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Building BIM Energy Consumption Prediction Based On Intelligent Computing Wavelet Neural Networks

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Abstract. *Urban energy planning is a crucial instrument for increasing the effectiveness of urban energy usage, as well as for reducing emissions and conserving energy. However, as only limited building information is available at the urban planning stage, this makes it difficult to apply conventional energy consumption prediction methods to current urban energy planning efforts. To address this problem, this work proposes a building energy consumption prediction method based on intelligent computational wavelet neural networks and BIM software. Firstly, a civil building is used as the research object, and the parameter values for a standard building are set. At the same time, a standard building information model was constructed using BIM software, taking a business-type apartment building as an example. Then, wavelet neural networks were used to predict and calculate the energy consumption of the model. The weights of the wavelet neural network model were optimized using the discrete particle swarm optimization algorithm in intelligent computing. The discrete particle swarm optimization algorithm introduces linear differential decreasing inertia weights and asymmetric linear transformation learning factors so as to promote the convergence speed and convergence accuracy. The simulation results show that the optimal prediction performance can be obtained when the number of nodes in the hidden layer is 12. In terms of the annual hour-by-hour energy consumption prediction results, the relative error of the intelligent computational wavelet neural network is smaller than that of other neural networks, which can actually satisfy the precision demand for practical application.*
Keywords: Energy consumption Prediction; Building energy consumption; Wavelet Neural Networks; Discrete particle swarm optimization algorithms; BIM software

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1. **Introduction.** Energy consumption in buildings occupies an important place in global energy consumption. According to the International Energy Agency (IEA), the building sector accounts for about 40 % of the total global energy demand and this share is growing

[1,2]. Rational prediction of energy consumption in buildings is important for optimizing energy use, reducing carbon emissions and achieving sustainable development goals.

Building energy forecasting is vital to improving energy efficiency and operational efficiency in buildings. Accurate prediction of building energy consumption can provide a scientific basis for building design, equipment selection and operation management. Based on the prediction results, reasonable energy management strategies can be developed to facilitate the application and promotion of building energy efficiency technologies [3,4], reduce energy costs, improve indoor comfort and increase the overall operational efficiency of the building. The prediction of building energy consumption involves the comprehensive consideration of several complex factors. Building energy consumption is influenced by a number of factors such as climatic conditions, building structure, usage patterns, equipment and facilities [5,6]. By studying in depth the interrelationships and influence mechanisms between these factors, the patterns of building energy consumption can be better understood and provide a scientific basis for energy managers and policy makers.

With the rapid development of smart buildings and IoT technologies, the acquisition and processing capacity of building energy consumption data has increased significantly, providing more opportunities and challenges for building energy consumption prediction research. Through the effective use of sensors, smart metering systems and big data analysis technologies, building energy consumption data can be collected and processed in real time, helping to build more accurate and timely prediction models [7,8] and further promoting the intelligence and automation of energy management. The prediction of building energy consumption can also help optimise building design and operation. In the building design phase, accurate prediction of energy consumption can guide the optimisation of building structure, material selection and power system design, thereby achieving energy saving targets.In the operational phase of a building, real-time monitoring and prediction of energy consumption can help identify abnormalities and take appropriate measures to improve energy efficiency and indoor comfort.

Building energy consumption prediction also has a greater research value in related engineering fields [9,10]. For example, for the development of new building materials and technologies, predicting energy consumption can assess their energy efficiency performance and provide a scientific basis for their promotion and application. At the same time, building energy consumption prediction also involves research content from several interdisciplinary disciplines such as machine learning, data mining and model building, which promotes interdisciplinary cooperation and innovation.

1.1. **Related work.** Currently, there are three basic categories that may be used to group building energy forecasting techniques:

(1) Computer-based simulation methods. Currently, software that enables building energy simulation includes Energy-Plus, DeST, HKDLC, DOE-2 and BLAST, etc. Seyedzadeh et al. [11] carried out a comparative analysis of DeST, EnergyPlus and DOE-2 building energy simulation software. Wong et al. [12] used the EnergyPlus simulation software to simulate radiant floor and displacement ventilation and air conditioning systems.

(2) Scenario analysis-based approach. The scenario analysis method is a method of predicting energy consumption based on the energy consumption estimation method. In particular, energy consumption estimation refers to a method of making subjective judgments on energy consumption values by referring to relevant codes and manuals and relying on certain experience. The indicator method is one such method [13]. The accuracy and precision of the estimations are often poor when utilizing the indicator approach to predict building energy consumption, making it unsuitable for regional predictions of building energy consumption. In addition, the index method only reflects the peak energy

consumption of a building due to the combined effect of various influencing factors and does not reflect the dynamic demand of individual building energy consumptions and the energy consumption of a building group at the planning stage.

