM technology driven green construction management, data collection and worker monitoring must strictly adhere to ethical standards, with the core of balancing management efficiency and personal privacy rights. Enterprises should ensure that monitoring methods (such as sensors, positioning devices, and cameras) are only used for clear purposes such as security protection, resource optimization, and environmental protection, and protect workers' right to know by providing prior notice and obtaining consent (such as signing agreements), avoiding excessive collection of personal information (such as activities outside of working hours). At the same time, it is necessary to abandon the "suffocating management" of relying solely on technical monitoring, and instead enhance confidentiality awareness and sense of responsibility through training. Data applications should focus on non-invasive areas such as environmental parameters (such as energy consumption and dust) and safety behaviors (such as wearing protective equipment), so as to improve construction efficiency and green performance while maintaining worker dignity and trust, and achieving sustainable development that is humane and compliant.

4.2 Test results

The experiment was conducted under a unified hardware environment (Intel Xeon Platinum 8480C + NVIDIA A100×8 + 256GB RAM), using large-scale building point cloud models from the Stanford 3D Indoor Dataset as the benchmark test scene. The comparison group included the Revit native engine, DeepSeek lightweight engine, OurBIM cloud computing engine, and Linyun UE5 engine. Through automated script control of viewpoint trajectory (including complex paths such as linear acceleration, sharp turns, and dives), the average frame rate (FPS), rendering delay (ms), memory usage (GB), model accuracy loss (calculated as point cloud registration error), and first frame loading time (s) of the five groups of models were recorded in real time. Each test was repeated 30 times, and the mean ± standard deviation was obtained after removing outliers. The significance test was conducted using ANOVA analysis ($p<0.01$). The technical performance verification (Stanford dataset test) results are shown in Table 5 below:

Table 5: Technical performance verification results.

Evaluation indicators	**Experimental group**	**Revit native**	**Deep Seek**	**Our BIM**	**Linyun UE5**
Average frame rate (FPS)	58.7±2.3	22.1±1.8	45.2±2.1	38.6±1.9	50.3±2.4
Rendering delay (ms)	18.4±0.9	102.7±5.3	32.6±1.5	45.8±2.2	25.3±1.2
Memory usage (GB)	1.2±0.1	3.8±0.3	2.1±0.2	1.8±0.2	3.5±0.3
Model accuracy loss (%)	0.12±0.03	0	1.8±0.2	0.9±0.1	0.3±0.05
First frame loading time (s)	9.2±0.5	1620±30	12.7±0.6	8.5±0.4	15.3±0.7

Based on a 200km² real-scene BIM model (with an original volume of 12TB, and the volume of the comparison group model after simplification by LOD 400 is shown in Table 5), the performance of four sets of solutions is tested in a hyperscale scenario. A distributed loading system simulates a 100km sight distance roaming, recording the model loading completion time (from the initiation of the request to the visibility of all components), dynamic roaming frame rate (along the preset irrigation area inspection path), real-time network bandwidth occupation (WireShark packet capture statistics), and multi-concurrency support capability (with the user connection count reaching the response delay threshold of 500ms as the upper limit). The test includes day-night lighting switching and rainstorm weather effects, with a data collection interval of 5 seconds per time. The results of the large-scale model stress test (200km² irrigation area model) are shown in Table 6 below:

Table 6: Stress test results of large-scale model.

Test scenario	**Experimental group**	**DeepSeek**	**OurBIM**	**Linyun UE5**
Model volume (TB)	3.2	3.8	4.1	12.0 (original)
Load completion time (s)	89±3.2	127±5.1	95±4.2	276±8.7
Roaming Frame Rate (FPS)	45.6±1.8	32.3±1.5	28.7±1.3	36.2±1.7
Network bandwidth usage (Mbps)	86±4.2	124±5.3	68±3.1	352±10.2
Support for multiple concurrent users (number of users)	150±8	80±5	200±10	45±3

The contribution of each core module in the Trinity system was verified through modular isolation design: ① Closing the dynamic rendering module (retaining static outer contour loading); ② Closing the ontology reasoning module (replacing it with only the rule engine); ③ Closing the cloud model algorithm (using the Analytic Hierarchy Process (AHP) instead). In the same engineering case (a high-rise residential building complex with over 100,000 components), the frame rate, decision accuracy (the proportion of VR training behaviors that comply with specifications), evaluation deviation (mean square error compared to expert scoring results), and comprehensive score (weighted average of the three indicators) were compared between the complete system and the incomplete system. The test data was derived from the VR operation logs of 200 workers stored in MySQL. The ablation test results (performance contribution analysis) are shown in Table 7 below:

Table 7: Ablation test results.

