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BIM-Driven Building Energy Consumption Prediction Model Construction and Energy-Saving Design Strategy Optimization

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Abstract

Amid the rapid development of the construction industry, building energy consumption has become more prominent. To cut consumption and enhance efficiency, a prediction model is built based on building information model (BIM), and an optimization method for energy-saving design is explored. Via in-depth data analysis, an energy consumption prediction approach integrating BIM and machine learning is proposed. The experimental results show that the model accurately predicts building energy consumption. In this study, 100 representative buildings were selected for energy consumption data collection, BIM technology was used to model these buildings in three dimensions, and relevant parameters were extracted. On this basis, the support vector machine (SVM) algorithm predicts building energy consumption. Compared with the actual energy consumption data, the model's prediction error is within 5%, which verifies the model's reliability. In order to optimize the energy-saving design strategy further, based on the prediction model, this study analyzes the energy-saving potential of the building envelope, heating, ventilation and air conditioning system, lighting system, etc. By adjusting the design parameters, 10 energy-saving design schemes are proposed. After simulation calculation, these schemes can reduce building energy consumption by 15%-25% compared with traditional designs. Among them, optimizing envelope thermal performance and HVAC operation strategy has the most significant impact on cutting building energy consumption. SVM algorithms are key in research. It can process small-sample, nonlinear, and high-dimensional data, and accurately grasp the complex nonlinear relationships between data through kernel function mapping, helping to build high-precision energy consumption prediction models that comprehensively consider the impact of multiple factors on building energy consumption. The numerical results of the study are closely related to the energy efficiency of the building industry, and the improvement of the accuracy of energy consumption prediction can optimize the energy-saving design and reduce the energy consumption of the whole life cycle. This connection allows readers who are not familiar with the field to quickly understand the innovation of the research, that is, to achieve breakthroughs in building energy consumption prediction and energy-saving design through innovative algorithms, and to promote the sustainable development of the industry. The BIM-based prediction model in this study has high accuracy, strongly backing building energy-saving design. By optimizing the design strategy, building energy consumption can be significantly reduced, contributing to the green development of the construction industry.

Keywords: BIM, Energy consumption prediction, Energy-saving design, Optimization strategy.

1. Introduction

In the case of global climate change and the worsening of resources and environmental problems, the energy consumption of the construction industry has become the focus of international attention [1]. As a key part of society's total energy use, efficient building energy management and optimal design are essential for sustainable development. Therefore, the rapid development of BIM (Building Information Model) technology provides a new way for building energy saving prediction [2].

With the advantages of multi-dimensional information integration, collaborative work and simulation analysis, BIM technology has shown great application potential in the whole process of architectural design [3, 4]. It can integrate a full range of data such as building geometry, materials, and equipment to provide a basis for accurate prediction of energy consumption, and its simulation analysis function can also dynamically simulate energy consumption to help designers save energy [5, 6].

However, traditional building energy consumption prediction methods rely on static data and empirical formulas, which are difficult to accurately reflect the complex energy consumption in the actual operation of buildings, and energy-saving design strategies often lack systematization and optimization, making it difficult to achieve ideal energy-saving effects.

The purpose of this study is to explore the construction method of BIM-based building energy consumption prediction model, integrate the multi-dimensional

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information of BIM model, fully consider the influence of building geometric characteristics, material attributes, equipment efficiency, climatic conditions and other factors on energy consumption, and establish an energy consumption prediction model that can reflect the actual operation of buildings. Through simulation and analysis of the impact of different design strategies, we can explore optimization methods and find the optimal design solution.

Looking back at the existing literature, most of the research has focused on energy projection or energy efficiency design for a single building type. The innovation of this study lies in the construction of a general energy consumption prediction model for multiple types of buildings, which can adapt to the energy consumption analysis of buildings with different functions and structures. At the same time, an energy-saving design strategy covering the whole life cycle of the building and multi-discipline collaboration is proposed, and the impact of multiple factors such as building structure, equipment system and user behavior on energy consumption is comprehensively considered to achieve multi-dimensional optimization. This innovation makes up for the shortcomings of existing research, opens up new ideas for BIM-based research on building energy consumption, and provides feasible methods and theoretical support for energy efficiency in a wider range of building scenarios.

During the research process, we will focus on the following aspects: First, the extraction and integration method of energy consumption-related data in BIM model to ensure the accuracy and reliability of energy consumption prediction model; Construction methods of energy consumption prediction model, including model structure design, parameter determination and verification, etc.; Optimization method of energy-saving design strategy, how to find out the optimal design scheme through simulation analysis. We compare existing methods and highlight our strengths. While existing methods mostly focus on a single factor, we integrate multi-source data based on BIM and comprehensively consider the combined impact of multiple factors on energy consumption, so as to realize the transition from static to dynamic simulation. As a result, the accuracy of energy consumption prediction and the effectiveness of energy-saving strategies are limited in the existing methods, and our study reduces the root mean square error and greatly improves the energy-saving efficiency. Compared with previous research, we have introduced advanced algorithms and technologies to achieve multi-factor coupling analysis, which not only provides accurate prediction tools for building design to help design energy-saving solutions, but also helps managers formulate scientific strategies in the operation stage to reduce energy consumption and costs, and promote the sustainable development of the building industry.

2. THEORETICAL BASIS

2.1. Building energy consumption prediction theory

To build an accurate and valid model, we carefully selected 100 buildings as a sample for study. The selection process was based on strict established criteria, and the diversity of the 100 buildings was analyzed in depth to increase the universality of the results [7, 8]. These buildings are of a wide range of types, with high-rise residential buildings of 20 - 30 floors, reinforced concrete structures; Multi-storey commercial complex 5 - 8 storeys, frame structure; 15-20 floors of the office building, core tube structure; The spatial structure of public cultural venues is complex. From the perspective of climate zones, it covers severe cold, cold, hot summer and cold winter, hot summer and warm winter and mild areas, corresponding to different envelope structures and door and window configurations [9, 10]. In terms of usage mode, there are perennial operations such as hospitals, seasonal operations such as seaside resort hotels, and intermittent operation buildings such as community activity centers. In addition, a variety of cases, such as green ecological buildings using ground source heat pumps and energy-saving renovation of historic buildings, are added to verify the scalability of models and strategies to enhance the validity of the conclusions. In the process of model construction, we chose RVFL (Random Vector Functional Link Network) and SVM (Support Vector Machine) algorithms. RVFL was selected because of its fast-learning ability and good generalization performance, which can efficiently extract data features when processing large-scale building energy consumption data, accurately capture the complex nonlinear relationship between energy consumption and various influencing factors, and do not require complex parameter adjustments, saving modeling time and calculation costs. The SVM algorithm is known for its excellent performance in small-sample, nonlinear classification and regression problems, which can effectively deal with the high-dimensional and small-sample problems existing in building energy consumption data, and map low-dimensional data to high-dimensional space through kernel functions, so as to achieve accurate modeling of complex data distribution and improve the accuracy of prediction. We elaborate on the reasons for the selection of these algorithms, aiming to make the description of the entire research method more transparent and reproducible, so that other researchers can carry out further research and verification on this basis.

This study proposes an improved ensemble model to balance prediction accuracy, time, and edge-side resources [11, 12]. To reduce the impact of noise, this study proposes a prediction model based on EEMD, which uses multi-edge parallel computing to allow each park to directly upload the total energy consumption to the central service pool, reducing the consumption of central computing power resources.