(3) Statistical regression-based methods. Statistical regression-based forecasting methods are currently the most widely used technical tools, such as stochastic time series and regression models. Mocanu et al. [14] proposed a time series method applied to the prediction of energy consumption in office buildings. Deb et al. [15] put forward an ARMA model-based scheme for predicting energy consumption in commercial building clusters. However, the existing statistical regression forecasts belong to a short-term forecasting scenario, while the urban planning stage forecasts belong to a medium- to long-term forecasting scenario.

The energy consumption of buildings is dynamic, stochastic and non-linear. Marvuglia and Messineo [16] used neural networks to predict the energy consumption of air conditioning and achieved good results. Researchers have suggested several enhanced neural network prediction models in an effort to increase the prediction accuracy of neural networks. For example, Moayedi and Mosavi [17] combined chaos optimisation methods with neural network methods and introduced them into their work on HVAC energy consumption prediction. Liao [18] combined wavelet transform with neural networks to predict the time-to-time energy consumption of air conditioners. Wavelet Neural Network (WNN) can show good performance in dealing with nonlinear problems, signal processing, pattern recognition and prediction. Wavelet Neural Networks have the following advantages for building energy prediction:

(1) Multi-scale analysis capability: WNN is able to decompose signals into frequency bands at different scales through wavelet transform, thus enabling analysis of energy consumption data at different time scales. This allows WNN to capture more comprehensive and accurate features in building energy consumption prediction.

(2) Non-linear modelling capability. Wavelet neural networks are able to generate complex linkages between inputs and outputs by non-linear mapping of input data to a higher dimensional feature space and through the neural network's learning capabilities. This enables wavelet neural networks to model the non-linear characteristics of building energy consumption more accurately.

(3) Adaptive learning capability. Wavelet neural networks are capable of adaptive learning of weights and thresholds through back propagation algorithms, i.e. adjusting network parameters through multiple iterations to continuously optimise model performance. This makes wavelet neural networks have good adaptability and learning ability in building energy consumption prediction.

However, there are many parameters in WNN that need to be tuned and optimised, such as weights and thresholds. In order to obtain the best prediction accuracy, manual adjustment by experts with extensive experience is required and can be time and energy consuming.

1.2. **Motivation and contribution.** The goal of intelligent computing is to achieve solutions and decisions for complex problems based on artificial intelligence, pattern recognition and other methods. Intelligent computing is a broad field covering a variety of optimisation algorithms, including Particle Swarm Optimization (PSO) [19,20].

PSO algorithm is an important part of intelligent computing and plays a unique advantage in specific problem domains.PSO algorithm has better performance in dealing with continuous optimization problems and is widely used in function optimization, machine learning, image processing and other fields. Therefore, this work proposes a method for predicting building energy consumption based on intelligent computing WNN and Building Information Model (BIM) software.

The main innovations and contributions of this work include:

(1) A standard building model was created based on the constraints and the building model was parameterised by BIM software using a business-type apartment building as an example.

(2) We proposed the use of a discrete PSO algorithm to search the parameter space so as to adaptively adjust the weighting parameters and threshold parameters in the wavelet neural network to improve its performance and prediction accuracy, saving a lot of time and cost.

(3) Since discrete PSO suffers from the problems of easily falling into local optimum and premature convergence, this paper introduces Linear Decreasing Inertia Weight (LDIW) [21] and Asymmetric Linear Transformation Learning Factor (ALTLF) [22,23] to upgrade the convergence speed and convergence precision of the discrete PSO.

2. Creation of a standard building model.

2.1. Classification of standard buildings.

As detailed building information is relatively difficult to obtain in the planning stage, this work introduces the concept of standard buildings to complete the modelling of building energy consumption prediction. A standard building is a representative building that reflects the current building form, building scale, building envelope composition and internal building disturbance of a certain type of building in society.

Buildings are typically divided into productive and non-productive categories based on their intended use. Examples of productive buildings include industrial and agricultural structures, while non-productive structures, also known as civil structures and divided into residential and public buildings, are the focus of the study. As different buildings have different energy consumption characteristics, this work will be classified mainly on the basis of the nature of use and functional characteristics of the buildings. The standard building classification of civil buildings in this work is shown in Table 1.

