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# Hybrid Ivy growth optimization and BP neural network model for accurate of building energy efficiency



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## Highlights:

- Novel IVY-BP hybrid model: first IVY application in building energy prediction.
- Achieves  $R^2 > 0.99$  for both loads, outperforming CNN, ELM, RF, BP, and GA-BP.

**Abstract:** Accurate prediction of building energy consumption is crucial for optimizing energy efficiency and reducing carbon emissions. Although the Backpropagation (BP) neural network is widely adopted for its strong nonlinear mapping capability in modeling complex architectural-energy relationships, it often suffers from slow convergence and a tendency to become trapped in local minima. To address these limitations, this study proposes a novel hybrid forecasting framework, IVY-BP, which integrates the Ivy Growth Optimization (IVY) algorithm with a BP network. The model utilizes architectural features as inputs to precisely predict two key outputs: Heating Load (HL) and Cooling Load (CL). Specifically, the IVY algorithm is employed to globally optimize the initial weights and thresholds of the BP network, significantly enhancing its robustness. Utilizing the UCI Energy Efficiency dataset, the model's performance was rigorously evaluated against benchmarks including CNN, RF, ELM, and GA-BP. Experimental results demonstrate that IVY-BP achieves superior accuracy, with  $R^2$  values reaching 0.9976 for HL and 0.9902 for CL, while maintaining the lowest MAE and RMSE. In conclusion, the proposed IVY-BP model provides a precise tool for smart building management systems, enabling intelligent regulation of HVAC systems to achieve sustainable energy goals.

**Keywords:** IVY; BP neural network; cool load; heat load



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## 1. Introduction

With the rapid development of Internet of Things (IoT) technology, more and more physical devices are connected to the Internet, forming a highly interconnected and intelligently perceived environmental system [1]. This technological innovation is widely changing human production and lifestyle, especially showing significant potential in improving energy efficiency and achieving sustainable development goals [2]. In smart building systems, various types of equipment generally rely on electric energy to drive operation [3]. Therefore, how to achieve reasonable allocation and efficient use of energy while meeting user comfort has become an important issue that needs to be solved urgently [4]. Especially in the operation of air-conditioning systems, the heating load (HL) and cooling load (CL) required by the building account for most of the building's energy consumption [5]. Therefore, in-depth analysis of the correlation between building structural parameters (such as wall area, roof structure, window ratio, material thermal conductivity, *etc.*) and energy consumption is the key to promoting the intelligent design and operation of building energy conservation.

According to statistics from the International Energy Agency, energy consumption in the building sector accounts for about 30% of the world's total energy consumption, and carbon emissions generated in 2021 account for about 33% of the world's total emissions [6]. Although a lot of progress has been made in green buildings, energy-saving equipment and intelligent control systems, the overall situation is still not enough to meet the goal of controlling global warming within 1.5 °C proposed in the Paris Agreement [7]. This further highlights the urgent need for intelligent and sustainable infrastructure, and accurate modeling and prediction of building energy consumption is the basic work for building such systems [8].

At present, building energy consumption modeling can be mainly summarized into three types of methods: white box modeling based on physical mechanisms, black box modeling relying on historical data (data-driven method), and hybrid modeling that integrates the two [9]. In comparison, data-driven methods have become the mainstream means of current smart home and building energy consumption prediction due to their lower modeling threshold, stronger adaptability and easy deployment. With the help of high-frequency and multi-dimensional data generated by the Internet of Things technology, machine learning and deep learning technologies have been widely used in the modeling tasks of building energy consumption, significantly improving the automation level and real-time performance of prediction [10]. However, there are still many problems to be solved in current research: First, many studies still focus on a single learning model and lack systematic research on integrated optimization strategies; second, the model still has a lot of room for improvement in prediction accuracy, generalization ability and robustness; third, the selection and evaluation of input features, especially the influence mechanism of building structural parameters such as roof area, window-to-wall ratio, and glass thickness on energy consumption has not been fully explored [11].

Several similar hybrid schemes have been explored to enhance the performance of building energy forecasting. For instance, meta-heuristic algorithms such as Genetic Algorithm (GA) [12], Particle Swarm Optimization (PSO) [13], and Grey Wolf Optimizer (GWO) [14] have been integrated with BP neural networks to optimize their initial parameters. While these approaches offer improvements over standalone models, they frequently struggle with a slow convergence rate or a tendency to stagnate in local optima during high-dimensional optimization. Furthermore, although deep learning models like

CNNs [15] can capture spatial features, they often require extensive datasets and lack the interpretability needed for architectural parameter analysis.

To overcome these specific challenges identified in prior research, this study proposes a building cooling and heating load prediction model that combines the Ivy Growth Optimization (IVY) algorithm and the backpropagation neural network (BPNN). Unlike GA or PSO based optimization approaches, the IVY algorithm draws inspiration from the phototactic growth behavior and interspecific competition strategies observed in ivy plants, achieving a more effective equilibrium between global search capability and local refinement. By employing this algorithm to pre-optimize the initial weights and architectural parameters of the BP neural network prior to training, the inherent tendency of conventional BP networks to converge prematurely toward local optima is substantially mitigated. Consequently, the predictive accuracy and overall stability of the proposed model in building energy consumption forecasting tasks are markedly enhanced.