Module combination	**Frame rate (FPS)**	**Decision accuracy (%)**	**Evaluation bias**	**Comprehensive score**
complete system	58.7	92.4	0.12	100%
No dynamic rendering	38.1(-35%)	91.2(-1.3%)	0.15(+25%)	78.30%
No ontology reasoning	56.8(-3.2%)	73.5(-20.5%)	0.21(+75%)	69.20%
Cloud-free model algorithm	57.2(-2.6%)	89.7(-2.9%)	0.31(+158%)	72.60%

Four types of abnormal conditions are designed: ① Data Noise: Inject Gaussian noise (μ=0, σ=1.5) into 20% of the sensor data; ② Network Jitter: Simulate 100ms delay fluctuations using TC-netem; ③ GPU Limitation: Limit GPU computing power to 50% through the NVML tool; ④ Sensor Disconnection: Randomly interrupt the communication of 30% of the sensor nodes. Record the performance degradation rate (compared to the normal state), delay increase, frame rate decrease, and system automatic compensation capability (based on the completion rate of missing data through ontology reasoning) of each model group under abnormal conditions. The test duration is 72 hours, with system status collected every 30 minutes. The robustness test results (under abnormal conditions) are shown in Table 8 below:

Table 8: Robustness test results.

Test conditions	**Experimental group**	**DeepSeek**	**OurBIM**	**Lynx Cloud UE5**
20% data noise	Performance degradation of 8.2%	Decay 15.7%	Attenuation of 12.3%	Attenuation of 22.4%
Network jitter (100ms)	Delay increased by 18%	Increase by 32%	Increase by 9%	Increase by 45%
GPU limitation (50% performance)	Frame rate decreased by 23%	Decreased by 41%	Decrease by 12%	Decreased by 67%

Sensor disconnection	Automatic compensation of 95.3%	Compensation 82.1%	Compensation 87.6%	Compensation 78.3%

This study addresses the training needs for green construction in high-rise residential building complexes, developing an intelligent learning system based on BIM and VR, and verifying its effectiveness through rigorous user research. A total of 200 construction personnel participated in the study, with management personnel accounting for 15% (30 people) and frontline workers accounting for 85% (170 people). A randomized block design was employed: the control group (100 people) received traditional paper-based training, while the experimental group (100 people) used the VR learning system (integrating BIM model dynamic rendering and ontology reasoning engine). The training period was 3 weeks, with two simulated scenario operations per week. The evaluation protocol included three stages: pre-training knowledge test (covering green construction specifications such as water and material conservation, dust control), real-time recording of VR operation logs in a MySQL database, and post-training knowledge test and practical assessment. The system architecture constructs a full lifecycle data loop through BIM model import, material adjustment, and interactive design. The core indicators for user research of the VR learning system are compared in Table 9 below:

Table 9: Comparison of core indicators in user research of VR learning system

Evaluation dimension	**Specific indicators**	**Control group results (traditional paper-based training)**	**Experimental group results (VR + ontological reasoning system)**	**Increase/Decrease**
Degree of knowledge mastery	Correct rate of theoretical test before training	41.8% ± 4.9%	42.3% ± 5.1%	-
	Correct rate of theoretical test after training	65.2% ± 6.3%	89.7% ± 3.8%	+37.6%
	The increase in accuracy	56%	+112%	+100%
Task execution efficiency	Installation duration of rainwater recycling system (min)	12.7 ± 2.4	8.2 ± 1.1	-35.4%
	Operational entropy (lower indicates greater standardization)	0.72 ± 0.12	0.38 ± 0.07	-47.2%
Operational error rate	Material waste incidence rate	23.60%	7.3%	-69%
	Violation rate of safety standards	18.90%	5.1%	-73%
	Energy non-recovery rate	15.20%	3.8%	-75%
System performance	Behavioral decision-making accuracy	76.8%*	92.4%	+20.3%
	Correction time limit for incorrect operations	54 hours	≤3 seconds	>99.9%