The intrinsic modal function (IMF) is a component obtained by decomposing the original building energy consumption time series data by using methods such as ensemble empirical modal decomposition (EEMD), which represents the fluctuation characteristics of different time scales. The high-frequency IMF corresponds to the rapid changes in energy consumption caused by short-term frequent start-up and shutdown of equipment, while the low-frequency IMF reflects the impact of long-term factors such as seasonal changes on energy consumption. Residuals are the difference between the raw energy consumption data and the sum of all IMF components, including long-term trends and complex factors such as changes in energy consumption due to aging buildings. The decomposition of raw energy consumption data into IMF and residuals is of great research significance. When constructing energy consumption prediction models, the analysis of IMF and residuals can provide a deep understanding of building energy consumption laws, make the prediction model more comprehensive and accurate, and provide a reliable basis for the optimization of energy-saving design strategies. From an engineering point of view, this can help engineers understand the mechanism of energy consumption formation and develop effective energy-saving measures, such as optimizing the operating logic of the equipment and arranging equipment maintenance or updates.EMD(Empirical Mode Decomposition) can extract intrinsic modal functions (IMF) from complex time series, and these IMFs meet specific conditions [13, 14]. The EMD decomposes the time series *y (i)* into IMF and residual by an adaptive process, as shown in equation (1).

$$y(i)=\sum_{j=1}^{q}imf_j(i)+r(i) \tag{1}$$

Where q is number of IMFs, $r(i)$ is final residual, which represents overall trend of the signal, and *IMFs* $(imf_1, imf_2, \ldots, inf_q)$ represent different frequency bands from high to bottom [15, 16]. In this study, the EMD method is improved and EEMD is proposed, which effectively reduces the modal mixing phenomenon and enhances the algorithm stability. EEMD adds white noise to the data and performs integrated averaging to eliminate the influence of noise, captures modal components more accurately, and finally reduce the error standard deviation, EMD and EEMD are used to process building energy time series data. Traditional EMD directly decomposes the original data, which is susceptible to noise interference and modal aliasing, resulting in unstable decomposition results and affecting the accuracy of energy consumption feature extraction and prediction models. However, EEMD effectively suppresses modal aliasing by adding different white noise sequences to the original data for multiple times and then decomposing them, and taking the average results. For example, when analyzing the energy consumption data of an office building, the IMF component decomposed by traditional EMD fluctuates significantly, and it is difficult to accurately correspond to the energy consumption change factors. The EEMD decomposition results are smoother and more stable, clearly showing the characteristics of energy consumption at different time scales, providing a more reliable data basis for energy consumption prediction and energy-saving design, and showing significant advantages in noise reduction and stabilizing the model. As shown in equation (2).

$$s=\frac{\varepsilon}{\sqrt{NE}} \tag{2}$$

Where NE represents number of iterations and ε is standard deviation of white noise. s represents the standard deviation of error. RVFL network model RVFL network keeps the weights and deviations between input layers and hidden layers fixed during the learning process, thus achieving fast convergence and high-precision analysis [17, 18]. In order to make the mathematical derivation closely related to practical research, we introduce concrete examples. For example, the energy consumption of a commercial building is affected by various factors such as season and operation mode, and fluctuates irregularly. Using EEMD technology, complex energy consumption data can be decomposed into different fluctuation characteristics, such as high-frequency fluctuations corresponding to frequent start and stop of equipment, and low-frequency fluctuations reflect the long-term impact of the season on energy consumption, so as to clearly present the rules of energy consumption data and provide high-quality data for subsequent predictions. In terms of predictive model construction, taking the prediction of the daily energy consumption of an office building in summer as an example, RVFL technology quickly builds a network by randomly generating the connection parameters from the input layer to the hidden layer. The input variables include outdoor temperature, the number of people indoors, etc., and the nonlinear function is used to calculate the output of the hidden layer, and then the output layer weight is determined by the least squares method, so that the energy consumption can be predicted efficiently and accurately. In actual construction projects, such as the construction and operation management of large hospitals, BIM technology integrates multi-dimensional data such as building geometry, materials, and equipment, which not only provides key information for EEMD to process energy consumption data and RVFL to build prediction models, but also to visually simulate different energy-saving design strategies, change the thickness of external wall insulation materials, and intuitively see the changes in building energy consumption, help optimize energy-saving design strategies, and achieve accurate prediction of building energy consumption and high efficiency and energy saving. In the RVFL network architecture, the power generation module converts alternating current to direct current, and its power supply affects the energy consumption balance. The building is connected through modules, or outputs its own power generation or feedback electricity demand, which affects the distribution of energy consumption; The fuel cell is connected with the help of a module, and its output affects the energy consumption of the system. The energy consumption model integrates various energy information for simulation and prediction, which provides a basis for energy consumption management. DC Bus 1 and DC Bus 2 are the transmission channels for electrical energy, and their transmission efficiency affects energy consumption. The constant power demand of constant power load affects the distribution of energy consumption, and the change of power demand of DC load directly affects energy consumption. Batteries store and regulate electrical energy to optimize energy consumption. The dual-power converter uses solar energy to realize power conversion and regulation through switching elements, reducing dependence on other energy sources and reducing energy consumption. The RVFL network architecture is shown in Figure 1.

Suppose there are N samples $\{x_i,y_i|,x_i\in R^n,y_i\in R^s\}$ and P is hidden layer nodes. Accordingly, the input-output mapping is expressed as equation (3):

$$f(x_i)=\sum_{j=1}^{P}\omega_j G(\delta_j x_i+b_j)+\sum_{j=P+1}^{P+n}\omega_j x_i, i=1,\ldots,n \tag{3}$$

Where $G(\cdot)$ represents activation function, δ_j represents weight of the *j-th* node, ω_j is weight of hidden output layer, and$b_j$is bias of *j-th* hidden layer node [19]. Input nodes can simply be regarded as combinations of $\sum_{j=P+1}^{p+n}\omega_j x_i$.The input node actually connects input layer and output layer as a direct link. Therefore, each output node has a total of $(P + n)$ inputs. After randomly obtaining input weight δ_j and bias b_j, the network can be simplified as equation (4) for all samples during training:

$$Y=\omega X \tag{4}$$

Where Y represents the label matrix corresponding to the feature matrix X, and ω represents the output weight. The purpose of network training is to obtain weight ω, so the learning problem is shown in equation (5):

$$\min_{\omega}\frac{1}{2}H\omega-Y_2^2+\frac{\lambda}{2}\omega_2^2 \tag{5}$$

Where λ is the regularization coefficient. *min* represents the minimum value and H is the optimization matrix. Compared with RVFL, RVFL + algorithm fuses LUPI normal form [20], and the input data has an additional set of privileged information, which can obtain better learning effect. The added privilege information is $\{x_i^* \in R^d, i = 1,\ldots, N\}$, then the training data set is $(x_i,x_i^*,y_i)|x_i \in R^n, x_i^* \in R^n, y_i \in R^s, i=1,\ldots,N\}$, where x_i represents input, y_i is label corresponding to x_i, and the parameter can be transformed into equations (6) and (7):

$$\min_{\omega,\omega^*,\xi} \frac{1}{2}\omega_2^2 + \frac{\varphi}{2}\omega_2^{*2} + Q\sum_{i=1}^{N}\xi_i(\omega^*, h^*(x_i^*)) \quad (6)$$

$$s.t. h(x_i)\omega = y_i - \xi_i(\omega^*, h^*(x_i^*)), \forall 1 \le i \le N \quad (7)$$