## 2. Related work

Accurate estimation of thermal energy demand in buildings, encompassing both heating and cooling loads, has emerged as a prominent topic in the field of building energy research. In recent years, driven by the growing demand for energy efficiency and sustainable building management. A foundational resource in this domain is the open dataset introduced by Miller *et al.* [16], which contains over 53 million measurements from 1636 non-residential buildings. This dataset offers detailed time-series meter readings, building metadata, and weather information, providing a rich foundation for the development and validation of predictive models. In addition to data-driven approaches, studies focusing on building performance assessment using innovative materials and design strategies have also contributed to a deeper understanding of load prediction. For instance, Cal *et al.* [17] evaluated the thermal performance of construction and demolition waste-based materials through monitoring data and calibrated simulations across multiple climate zones. Such studies emphasize the value of accurate modeling in estimating potential energy savings and optimizing thermal performance through architectural design. Machine learning techniques have emerged as prominent tools for predicting heating and cooling demands. Pachauri *et al.* [18] employed regression tree ensemble learning for residential load forecasting, demonstrating the effectiveness of ensemble methods in capturing nonlinear and complex relationships. Similarly, Yan *et al.* [19] integrated multi-layer perceptron neural networks with adaptive chaotic grey wolf optimization, achieving improved prediction accuracy for multi-energy loads and showcasing the advantages of hybrid algorithmic frameworks. Neural networks, in particular, have been extensively explored in this context. Wang *et al.* [20] developed a backpropagation (BP) neural network to predict environmental temperature, humidity, and energy-saving potential in underground tunnels, illustrating the applicability of neural models in dynamic and constrained environments. Furthermore, Abdou *et al.* [21] investigated hybrid machine learning models for low-energy buildings in Morocco, highlighting the importance of model customization based on specific climatic and architectural characteristics for effective thermal load prediction and optimization. Advanced ensemble learning algorithms such as Light Gradient Boosting Machine (LightGBM) have also been applied to building load prediction. Guo *et al.* [22] demonstrated that LightGBM can achieve high accuracy in forecasting heating and cooling loads, reflecting the ongoing advancement of efficient algorithms in the field of energy modeling. Moreover, Jhamb *et al.* [23] evaluated various machine learning models by incorporating

diverse building attributes, including geometry, orientation, and glazing characteristics. Their results underscore the importance of considering multiple architectural parameters to improve the accuracy of energy consumption predictions. Lastly, Abdel-Jaber *et al.* [24] presented a comprehensive review of data-driven techniques for load prediction, encompassing ensemble learning, support vector machines, artificial neural networks, and probabilistic models. This review highlights the current state of the art and the continuous evolution of machine learning applications in building energy prediction.

Although a series of research results have been achieved in building cooling and heating load prediction, it still faces many challenges in terms of model integration, feature interpretability, generalization ability and actual deployment. Therefore, it is urgent to build a high-performance prediction framework that integrates optimization algorithms, interpretable feature selection and multi-source data integration to meet the energy consumption modeling needs in different building scenarios. The main contributions of this study are summarized as follows:

(1) IVY-BP Model Construction: A hybrid prediction framework is constructed by combining the IVY algorithm with a BP neural network. The IVY algorithm is used to optimize the initial weights and thresholds of the BP network, thereby reducing its sensitivity to initial parameter settings and improving convergence stability.

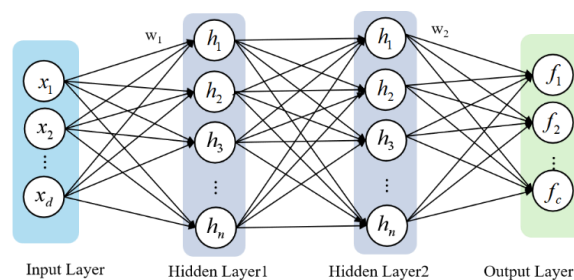
(2) Validation through Comparative Experiments: The performance of the IVY-BP model is validated by comparing it with several standard models, including CNN, RF, and GA-BP. The results are evaluated using the Coefficient of Determination ( $R^2$ ), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), demonstrating that the proposed model can reliably and consistently predict heating and cooling loads.

### 3. Materials and methods

#### 3.1. BP neural network

BP neural network was proposed by scientists such as Rumelhart and McClelland in 1986 [25]. It is a multi-layer feedforward neural network trained based on the error back propagation algorithm and is also one of the most widely used neural network models [26].

BP neural network has strong pattern recognition ability and excellent multi-dimensional nonlinear function approximation ability, successfully overcoming the limitations of the early perceptron model that could not handle the exclusive OR (XOR) problem [27]. Structurally, BP network usually consists of an input layer, one or more hidden layers and an output layer; in terms of algorithmic nature, BP uses the square of the total network error as the objective function and uses the gradient descent method for iterative optimization to achieve parameter training and learning. The BP neural network structure diagram is shown in Figure 1.



**Figure 1.** Structure diagram of BP neural network.

The BP neural network represents a classic form of multilayer feedforward architecture, typically comprising three fundamental components: an input layer, one or more intermediate hidden layers, and an output layer, with full connectivity maintained between adjacent layers. The input layer receives external feature variables and transmits them to the hidden layers, where nonlinear transformations are performed through weighted summations and activation functions to extract high-level feature representations. The resulting outputs are subsequently passed to the output layer, which generates the final predicted values. From a structural perspective, each neuron within a given layer establishes weighted connections with all neurons in the preceding layer, forming a dense many-to-many mapping relationship. The learning mechanism of the BP neural network is governed by the error backpropagation algorithm, which proceeds in two alternating phases: during forward propagation, input signals are sequentially transmitted through the network to produce predicted outputs, and the discrepancy between these outputs and the corresponding target values is then quantified as the prediction error. Comparing it with the true label [28–30]. Then, the gradient of the error to the weight of each layer is calculated by the chain rule through the back propagation algorithm, and the weight is iteratively updated using the gradient descent method to gradually minimize the loss function.

The BP neural network obtains the prediction output through forward propagation, calculates the gradient layer by layer through back propagation, and continuously updates the parameters in combination with the gradient descent method, thereby gradually optimizing the model performance [31]. Although gradient descent may fall into a local optimal solution during the training process, BPNN is still widely used in many fields due to its structural flexibility and good adaptability. In order to further improve the convergence speed and prediction accuracy, research in recent years tends to combine BPNN with intelligent optimization algorithms to build a hybrid optimization model with stronger robustness and global search capabilities to overcome the limitations of traditional methods in complex problems.

### 3.2. IVY algorithm

The Ivy Growth Optimization Algorithm (IVYA) is a biologically inspired heuristic that emulates the natural behavior of ivy plants during their lifecycle—namely initialization, adaptive growth, phototactic movement, propagation, and survivor selection [32]. The algorithm models each candidate solution as an ivy branch that climbs and spreads toward optimal areas under the influence of both local and global environmental cues. The five stages of IVYA are described as follows.