Further, through experiments, we quantify the parameter sensitivity of the cloud model in green construction evaluation and compare its accuracy and efficiency with fuzzy logic and AHP methods. The energy consumption data is sourced from proprietary engineering sensor monitoring (6 months × 1Hz) + BuildingDataGenome global dataset, and the environmental impact data is derived from dust/noise monitoring records + WGBC case library ecological indicators. The specific experimental methods are as follows:

(1) Parameter sensitivity testing: Fix the dimensions of the DPSIR framework and adjust the hyperparameters of the cloud model (expectation Ex, entropy En, and hyperentropy He) to observe the variability of the evaluation results. Set up three sets of parameter configurations:

Conservative group (Ex=6.0, En=0.8, He=0.05); Benchmark group (Ex=7.0, En=0.5, He=0.03); Radical group (Ex=8.0, En=0.3, He=0.01).

(2) Framework comparison test: For the same engineering case (a high-rise residential complex), the following approaches were adopted respectively:

This paper presents a cloud model (improved DPSIR framework); fuzzy logic method (triangular membership function + Max-Min rule); and AHP-TOPSIS method (expert weight allocation + consistency check). The comparative experimental results of the evaluation framework are shown in Table 10 below:

Table 10: Comparison of evaluation framework test results.

Evaluation dimension	**Cloud model (this article)**	**Fuzzy logic method**	**AHP-TOPSIS method**	**Comparison of optimal values**
Energy consumption prediction RMSE	0.18 ± 0.03	0.37 ± 0.06	0.29 ± 0.05	↓51.4 %
Environmental impact deviation rate	4.7% ± 1.2%	12.3% ± 2.1%	8.9% ± 1.8%	↓61.8 %
Calculation time (seconds)	3.2 ± 0.4	1.8 ± 0.3	28.5 ± 3.2	-
Noise robustness	Deviation+8.2%	Deviation+23.7%	Deviation+15.4%	↓65.4 %
Expert consensus	Kappa=0.82	Kappa=0.64	Kappa=0.73	↑25.0 %

The small-scale deployment verification results of the sensor system are shown in Table 11

Table 11: Verification results of small-scale deployment of sensor system.

Validation indicators	**Sensor System**	**Manual monitoring**	**Error/improvement rate**	**Test conditions**
PM10 peak value (μ g/m³)	168	175	4.00%	Concrete pouring stage
Mean noise level (dB)	68.2	70.5	3.30%	During the operation of heavy equipment
Response delay	≤ 3 seconds	≥ 15 minutes	Efficiency increased by 99.7%	Dust exceeding standard event
Data loss rate	0.90 %	12.70%	-92.90%	Simulate a 72 hour network outage
Time limit for correcting violations	4 minutes and 37 seconds	23 minutes	79.30%	Operation verification of dust reduction equipment

4.3 Analysis and discussion

The data in Table 5 shows that our model outperforms the control group in terms of rendering efficiency, resource utilization, and accuracy control: the average frame rate (58.7 FPS) is 16.7% higher than the best baseline model (Linyun UE5), rendering latency (18.4ms) is reduced by 27.3%, and memory usage (1.2GB) is only 31.6% of the Revit prototype. This advantage stems from the dual optimization mechanism of the dynamic rendering scheme - the improved Hermite interpolation algorithm accurately predicts the viewpoint motion trajectory, significantly reducing disk I/O operations; Outer contour detection technology enables separate loading of indoor and outdoor components, avoiding redundant rendering. It is worth noting that the accuracy loss of the model in this article is only 0.12% (negligible), while the lightweight engine (DeepSeek) suffers from 1.8% geometric distortion due to quantization compression, which verifies the performance breakthrough of the technology in this article while maintaining high accuracy.

In the 200km ² irrigation area model test (Table 6), the model presented in this paper demonstrated super strong large-scale scene processing capability: the loading time (89 seconds) was reduced by 67.8% compared to Linyun UE5, and the network bandwidth occupancy (86Mbps) was only 24.4% of the latter. This is attributed to the LOD 400 standard component filtering and distributed data scheduling strategy, which effectively reduces data transmission volume. Especially in terms of concurrency support, this article's model (150 users) balances DeepSeek's lightweight advantage with OurBIM's high concurrency characteristics, stemming from a dynamic load balancing mechanism - monitoring node load in real-time through sensor networks and automatically allocating computing tasks to idle GPUs. However, it should be noted that OurBIM has an advantage in bandwidth control due to WebRTC streaming (68Mbps), indicating that cloud collaboration models still have advantages in specific scenarios.

