Prediction of Energy Consumption of Group Buildings Based on BP-LSTM Neural Networks

Xiaotong Yan

School of Civil Engineering, Guangdong University of Technology, Guangzhou, 510006, China

dawnwhiteyan@163.com

Abstract. Aiming at the problem that it is difficult to collect the variables that affect the prediction of building energy consumption, this paper proposes a BP-LSTM neural networks prediction model based on the combination of natural factors and human factors. First, the three basic natural factors of sunshine time, temperature, and precipitation are used to predict BP neural networks. Then according to the corresponding time, LSTM neural networks are used to predict, and a BP-LSTM combined building energy consumption prediction model is established. Taking the data of the past ten years in South China as an example, the sequential combined prediction model has higher precision and wider applicability, thus providing an effective treatment method for group architectural planning.

Keywords: energy consumption prediction; BP neural networks; LSTM neural networks; group building; building planning

1 Introduction

1.1 Background and current situation

In recent years, in response to the development needs of the times, the energy consumption of various countries and regions is on the rise, and building energy consumption accounts for the main part. A few policies have put forward clear energy conservation and emission reduction goals, and the focus is also biased toward the construction sector[4]. China's building energy consumption accounts for about one-third of the total energy consumption of society, and its proportion in the total energy consumption of the whole society has risen from 10% in the late 1970s to 30% in recent years[3]. Adding the amount of energy consumed in the production of building materials, the proportion of building energy consumption is as high as 46.7%. Data show that China's annual new housing is 2 billion square meters, more than 99% of high-energy buildings, heating energy consumption per unit of building area for more than three times the new buildings in developed countries[5].

The second meeting of the Central Committee for Comprehensively Deepening Reform recently held in China emphasized the construction of a new higher- level open

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economy system to promote the gradual shift from energy consumption dual control to carbon emission dual control, improve the energy consumption dual control system, and strengthen the basic capacity building of carbon emission dual control., improve various supporting systems for carbon emission dual control.

Chinese scholars Xian Guo Wu, Ting Ting Deng, Bin Chen, and others obtained energy consumption data sets through simulation models and then used the models to predict energy consumption, which provided a feasible solution in the design stage[6]. Similarly, scholar Ting Fei Zhang and others constructed a network algorithm for long short-term memory by analyzing the characteristics of building energy consumption data and combining recurrent neural networks and considering the time lag property according to the data characteristics, which has a certain degree of research significance[2]. Scholar Patrick Shiel et al. calibrated the existing model basis and conducted a sensitivity analysis, and Quantitative Analysis was performed on the identification of buildings with different parameter settings after testing[8]. Many scholars have simulated and analyzed various possible energy consumption influencing factors in building energy consumption prediction with different dimensions, using a variety of algorithms, including support vector machines, artificial neural networks, random forests, etc., and from a three-dimensional view Display the impact of building parameters on energy consumption, providing the necessary elements for visual analysis[10].

1.2 Purpose and development direction

Building energy consumption, in a broad sense, refers to the energy consumption generated by the building from construction to completion, and in a narrow sense, refers to the energy consumption of the building, mainly including heating, air conditioning, lighting, household appliances, work equipment, water supply, and other energy consumption. There are many types of energy consumption, and the factors affecting energy consumption are also more diverse.

At present, the building energy consumption objects studied in China are mainly concrete single buildings, the data involved are very accurate, and the applicable groups for its energy consumption prediction are relatively specific. China has a large building group. Compared with single buildings, group buildings are larger in scale and have relatively complex influencing factors, such as building orientation and local climate. Every single building in a group building also has different characteristics, and the group building lacks sufficient group building information and measured building energy consumption data. It is difficult to apply group buildings in practice only by relying on the energy consumption research of existing single buildings. Therefore, this study starts from the whole, extracts common data, introduces the overall energy consumption through various connections, and then combines the existing three-dimensional urban geographic information system research to improve the built model.

2 Establishment of BP-LSTM Energy Consumption Prediction Model

2.1 Establishment of BP neural networks energy consumption prediction model

According to the data of South China from 2012 to 2021 in China Statistical Yearbook, the indoor temperature (A), sunshine time (H), and precipitation (R) are extracted as the input nerve cells of the BP network in annual time units, and the annual electricity consumption is defined as the output.

Since South China includes Guangdong Province, Guangxi Zhuang Autonomous Region, and Hainan Province, the average value of each variable of the three is used as the input variable of the entire South China region in the data processing process, and then the data is normalized.

Therefore, the normalized result of the input vector of the neural networks is:

$$X = A1H1R1 \vdots\vdots\vdots A10H10R10 = -0.221, -0.912, -0.931 \vdots\vdots\vdots 0.698, 1.208, -1.125 \tag{1}$$

$$Ai = 13ai; Hi = 13hi; Ri = 13ri; i = 1,2,3 \tag{2}$$

Among them, "1" represents Guangdong Province, "2" represents Guangxi Zhuang Autonomous Region, and "3" represents Hainan Province.