#### (1) Population initialization

At the beginning of the algorithm, the ivy individuals are randomly initialized across the search space to ensure diverse coverage. The initial position of each individual  $I_i \in \mathbb{R}^D$  is calculated as:

$$I_i = I_{\min} + \text{rand}(1, D) \odot (I_{\max} - I_{\min}), i = 1, \dots, N_{\text{pop}} \quad (1)$$

where  $I_{\min}$  and  $I_{\max}$  are the lower and upper bounds of the search space, respectively [33].  $\text{rand}(1, D)$  denotes a uniformly distributed random vector, and  $\odot$  represents the Hadamard (element-wise) product.  $N_{\text{pop}}$  represents the population size. This initialization strategy provides the algorithm with a well-distributed starting population for effective global exploration.

#### (2) Coordinated population growth

To simulate the self-regulating growth rate observed in natural ivy systems, a dynamic update mechanism for the growth vector  $Gv_i$  is employed. The change in growth vector at time  $t + 1$  is expressed as:

$$\Delta Gv_i(t+1) = \text{rand}^2 \odot (N(1, D) \odot \Delta Gv_i(t)) \quad (2)$$

Here,  $\text{rand}^2$  represents the square of a random variable sampled from a uniform distribution in  $[0, 1]$ , while  $N(1, D)$  denotes a  $D$ -dimensional standard normal random vector. This formulation integrates stochastic perturbations with historical trends, enabling the population to adaptively expand while mitigating premature convergence.

### (3) Phototactic growth toward light sources

Ivy plants exhibit phototropism, growing preferentially toward light-rich regions [34,35]. In IVYA, this behavior is translated into a local climbing mechanism driven by neighbor-guided movement. The new position of each ivy individual is updated according to:

$$I_i^{\text{new}} = I_i + |N(1, D)| \odot \left( \frac{I_{ii} - I_i}{|I_{ii} - I_i|} \right) + N(1, D) \odot \Delta Gv_i \quad (3)$$

The algorithm further defines a conditionally updated growth vector depending on the iteration:

$$\Delta Gv_i = \begin{cases} I_i \odot (I_{\max} - I_{\min}), & \text{Iter} = 1; \\ \text{rand}^2 \odot (N(1, D) \odot \Delta Gv_i), & \text{Iter} > 1 \end{cases} \quad (4)$$

where  $I_i$  is a random vector for initialization. This step mimics the adaptive nature of ivy seeking light and allows individuals to refine their positions through local exploitation.

### (4) Propagation and evolution

To reflect ivy's natural tendency to propagate and colonize favorable regions, IVYA implements a global guidance mechanism that directs each individual toward the current best-performing solution  $I_{\text{best}}$ :

$$I_i^{\text{new}} = I_{\text{best}} + (\text{rand}(1, D) + N(1, D)) \odot \Delta Gv_i \quad (5)$$

To support future directional movement, the updated growth vector is redefined as:

$$\Delta Gv_i^{\text{new}} = I_i^{\text{new}} \oslash (I_{\max} - I_{\min}) \quad (6)$$

here,  $\oslash$  represents the Hadamard division (element-wise division). This mechanism ensures that the population steadily moves toward global optima while preserving diversity in the evolutionary process.

### (5) Survivor selection

Inspired by natural selection, IVYA incorporates a survival mechanism that filters the population based on fitness. A candidate solution  $I_i$  survives to the next generation if:

$$f(I_i) < \beta \cdot f(I_{\text{best}}), \text{ with } \beta = \frac{2 + \text{rand}}{2} \quad (7)$$

where  $f(I_i)$  is the objective function to be minimized and  $\text{rand} \in [0, 1]$  is a uniformly distributed random scalar. The selection pressure is dynamically adjusted via  $\beta$ , allowing both elite and moderately fit individuals to coexist. This hybrid retention policy balances exploration and exploitation, enhancing convergence speed while avoiding local optima.

## 3.3. IVY - BP model

The IVY-BP neural network combination model proposed in this study innovatively combines the advantages of the IVY Algorithm and the BP Neural Network, aiming to improve the modeling accuracy

and stability of the heating load and cooling load in the building energy consumption prediction task [36]. This combination model not only shows stronger generalization ability in the feature space, but also effectively alleviates the problems of the traditional neural network model being sensitive to the initial weights and prone to falling into local optimality.

To address the well-known vulnerability of conventional BP neural networks to local minima entrapment, a hybrid modeling framework is constructed by coupling the IVY optimization algorithm with the BP neural network architecture. In this integrated scheme, the IVY algorithm serves as a global search mechanism responsible for determining the optimal initial weights and biases of the network prior to gradient-based training, thereby enhancing both predictive accuracy and model robustness. The procedural logic of this parameter optimization strategy is formally presented in Algorithm 1, and the complete workflow of the proposed prediction framework is elaborated in the following steps.

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**Algorithm 1 IVY-Based Optimization of BP Neural Network Parameters**

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1:   Input: Training data (Xtrain, Ytrain), Testing data (Xtest, Ytest), IVY parameters N, M axIt, BP architecture [16, 8]
2:   Output: Performance metrics on training and testing sets
3:   Step 1: Data Preprocessing
4:   Read dataset from ENB2012 data.xlsx
5:   Split into features X and labels Y
6:   Normalize data using mapminmax and zscore
7:   Step 2: Network Initialization
8:   Define BP neural network with hidden layers [16, 8]
9:   Initialize weights using Xtrain and Ytrain
10:  Step 3: IVY Optimization
11:  Initialize N IVY individuals with random values in [-1, 1]
12:  for t = 1 to M axIt do
13:  for i = 1 to N do
14:  if rand < 0.5 then
15:  Update position via Brownian walk and growth vector GV
16:  else
17:  Move toward a randomly selected leader IVY
18:  end if
19:  With 10% probability, apply mutation
20:  Set BP weights using IVY position
21:  Evaluate RMSE on training data
22:  end for
23:  Update global best IVY if current best is improved
24:  end for
25:  Set final BP weights as the best IVY solution
26:  Step 4: Train Neural Network
27:  Train BP network using optimized weights
28:  Step 5: Evaluate Performance
29:  Predict outputs for training and testing sets
30:  De-standardize predictions using  $\mu, \sigma$ 
31:  Compute  $R^2$ , MAE, and RMSE
32:  Return: Performance metrics and visualization results

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(1) Data preprocessing and normalization

The model utilizes the ENB2012 dataset as input, where the feature matrix is denoted as  $X \in \mathbb{R}^{d \times n}$  and the target vector as  $Y \in \mathbb{R}^{1 \times n}$ , with  $d$  representing the feature dimension and  $n$  the number of samples. The data is randomly partitioned into training and testing sets (e.g., 700 for training and 60 for testing). Feature normalization is conducted using min-max scaling, while the targets are standardized using Z-score normalization:

$$X_{\text{norm}} = \frac{X - \min(X)}{\max(X) - \min(X)}, Y_{\text{norm}} = \frac{Y - \mu}{\sigma} \quad (8)$$

where  $\mu$  and  $\sigma$  are the mean and standard deviation of  $Y$  in the training set.