Table 1. Sample data

Basis of classification	**Building classification**			
Nature of use and functional characteristics	Residential buildings	Office buildings	Shopping mall building	Hotel buildin

In order to ensure a hot and humid environment in a building, energy consumption is defined as the amount of energy that needs to be supplied to a room at a given moment in time. There are many factors that have an impact on the building energy consumption, such as outdoor temperature and humidity, solar radiation intensity, occupant density, equipment power, envelope structure, etc. To facilitate the analysis of the many influencing factors, this work summarises these influencing factors into three types: external building disturbances, internal building disturbances and the building principal.

External building disturbance refers to the outdoor climate factors. The internal disturbance factors of the building include the occupancy rate of indoor people, the density of people, the installed power of equipment and lighting, the running time of air conditioning, the set temperature and humidity of the room, etc. The building principal is the influence factor consisting of the building's own parameters.

2.2. **Standard building model.** The research of this work is about the parameterisation of the standard building model by BIM software [24] and the predictive analysis of the energy consumption of the standard building model by using wavelet neural network.

The parameters of the standard building model are mainly obtained from studies, building standards and building codes. The model factors for standard buildings and their sources are shown in Table 2. The parameters were selected based on the principle of selecting parameters with a high correlation to the energy consumption of the building.

Table 2. Model factors for standard buildings and their sources

Classification	Model parameters	Source
	Building bottom shape	rectangle
	Building bottom aspect ratio	research report
	building storey height	Standards, specifications
	building height	Standards, specifications
Building ontology	Building orientation	Standards, specifications
	glazing ratio	Standards, specifications
	heat transfer coefficient	Standards, specifications
	transmittance	Standards, specifications
	absorptivity	Standards, specifications
	personnel density	Standards, specifications
Interior of the building	equipment power	Standards, specifications
	Lighting power	Standards, specifications
	fresh air	Standards, specifications
Outside the building	Indoor temperature and humidity	Standards, specifications
	Outdoor temperature and humidity	Standards, specifications
Local conditions	Air conditioning schedule	Standards, specifications

2.3. **Parameterisation of the building model based on BIM software.** In order to facilitate simplified calculation, certain information of the building is simplified in this paper. For example, (1) the shape of the bottom surface of the building model is considered as a rectangle; (2) the windows of all walls of the building are considered as a single unit and the window-to-wall ratio is fixed; (3) the heat transfer of the indoor envelope is not considered [25] and the floor height of the building is consistent.

On the basis of the above simplified calibrated building model, this paper takes a business-type apartment building as an example and parameterises the building model through BIM software. As an emerging information technology, BIM has gradually been widely used in the field of construction engineering, and BIM refers to the creation and application of one-to-one, internally coordinated and computable information in the design, construction, operation and management of construction projects. The use of BIM technology for building modelling has the following advantages: (1) it enables visual editing; (2) the model has automatic change capability; and (3) parameter editing is more convenient and efficient.

This work has been modelled using BIM software for a 13-storey business-type apartment building, the specific 3D effect of which is shown in Figure 1. The detailed parameters for each floor are shown in Table 2. The external windows on all walls of each floor of the business-type apartment building are considered as a whole, and each floor is also considered as a whole in the energy consumption prediction process. The details of each floor of the building model are shown in Table 3. It can be seen that the window-to-wall ratios for each floor of the building model range from 0.3 to 0.4 and the model has a volume factor of 0.14.

Table 3. Model factors for standard buildings and their sources

Floor	Area/m^2	Volume/m^2	Total wall area/m^2	Total window area/m^2	Total window-to-wall ratio	Body shape factor
1 storey	1603.31	8737.7	902.2	323.47	0.36	-
2, 3 storeys	1603.31	7134.4	736.65	271.3	0.37	-
4 storeys	1603.31	7775.72	802.87	292.17	0.36	-
5-15 storeys	1047.23	3612.74	435.87	168.29	0.39	-
Total	17932.8	70522.37	7972.94	3009.4	0.38	0.14

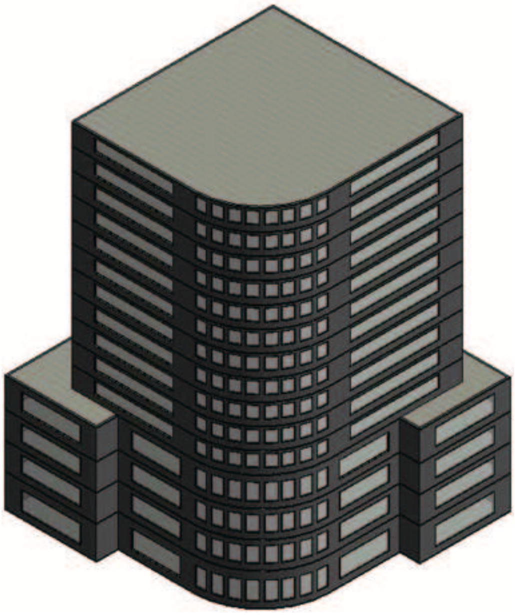

Figure 1. Example of figure

3. Building energy forecasting.

3.1. Several definitions and theorems. The main methods of predicting energy consumption in traditional buildings at this stage include:

(1) Stochastic time series forecasting method. The most typical algorithm is the autoregressive moving average model ARMA model, with the univariate ARMA model expressed as follow:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \ldots + \varphi_p x_{t-p} + \varepsilon_t - \theta_t x_{t-1} - \ldots - \theta_q x_{t-q} \tag{1}$$

where ε_t denotes random interference noise.

(2) Regression model forecasting methods. This type of method includes one-dimensional linear regression models and multiple linear regression models. Taking the one-dimensional linear regression model as an example, the expressions for the explanatory variables in the model are shown as follow:

$$Y_i = \beta_0 + \beta_1 X_i + u_i,\ i = 1, 2, ..., n \tag{2}$$

where X_i denotes the explanatory variables, β_0 and β_1 are theoretical parameters, u_i denotes the random disturbance term.

(3) Artificial neural network forecasting method, of which the most typical is the BP neural network forecasting model.

3.2. **Construction of wavelet neural networks.** The correlation factors in the stochastic time series forecasting method and the regression model forecasting method are usually selected empirically, and the artificial interference factors are too strong, making it impossible to attenuate the causal relationship between some variables and the predictor variables, which may adversely affect the accuracy of the predictor variables.

Compared with BP neural networks, WNN is a new type of layered, multi-resolution artificial neural network constructed based on wavelet analysis theory [27], which can lower the network's parameter count, simplify computation, and increase the network's capacity for generalization by choosing the right wavelet basis functions and scale parameters. Therefore, the WNN used in this paper predicts the energy consumption of building models. WNN consists of m input layer nodes, n output layer nodes and s hidden layer nodes.

$$\phi = \left\{ \phi_j = \frac{1}{\sqrt{|a_j|}} \phi(\frac{x - b_j}{a_j}) : a_j, b_j \in R^n, j \in Z \right\} \tag{3}$$

where $\phi\,(x)$ denotes a mother wavelet in time and frequency space, $a_j = \{a_{j1}, a_{j2}, ..., a_{jm}\}$ denotes the scale parameter, $b_j = \{b_{j1}, b_{j2}, ..., b_{jm}\}$ denotes the transformation parameter and $x = \{x_1, x_2, ..., x_m\}$ denotes the input to the WNN.

The 3-layer wavelet neural network structure is shown in Figure 2.

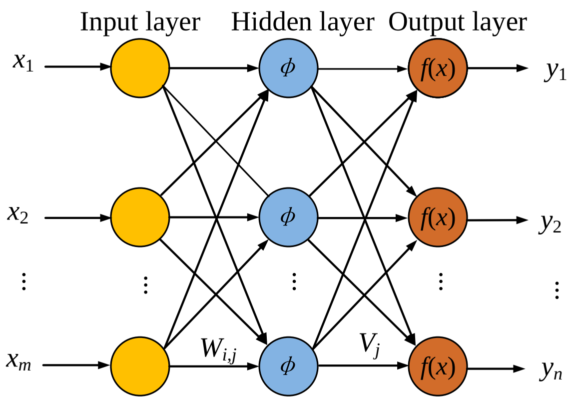

FIGURE 2. Three-layer wavelet neural network

The intra-network activity of neuron j is shown as follow:

$$v_j = \sum_{i=0}^{m} W_{ij} \cdot x_i \tag{4}$$

where W_{ij} denotes the weight between input i and hidden node j. The definition of Morlet mother wavelet [28] is shown as follow:

$$\phi(v) = \cos(1.75x)e^{-\frac{x^2}{2}} \tag{5}$$

Thus, the output of the j-th neuron is shown as follow:

$$\phi_j = \frac{1}{\sqrt{|a_j|}} \phi\left(\frac{v_j - b_j}{a_j}\right) \tag{6}$$

where a_j denotes the frequency parameter and b_j denotes the time parameter. The transform and translation parameters for the initialised wavelet are shown as follow:

$$a_i = 0.2\,(x_{\max} - x_{\min}) \tag{7}$$

$$b_j = 0.5\,(x_{\max} + x_{\min}) \tag{8}$$

where $x_{\max}$ indicates the maximum input value and $x_{\min}$ the minimum input value. In the standard form of WNN, the output is 'shown as follows:

$$f(x) = \sum_{j=1}^{n} W_j \phi_j(v) \tag{9}$$

where W_j denotes the weight between the j-th neuron and the output node.