Where φ represents coefficient and $h(x_i)$ is output vector corresponding to x_i. Similar to $h(x_i)$, $h^*(x_i^*)$ is hidden layer output vector corresponding to the privilege information x_i^*, ξ_i represent error vector, ω represent output weight vector, and ω^* represent the output weight vector of $\xi_i(\omega^*,h^*(x_i^*))$ correction function in the privileged information space, Q is the trade-off parameter. It can be seen from equation (8) that in training stage, the objective function is determined by ω^* and ω, which indicates that both the original features and privileged information will affect the learning performance of RVFL +. The following Lagrangian function L can be constructed to solve the optimization problem in equation (8).

$$L(\omega,\omega^*,\lambda) = \min_{\omega,\omega^*,\lambda} \frac{1}{2}\omega_2^2 + \frac{\varphi}{2}\omega_2^{*2} + Q\sum_{i=1}^{N}\omega^* h^*(x_i^*) - \sum_{i=1}^{N}\lambda_i(h(x_i)\omega - y_i + \omega^* h^*(x_i^*)) \quad (8)$$

Where $\lambda=[\lambda_1,\ldots,\lambda_N]^T$ is the Lagrange multiplier. This is then solved using the KKT (Karush-Kuhn-Tucker) condition. Therefore, the parameter optimization function of RVFL + can be obtained, as shown in equation (9):

$$\omega = H^T(HH^T + \frac{1}{\varphi}H^*H^{*T} + \frac{I}{Q})^{-1}(Y - \frac{QE}{\varphi}H^*H^{*T}) \quad (9)$$

Where E is an $N \times s$ dimensional matrix with values, H is mixed matrix of connection input and hidden layer output, H^* is mixed matrix corresponding to privilege information, and Y represents label matrix. The Lagrange multiplier method cleverly constructs the Lagrangian function by introducing the multiplier, and transforms the constrained optimization problem into an unconstrained problem to solve it. On the one hand, the value of the Lagrangian multiplier can intuitively reflect the influence of the constraint on energy consumption, and the larger the value, the more obvious the influence of the constraint on energy consumption under the current optimal solution. On the other hand, it can deal with various constraints such as equality constraints and inequality constraints within a unified framework, providing a systematic and comprehensive approach to the optimization of building energy consumption models, and helping researchers and engineers to formulate more energy-efficient and reasonable design strategies while meeting various practical constraints.

EEMD, RVFL, and BIM technologies work closely together to help predict energy consumption and design energy efficiency in buildings. EEMD decomposes the hourly energy consumption data that fluctuates and fluctuates complex due to business hours, seasons and other factors into high-frequency and low-frequency fluctuation components, sorting out clear data patterns and providing high-quality data for follow-up work. RVFL uses the data processed by EEMD to quickly build an energy consumption prediction network based on input variables such as outdoor temperature and office capacity, and predicts the energy consumption of the office area during the summer working day with an error of less than 5%. BIM runs throughout, integrating multi-dimensional information of the building in the design stage, and selecting the optimal solution by simulating the energy consumption of different design schemes. Combined with real-time energy consumption data during operation, with the help of EEMD and RVFL analysis results, real-time monitoring and visual management of energy consumption can be realized, and once an abnormality is found, the problem area can be quickly located and energy-saving measures can be taken to improve energy efficiency.

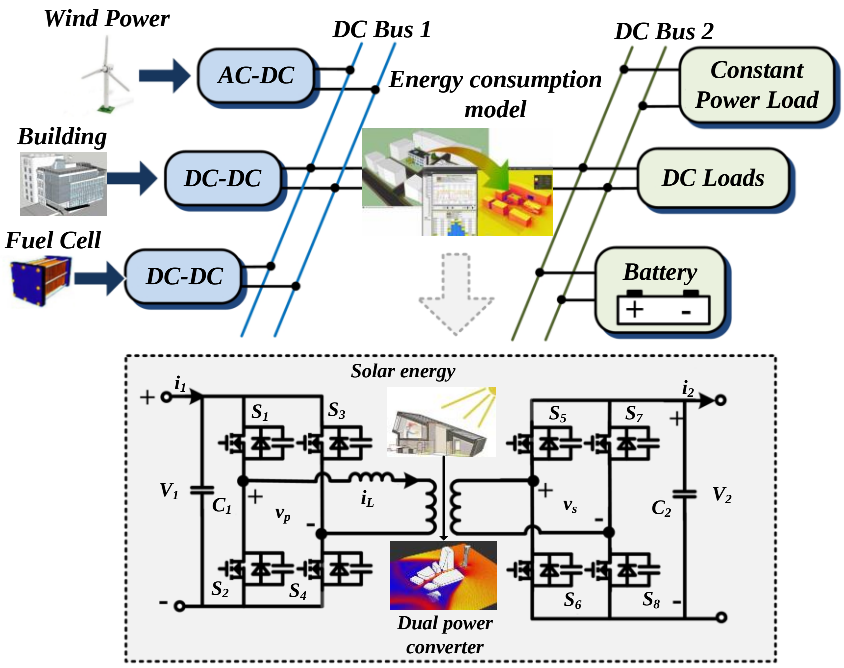

Figure 1. Multi-energy and building energy consumption module RVFL network architecture

2.2. BIM technology

BIM is a digital model of a building, covering its physical and functional characteristics and providing a reliable information-sharing resource for whole life cycle of a building [21]. BIM is a process that is applied to architectural design and construction while affected affects engineering management. BIM covers entire life cycle of a construction project [22]. As a platform, the core advantage of BIM lies in promoting collaborative work and realizing information sharing throughout the project life cycle. It integrates the information required by each specialty into a model. It guides all parties to clarify their roles and tasks through unified language and visualization means, thus improving construction quality and efficiency [23, 24]. Managers can use BIM's communication, sharing and analysis data to optimize architectural engineering project management [25] continuously.

BIM technology transforms two-dimensional CAD drawings into three-dimensional models containing project data for easy analysis and communication. Three-dimensional models are more vivid than two-dimensional and can show architectural details in detail, such as structural and decorative parts. Visualization runs through the whole construction process and serves as a communication platform to promote the collaborative work of scheme design, construction management and later operation and maintenance, and improve efficiency [26]. BIM technology realizes data sharing among project participants, making the information more accurate, three-dimensional, precise and updated in real-time. Before the start of construction, participants can be familiar with the construction steps through simulation, predict and prevent emergencies, and negotiate effectively. Use BIM technology to coordinate all stages of construction to ensure that the project is completed on schedule and saves costs. Component information, such as dimensions, attributes, relationships, etc., in BIM models, are parameterized, and different professional models are associated with data and collaborated in real-time. The model information includes geometric and non-geometric attributes, which can be automatically generated when components are changed to ensure the unity of the model [27]. The traditional model has no associated attributes, and it is easy to make errors when changing, which affects the construction. The BIM simulation model is the same as the actual building, simulating energy consumption, wind field, lighting and other factors, reducing the contradiction of work types and improving the rationality of the project. 4D construction simulation combines a 3D model and time dimension, and a 5D model adds cost information to help managers choose solutions, control resources, save time and improve efficiency.

Potential integration of cutting-edge technologies such as IoT and big data. IoT technology can use various smart sensors to collect massive data such as temperature, humidity, light intensity, and equipment operation status in the building in real time, and these data can be transmitted to the BIM model through the network, which can make the model's real-time monitoring of building energy consumption more accurate. For example, sensors capture the movement of people in the room and intelligently adjust the lighting and air conditioning systems according to actual needs, avoiding wasted energy. Big data technology can deeply mine and analyze these massive data to find out the potential rules and influencing factors of building energy consumption. By establishing an energy consumption data model, the energy consumption trend under different working conditions is predicted, which provides strong data support for the optimization of energy-saving design strategies. This technology integration significantly enhances the effect of BIM-based energy optimization, transforming energy management from traditional empirical to intelligent and refined. Exploring the integration of these technologies is not only an important direction of current building energy consumption research, but also an inevitable move to comply with the future development trend of digitalization and intelligence in the building industry, so as to ensure that the research results can be closely linked to the future research direction, and provide forward-looking ideas and methods for the efficient management and optimization of building energy consumption.