### (2) Network architecture construction

A feedforward neural network is constructed with two hidden layers, comprising 16 and 8 neurons, respectively. The architecture is defined as:

$$\text{Input} \rightarrow \text{Hidden}_1(16) \rightarrow \text{Hidden}_2(8) \rightarrow \text{Output}(1) \quad (9)$$

Each layer applies a nonlinear activation function (e.g., tansig) and uses the weighted sum of inputs with biases to propagate forward:

$$a^{(l)} = f(W^{(l)} \cdot a^{(l-1)} + b^{(l)}) \quad (10)$$

### (3) Global optimization via IVY algorithm

To initialize the network with near-optimal weights, the IVY is employed to search the global solution space. Each solution (ivy individual)  $X_i \in \mathbb{R}^d$  represents a set of candidate network parameters. The objective function is defined as the RMSE between the network prediction and standardized targets:

$$\text{Fitness}(X_i) = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2} \quad (11)$$

where  $y_j$  and  $\hat{y}_j$  denote the actual and predicted normalized target values, respectively. IVY conducts population-based updates through local Gaussian perturbation and directional growth toward superior solutions. The best individual is selected as the initial weight configuration of the neural network.

### (4) Neural network training and prediction

The optimized weights  $w_{\text{opt}}$  from IVY are set into the BP network:

$$\text{net} \leftarrow \text{setwb}(\text{net}, w_{\text{opt}}) \quad (12)$$

Then, backpropagation training is performed using gradient descent to fine-tune the weights. Predictions are made for both training and testing sets and denormalized using:

$$\hat{Y} = \hat{Y}_{\text{norm}} \cdot \sigma + \mu \quad (13)$$

### (5) Performance evaluation metrics

Model performance is quantitatively evaluated using three widely adopted metrics: Root Mean Square Error, Mean Absolute Error, and the coefficient of determination, whose mathematical formulations are presented as follows:

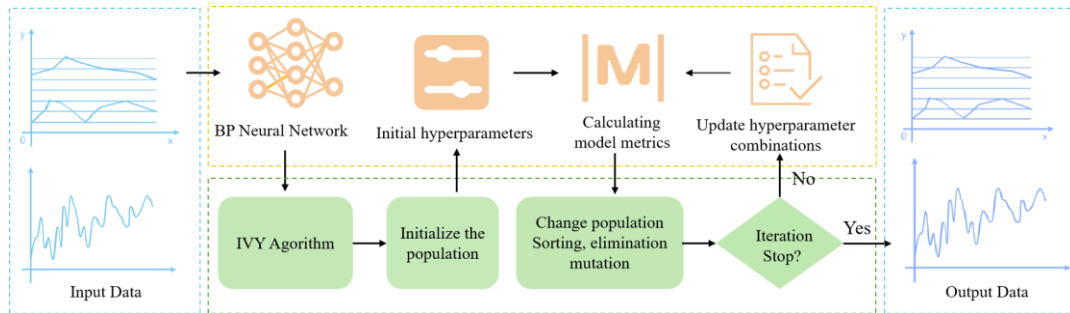
$$\text{RMSE} = \frac{1}{n} \sum_{i=1}^n (F_i - R_i)^2 \quad (14)$$

$$\text{MAE} = \sum_{i=1}^n \left| \frac{F_i - R_i}{R_i} \right| \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (F_i - R_i)^2}{\sum_{i=1}^n (F_i - A_i)^2} \quad (16)$$

where  $F_i$  denotes the predicted value at the  $i$ -th sample,  $R_i$  denotes the corresponding observed value,  $n$  represents the total number of samples; and  $A_i$  denotes the mean of all actual observations. With respect

to interpretation, lower values of RMSE and MAE are indicative of reduced prediction error and superior model precision. The  $R^2$  coefficient ranges from 0 to 1, where values approaching unity signify a closer agreement between the model outputs and the ground-truth data, thereby reflecting stronger overall fitting performance. The IVY-BP hybrid model significantly improves predictive performance by integrating global search capabilities of the IVY algorithm with the learning power of BP neural networks. It is especially suitable for complex nonlinear regression tasks such as building energy consumption forecasting. The hybrid structure enables robust convergence and avoids premature local minima, making it a valuable tool in engineering applications. The schematic diagram of IVY-BP model prediction is shown in Figure 2.



**Figure 2.** IVY-BP model prediction diagram.

#### 4. Experimental result and analysis

This study constructs a hybrid prediction model combining IVY algorithm and BP neural network to improve the accuracy and stability of building energy efficiency (such as cooling load or heating load) prediction. The model uses IVY algorithm to globally optimize the initial weights of the network to effectively avoid falling into the local optimal solution; then the BP algorithm is used for local fine adjustment to achieve faster and more stable convergence. At the same time, the standardized and normalized data preprocessing strategy is adopted to improve the consistency of data processing and the efficiency of model training. The study also designed a variety of performance indicators to comprehensively evaluate the performance of the model, and clearly demonstrated the model's fitting ability and generalization ability through visualization. In this experiment, the random seed of the test set was fixed to predict the heating load and cooling load of 60 data respectively. This experiment is configured to run on a Windows 11 operating system equipped with a 13th generation Intel(R) i7-13620H processor and 24 GB of memory, and the Matlab 2023a environment is used for the experiment.