3.3. **Learning steps for the WNN.** The WNN is trained using a back propagation method in order to find the percentage of each weight that causes the error . In addition, the steepest descent method is used to minimise the instantaneous error generated by the time t.

$$E(t) = \frac{1}{2}e^2(t) = \frac{1}{2}(f(t) - d(t))^2 \tag{10}$$

where f indicates the model output and d indicates the target output.

The aim of network training is to find the complete vector network parameter weights $w = (a_i, b_i, W_{ij}, W_j)$, thus minimising the error function. In this paper, an iterative approach is used to process a training sample of size N. Firstly, the error derivative of the weight vector is calculated at each iteration t. The weight vector is then updated by Equation (9).

$$\Delta w(t+1) = -\eta \cdot \frac{\delta E(t)}{\delta w} + \mu \cdot \Delta w(t) \tag{11}$$

where η denotes the learning rate and μ denotes the constant momentum term. The μ can improve the speed of training and avoid bias when updating the weights.

In the weight vector, the different parameters are updated based on the partial derivatives of the error function.

$$\Delta W_{ij}(t+1) = -\eta \cdot \frac{\delta E(t)}{\delta W_{ij}} + \mu \cdot \Delta W_{ij}(t) \tag{12}$$

$$\frac{\delta E(t)}{\delta W_{ij}} = e(t) \cdot \frac{\delta f(t)}{\delta W_{ij}} \tag{13}$$

$$\Delta W_{ij}(t+1) = -\eta \cdot e(t) \cdot W_k \cdot \phi_k(x_i(t)) \cdot \frac{x_i(t)}{a_i(t)} + \mu \cdot \Delta W_{jk}(t) \tag{14}$$

The weights W_j between the hidden and output nodes are updated as follows:

$$\Delta a_j(t+1) = -\eta \cdot \frac{\delta E(t)}{\delta a_j} + \mu \cdot \Delta a_j(t) \tag{15}$$

$$\frac{\delta E(t)}{\delta W_j} = e(t) \cdot \frac{\delta f(t)}{\delta W_j} = e(t) \cdot \phi_j(v_j(t)) \tag{16}$$

$$\Delta W_j(t+1) = -\eta \cdot e(t) \cdot \phi_j(v_j(t)) + \mu \cdot \Delta W_j(t) \tag{17}$$

The expansion factor a_j is updated as follows:

$$\Delta a_j(t+1) = -\eta \cdot \frac{\delta E(t)}{\delta a_j} + \mu \cdot \Delta a_j(t) \tag{18}$$

The conversion factor b_j is updated as follows:

$$\Delta b_j(t+1) = -\eta \cdot \frac{\delta E(t)}{\delta b_j} + \mu \cdot \Delta b_j(t) \tag{19}$$

3.4. **Discrete PSO-WNN.** In this paper, the discrete PSO algorithm [29,30] is used to optimize the weights and thresholds of WNN. Each particle represents the state of a set of switches, with the corresponding bit in the particle taking the value 1 if the switch is closed and 0 if it is broken. the initial weights and thresholds of the WNN are used as the particles of the particle swarm. Multiple weight and threshold matrices are used as the input set to the PSO to settle for the weights and thresholds that minimise Equation (10).

Let the speed of flight of the i-th particle $x_i = (x_{i1}, x_{i2}, ..., x_{iN})$ be $v_i = (v_{i1}, v_{i2}, ..., v_{iN})$. Using the energy prediction accuracy as the fitness function, solve for the fitness maximum $p_i = (p_{i1}, p_{i2}, ..., p_{iN})$ of the i-th particle. Then, calculate the maximum value $p_g = (p_{g1}, p_{g2}, ..., p_{gN})$ of all particles. The velocity update method for each binary bit is shown as follow:

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k}\right) \tag{20}$$

$$x_{id}^{k+1} = x_{id}^{k} + r v_{id}^{k+1} \tag{21}$$

where c_1 and c_2 are learning factors, ω denotes inertia weights, and r denotes a random constant.

As discrete PSO itself suffers from the problems of being prone to local optima and premature convergence, LDIW and ALTLF are introduced to improve the convergence speed and convergence precision of the conventional discrete PSO.