In terms of data sharing, the design, construction, and operation teams share information in real time through the BIM platform, the design team uploads the building geometry, and the construction team adds material data, so that the operation team can formulate an energy management plan, such as rationally adjusting the air conditioning operation strategy based on these data. When it comes to lifecycle management, BIM is the entire process. During the design, the energy consumption of different schemes was simulated, and the energy-saving design was found to reduce energy consumption by 20%. During construction, the progress and resources are managed according to the model to ensure the installation of energy-saving equipment; Combined with the Internet of Things in operation, real-time collection of energy consumption data, compared with the predicted value, found that the energy consumption is abnormal, can be retrospectively designed and construction information troubleshooting, such as timely remedies due to insulation material laying problems. In addition, BIM integrates multi-dimensional information to provide accurate data for energy consumption prediction, and the model built based on this has higher prediction accuracy, and can also simulate and evaluate different energy-saving strategies to select the optimal solution to achieve energy consumption reduction and energy efficient use.

The core advantage of BIM technology lies in its ability to collect, update, and scientifically apply maintenance information in real-time and continuously analyze the data of the whole cycle of construction projects [28, 29]. BIM technology has four main applications and advantages: BIM model collision detection can find errors in design and construction, reduce rework, and save costs. For example, the pipeline layout can be optimized through collision reporting to ensure the construction meets the requirements [30]. BIM 5D functions simulate construction activities to detect unexpected situations in time, improve project efficiency and quality, and achieve cost control and progress display. BIM's real-time tracking and coordination management links material parameters and models through QR codes to ensure transparency and quality control in material production, transportation, acceptance, and other links. The database function of BIM records and maintains the project's full-cycle data. Even if the building space changes, BIM can be continuously updated to provide information support for project management.

3. BIM-BASED BUILDING ENERGY CONSUMPTION PREDICTION AND ENERGY-SAVING DESIGN MODEL CONSTRUCTION

3.1. Energy consumption prediction model

We adopt a structured approach to work. When collecting data, BIM extracts geometric structure and material thermal parameters from architectural design drawings, and IoT sensors collect environmental and energy - consumption data during operation and perform cleaning verification. Model development integrates multi - source data via BIM, inputs variables like building geometry, materials, equipment and environmental factors, and combines machine - learning algorithms to build an energy - consumption prediction model, breaking traditional limitations and considering multiple factors' impact on building energy consumption throughout the life cycle. Model evaluation establishes a rigorous system, uses indicators such as RMSE, MAE, R^2 to compare predicted and actual energy consumption, and ensures generalization ability through cross - validation to show the model's uniqueness.

Figure 2 shows the model process. First, the original building energy - consumption data is decomposed by EEMD, then a sub - signal prediction model is constructed, and finally the outputs of sub - signals are integrated for the final prediction. In the EEMD - RVFL + - SVR model, EEMD decomposes the data and suppresses modal aliasing. The RVFL network constructs a sub - signal prediction model with quick convergence and high accuracy. In the multi - module interaction part, fast Fourier transform and its inverse transform convert the time - domain frequency domain, multi - head Fourier transform extracts integration features, and multi - head target attention highlights important information. The SVR integrates sub - signal prediction results and calculates the final energy - consumption prediction. Additionally, AVG is used for data smoothing, parameter and feature search, and model accuracy testing for optimization.

In the early architectural design stage, BIM models analyze the site considering factors like solar radiation, wind direction, terrain. During the architectural scheme design phase, multiple scheme adjustments are made using BIM models. Energy analysis software conducts energy - consumption analysis based on BIM models, and buildings' energy consumption is compared and optimized for different seasons. After multiple adjustments, the building's annual energy consumption is reduced. During the construction drawing design phase, BIM models are used for collaborative design among disciplines.

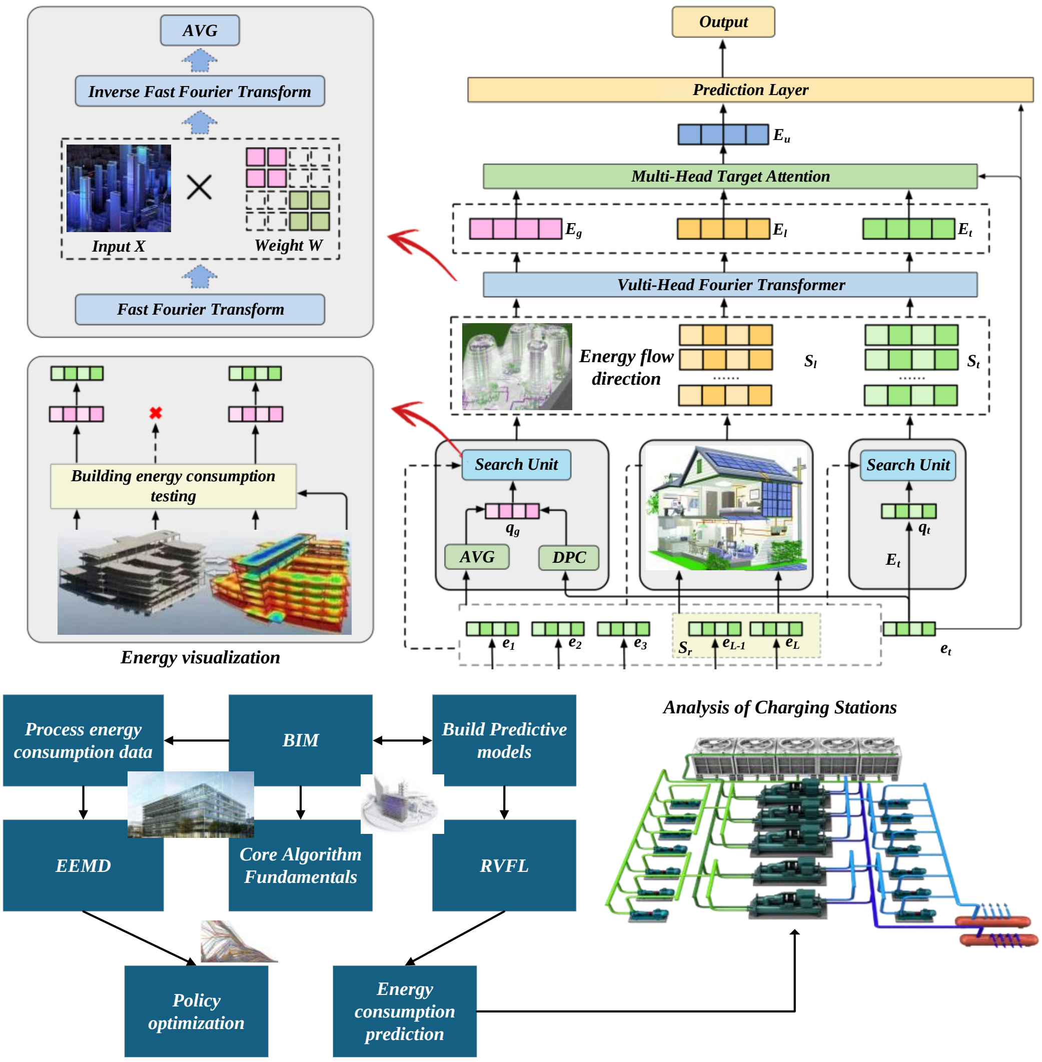

Figure 2. EEMD-RVFL +-SVR model

In the study, RMSE, R2, and MAE were introduced to evaluate model performance. The RMSE measures the average magnitude of the forecast deviation within a baseline of 3.5kWh/m²; R2 reflects goodness of fit, with an expectation of more than 0.85; The MAE reflects the average absolute value of the forecast error, which is limited to 2.0kWh/m². Through multi-dimensional comparison with the traditional baseline model and significance test, the effectiveness and advancement of the BIM-based model in energy consumption prediction and energy-saving strategy optimization are verified, which lays a solid data foundation for practical application.