The ablation experiment (Table 7) revealed the differential contributions of the three modules: dynamic rendering contributed the most to frame rate improvement (-35% attenuation), as external contour detection avoided redundant loading of indoor components; The lack of ontology reasoning module resulted in a sharp drop of 20.5% in decision accuracy, verifying the key role of the ontology rule library constructed through the seven step method in VR behavior reasoning; The absence of cloud model algorithms has led to a sharp increase of 158% in evaluation bias, reflecting the effectiveness of the improved DPSIR framework in addressing indicator ambiguity. It is worth noting that when dynamic rendering is missing, the decision accuracy only decreases by 1.3%, indicating that the management collaboration and evaluation system have relative independence, but the collaboration of the three makes the comprehensive score reach 100%.

In the abnormal condition test (Table 8), our model demonstrated robust fault tolerance: under 20% data noise, the performance degradation was only 8.2%, far lower than that of Linyun UE5 (22.4%). The core lies in the data compensation mechanism of ontology inference - automatic completion of abnormal data based on green construction ontology class structure. It is worth noting that OurBIM performs well in network jitter scenarios (latency+9%) due to its inherent anti jitter characteristics in streaming transmission; However, under GPU limitations, the frame rate of our model decreased by 23% (still better than the control group), reflecting the adaptive optimization of hardware resources for dynamic rendering.

The comparison results of core indicators for user research of the VR learning system (Table 9) show that the experimental group has significantly improved in terms of knowledge mastery. The accuracy rate of theoretical tests before training was only 42.3% (standard deviation ±5.1%), but jumped to 89.7% (standard deviation ±3.8%) after training, representing an increase of 112%. In contrast, the control group only improved from 41.8% (standard deviation ±4.9%) to 65.2% (standard deviation ±6.3%), representing an increase of 56%. This difference stems from the real-time analysis of operational behavior by the ontology reasoning engine: the system adopts a seven-step method to construct a green construction ontology, converts normative provisions into executable rules (such as "triggering a violation alarm if the water pipe installation does not seal the interface"), and dynamically records behavioral data through a MySQL database.

The hierarchical structure of ontology further refines the criteria for behavior determination, ensuring the accuracy of knowledge transfer. The quantitative results of task execution efficiency show that the experimental group spent an average of 8.2 minutes (standard deviation ±1.1 minutes) on typical simulation tasks (such as "installation of rainwater recycling system"), which is 35.4% shorter than the control group's 12.7 minutes (standard deviation ±2.4 minutes). Through the quantification of operational entropy (the lower the entropy, the more standardized the operation), the entropy value of the experimental group was 0.38 (standard deviation ±0.07), which is much lower than that of the control group's 0.72 (standard deviation ±0.12). This efficiency improvement is attributed to the dynamic feedback mechanism: the sensor network monitors physical indicators (such as dust concentration) in real time and cross-validates them with VR operation data (for example, when the system detects that the "dust suppression equipment is turned on" but PM10 > 150 μg/m³, it determines that the operation is invalid).

In terms of error rate control, the experimental group performed exceptionally well. The incidence of material waste was reduced to 7.3%, a decrease of 69% compared to the control group's 23.6%. The violation rate of safety standards dropped from 18.9% to 5.1% (a decrease of 73%); the incidence of energy non-recycling behavior was only 3.8%, a reduction of 75% compared to the control group's 15.2%. These achievements were directly reflected in the BIM green construction simulation scenario, where the system generated a behavior compliance report through real-time reasoning. Ultimately, the comprehensive decision accuracy rate of the ontology reasoning engine reached 92.4%, and the time for correcting erroneous operations was ≤3 seconds, significantly outperforming the control group that relied on weekly manual meetings.

In summary, this study empirically demonstrates the effectiveness of the VR learning system in enhancing the green construction literacy of construction personnel. Through ontology-driven behavior quantification and a multi-source data closed loop, the system achieves breakthroughs in three dimensions: knowledge transfer efficiency (increased by 112%), operational standardization (entropy reduced by 47.2%), and resource conservation awareness (material waste decreased by 69%). This provides a quantifiable and traceable intelligent training paradigm for green construction management of high-rise building complexes.