(1) Introduction of LDIW. Inertia weights ω affects the search capability of the discrete PSO algorithm, the global search capability of the discrete PSO algorithm is stronger when the value of inertia weights is larger, and vice versa for local search capability. Therefore, to make the discrete PSO have a strong global search capability in the early stage and an accurate local search in the later stage, LDIW inertia weights are introduced as follows:

$$w(k) = w_{\text{start}} - \frac{w_{\text{stan}} - w_{\text{end}}}{K_{\max}^2} k^2 \tag{22}$$

Where w_{start} is the initial inertia weight [31], w_{end} is the inertia weight at the maximum number of iterations, and K is the maximum number of iterations. In general, the discrete PSO algorithm performs best for $w_{\text{start}} = 0.9$ and $w_{\text{end}} = 0.4$ [32].

(2) Introduction of ALTLF. learning factor affects the search capability and convergence speed of the discrete PSO algorithm. in order to make the global search capability of the discrete PSO algorithm stronger in the early iterations and convergence speed faster in the later ones, this work uses ALTLF to improve the learning factor by updating it as shown as follows:

$$c_1 = c_{1\text{ s}} + \frac{(c_{1\text{e}} - c_{1\text{ s}})k}{K_{\max}} \tag{23}$$

$$c_2 = c_{2\text{ s}} + \frac{(c_{2\text{e}} - c_{2\text{ s}})k}{K_{\max}} \tag{24}$$

where $c_{1\text{ s}}$ and $c_{2\text{ s}}$ represents the learning factors' beginning values, while $c_{1\text{e}}$ and $c_{2\text{e}}$ represents their end values [33].

3.5. **Building energy consumption prediction process.** The discrete PSO-WNN based building energy consumption prediction process is:

Step 1: Data pre-processing, normalizing the original economic sample data as follows:

$$y = \frac{x - \min}{\max - \min} \tag{25}$$

where x represents the original sample data, max represents the maximum value of the sample data and min represents the minimum value of the sample data.

Step 2: Split the data into training samples and test samples;

Step 3: initializing the parameters of the WNN and the parameters of the discrete PSO algorithm;

Step 4: Optimization of the weight parameters and threshold parameters of the WNN using the discrete PSO;

Step 5: Calculating the WNN's output and error numbers while training it with the best possible parameters;

Step 6: Building energy prediction using test samples.

4. **Experimental results and analysis.**

4.1. **Evaluation metrics.** In this work, the Root-Mean-Square Error (RMSE) is used to quantitatively evaluate the results of energy consumption forecasting in order to verify the feasibility of the proposed forecasting method.

$$\mathrm{RE} = \frac{|\mathrm{AEC} - \mathrm{FEC}|}{\mathrm{AEC}} \times 100\% \tag{26}$$

$$\mathrm{AE} = \sum_{i=1}^{N} \frac{\mathrm{RE}_i}{N} \tag{27}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \mathrm{RE}_i^2}{N}} \tag{28}$$

where AEC indicates actual energy consumption and FEC indicates predicted energy consumption.

400 data were randomly selected as training data and 100 data as test data for the building energy prediction method proposed in this paper.

4.2. **Evaluation metrics.** After setting the initial parameters, the number of nodes (S) of the hidden layer of the neural network was first differentially set so that the optimal neural network size could be set for the building energy prediction simulation. The simulation results are shown in Table 4.

It can be seen that when S is 12 and 10 respectively, the hourly and daily forecasts of the annual energy consumption tend to stabilise. Therefore, the optimal number of nodes in the hidden layer of the WNN structure is 12 for the time-to-time prediction of the business-type apartment building model in the subsequent simulation.

TABLE 4. Tracking performance for different network sizes

Annual energy consumption	**S**	**Max. error/KW**	**Average error/KW**
Time-by-time forecast results	3	0.903	0.88
	5	0.769	0.73
	8	0.665	0.641
	10	0.533	0.52
	12	0.42	0.394
	15	0.42	0.394
Day-by-day forecast results	3	8.65	8.39
	5	6.25	6.02
	8	4.91	4.67
	10	4.01	12.85
	12	4.01	12.85
	15	4.01	12.85