When the energy consumption data is decomposed, the white noise sequence $\varepsilon(t)$ is added to original sequence $x(t)$, and then the new sequence is decomposed, and the mean value of components is taken as final component. Specific process is as follows:

(1) Add multiple groups of white noise to correct the *k-th* iterative time series, as shown in equation (10):

$$X_k(t)=x(t)+\varepsilon_k(t),(k=1,2,\cdots,K) \tag{10}$$

(2) Segment new sequence $X_k(t)$ to obtain the IMF and a residual, as shown in equation (11):

$$X_k(t)=\sum_{i=1}^{q} imf_{ki}(t)+r_k(t) \tag{11}$$

Repeat above two steps K times to obtain the correction sequences $X_1(t)$, $X_2(t)$, …, $X_K(t)$. The final corresponding IMF after decomposition is equation (12):

$$imf_i(t)=\frac{1}{K}\sum_{j=1}^{K} imf_{ji}(t),i=1,2,\cdots,q \tag{12}$$

(5) At the same time, the final residual is equation (13):

$$r(t)=\frac{1}{K}\sum_{j=1}^{K} r_j(t) \tag{13}$$

After completing the above steps, the final decomposition q sub-signals $imf_i(t)$ and a residual $r(t)$ are obtained. Suppose we have a set of raw building energy time series data of length N. For example, if white noise is added three times, Gaussian white noise with a mean value of 0 and a standard deviation of 0.5 is added each time to obtain a new sequence. Empirical mode decomposition is performed for each new sequence, assuming that 2 intrinsic mode function components and residuals are decomposed. The corresponding intrinsic mode function components obtained by each decomposition are averaged separately to obtain the final intrinsic mode function. Average the residuals obtained each time to get the final residuals. In this way, the white noise correction process is completed, and the results obtained can be used for subsequent analysis and prediction of the building's energy consumption.

3.2. Energy-saving design strategy optimization

In terms of cost, the preliminary investment and later operation and maintenance costs required for adopting new energy-saving equipment, optimizing the enclosure structure, and other solutions were carefully calculated, and their impact on the overall project budget was evaluated. In terms of implementation difficulty, the challenges that different energy-saving strategies may face in terms of construction technology, duration, and adaptability to existing building renovation were analyzed. For example, the installation of complex energy-saving equipment requires high professional skills from construction personnel, and space limitations may increase construction difficulty in the renovation of old buildings. At the same time, potential industry and market factors are also taken into consideration, including import and export policies for energy-saving materials, the impact of market supply and demand on material costs and supply stability, and so on.

To further deepen the research, we supplemented the cost-benefit analysis, quantified the relationship between the energy consumption reduction benefits brought by energy-saving strategies and the implementation costs, and visually demonstrated their economic feasibility. At the same time, in-depth discussions were held on the challenges faced in practical implementation, such as inadequate implementation of policies and regulations, weak awareness of energy conservation among owners, and inconsistent technical standards. The depth of research was enhanced from multiple dimensions, providing more practical references for the practical application of BIM based building energy consumption prediction and energy-saving strategies.

After completing BIM based energy consumption prediction, optimizing energy-saving design strategies has become a key link in achieving building energy-saving and consumption reduction goals. Optimization work not only needs to consider the physical characteristics, environmental factors, and user behavior of the building itself, but also fully utilize the information integration and simulation analysis capabilities of BIM technology.

By using BIM models for detailed prediction of building energy consumption, high energy consuming areas and parts such as exterior walls, roofs, doors and windows can be identified. Corresponding energy-saving design measures can be taken for these key areas, such as improving insulation performance, optimizing lighting design, and using high-efficiency energy-saving building materials. These measures can be verified and optimized through BIM model simulation analysis to ensure that they can achieve the expected energy-saving effect in practical applications.

The optimization of energy-saving design strategies also needs to consider the overall energy system of the building, including heating, cooling, lighting, ventilation, etc. Through BIM models, different energy system solutions can be simulated and compared to optimize energy configuration and operational strategies. For example, by combining local climate conditions and energy resources, the utilization plan of renewable energy such as solar and wind energy can be optimized to reduce dependence on traditional energy sources.

Meanwhile, optimization should focus on the use and maintenance stages of the building. By relying on BIM models, real-time monitoring and dynamic management of building energy consumption can be achieved, and abnormal energy consumption problems can be detected and solved in a timely manner. It can also be combined with intelligent building technology to achieve automatic control and optimized operation of building equipment, further reducing energy consumption. BIM based energy-saving design optimization is a multi-level and multi link systematic process that requires full utilization of BIM technology advantages, comprehensive analysis based on actual needs and conditions, in order to significantly improve building energy efficiency and support the achievement of sustainable development goals.

4. EXPERIMENT AND RESULTS ANALYSIS

Figure 3 shows the earliest completion time comparison of two models under different network delays. The upper one is the centralized data centre model, and the lower is the dual-service pool architecture model. The simulation reveals that the dual-service pool model has a shorter earliest completion time across various network delays. Its advantages are more pronounced when the central service pool network latency rises and the virtual machine task load drops. This model can effectively cut service response time, and the benefits become more evident as the network delay gap widens. However, as the task size increases, the response time gap decreases. It is calculated that under different network latencies, the average earliest completion time of the dual service pool architecture model is 11.3%, 17.2% and 20.9% lower than that of the centralized data centre model, respectively.

To investigate the impact of the number of neurons in the hidden layer of the generator on the prediction results, the number of neurons was set to 128, 256, 512, and 1024, and experiments were conducted on the validation set. Table 1 shows overall prediction results, which indicate that as the number of neurons increases, MAE and RMSE decrease, while R^2 increases. However, after exceeding a certain number, the prediction indicators decrease. In order to explore the influence of the number of neurons in the hidden layer of the generator on the prediction of building energy consumption, the experiments were set to 128, 256, 512 and 1024 in the validation set. The 95% confidence interval data showed that R2, RMSE, and MAE were 0.88 (0.85 - 0.90), 27.59 (26.00 - 29.18), and 19.64 (18.20 - 21.08) for 128 neurons, respectively. 256 at 0.92 (0.90 - 0.94), 23.98 (22.50 - 25.46), 17.73 (16.40 - 19.06), etc. After testing, there were significant differences in R2, RMSE, and MAE between 256 and 128 (p-value < 0.05). Overall, the number of models increased from 128 to 256, and the performance of the model increased, and the indicators decreased beyond 256, and 256 models were selected, which showed better performance and reliability.

Table 1. Overall prediction results

Number of neurons	R^2	RMSE	MAE
128	0.88	27.59	19.64
256	0.92	23.98	17.73
512	0.90	25.16	18.64
1024	0.89	26.74	20.10

Figure 4 shows the objective evaluation metrics in the validation set, showing that the generative adversarial network using GRU outperforms other models in RMSE, MAE and R^2 metrics. This indicates that GRU performs well in time series processing and classification tasks, so this study selects GRU as the discriminator structure.