##### 4.1. Experimental dataset

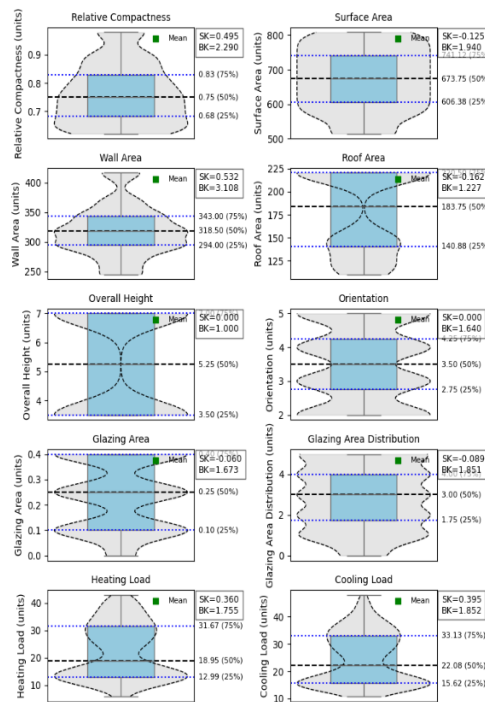
The dataset used in this study comes from the UCI Machine Learning Library, named "Energy Efficiency", which was donated by Athanasios Tsanas and Angeliki Xifara in 2012. This dataset evaluates the energy efficiency of buildings by predicting heating load and cooling load. The dataset contains 768 samples and 8 features. The input variables include Relative Compactness, Surface Area, Wall Area, Roof Area, Overall Height, Orientation, Glazing Area, Glazing Area Distribution. The output variables include Heating Load and Cooling Load. There is a complex nonlinear relationship between

Heating Load and Cooling Load and the feature indicators in this data. Table 1 provides a detailed description of each field of the dataset.

**Table 1.** Statistical summary of the energy efficiency dataset.

Type	Variable	Minimum Value	Maximum Value	Average Value	Unit
Input variables	Relative Compactness	0.62	0.98	0.77	-
	Surface Area	514.5	808.5	671.74	m <sup>2</sup>
	Wall Area	245.0	416.5	318.5	m <sup>2</sup>
	Roof Area	110.25	220.5	176.66	m <sup>2</sup>
	Overall Height	3.5	7.0	5.25	m
	Orientation	2	5	3.00	categorical
	Glazing Area	0	0.4	0.23	ratio (0–1)
Output variables	Glazing Area Distribution	0	5	2.50	categorical
	Heating Load (Y1)	6.01	43.10	22.31	kWh/m <sup>2</sup>
	Cooling Load (Y2)	10.90	48.03	24.99	kWh/m <sup>2</sup>

Figure 3 presents statistical analyses of key parameters related to building energy efficiency through multiple box plots. Each box plot displays the median (50th percentile), upper and lower quartiles (25th and 75th percentiles), and the overall range of the data distribution. Additionally, the mean, skewness, and kurtosis are labeled to characterize the shape of the data distribution. For instance, the mean relative compactness is 0.75 with a slightly positively skewed distribution; the mean wall area is 318.5, also positively skewed; the overall height distribution is symmetric with moderate kurtosis; while parameters like glazing area and cooling load exhibit varying degrees of skewness and peakedness. Collectively, these statistics reveal the central tendency, dispersion, and shape of each parameter's distribution, providing foundational data support for building energy performance analysis.



**Figure 3.** Distribution of building energy efficiency parameters.

#### 4.2. Data preprocessing strategy

To ensure effective training and fair model comparison, a dual preprocessing mechanism is applied: input features are normalized to  $[0, 1]$  using min-max scaling (mapminmax), ensuring equal contribution

from features of different scales, while output targets are standardized using Z-score normalization to have zero mean and unit variance, which stabilizes gradient flow and accelerates convergence. The dataset is randomly partitioned into 708 training samples (92.2%) and 60 testing samples (7.8%), with a fixed random seed (2024) to ensure reproducibility across experiments.

#### 4.3. Network architecture and hyperparameter configuration

The IVY-BP model employs a multilayer feedforward neural network architecture with carefully selected hyperparameters to balance model complexity and generalization capability. The network consists of an input layer with 8 neurons corresponding to the 8 architectural features, two hidden layers with 16 and 8 neurons respectively, and a single output neuron for predicting either heating load or cooling load.

The choice of the [16, 8] hidden layer configuration was motivated by the principle of progressive dimensionality reduction, which facilitates hierarchical feature extraction from high-dimensional input space to the scalar output. The first hidden layer captures complex nonlinear interactions among building parameters, while the second layer performs feature consolidation and abstraction. Activation functions play a crucial role in introducing nonlinearity: the hyperbolic tangent sigmoid (tansig) function is applied in hidden layers to enable the network to model complex nonlinear relationships, whereas a linear transfer function (purelin) is used in the output layer to allow unrestricted prediction ranges suitable for regression tasks. The training process utilizes the Levenberg-Marquardt backpropagation algorithm, known for its fast convergence and high accuracy in small to medium-sized networks. The maximum training epoch is set to 1000 with adaptive learning rate adjustment, ensuring sufficient convergence while preventing overfitting through early stopping mechanisms.

#### 4.4. IVY algorithm optimization configuration

Prior to BP training, the IVY algorithm optimizes the initial weight configuration through global search. A population of 50 ivy individuals explores the weight space over 100 iterations, with each individual representing a complete set of network weights and biases. As shown in Tables 2. The search space is bounded within  $[-1, 1]$  to maintain numerical stability and facilitate gradient-based training in the subsequent BP phase. A mutation probability of 0.1 is incorporated to maintain population diversity and prevent premature convergence to local optima.

**Table 2.** IVY-BP neural network configuration parameters.

Parameter Category	Parameter Name	Value/Setting
Network Architecture	Input layer neurons	8
	Hidden layer 1 neurons	16
	Hidden layer 2 neurons	8
	Output layer neurons	1
	Network type	Feedforward
Activation Functions	Hidden layers	tansig
	Output layer	purelin
IVY Optimization	Population size (N)	50
	Maximum iterations	100
	Search space bounds	$[-1, 1]$
	Mutation probability	0.1
	Fitness function	RMSE, $R^2$

The fitness function is defined as the Root Mean Square Error (RMSE) between predicted and actual training outputs, directly reflecting prediction accuracy. This hybrid initialization strategy significantly improves upon random weight initialization, providing the BP network with a near-optimal starting point that accelerates convergence and enhances final model performance.

