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Building HVAC Electric Load Demand Prediction: Balancing Learning Rate and Hidden Layers for Improved Model Performance

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Abstract: This study examines the performance of a predictive model for building HVAC electric load demand under three distinct conditions. The analysis focuses on two key metrics: the coefficient of variation of the root mean square error (CVRMSE) and the coefficient of determination (R^2). Results indicate a notable disparity in model fitting across the conditions. For conditions 1 (learning rate =0.0001, hidden layer =7) and 3 (learning rate =0.0001, hidden layer =5), an increase in iteration rounds leads to a decrease in CVRMSE, signifying enhanced prediction accuracy. Conversely, condition 2 (learning rate =0.01, hidden layer =7) exhibits an increase in CVRMSE with more iterations, suggesting reduced accuracy. The R^2 values consistently rise with additional iterations across all conditions, indicating improved model fit. However, condition 2 presents a slightly larger discrepancy between the training and test sets compared to conditions 1 and 3. These findings highlight the varying impacts of iteration on model performance across different scenarios. The study underscores the importance of tailoring model parameters, such as learning rate and hidden layers, to specific conditions to optimize predictive accuracy. This research contributes to the understanding of how iterative processes and model configurations affect the accuracy and reliability of HVAC load predictions, offering insights for future model development and application in energy management systems.

Keywords: Neural Network; Machine Learning; Learning Rate; Hidden Layer; Electric Load Demand Prediction

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1.Introduction

Energy is a crucial foundation for a country's long-term stable development. However, as society continues to develop, modernization is rapidly advancing. With population growth, the demand for a higher quality of life increases, leading to a rising demand for energy. Energy production is gradually failing to keep up with consumption, resulting in an energy crisis. Nowadays, it has become the most concerned global issue. According to Energy Information Administration (EIA) of the US, global energy demand is expected to rise by 50% over the next 30 years, with carbon emissions projected to increase by 35% compared to 2020 [1]. Among the global energy consumption, the building sector contributes to 36 % [2], the heating, ventilation, and air conditioning (HVAC) system accounts for about 50% [3] of the total energy consumption in a typical building. Therefore, optimizing HVAC operations off ers signifi cant potential for energy savings. Among the existing methods for optimizing operations, deep learning models present significant advantages. These models can use raw data to predict the short-term power demand of HVAC systems. This allows for the identification of daily peaks and troughs in power demand and helps outline the approximate demand curve. By analyzing the influence of each variable on power demand, deep learning models enable the development of more effective energy-saving plans.

Currently, there are three main types of methods for predicting energy consumption: white-box models, black-box models, and grey-box models. The white-box model is a physical energy model of a building, based on detailed building parameters and heat balance equations. However, it is time-consuming and requires prior knowledge. The grey-box model combines building physical information with historical data sources. But a notable disadvantage is that it does not account for internal heat gains and occupant behavior [4]. The most representative of these is the RC model (resistance-capacitance model), a widely used hybrid model. It effectively represents both the physical components of a building and its dynamic processes. For example, it models heat transfer through the external envelope and changes in regional air. Usually, physical models offer higher prediction accuracy compared to statistical models. However, developing detailed physical energy models for each building can be a tedious task. As an alternative, black-box models have gained popularity in recent years due to the rapid development of big data technologies.

Based on previous studies, some studies have identified a variety of machine learning algorithms. Common algorithms include Support Vector Regression (SVR) [5, 6], Random Forest (RF) [6, 7], XGBoost [8, 9], Deep Learning, and Artificial Neural Networks (ANNs) [10]. ANN is a nonlinear statistical algorithm inspired by biological neural network, which has powerful learning, training and prediction functions.

The BP neural network is a common artificial neural network model known for its strong nonlinear mapping ability and adaptability. In this study, the BP neural network is used to model the HVAC electric load demand of buildings. The neural network is trained and optimized using historical data. Once training is complete, new data is input into the neural network for prediction, yielding the corresponding output results. Through this method, the key parameters such as learning rate and the number of hidden layers are explored. The proposed method, based on the BP neural network prediction model, offers several advantages: (1) It has strong nonlinear mapping ability and adaptability, allowing for more accurate predictions of electric load demand; (2) It features low computational complexity, enabling fast predictions. The HVAC electric load demand prediction method is implemented using the MATLAB programming language, and the method's effectiveness and accuracy are verified. The research findings provide valuable insights for the rational planning of air-conditioning electric load demand.

2. Methods

2.1 Determination of influencing factors

The electricity consumption of air conditioning systems generally includes three main components: the heating and cooling sources, the working fluid transmission systems, and the air conditioning units along with terminal equipment. Each of these components involves numerous and complex influencing factors, resulting in a wide variety of elements affecting the overall air conditioning load. Therefore, it is necessary to analyze and identify the primary influencing factors. Below are several key areas:

Building Characteristics and Thermal Load Factors: This section focuses on building area and volume, the thermal insulation performance of the building envelope, and fresh air requirements. These factors significantly influence the thermal load and, consequently, the electricity consumption of air conditioning systems.