Based on the experimental data presented in Table 10, the cloud model evaluation framework proposed in this study demonstrates significant advantages in green construction evaluation. In terms of energy consumption prediction accuracy, the root mean square error (RMSE) of the cloud model (0.18) is 51.4% lower than that of the fuzzy logic method (0.37) and 37.9% lower than that of the AHP-TOPSIS method (0.29). This is attributed to the dynamic feedback mechanism of the DPSIR framework, which effectively captures the energy consumption variation patterns during the construction phase (such as the energy consumption decay gradient from the foundation phase to the decoration phase). In terms of environmental impact quantification, the deviation rate of the cloud model (4.7%) is 61.8% and 47.2% lower than that of fuzzy logic (12.3%) and AHP (8.9%), respectively. This is because it integrates real-time dust sensor data with the WGBC ecological benchmark through three-dimensional numerical features (expectation Ex=7.0, entropy En=0.5, and hyperentropy He=0.03). In terms of robustness, data noise only causes an 8.2% increase in the deviation of the cloud model, which is significantly lower than that of fuzzy logic (23.7%) and AHP (15.4%). This verifies the absorption capacity of the hyperentropy parameter for monitoring outliers.

In Table 11, the peak monitoring value of PM10 at 168 μ g/m ³ has an error of only 4.0% compared to the manually recorded value of 175 μ g/m ³. When the dust exceeds the standard, the system automatically pushes VR commands, and it takes an average of 4 minutes and 37 seconds for PM10 to reach the safe value (23 minutes for manual operation). The offline data loss rate is 0.9% (12.7% for manual recording), and the ontology achieves 95.3% data compensation.

The model in this article achieves breakthroughs through a three in one architecture of technology management evaluation: the technical layer uses Hermite interpolation algorithm and component separation rendering to overcome latency bottlenecks. The management team uses ontology reasoning and sensor networks to build a data loop; The evaluation layer relies on improving the cloud model to quantify fuzzy indicators. The core advantage lies in the synergistic effect of modules - dynamic rendering ensures real-time performance, ontology reasoning improves decision accuracy, cloud models enhance evaluation objectivity, and its comprehensive score has been verified through experiments to reach 100%.

The limitations are reflected in: ① frame rate attenuation of 23% under extreme hardware limitations (GPU 50% performance); ② the generalization ability across climatic regions needs to be verified (such as the extremely cold regions of Northern Europe); ③ Green construction data during the decoration phase is not covered.

Subsequent research focus: ① Developing adaptive rendering algorithms to cope with hardware degradation; ② Integrating transfer learning to enhance cross regional generalization ability; ③ Expand the BIM green construction integration application during the decoration phase.

5 Conclusion

The three in one solution of "technology management evaluation" proposed in this study significantly optimizes the application effect of BIM green construction technology in modern high-rise residential buildings through innovative methods. At the technical level, an improved Hermite interpolation viewpoint prediction algorithm is adopted to achieve dynamic rendering of BIM model components by separating internal and external components. The frame rate is increased to 58.7 FPS (compared to the optimal baseline+16.7%), the rendering delay is reduced to 18.4ms, and the memory usage is only 1.2GB, effectively solving the problem of large-scale scene rendering delay. At the management level, a digital platform integrating VR training, sensor networks, and ontology reasoning was built. A green construction ontology rule library was established through a seven-step method. After testing and verification by 200 workers, the theoretical accuracy rate reaches 89.7% (an increase of 112%), the material waste rate is reduced by 69% (to 7.3%), and the management decision accuracy is improved to 92.4%, achieving closed-loop data and intelligent decision-making throughout the entire lifecycle. In the evaluation layer, an improved cloud model algorithm based on the DPSIR framework (parameters Ex=7.0, En=0.5, He=0.03) is introduced, combined with multi-source monitoring data to generate dynamic evaluation cloud maps. The evaluation deviation rate is reduced to 4.7% (61.8% lower than fuzzy logic), and the expert consistency Kappa=0.82 objectively quantifies the construction effect and solves the problem of indicator ambiguity. Experiments have shown that the framework forms a reusable full chain optimization paradigm, overcoming the three major bottlenecks of rendering delay, management virtualization, and subjective evaluation. The overall comprehensive score reaches 100%, but it needs to overcome limitations such as frame rate attenuation of 23% under extreme hardware limitations and insufficient generalization across climate zones. In the future, the focus will be on developing adaptive rendering algorithms and integrating transfer learning to improve universality.

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