#### 4.5. BP neural network configuration

To ensure a fair comparison and optimal performance of the baseline BP network, the structural parameters are determined through a combination of empirical formulas and systematic trials. Specifically, the number of neurons in the hidden layer is determined using the empirical formula  $l = \sqrt{n + m} + a$ , where  $n$  and  $m$  represent the number of input and output nodes, respectively, and  $a$  is a constant between 1 and 10. Through grid search, the optimal number of hidden neurons is settled.

Regarding the parameter tuning during training, a gradient descent algorithm with momentum is adopted. The learning rate is initially set to 0.01 and is adaptively adjusted based on the error gradient to prevent oscillations. The initial weights and thresholds are assigned using the Xavier initialization method to maintain variance across layers. During each epoch (online training phase), these parameters are updated via backpropagation to minimize the Mean Squared Error (MSE) until the convergence criterion of  $1e-6$  is met.

#### 4.6. Experimental process of IVY-BP algorithm

This study predicts the building cooling load by constructing an IVY-BP hybrid model. The overall process includes parameter setting and data loading, normalization and standardization preprocessing, neural network construction, IVY algorithm optimization of initial weights, BP algorithm fine-tuning training, and final performance evaluation and visualization. This method fully combines the global search capability of IVY and the local fine-tuning advantages of BP. While improving the prediction accuracy and stability of the model, it also shows good convergence efficiency and generalization ability. The experimental steps of the IVY-BP algorithm are as follows:

(1) Parameter initialization and data loading. To ensure reproducibility, a fixed random seed was set using `rng(2024)`. The number of individuals in the IVY algorithm was defined as  $N = 50$ , with a maximum of 100 iterations. The BP neural network was configured with two hidden layers consisting of 16 and 8 neurons, respectively. The ENB2012 dataset for building energy efficiency was loaded, with the first 8 features used as inputs and the 10th column (Cooling Load) as the prediction target. To prevent sampling bias, the dataset was shuffled and split into a training set (708 samples) and a test set (60 samples).

(2) Data preprocessing. To enhance training efficiency and model stability, the input features were normalized to the  $[0, 1]$  range using min-max scaling, while the output target values were standardized to have zero mean and unit variance. This preprocessing strategy effectively mitigates the impact of inconsistent feature scales and accelerates model convergence.

(3) Neural network construction. A feedforward neural network was constructed using the `feedforwardnet` function. The network was configured according to the input and output dimensions but not trained at this stage. The initial weights and biases were preserved for subsequent optimization using the IVY algorithm. The training visualization window was disabled to improve execution efficiency.

(4) IVY optimization of initial weights. The IVY algorithm was applied to optimize the initial weights of the BP network. The search space was set between  $[-1, 1]$ . The algorithm simulates the stochastic growth and guided propagation of ivy vines to iteratively explore the optimal weight configuration. The fitness function was defined as the RMSE between predicted and actual training outputs. The optimization process yields the best-performing weight vector and a convergence curve, effectively avoiding the local minima often encountered in traditional BP training.

(5) BP neural network fine-tuning. The BP neural network was fine-tuned using the optimal weights obtained from IVY as the initial configuration. This step refines the model locally using backpropagation, achieving faster convergence and improved accuracy. The result is a hybrid IVY-BP model that combines global and local optimization strategies.

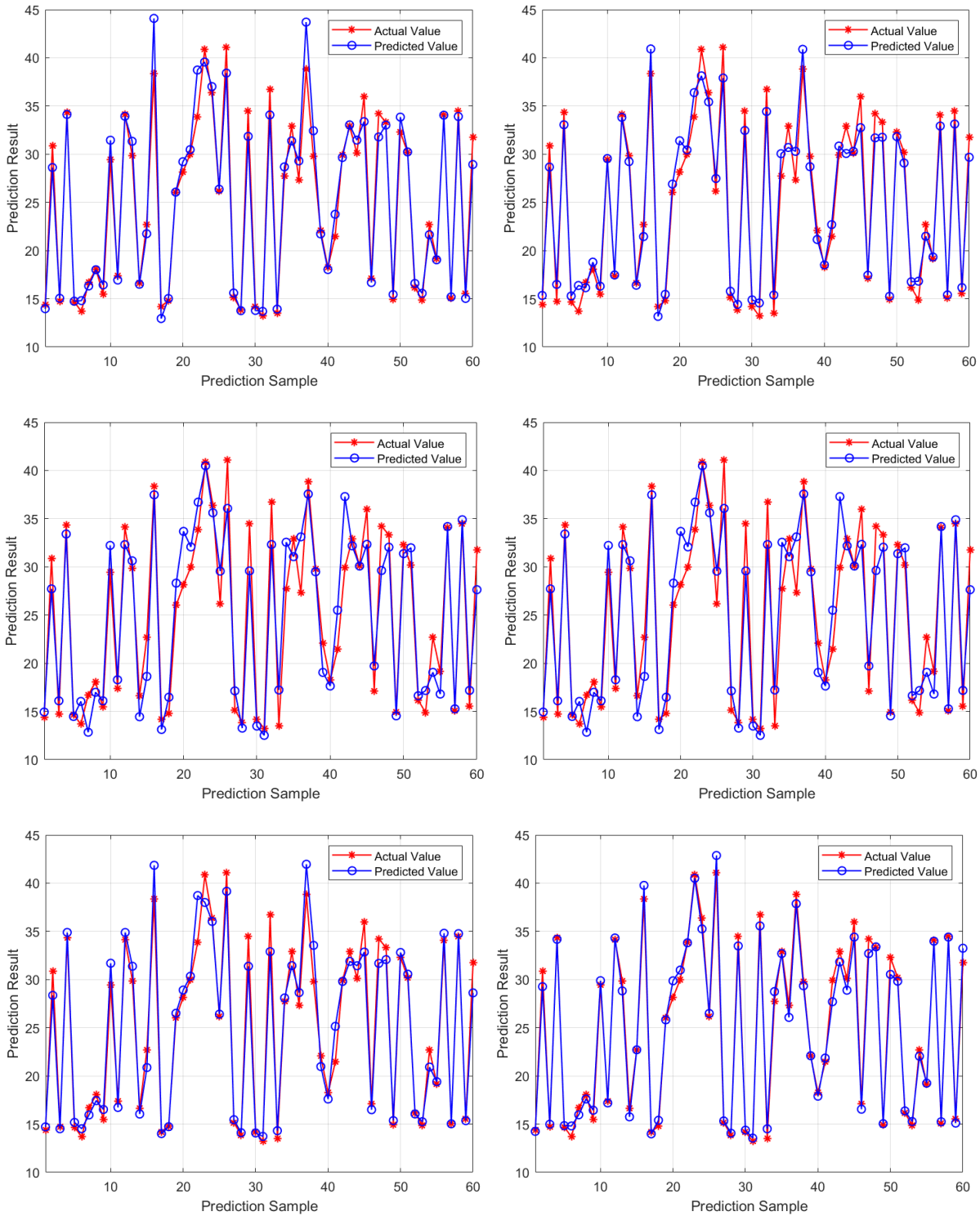
(6) Prediction and Performance Evaluation. After training, the model made predictions on both training and test sets. The outputs were inverse-transformed to obtain real-world values. Model performance was comprehensively evaluated using five metrics:  $R^2$ , MAE, and RMSE. These indicators capture the model's fitting accuracy and generalization performance from multiple perspectives.