The output vector is:

$$Y = y1 \ldots y10T \tag{3}$$

Using Bayesian regularization to train it can limit the weights of neural networks and solve the problem of overfitting the training data[1]. First, a measure of the weight size is added as a regularize to the loss function, assuming that the loss function is the average square of the prediction error.

$$L = (1/N) sigma\ Y - F\ X2 \tag{4}$$

Where X and Y are input and output vectors, F(X) is the prediction of neural networks, and "N" is the number of observations with a value of 10.

With the addition of the L2 regularizes, this becomes

$$L = (1/N) sigma\ Y - f\ X2 + \lambda 2 \times sigma\ w2 \tag{5}$$

Where λ is the regularization coefficient and w is the weight vector of the neural networks. For this new loss function, the weights in backpropagation are updated to:

$$\Delta w = \eta \times\ Y - f\ X \times F'X \times X - \lambda \times w \tag{6}$$

Where F (X) is the derivative of f and η is the Learning Rate. Set the number of layers to 10, select 70% of the data as the training dataset, and 30% of the data as the test set, integrate the training and test results, select the optimal parameters, improve the generalization ability of the model, and obtain a correlation coefficient of 0.9711.

It can be seen from Fig.1. that the effect of Model Training is better. Although the test results are slightly biased, the final fitting effect is in line with expectations. Since brief elements are the main elements in the model-building process, and the other influencing factors involving energy consumption are only set up with fixed values to reduce errors, the dynamic adjustment aspect has not been specifically tested, so the use of the model still needs to be strengthened. But in terms of the overall effect, this direction is more feasible.

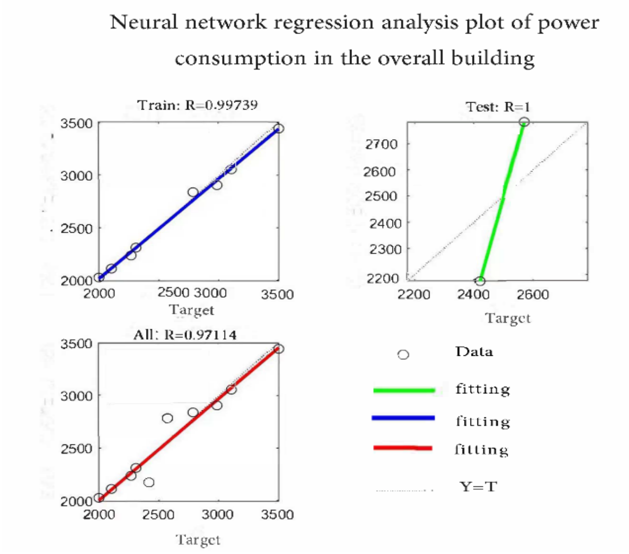

Fig. 1. Neural network regression analysis plot of power consumption in the building

2.2 Establishment of LSTM neural networks prediction model

Since the models studied above need to be carried out under the relevant data of existing natural factors, there is no clear prediction method for specific natural data. This study predicts all aspects of climate data from the time series based on the interrelationship of climate so that it can be further inverted and applied to the energy consumption prediction model of BP neural networks.

LSTM is a special type of recurrent neural network (RNN). The advantage of LSTM over ordinary RNNs is that it can solve long-term dependency problems more efficiently. A basic form of the formula is as follows:

$$\text{Input gate (i): } i = sigmoid\ (Wi \times [h\ (t-1), x\ (t)\ ]) \quad (7)$$

$$\text{Forgetting gate (f): } f = sigmoid\ (Wf \times [h\ (t-1), x\ (t)\ ]) \quad (8)$$

$$\text{Output gate (o): } o = sigmoid\ (Wo \times [h\ (t-1), x\ (t)\ ]) \quad (9)$$

Cell state:

$$\text{New alternative memory (g): } g = tanh\ (Wg \times [h\ (t-1), x\ (t)\ ]) \quad (10)$$

$$\text{The updated memory unit (C): } C\ (t) = f\ (t-1) + i\ (g) \tag{11}$$

$$\text{Calculate the current state (h): } h\ (t) = o\ Treasury\ (C\ (t)) \tag{12}$$

Taking the average temperature as an example, 70% of the data is selected as the training dataset, and 30% of the data is selected as the test set. The initial number of layers is set to 10, and the number of time steps is 3. Combined with the error range and fitting effect, the reasonable number of layers and time lag are continuously adjusted. Through multiple Model Training results, the optimal number of layers is 50, the number of time steps is 5, the final mean square error is 0.8698, the correlation coefficient is 0.8343, and the error remains between [-1,1], as shown in Fig.2.