External Environment and Climatic Factors: Outdoor temperature, humidity, and wind speed are critical external factors impacting power consumption. Understanding these climatic influences is essential for accurate load prediction and energy management.

Air Conditioning System Factors: This includes the system type, equipment energy efficiency, pipeline design, and control systems. These internal factors determine how effectively the system operates and its overall energy efficiency.

This study begins by introducing the data sources for air conditioning load. A literature review is conducted to select factors influencing electricity demand, ensuring a comprehensive analysis of the factors affecting air conditioning load. Next, the preprocessing process of load data is described in detail. By constructing and selecting features, the diversity of input parameters for the model is enriched. Finally, the evaluation metrics for load prediction are introduced, and appropriate metrics are selected to ensure the accuracy of the model's predictions.

2.2 Data description

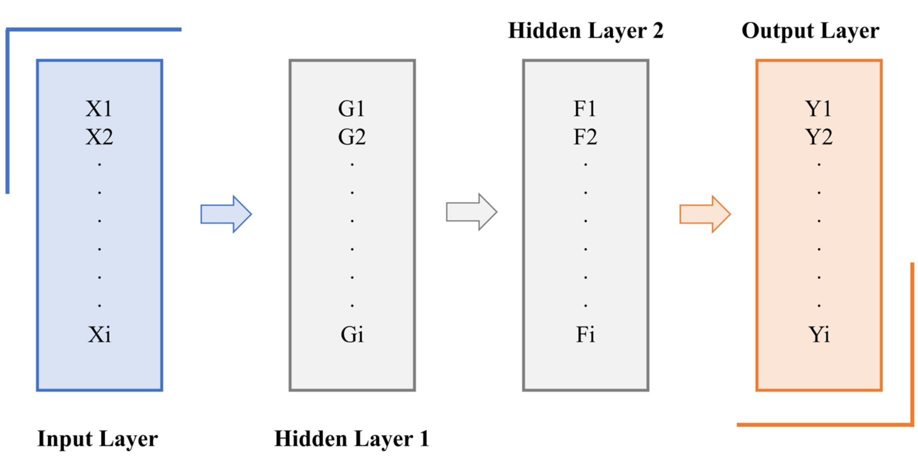
The data to be analyzed in this research are retrieved from a small office building. The total floor area is around 522.0 m^2. One month data are collected with a collection interval of 60 min. The variables included in this database contains five-time variables the dry bulb, relative humidity, wind speed, total floor area, cooling temperature set point. The building roof type is attic roof with wood joint [11]. The cooling type is air source heat pump. This study selected the most important input feature variables in Table 1 to simplify the model, and some not important variables such as airtightness are neglected.

Table 1. Input variable ranges for the small office buildings.

No.	Input Feature Variables	Unit	Value
1	Dry Bulb	℃	[−32.8, 37.0]
2	Dew Point	℃	[4, 100]
3	Relative Humidity	%	[0, 14.9]
4	Atmos Pressure	Pa	[81300,102800]
5	Wind Speed	m/s	[22.78, 25.00]

The power demand of the air conditioning system is related to the indoor and outdoor temperatures, the indoor area and Atmos pressure. Feature set is constructed using unsupervised deep learning. As shown in Fig. 1, the deep auto-encoder model developed has a symmetric structure with four layers in total.

Fig. 1: Schematic of the deep auto-encoder model for feature extraction.



The entire dataset is divided into training, validation, and testing data with proportions of 70%, 15%, and 15%, respectively. Deep learning models include several hidden layers, and the training process is complex. In this study, four parameters of the deep learning models are optimized: (1) the number of hidden layers, (2) the dropout ratio at the input layer, (3) the learning rate (LR), and (4) the activation function. It should be noted that the number of neurons in each hidden layer is set as constant in this study to reduce the computational load associated with parameter optimization. The rule of thumbs in neural network is Eq. (1).

$$\frac{No.of\ inputs + No.of\ outputs}{2} \tag{1}$$

Since the sample data units are not uniform, it is necessary to normalize the initial data before using MATLAB software to train the neural network. Normalization not only accelerates the training speed but also improves the model's generalization ability and expands its scope of application. The normalization process ensures that all input features are on a similar scale, which helps the neural network learn more effectively. The normalization formula is as follows:

$$Z = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

Where, X represents the original data value; $X_{\min}$ is the minimum value in the dataset, and the $X_{\max}$ is the maximum value.