#### *4.7. Prediction and analysis of building cooling and heating loads*

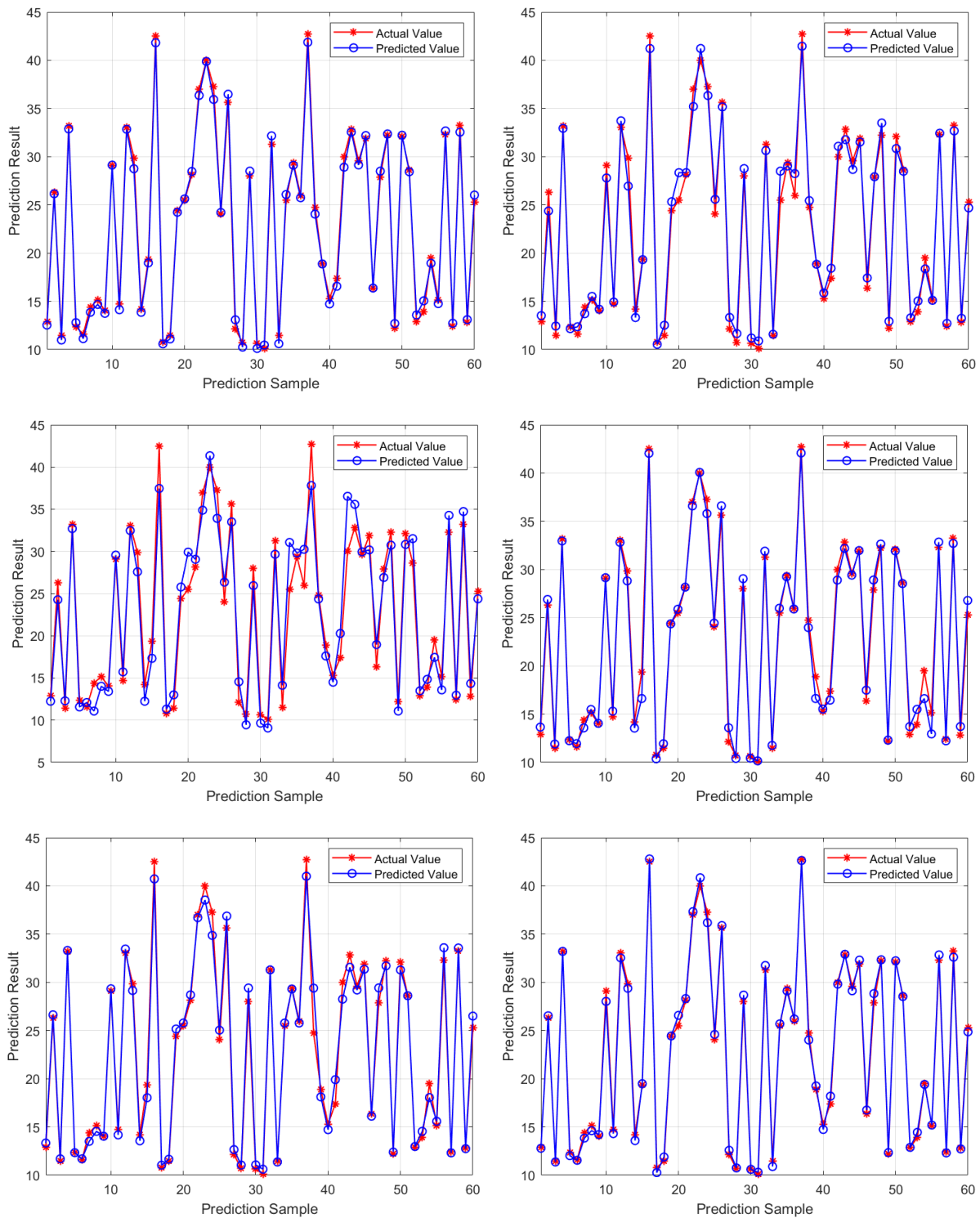
In order to evaluate the feasibility and advantages of IVY-BP neural network in the heating and cooling load of buildings, this study systematically compared the IVY-BP model with five other baseline models: unoptimized standard BP neural network [37], BP neural network model optimized by genetic algorithm (GA-BP) [38] convolutional neural network [39–41], random forest (RF) [42] and extreme learning machine (ELM) model [43]. A variety of optimization strategies were used in the study to adjust the parameters of the BP neural network while maintaining the consistency of input features to ensure a fair and comprehensive evaluation of the model performance under the same data set and experimental conditions. In order to more intuitively show the prediction performance of each model, the study provides prediction curves of predicted values and actual values. These charts show the performance of BP, GA-BP, ELM, CNN, RF and IVY-BP models on the test set.