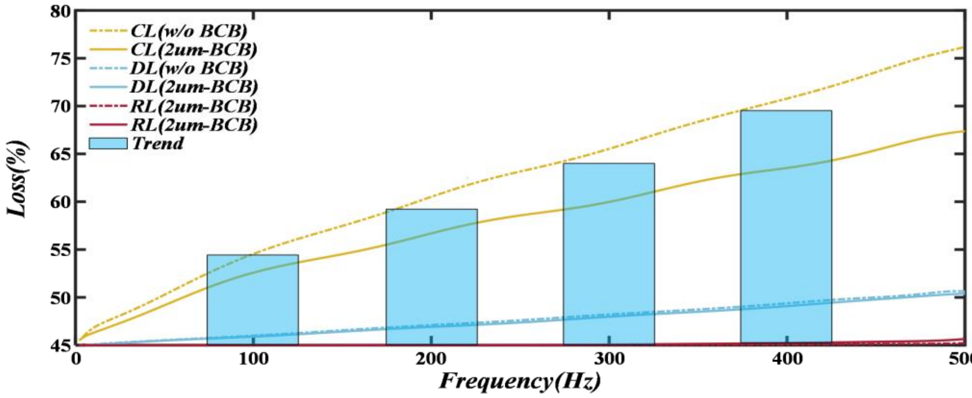

Figure 3. The trend of the earliest completion loss and cutting line of the dual-service pool model business at different frequencies

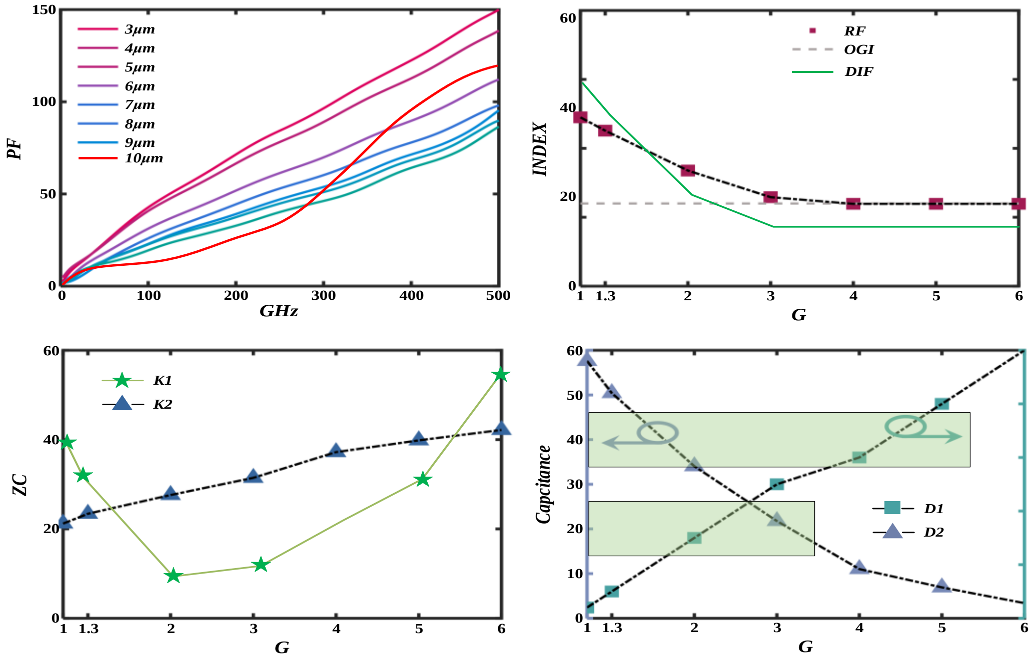

Figure 4. Comparison of experimental results of different discriminators

Figure 5 shows the prediction results of different models on weekdays and non-weekdays. The working day prediction shows that the model of this study has similar trends to the RF, SVR, LSTM, and GRU models but more accurately fits the peaks of the actual data. In the prediction of non-working days, RF, SVR and LSTM failed to capture the abrupt change of energy consumption, while GRU and GAN fitted. However, the effect was average, which indicated that the model did not perform well in dealing with the abrupt change of energy consumption. RMSE first calculates the square of the difference between the predicted and actual energy consumption values at each time point, averages and then takes the square root, which comprehensively considers deviations and is more sensitive to large deviations, which can reflect the model's ability to cope with energy consumption fluctuations. MAE calculates and averages the absolute value of the difference between the predicted and actual energy consumption values at each point in time, visually showing the average degree to which the predicted values deviate from the actual values. The two quantify the difference between the model prediction and the actual energy consumption data from different aspects, which is an important basis for evaluating the accuracy, reliability and performance of the model, helping researchers optimize the model and promote the development of building energy consumption prediction and energy-saving design strategies.

Table 2 compares the performance of different models on the test set, showing that the model in this study performs best on R^2, RMSE and MAE indicators with the slightest error. In the practical application of energy consumption forecasting, the performance of the models in Table 2 has a significant impact. The R^2 of radio frequency (RF) is 0.80, RMSE is 31.51, and MAE is 24.29, which has a limited degree of fit and a large prediction bias. The support vector regression (SVR) R^2 is 0.82, the RMSE is 30.66, and the MAE is 24.63, which is slightly better than RF but still not ideal, and the prediction accuracy is insufficient or misleading for energy management decisions. The R^2 of the Long Short-Term Memory (LSTM) network is 0.83, the RMSE is 30.02, and the MAE is 22.81, and the performance is improved, but the accuracy of its prediction may still not meet the needs of precise energy regulation in complex energy consumption scenarios. With an R^2 of 0.88, an RMSE of 25.80 and a MAE of 19.23 for the Gated Recirculation Unit (GRU), the performance is further improved, which can predict energy consumption more reliably to a certain extent, and provide a relatively good reference for energy allocation. In this study, the model (Gan) is 0.90, the RMSE is 23.63, and the MAE is 17.70, with the best index and the smallest error.Specifically, the RMSE of the model decreased by 25.0%, 22.9%, 21.3%, and 8.4% compared to RF, SVR, LSTM, and GRU, respectively. This shows that by integrating the adversarial mechanism of the generative adversarial network, the model can better handle complex nonlinear energy consumption data and learn the implicit relationship between energy consumption and influencing factors, thereby improving prediction accuracy.

Figure 6 clearly shows a comparison of the results of different models in terms of building energy consumption prediction. As you can see from the graph, the prediction curve 24 hours ahead visually reflects the performance of models such as RGAN during the workday. In the energy consumption prediction of working days, the RGAN model can accurately capture the change trend of building energy consumption, especially during the peak energy consumption period, and its prediction curve is highly consistent with the actual energy consumption peak, which can more accurately predict the time point and energy consumption value of the energy consumption peak compared with other models, which is of great significance for energy allocation and equipment operation planning in advance. Switching to the forecast for non-working days, it is clear from the degree to which the data in the graph fits well with the actual energy consumption data. The RGAN model is particularly advantageous when there are drastic changes in the energy consumption series, and the prediction curves of other models may be greatly deviated, while the RGAN model can still track the rapid fluctuations of energy consumption well and accurately reflect the changes in actual energy consumption. Throughout the figure, the prediction curve of the RGAN model is closer to the actual energy consumption curve as a whole, whether it is a working day or a non-working day, which fully shows that the RGAN model can capture the energy consumption trend more accurately as a whole, provides strong support for the accurate prediction of building energy consumption, and helps building energy management to be more scientific and efficient.