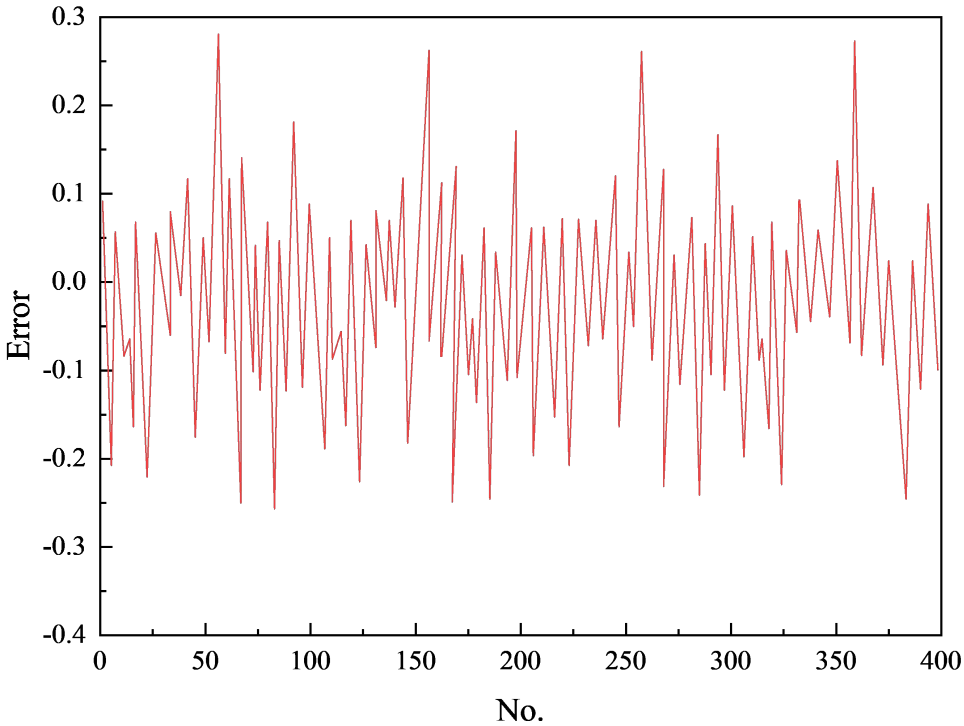

FIGURE 3. Training error curve

4.3. **Training error analysis.** The prediction results satisfy convergence after the training count reaches 524. The relative training error is shown in Figure 3, and the energy consumption prediction results of the discrete PSO-WNN are shown in Figure 4.

It can be seen that the average RMSE for training is 8.31 $ and the standard RMSE for training is 4.89 % after discrete PSO-WNN training. The predicted average RMSE was 11.06 %, the predicted standard RMSE was 8.13 % and the predicted maximum RMSE was 24.25 %. This shows that the discrete PSO-WNN building BIM energy prediction algorithm proposed in this paper is feasible.

4.4. **Comparative results of energy consumption predictions.** The experiment divided the 365 days of the year into 8760 hours (0:00 on December 1 to 24:00 on January

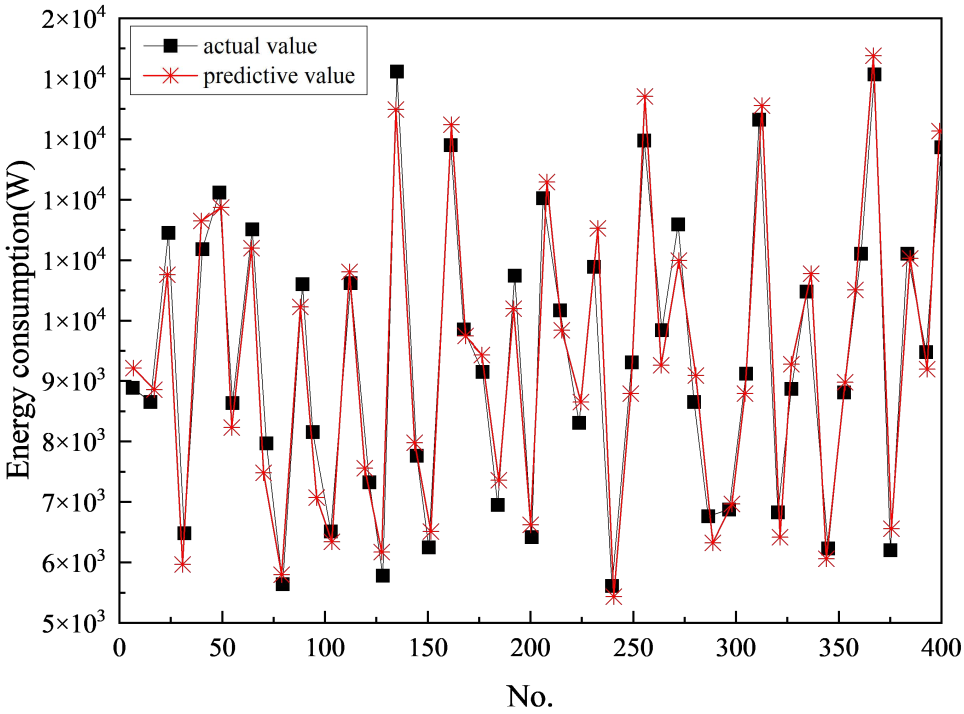

FIGURE 4. Comparison of predicted sample output vs. original energy consumption

31). The hour-by-hour energy consumption forecast results for the 8760 hours are shown in Figure 5.