3.Results and discussion

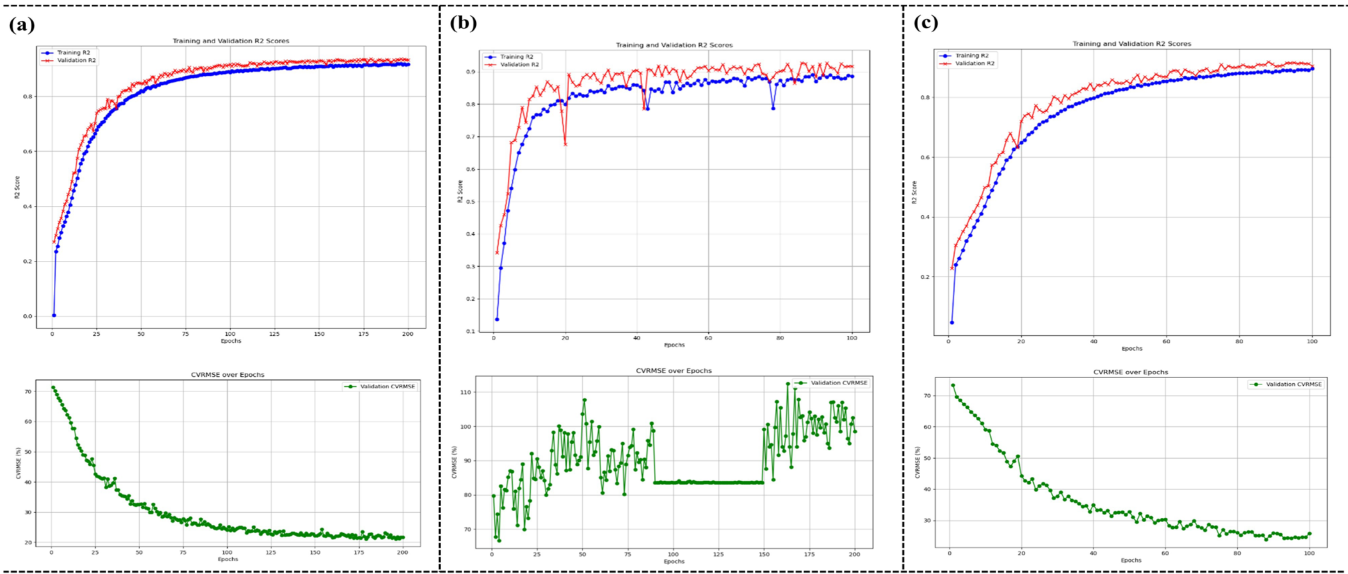
As shown in Table 2, three working conditions are set to compare the influence of learning rate (LR) and hidden layer on the Electric load demand prediction of building air-conditioning.

Table 2. Working condition setting.

Parameters	**Condition 1**	**Condition 2**	**Condition 3**
LR	0.0001	0.01	0.0001
Hidden layers	7	7	5
The Proportion of Testing Data	0.2	0.2	0.2

Fig. 2 illustrates the fitting results under three different conditions, revealing a significant gap among them. The CVRMSE (Coefficient of the variation of the root mean square error) values indicate that as the number of iteration rounds increases, the overall trend of CVRMSE decreases in working conditions 1 and 3, leading to improved model prediction accuracy. In contrast, working condition 2 shows an opposite trend. Similarly, the R^2 (R2 scores) values increase with more iteration rounds across all three conditions. However, the difference between the training set and the test set in condition 2 is slightly higher compared to conditions 1 and 3.

Fig. 2: Results: (a) Condition 1, (b) Condition 2, and (c) Condition 3.



Additionally, research indicates that increasing the number of hidden layers can enhance the model's complexity, thereby improving its ability to handle nonlinear problems. This improvement helps the model fit complex data more accurately. However, adding more hidden layers also significantly extends the training time. Moreover, too many hidden layers may lead to decreased performance on the validation set, as indicated by an increase in CVRMSE.

On the other hand, the choice of learning rate also significantly impacts the model's training effectiveness. A lower learning rate can help the model converge more stably, avoiding overshooting the global optimum. However, if the learning rate is too low, it may result in excessively long training times. Conversely, a higher learning rate can speed up training but may cause the model to get stuck in local optima, increasing the risk of overfitting. Therefore, it is crucial to find a balance between the learning rate and the number of hidden layers during model training to ensure both accuracy and generalization capability.

4.Conclusion

This study underscores the crucial role of learning rate and hidden layer configuration in predicting building HVAC electric load demand. The findings indicate that scenarios with a lower learning rate and an optimal number of hidden layers, such as conditions 1 and 3, generally achieve superior prediction accuracy. This is reflected in the decreasing CVRMSE values and increasing R^2 scores as iteration rounds increase. Conversely, condition 2, which employs a higher learning rate, yields less favourable outcomes, highlighting the need for careful parameter selection.

The research suggests that adding more hidden layers can improve the model's capacity to manage complex, nonlinear data. However, this can lead to longer training times and potential overfitting, as indicated by higher CVRMSE on the validation set. Similarly, while a lower learning rate supports stable convergence, it may extend training duration. In contrast, a higher learning rate can speed up training but may cause the model to become stuck in local optima.

Thus, finding the right balance between learning rate and hidden layer configuration is essential for optimizing both the model's accuracy and its ability to generalize. This balance ensures that the model not only fits the training data effectively but also performs well on new, unseen data.

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no

Conflict of Interests

The author(s)declare(s) that there is no conflict of interest regarding the publication of this paper.

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