Since the second layer model is generated based on time lag, the impact on energy consumption mainly refers to the past time, and the possible factors in the future will be ignored to a certain extent. For the error in Fig.2., it is initially explained as unpredictable and unnecessary factors, which have little impact on the overall forecast target.

For the average annual temperature, the data in winter and summer are quite different. Since South China is in the subtropical region, the difference is smaller than that in other regions, so the error is adjusted to within 1 degree Celsius. The final neural network time sequence model training is Consistent with preliminary assumptions.

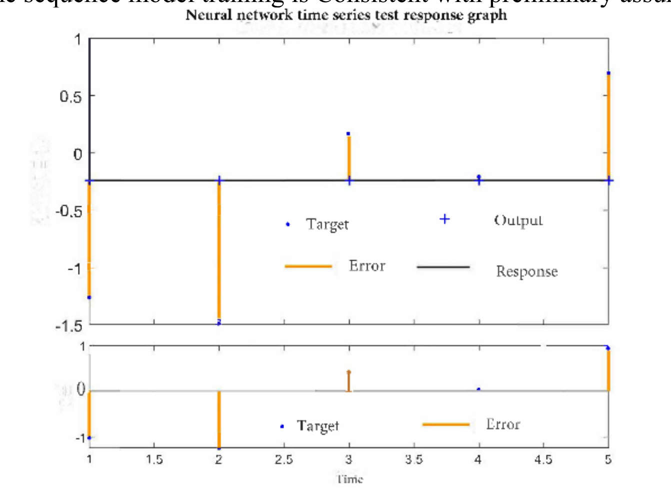

Fig. 2. Neural network time series test response graph

2.3 Analysis and Fusion of BP-LSTM Algorithm for Energy Consumption Prediction

The energy consumption prediction based on the BP neural networks algorithm is based on the data of the three natural factors of temperature, sunshine time, and precipitation, and obtains the electricity consumption of the year; while the energy consumption prediction based on the neural networks time series algorithm based on LSTM is Based on the premise of accumulating data from each natural factor, using past data and climate correlation to predict the data of the next year.

Aiming at the problem that individual users are difficult to collect specific relevant data, from the perspective of facilitating client base, the corresponding building energy consumption can be inferred by knowing the user's regional information. In this study, the BP-LSTM double-layer prediction model is used, and the input information is first set as common information, such as city, region, prediction time, predicted energy consumption, etc. Secondly, the independent prediction of the first layer is carried out, and the relevant data of the specified time can be deduced according to the LSTM prediction model; then the prediction of the second layer is carried out, and the corresponding energy consumption is calculated according to the BP neural networks energy consumption prediction model.

3 Model Application and Extension

The model prediction of the first layer can calculate the output value of the prediction time based on historical data, and the prediction model of the second layer substitutes the output value corresponding to the prediction time into the trained BP network[9].Output layer backpropagation to the input layer updates and optimizes the weights, and the final output value is the output data initially selected by the user. The two-layer prediction model can effectively respond to user requests, the input data of the front end is not difficult to collect, the output data of the endpoint is more accurate, and finally, the weight analysis of the proportion of building energy consumption is carried out to obtain the final energy consumption data. The accuracy of this output value compared with the energy consumption prediction of single buildings needs to be improved, but the client base involves a wide range and can go deep into the relevant users of commercial buildings, civil buildings, industrial buildings, and other types of buildings. For commercial buildings, the output value of the double-layer prediction model can be used as a reference value, combined with the corresponding policies to provide enterprises with more reasonable energy-saving suggestions; for residential users, the output value of energy consumption prediction can be combined with the corresponding energy charging standards. Provide users with early warnings and corresponding energy-saving suggestions in a numerical range.

Taking China's tiered electricity tariff as an example, the three known influencing factors are input into the model to obtain the predicted value for a specified time, and an early warning trigger condition is embedded before that[7].Here, it is set as the boundary value between the three grades, and the year is used as the time unit, that is, the value is less than 24kW/h, between 2892kW/h and 4800kW/h, and greater than 4800kW/h. When the predicted value is close to the above boundary value, an iconic early warning signal will be displayed on the visual interface for user reference.

4 Conclusions

Through long-term data query and data collection, this study aims to extend the prediction of building energy consumption to more client bases, simplify complex data elements as much as possible while maintaining the accuracy of the prediction, and use recurrent neural networks and backpropagation neural networks to combine into a two-layer prediction model to deepen the connection between the data and obtain the energy consumption. The key findings of this study include that the corresponding output values will change depending on building types, and the energy consumption of group buildings of the same type basically remains within a unified numerical range; at the same time, using the neural networks algorithm of long short-term memory, It is more reasonable to control the number of time steps within 4-5, and the comprehensive weight predicts future data more accurately. This research is of great significance to the early design and end-point feedback of engineering project management. Combined with a powerful data system, it can make early design opinions, real-time monitoring, early warning, and reasonable improvement suggestions for the planning and management of large group buildings.

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