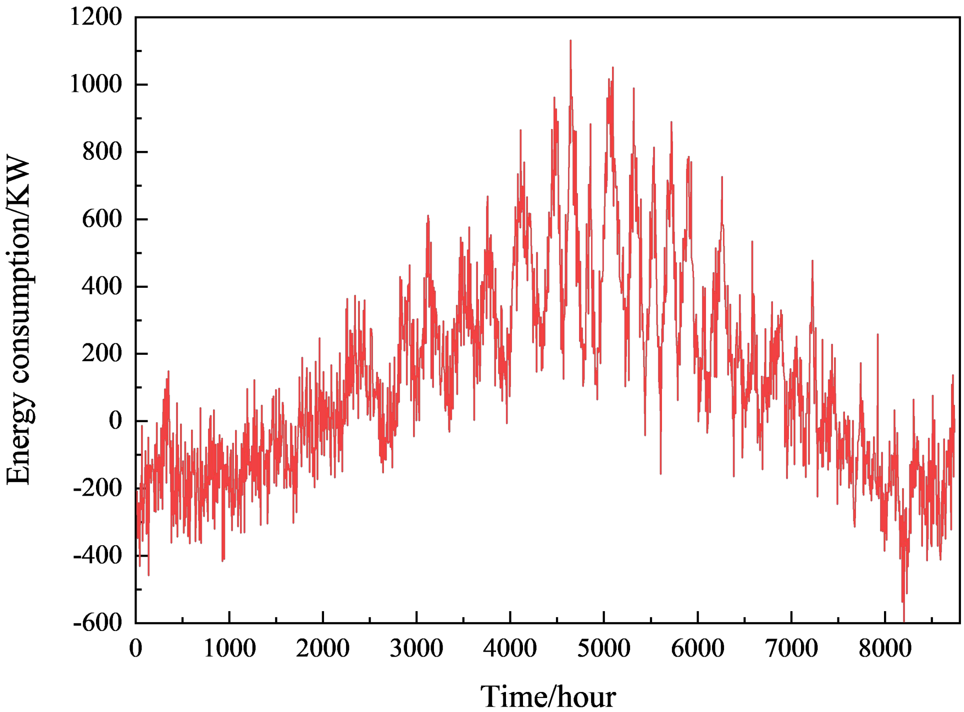

FIGURE 5. Time-to-time forecasting results of annual energy consumption

It can be seen that the discrete PSO-WNN can accurately predict the air conditioning energy consumption values for every hour of the year. To verify the optimisation performance of the discrete PSO algorithm, the energy consumption predictions of the conventional WNN and the discrete PSO-WNN were simulated separately and the simulation results are shown in Figure 6.

It can be seen that the predicted energy consumption for both calculation methods increases gradually from around 5:00 am onwards. In other words, the hour-by-hour trend of energy consumption is more or less the same for both methods. However, the predicted values of the discrete PSO-WNN are closer to the actual values than those of the conventional wavelet neural network. Therefore, in terms of the dynamic characteristics of the time-to-time energy consumption, the discrete PSO-WNN BIM energy consumption prediction method can meet the requirements of practical prediction accuracy.[**?**]

5. **Conclusions.** In this work, a building energy consumption prediction method based on discrete PSO-WNN and BIM software was proposed. In this paper, a standard building information model was constructed using BIM software, taking a business-type apartment building as an example. Then, WNN was applied to predict and calculate the energy consumption of the model. The discrete PSO algorithm was used to optimise the weights of the WNN model. The discrete PSO algorithm introduces LDIW and ALTLF in order to improve the convergence speed and convergence accuracy. The simulation results show that the optimal number of hidden layer neuron nodes in the WNN structure is 12 for the hour-by-hour prediction of business-type apartment buildings, and that the relative error of the discrete PSO-WNN is smaller than that of other neural networks in terms of the annual hour-by-hour prediction results, which can meet the requirement of meeting the prediction accuracy in practice. However, WNNs are prone to overfitting in building energy consumption prediction applications, especially when the sample data is small. In addition, there are certain uncertainties in building energy consumption forecasting, such as errors in weather forecasts or unknown external disturbances. Therefore, further research will be carried out to address these two issues in the follow-up.

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