Table 2. Evaluation indicators of different model

Model	R^2	RMSE	MAE
RF	0.80	31.51	24.29
SVR	0.82	30.66	24.63
LSTM	0.83	30.02	22.81
GRU	0.88	25.80	19.23
GAN	0.90	23.63	17.70

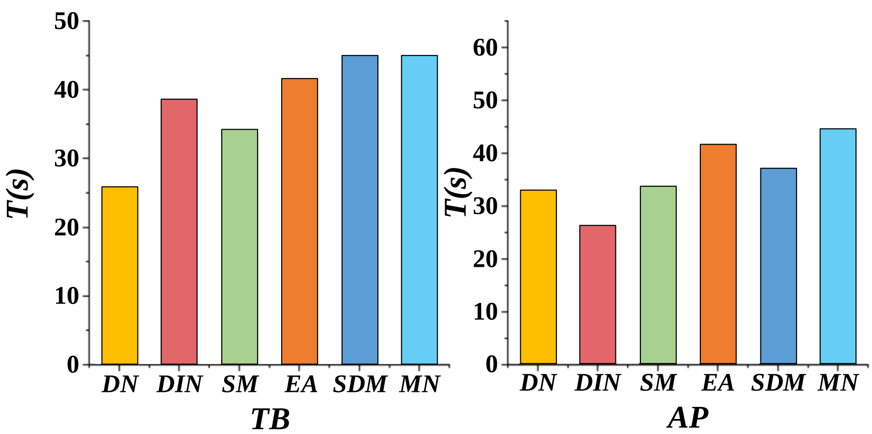

Figure 5. Model evaluation index

The results for each group are shown in Figure 7. In the first group, after stacking the SVM metamodel, the prediction error of the RBF model was the smallest, followed by the SVM model, and the error of the BP model was the most significant, and the performance ranking of the basic model did not change. The distribution of the data can be seen from the BP-based sampling-based chart on the left side of the figure. In the second group, RBF + ELM, SVM + RBF, and BP + RBF performed better, and they all contained RBF-based models. BP+SVM and BP+ELM, which included BP-based models, performed the worst. In the third group, the prediction error of ELM + SVM + RBF is the smallest, and the basic model also determines the ranking of other models.

The training error of the load forecasting model is RMSE (P) = 0.42 kW and RMSE (E) = 0.18 kW. Figure 8 shows the verification process and error curve of building cooling and electrical load forecasting models, in which the maximum relative error of cooling load verification of the HCMAC neural network model is 3.9%, the average relative error is 1.0%, the maximum relative error of load verification is 3.8%. Average relative error is 1.2%. Simulation results show that the neural network model can provide high accuracy and universal building load forecasting.

Figure 9 is the comparison of load demand and distributed energy output. The particle swarm optimization results show that the distributed energy resource is highly matched with the load demand of the building. The optimized energy output is slightly higher than demand, and it is recommended that small-capacity energy storage devices be equipped. This optimization strategy achieves the lowest cost operation of demand-based distributed energy resources and meets buildings' "1 production 1" requirement.

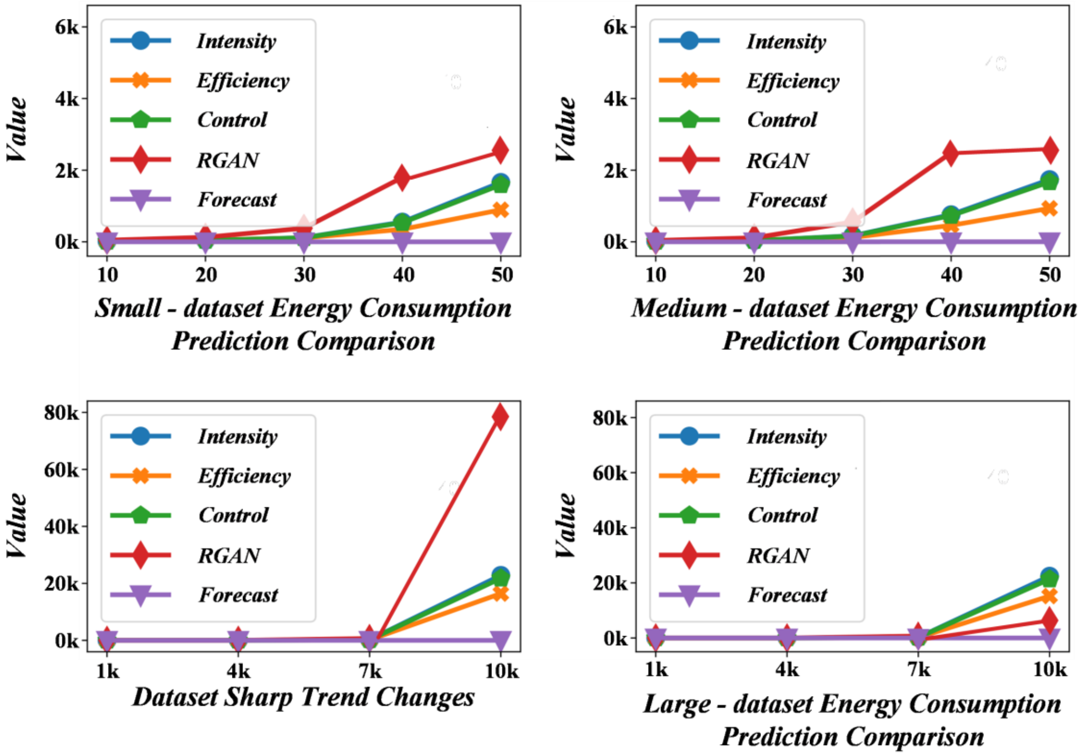

Figure 6. Comparison of prediction results

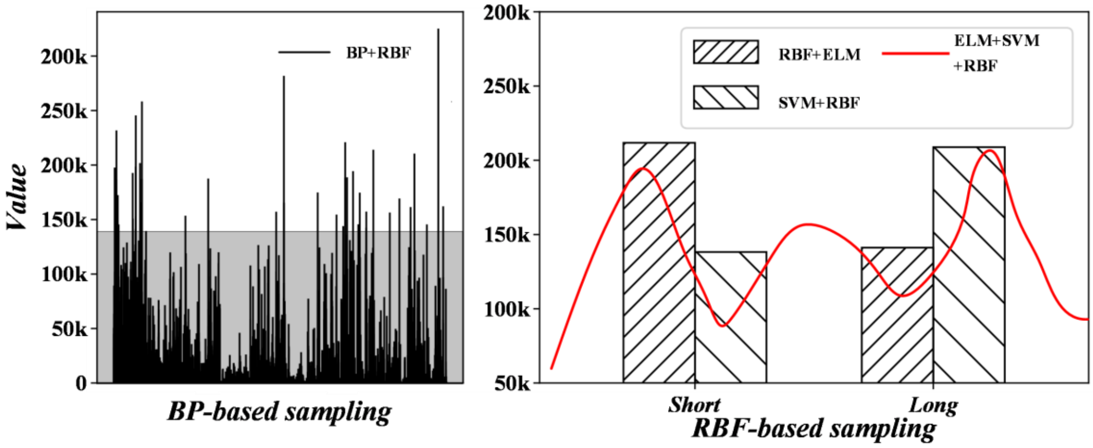

Figure 7. Comparison of performance evaluation indexes of different groups of models in a stacked composite model