This paper shows the performance of six models (CNN, ELM, BP, RF, GA-BP and IVY-BP) in the building energy efficiency prediction task through Figures 4 and 5, and makes a visual comparison for heating load and cooling load respectively. Overall, the IVY-BP model shows the best prediction accuracy and stability in both tasks, followed by the CNN and GA-BP models, which can better fit the actual load change trend. However, the prediction curves of the ELM and RF models fluctuate greatly, have obvious errors, and perform relatively poorly. The difference in the prediction effect of the models is mainly attributed to the differences in their structural design, optimization mechanism and nonlinear modeling capabilities. IVY-BP enhances the global search and parameter adjustment capabilities by introducing the ivy optimization algorithm, effectively avoiding falling into the local optimum, and thus performs best in the prediction of heating load and cooling load. CNN relies on the convolution structure to have good feature extraction and nonlinear fitting capabilities, and the prediction results are also relatively accurate. GA-BP improves the generalization of the model with the support of the genetic algorithm, which is better than the basic BP network. In contrast, ELM has poor prediction stability due to random initialization and lack of weight optimization in the training process; the RF model is easily affected by sample fluctuations and overfits, resulting in large fluctuations in results. Therefore, models with optimization mechanisms and strong expression capabilities have more advantages in building load

forecasting tasks. Comprehensive analysis shows that IVY-BP is more suitable for high-precision building energy consumption prediction scenarios and has stronger practical application value.



**Figure 4.** Comparison of cooling load prediction results of different models (From top to bottom: BP model, CNN model, ELM model, GA BP model, RF model, IVY-BP model).



**Figure 5.** Comparison of heating load prediction results of different models (From top to bottom: BP model, CNN model, ELM model, GA BP model, RF model, IVY-BP model).

After evaluating the performance of the heat load and cooling load prediction tasks in building energy consumption, it was found that the performance of each model on different load types was significantly different, as shown in Tables 3 and 4. Overall, the IVY-BP model achieved the best performance in both types of load predictions, mainly due to its introduction of the Ivy optimization algorithm, which effectively improved the global search ability and fitting accuracy of the model.

In terms of cooling load prediction, IVY-BP showed excellent stability and accuracy with the lowest MAE (0.6636) and RMSE (0.8709), and the highest  $R^2$  (0.9902); GA-BP and BP followed closely, indicating that the BP network has good prediction ability after optimization. However, the CNN and ELM models have large errors, especially ELM, which lacks a weight adjustment mechanism during training, and its generalization ability is obviously insufficient when facing complex fluctuations in cooling load.

**Table 3.** Performance comparison of models on heat load prediction.

Model	MAE	RMSE	$R^2$
CNN	0.9904	1.4442	0.9634
ELM	1.8281	2.2776	0.9423
RF	0.7315	1.0665	0.9874
BP	0.6749	0.9121	0.9901
GA-BP	0.6647	0.9231	0.9893
<b>IVY-BP</b>	<b>0.3691</b>	<b>0.4642</b>	<b>0.9976</b>

**Table 4.** Performance comparison of models on cold load prediction.

Model	MAE	RMSE	$R^2$
CNN	1.8345	2.2954	0.9435
ELM	2.1606	2.7513	0.9022
RF	1.2181	1.7046	0.9625
BP	1.1198	1.6804	0.9635
GA-BP	0.9806	1.4531	0.9727
<b>IVY-BP</b>	<b>0.6636</b>	<b>0.8709</b>	<b>0.9902</b>

In heat load forecasting, IVY-BP also showed the best forecasting ability, with  $R^2$  as high as 0.9976, indicating that its fit is close to perfect; GA-BP and BP performed stably with small errors, showing strong nonlinear modeling capabilities; CNN performed moderately and was suitable for load data with relatively stable trends; ELM and RF models still performed poorly in this task, reflecting their lack of adaptability to complex patterns.

IVY-BP performed well in both load types, and the model effect for building energy consumption forecasting was relatively good, and the optimized BP network (such as GA-BP) also had high application value. For models with simple structures but lack of training mechanisms (such as ELM and RF), it is not recommended to be used in high-precision energy consumption forecasting scenarios.

## 5. Discussion

The sample size has a significant impact on the stability and performance of deep learning models. Especially in models like BP neural networks, insufficient or imbalanced sample sizes can lead to overfitting or poor generalization, thus affecting prediction stability. Research shows that the IVY-BP model exhibits high stability using 768 samples from the UCI energy efficiency dataset. This is attributed to the global optimization of the IVY algorithm, which effectively mitigates overfitting problems common with smaller datasets and helps the BP network avoid local minima. However, model performance is still affected by sample size; smaller samples may not adequately capture the complex patterns of energy consumption, thus impacting performance. Future research could explore the impact

of dataset size on model generalization ability and consider strategies such as data augmentation or synthetic sample generation to improve model stability with small sample sizes.

## 6. Conclusions

To address the complexity of building energy consumption prediction, this paper proposes an IVY-BP hybrid model that utilizes the swarm collaboration mechanism of the Ivy Growth Optimization algorithm to provide the BP network with superior initial weights and structure. Experimental results demonstrate that this model exhibits extremely high prediction accuracy and robustness in both HL and CL prediction tasks, comprehensively outperforming comparative models. The successful application of IVY-BP not only proves the advantages of hybrid heuristic algorithms in processing high-dimensional building data but also provides technical support for the intelligent control of air conditioning systems through accurate energy consumption prediction, resulting in significant social energy-saving benefits. Despite the current positive results, future research will further focus on improving the model's cross-climate regional generalization ability and exploring its hardware implementation on real-time online prediction devices.

## Data availability statement

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

## Declaration of generative AI and AI-assisted technologies

During the preparation of this work, the authors used generative AI and AI-assisted technologies (ChatGPT) to improve the clarity and readability of the manuscript, including language polishing and grammar checking. The authors confirm that all content generated with the assistance of AI tools was carefully reviewed, revised, and validated to ensure its accuracy and integrity. The authors take full responsibility for the final content of the manuscript.

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## Authors' contribution

Conceptualization, F.Y. and H.H.; methodology, F.Y.; validation, F.Y., J.G. and T.X.; formal analysis, F.Y. and J.G.; investigation, F.Y. and T.X.; resources, H.H. and Z.T.; data curation, F.Y. and Y.F.; writing—original draft preparation, F.Y.; writing—review and editing, J.G., T.X. and H.H.; visualization, F.Y. and Y.F.; supervision, H.H. and Z.T.; project administration, H.H.; funding acquisition, H.H. All authors have read and agreed to the published version of the manuscript.

## Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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