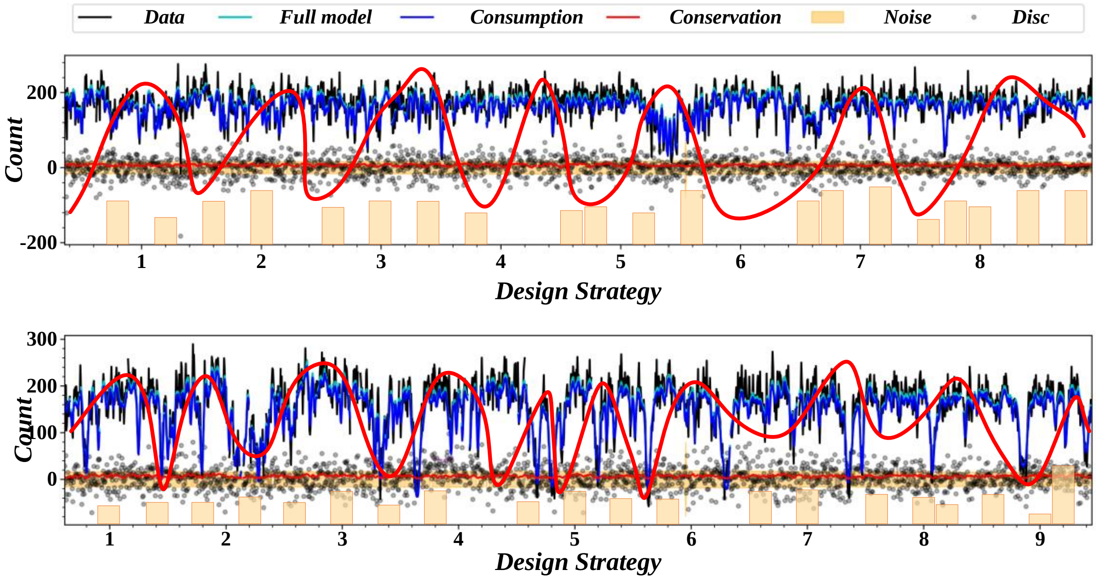

Figure 8. Load forecasting verification process and error curve

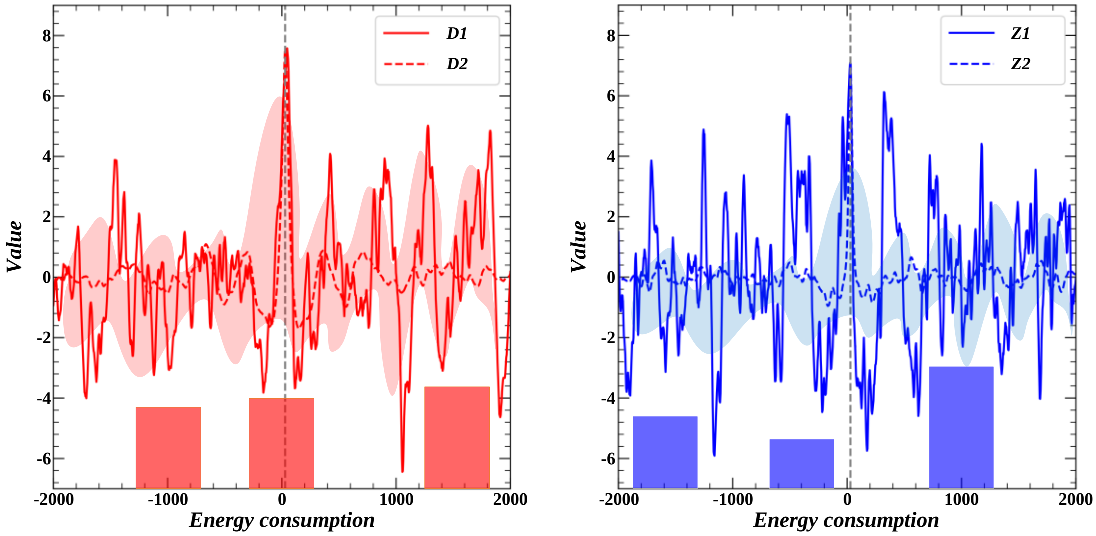

Figure 9. Comparison of load demand and distributed energy output

In the study, the results are of great significance for energy-efficient buildings. During the design, the BIM-based energy consumption prediction model can simulate the energy consumption of different schemes, and the designer can adjust the building parameters to select the low-energy consumption scheme. When optimizing, the high energy consumption links are located and rectified through the whole life cycle energy consumption analysis. However, the implementation of the results is facing challenges, the attention and willingness of stakeholders are different, the complexity of market materials and equipment affects the implementation of the plan, and the policies and regulations are not perfect.

5. CONCLUSION

Under the background of transformation and upgrading of the construction industry, building energy consumption has become a key factor restricting the industry's sustainable development. Focusing on the theme of "BIM-based building energy consumption prediction model and optimization of energy-saving design strategy", this study has achieved the following results through a series of experimental studies:

1. This study constructs building energy consumption prediction models based on BIM technology. Through detailed data collection of 50 buildings, including geometric parameters, material properties, equipment performance, etc., of buildings, BIM software is used for 3D modelling. Combined with a multiple linear regression algorithm, a prediction model of building energy consumption is established. Experimental results show that average prediction error of the model is 3.2%, and the maximum error is less than 6% when predicting the annual energy consumption of buildings.
2. This study optimized the energy-saving design strategy for buildings. Ten representative buildings were selected for energy-saving potential analysis of their enclosure structures, heating, ventilation, and air conditioning systems, and lighting systems. Three energy-saving design schemes were proposed by adjusting the design parameters. The experimental results show that the

optimized design scheme reduces building energy consumption by 18.5%, 21.2%, and 15.7% respectively compared to the original design scheme. Among them, optimizing the operation strategy of heating, ventilation, and air conditioning systems has the most significant effect on reducing building energy consumption, with an energy-saving rate of 21.2%.

3. This study conducted a comprehensive energy consumption assessment of 20 buildings by combining prediction models with energy-saving design strategies. By simulating the building energy consumption under different energy-saving design strategies, it is found that the energy-saving design scheme combined with the prediction model can further reduce the building energy consumption. Specifically, compared with the original design scheme, the energy consumption of the building with the comprehensive optimization strategy was reduced by 23.6%, of which the optimization of the envelope structure contributed by 10.8%, the optimization of the heating, ventilation and air conditioning system contributed by 8.9%, and the optimization of the lighting system contributed by 3.9%.

In the research, BIM technology constructs an energy consumption prediction model, integrates multi-source data to accurately predict energy consumption, and proposes an energy-saving design optimization strategy. However, there are limitations in the research, and in terms of data acquisition, it is difficult to complete the energy consumption data of old buildings, and there are errors in real-time data. The generality of the model is not good, and the adaptability to complex buildings is weak; The implementation of the strategy does not fully consider the impact of regional policies and economic costs. Future research can start from three aspects: data processing, model optimization and strategy improvement, develop algorithms to improve data quality, use deep learning to optimize models, and incorporate policy and cost factors to establish a comprehensive evaluation system to improve BIM-based building energy consumption research.

The energy consumption prediction model based on BIM in this study has high accuracy, and the energy-saving design it supports can significantly reduce building energy consumption, with good application prospects. However, it still faces challenges from verification to implementation: under the policy driven, the BIM data standards at the technical level are different, the model is disconnected from the operation, and the benefit quantification difficulties at the economic level and the process conflict at the coordination level jointly restrict the large-scale application of technology. In the future, while deepening the integration of BIM with big data and the Internet of Things, efforts should be made to build a full lifecycle data standard, connect data links, and establish quantifiable benefit mechanisms to promote the transformation of technological potential into actual energy-saving effects.

Declarations

Data availability statements

The data used and/or analysed during the current study available from the corresponding author on reasonable request.

Competing interests

No conflict of interest exits in the submission of this manuscript.

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